Vieira, Yesus Emmanuel Medeiros; Francisco, Fábio de Rezende; Silva
Júnior, Orivalde Soares da; Bandeira, Renata Albergaria; Leal, Jose Eugenio
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PRODUCTION
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Sustainability in bicycle sharing systems: evidences of travel mode choice changings in Rio de Janeiro

Yesus Emmanuel Medeiros Vieira[a]* , Fábio de Rezende Francisco[a] ,
Orivalde Soares da Silva Júnior[a] , Renata Albergaria Bandeira[a] , Jose Eugenio Leal[b]

[a]Instituto Militar de Engenharia, Rio de Janeiro, RJ, Brasil

[b]Pontifícia Universidade Católica do Rio de Janeiro, Rio de Janeiro, RJ, Brasil

*yesuscad@gmail.com

Abstract

Paper aims: This study aims to analyze the travel behaviors changings and the emissions reduction of CO_2, CO, NO_x and Particulate Matter (PM) promoted by the bicycle sharing system in the city of Rio de Janeiro.

Originality: The bicycle sharing systems have been experiencing rapid development in recent years, however, few empirical studies explore comprehensively the externalities of bicycle sharing, seeking to quantify the impacts of this travel system type on urban transport.

Research method: The research method used a modal distribution model calibrated with stated preference interviews and travel data provided by Tembici company.

Main findings: Results indicated a reduction in 2018 CO_2 emissions compared to the existing system in 2014, not only because of the increase in the bicycle sharing system offer, but also due to a higher transfer rates from motorized transport to bicycle, particularly those originated from public transport and Transportation Network Company (TNC) services.

Implications for theory and practice: Results reveal the bicycle sharing in the city of Rio de Janeiro should be understood as a part of a process of adopting multimodality, with effective reductions achieved by the incentive to change passenger's travel behavior.

Keywords

Bike sharing system, Environment benefits, Nested logit model.

1. Introduction

Passenger transport, as well as freight transport, plays a key role in urban environments. However, in recent years, there has been an increase in the levels of motorized individual transport in relation to public transport (Observatório das Metrópoles, 2012), imposing externalities on society, economy and the environment.

Urban transport in general, especially motorized individual transport, requires the use of fossil fuels, generating thus negative environmental impacts, such as the emission of greenhouse gases (GHG), air pollutants, noise, public health problems, road damage, accidents, traffic congestion and the excessive use of public spaces in cities. These problems represent challenges to public authorities and transport planners, who must address such externalities in order to promote a better quality of life to local population.

In this way, this theme has attracted the attention of the academy in the search of sustainable solutions for urban passenger transport (Campos, 2006; Litman, 2007; Guimarães & Leal Junior, 2017). Among the proposed solutions, bicycle sharing has emerged as a viable and sustainable transportation alternative and has received attention in recent years (Wang & Zhou, 2017).

Bicycle sharing systems are often implemented aiming to increase mobility in the first and last miles of passenger transport to other modes of transport, and thus reducing traffic congestion, energy consumption and environmental impact in cities, as well as improving the quality of life and urban population public health (Audikana et al., 2017). However, few empirical studies explore comprehensively the externalities of bicycle sharing, seeking to quantify the impacts of this type of travel system on urban transport.

In this context, this present paper seeks to quantitatively assess the externalities of bicycle sharing systems regarding its contribution to the reduction of CO_2, CO, NOx and Particulate Matter (PM) emissions in the city of Rio de Janeiro, Brazil. The three mentioned pollutants are, in the specific case of transport, among the ones that cause the most impact in urban areas (D'Agosto & Ribeiro, 2009). Additionally, this study aims to analyze travel behavior changings promoted by the bicycle sharing system in the city of Rio de Janeiro, using a modal split model calibrated with stated preference interviews and travel data provided by Tembici Company.

The number of bike sharing is growing worldwide (Suchanek, 2018). In Brazil, the municipality of Rio de Janeiro is the precursor of the national system, started in October 2011 and currently operated by the Tembici Company. Since then, bicycle sharing systems have been implemented in several cities in Brazil: São Paulo, Rio de Janeiro, Salvador, Recife e Porto Alegre. According to information from the Mobilize Website (2018), about 13,5 million bicycle trips were made in 2017. This paper is structured as follows: a history of the bicycle sharing system, the estimation of environmental impacts and its use are presented in Section 2. Section 3 describes the methodology used in the calculation of CO_2, CO, NOx and Particulate Matter (PM) emissions. In Section 4, the application of the proposed methodology in the bike sharing system in the city of Rio de Janeiro is presented, as well as the assessment of results obtained. Finally, Section 5 presents the conclusions, limitations of the research and suggestions for future research.

2. A brief history on bike sharing and estimation of the environmental benefits

The first initiative in the world involving the implementation of a Bike Sharing System (BSS) was in Amsterdam in 1965. The system, called White Bike, failed relatively quickly due to thefts and vandalism, which were facilitated by the fact that bicycles were not equipped with safety features (DeMaio, 2009). This first generation of BSS was characterized by the absence of a payment system or safety devices (Parkes et al. 2013).

The second generation appeared in 1995 in the city of Copenhagen that consisted of a coin's deposit system to perform the transport payment. However, the theft problems persisted (DeMaio, 2009). With developments in security systems such as bicycle tracking and electronic payment systems, risks have been reduced in the management of BSSs. These innovations, along with fixed anchoring stations enabled for Internet & Communication Technologies (ICT), portray the third generation of BSSs (Shaheen et al., 2014).

There has been a growing interest of public managers in the benefits associated with BSSs (Midgley, 2011; Shaheen et al., 2010). As a result, there was a significant increase in third generation BSSs around the world between 2004 and 2014, when the number of cities with bicycle sharing systems rose from 13 to 855 (Fishman, 2016). These cities adopted different operation and prices schemes. In Netherlands, for example, there is a single national bicycle sharing system, a program called "OV-fiets", which operates through the signature of "OV-chipkaart" - a contactless smart card. In London, supported by private sector, the Transport for London, responsible for BSSs system, allows the first 30 minutes to be subsidized with a payment of an access fee of £ 2.00 per credit card. In North America, a Montreal-based company, PBSC Urban Solutions, offers integrated BSS solutions (including bicycles, payment stations, locking systems and smartphone applications) to various cities such as Montreal and Toronto in Canada; Boston, New York and Washington, D.C. in the USA; and Guadalajara and Toluca in Mexico. In South America, the cities of Buenos Aires, Rio de Janeiro and Quito have established partnerships with private entities to operate BSSs. In this way, the fourth generation of BSSs has emerged. It includes features such as solar-powered docking stations, power assisted bikes, transit smartcard integration, and the use of smartphone applications for real-time updates (Parkes et al., 2013). In June 2017, the company Urbo started to operate dockless bicycle sharing programs in Ireland and across Europe.

There are a number of possible social, environmental and health benefits associated with BSSs, such as: (1) reduction in traffic jam, emissions of GHG, air pollutants and noise; (2) flexible mobility, improved transport connection; (3) health promotion; and (4) customer financial savings (Shaheen et al., 2010, 2013). Many of these benefits assume that the implementation of BSSs has encouraged their users to shift the mode of transportation of their trips, previously made by motorized vehicles, for the use of bicycle. For end users the main perceived benefits of BSSs are convenience and low travel cost (Fishman et al., 2013). However, empirical evidence has not reached consensus if such an assumption is actually based on reality (Midgley, 2011).

The first researches on the topic show general agreement with the assumption that the launch of BSSs demonstrated an increase in global cycling activities in urban areas. For instance, the percentage of trips made by bicycles after the launch of the BSSs increased from 0.75% in 2005 to 1.76% in 2007 in Barcelona, from 1.0% in 2001 to 2.5% in 2007 in Paris and from 0.5% in 1995 to 2% in 2006 in Lyon (García-Palomares et al., 2012). In addition, a BSS (OYBike) study in London revealed that 40% of the bike sharing system users previously traveled by cars (Noland & Ishaque, 2006). On the other hand, Pucher et al. (2010) argued that such results were inconclusive because, despite the fact that cycling has been increasing in cities since the introduction of BSSs, the growth of bicycle sharing mode may have been the result of the overall improvement of bicycle facilities. Even so, DeMaio (2009) showed explicitly that the BSS in Montreal was successful, reducing GHG emissions by more than 1,300 tons since its implementation in May 2009, although this figure represents only 0.009% of total greenhouse gases emission from Montreal (13.7 million tons of CO_2 equivalent) (Pembinas Institute, 2019). A recent study by Hamilton & Wichman (2018) revealed that BSSs reduced neighborhood jam in Washington, D.C.

It is important to note that, although several cities around the world have implemented BSSs to encourage the use of bicycles, the success of this system relies on how end-user demand would be met (Frade & Ribeiro, 2015; Wolf & Seebauer, 2014). For end users the main perceived benefits of BSSs are convenience and low travel cost (Fishman et al., 2013). It is noted that there has been no consensus on whether the launch of BSSs has promoted the transfer of trips previously performed by motor vehicles for bicycles.

Shaheen et al. (2011) conducted a survey of BSS users in Hangzhou, verifying that 78% of respondents who owned their own cars used public bicycles to replace their private vehicles. Among those interviewed without a car in their homes, 20% used public bicycles as a substitute for taxis. While this evidence suggests that BSSs are reducing vehicle use, more research is required to determine its true impact on reducing greenhouse gas emissions.

As noted by Fishman et al. (2013), a calculation of emission reductions requires knowledge of the distance traveled using public bicycles, as well as knowing the mode of transport that would have been used if the BSS not existed. Li et al. (2014) proposes a theoretical model that suggests a bicycle sharing system can result in net emission reductions if combined with a policy of taxing these emissions. The proposed model considered a travel disutility function for the auto mode, that consists on the following cost components: in-vehicle travel time, out-of-vehicle walking time, (monetary) travel cost, and additional emission taxes. This last term corresponds to a tax rate per unit of traffic emissions, which is measured in dollars per kilogram. This model, however, was not applied to an existing program. Zhang & Mi (2018), using big data techniques, estimated the impacts of bicycle sharing on energy use and emissions of carbon dioxide (CO_2) and nitrogen oxide (NO_x) in Shanghai from a space-time perspective. By 2016, bicycle sharing in Shanghai saved 8,358 tons of gasoline and reduced CO_2 and NO_x emissions by 25,240 and 64 tons, respectively, representing 0.06% of total transportation emissions (42 Mt). Qiu & He (2018) estimate the impacts of bicycle sharing on economy, energy use, environment and public health. The empirical results show that bicycle sharing programs have significant positive externalities. In addition, CO_2 emissions from road transport in Beijing would decrease by almost 616.04 thousand tons, and emissions of SO_2, NO_2 and CO would decrease by 22.50, 58.64 and 1586.66 tons, respectively, when compared to year 2015.

Although most of the papers and reports suggest that BSSs promote environmental benefits in terms of GHG and air pollutants emission, due to the replacement of cars by active transport, few demonstrate quantitatively this reduction. Thus, this article proposes to quantify the environmental benefits in terms of CO_2, CO, PM and NOx emissions reduction due to the use of the BBS in Rio de Janeiro, BikeRio. CO_2 is the main GHG, while atmospheric pollutants act locally and therefore have a greater impact on urban areas, are CO, NOx and PM (D'Agosto & Ribeiro, 2009).

3. Methodology and data collection

In this section, we present a contextualization of the study area, as well as the data collection process. Besides, it is presented the proposed method for estimating the reduction of GHG and Atmospheric Pollutants emissions due to the modal shift to the BSS.

3.1. Area of study and data collection

With an area of 1,255 km2 and a population of 6.68 million, Rio de Janeiro is the second largest city and the main international tourist destination in Brazil, representing one of the largest economic, cultural and financial centers in the country.

The BSS in the city of Rio de Janeiro, called BikeRio, was released in October 2011 in the South, North and West Zones of the city, through a partnership between Rio de Janeiro City Hall and Itaú Bank, and it is operated by the Serttel concessionaire. The system currently has more than 2,600 bicycles available at 193 dock stations in Ipanema, Copacabana, Leblon, Urca, Centro, Lagoa, Botafogo, Flamengo, Jardim Botânico, Gávea and other neighborhoods of the North and West Zone. In February 2018, the system was replaced by Itaú Bike, with the bicycles and technology provided by the Canadian company PBSC Urban Solutions and operated by Tembici Company.

Currently, Itaú Bike has stations in the North Zone, in the Center of Rio and in Port Zone, interconnecting with the already existing system in South Zone. Recently, this service was implemented in the regions of Barra da Tijuca and Recreio dos Bandeirantes, interconnecting them, according to the existing bicycle routes, with the local beaches, commercial points, and shopping malls, in addition to the BRT TransCarioca, BRT TransOeste and Metro Rio. The stations are powered by solar panels and use locking latches and pins as a security system to difficult bicycle theft. The stations are interconnected by wireless communication system, connected to the Control Center. Figure 1 shows a map of the stations and bicycles in a station.
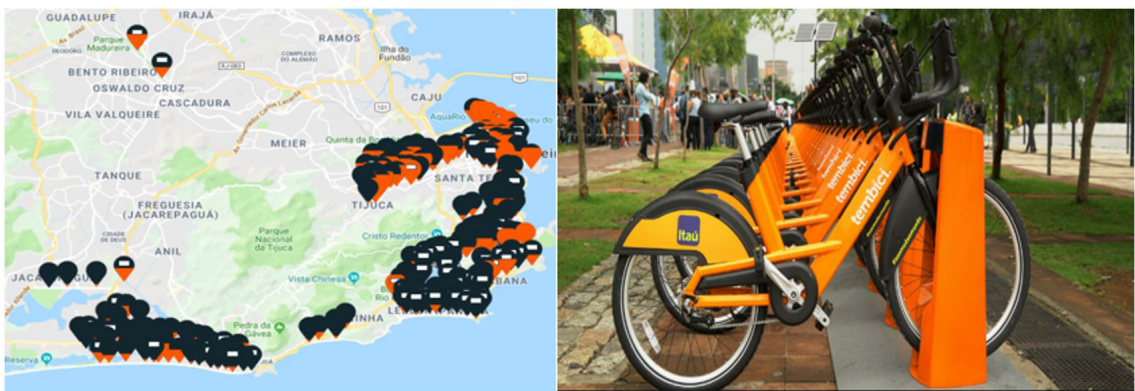

Figure 1. Map of the stations and bicycles in a station.

Data used in this research were provided by the company Tembici, and it corresponds to the period from 07/31/2018 to 10/01/2018. From August to September 2018, the average usage of this system in Rio de Janeiro was 17,476 trips per day with a total of 1,048,575 trips. After excluding trips with the same origin and destination, 926,069 was remained, for each of which data were collected regarding trip start time, longitude and latitude of origin, trip end time, longitude and latitude of destiny.

3.2. The proposed benefits estimation method for bike sharing systems

For estimating the reduction in GHG and air pollutants emissions due to the use of BSS in the city of Rio de Janeiro, we must understand how the modal transfer process occurs, identifying the number of motorized trips avoided. Therefore, it is necessary to define the transport alternatives that would be adopted by the BSS user, if this system were not available.

In this paper, the following alternative scenarios were considered: walking, bus and car transport service provided by Transportation Network Company (TNC), such as Uber or Cabify. It is important to reinforce that recently the use of other modes of individual transport is increasing in cities worldwide, such as the dockless scooter-share services, which were not considered in this research because they only started operating in Rio de Janeiro in 2019. Moreover, while the BSS are being offered for a longer period of time and are primarily used by individuals commuting to and from work, the scooter-share service is not, and it has not been offered for a period of time long enough to build trust within the community, and for many residents these scooters remain a novelty (McKenzie, 2019). The Subway mode was not considered, once this paper has focuses on last mile travel behavior along short travels scenarios up to 5 km, similarly to that adopted by Liu et al. (2019).

The Multinomial Logit Model, widely used in transport problems (Williams & Abdulaal, 1993; Ortúzar, 2000; Kuklys, 2002), was used for establishing the discrete choice model among the three travel alternatives. This model assumes that negative travel pattern factors, such as high direct cost, can be offset by positive factors such as

reduced travel time. Therefore, individuals choose a mode of transport (or a sub-mode), based on the total sum of positive or negative utilities that are associated with factors that influence the trip's accomplishment. Hence, the probability of choosing a given alternative is due to identifiable logical variables in an observed universe, as presented in Equation 1.

$$P_i = \frac{e^{V_i}}{\sum_{j=1}^{n} e^{V_j}}$$
(1)

Wherein: P_i: represents the probability of choosing the transport alternative i;

V_i: corresponds to the utility function of transport mode i.

For the case assessed, three substitute choice options for the BSS (car, bus and walking) are considered, so the probability of using the TNC mode, for example, can be defined by Equation 2.

$$P(TNC) = \left(\frac{e^{V_{TNC}}}{e^{V_{TNC}} + e^{V_{bus}} + e^{V_{walk}}} \right)$$
(2)

In this paper, we used the Nested Logit Model, which is an extension of the multinomial logit model designed to capture correlations between alternatives (Bierlaire, 1998). It differs from the multinomial logit model because it is possible to group alternatives that are similar in the same hierarchy. The grouping of transport alternatives was carried out in two hierarchical levels: (i) level one corresponding to the alternatives of walking and motorized transport; and (ii) level two corresponding to transport by TNC and bus. Figure 2 shows the structure of the Nested Logit Model in two levels, adopted in this paper.
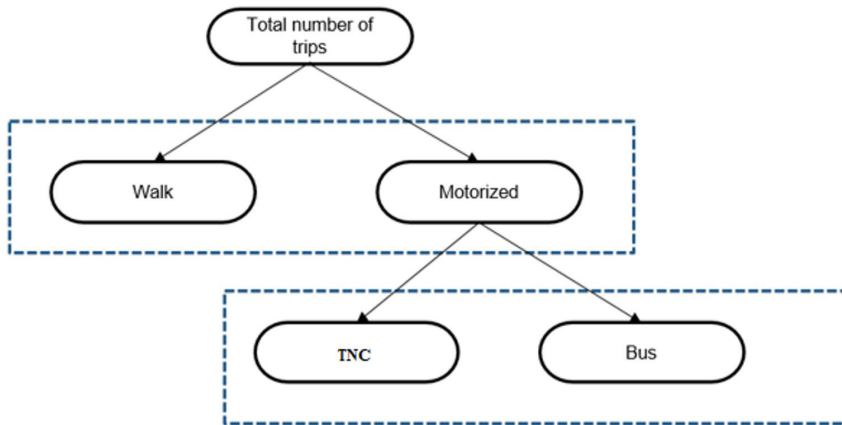

Figure 2. Structure of the hierarchical model used in the article.

The configuration commonly used for the utility function follows a linear additive model (Ben-Akiva & Lerman, 1985), in such a way that $V_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_k X_{ik}$, where $\beta_1, \beta_2 ..., \beta_k$ are the parameters of the model, k is the attribute of the alternatives, and $X_{i1}, X_{i2} ..., X_{ik}$ are the attribute values of the alternatives. In this paper, the following attributes were considered: driving time using TNC *ttnc*; cost of TNC utilization *ctnc*; travel time using bus *tbus*; cost of bus use *cbus*; and walking time *tpe*;

The parameters $\beta_1, \beta_2 ..., \beta_k$, presented in the utility functions of each transport alternatives, were calibrated to better explain the existing modal split. A total of 64 stated preference interviews were carried out with BSS users during November-December 2018, in the neighborhoods of Botafogo and Tijuca, which were chosen because they present a greater flow of passengers and also have BSS stations near subway terminals and transfer stations. The values of the independent variables presented in the questionnaires were determined by varying the hypotheses of the trip and the distances of the trip, in intervals between 0.6 km and 4.8 km. Thus, for each hypothesis of trip, the interviewee had to choose only one of three transport alternatives presented, having as decision criteria the cost and travel time associated with them (Table 1).

After selecting the variables and carrying out the interviews, the Logit calibration was performed using the SPSS 25.0 software, applying the maximum likelihood method to define the final model that minimizes the number of utility function variables of each travel alternative assessed, maximizing the accuracy of the model.

Table 1. Scenarios inserted in the interviews of stated preference.

Scenario	Distance (Km)	ttnc (min)	ctnc (R$)	tbus (min)	cbus (R$)	tpe (min)
1	0.95	5.00	7.50	6.00	4.00	12.00
2	1.4	9.00	7.50	15.00	4.00	18.00
3	4.5	17.00	13.00	19.00	4.00	56.00
4	2.4	11.00	9.00	14.00	4.00	29.00
5	0,6	6.00	9.00	5.00	4.00	8.00
6	1,9	3.00	9.00	11.00	4.00	21.00
7	4,8	14.00	13.00	32.00	4.00	59.00

It was applied the Forward Stepwise Wald (SPSS 25.0 software) (SPSS Inc., 2003), which consists of a regression technique in which the model begins with no variables in the equation, adding one variable at a time, until all of them are in the model or until one stop criterion is satisfied. This procedure starts from the assumption that there is no variable in the model, only the intercept, and the first variable selected is the one with the highest correlation with the response. The variable is kept in the model if the F statistic is greater than the critical point, which is calculated for a given critical alpha. Thus, assuming that a variable x_1 was selected for the model, the next step is to find a variable with the highest correlation with the response, considering the presence of the first variable in the model. This is called a partial correlation, and it is the correlation of the residuals of the model $\hat{y} = \widehat{\beta_0} + \widehat{\beta_1} x_1$ with the residuals of the model $\widehat{x_j} = \widehat{\alpha_{0j}} + \widehat{\alpha_1} x_1 \, j = 2,3 \ldots p$. Therefore, assuming that the largest partial correlation with y is x_2 and this implies that the largest partial F statistic is calculated by expression 3.

$$F_i = \left(\frac{SQR(x_2 \setminus x_1)}{QME(x_1, x_2)} \right)$$

(3)

Wherein: SQR: is the sum of the squares of the model;
QME: is the mean square of the errors, for variables x_1 and x_2. If the value of the statistic is greater than the critical point, x_2 is selected to compose the model.

The utility functions of the three transport alternatives were defined and calibrated. The resulting Logit model was then used to estimate the probability of choosing each transport mode (walk, TNC and bus), considering the case that the BSS was not available. For that, we considered the 37,249 trips between the 193 BSS stations in the origin-destination (OD) matrix formed by the data provided by Tembici. To construct this OD matrix, we used the Google Maps APIs with data from the afternoon peak hours, established as the period between 17h and 18h, as reported by the PDTU of Rio de Janeiro (2015). Moreover, since each pair of origin-destination of this matrix is associated with the geo-referenced localizations of two bicycle sharing stations, it was possible to estimate the travel times, costs and distances for these hypothetical trips, according to each of the three transport modes considered in this study.

The simplifying hypothesis, therefore, is that the distances evaluated in each mode of transport will correspond to the paths that provide the shortest travel time, as shown in Figure 3.

For estimating reductions in GHG and air pollutants emissions due to the modal shift, trip projections were made for the time interval of one year, adopting, in a simplified way, the average value of the trips made in the two months whose data were made available by Tembici. We followed the bottom-up methodology, using the emission factors proposed in the 2nd National Inventory of Atmospheric Emissions by Road Automotive Vehicles (Brasil, 2013). Data on the category and average age of the car fleet was obtained in the data provided by the authors of the Technical Report - GHG Emission Scenarios - 2050 (D'Agosto et al., 2018), and the average age of the bus fleet was obtained from the Summary Report of the transportation system by bus in the city of Rio de Janeiro (Federação das Empresas de Transportes de Passageiros do Estado do Rio de Janeiro, 2018). The percentage of the current fleet according to each type of fuel was obtained from the State of Rio de Janeiro - 2017-2031 Energy Matrix Report (Rio de Janeiro, 2018). Table 2 presents the summary of the factors considered for the calculation of emissions. Since it is not possible to estimate the exact proportion of consumption between gasoline or ethanol options for flex vehicle, the row corresponding to flex vehicle presents the range of values for the hypothesis of gasoline or ethanol use by flex-fuel vehicles, according to MMA (Brasil, 2013).

4. Findings and discussions

From the interviews conducted in Botafogo and Tijuca neighborhoods, we could estimate the number of trips that would be made by bus, TNC or walking, if the BSS was not available, such as shown in Figure 4. The sum of the scenarios 1 to 7 totalizes 256 answers. Since the questionnaire contains 4 possible scenarios, there has been therefore a total of 64 BSS users interviewed.
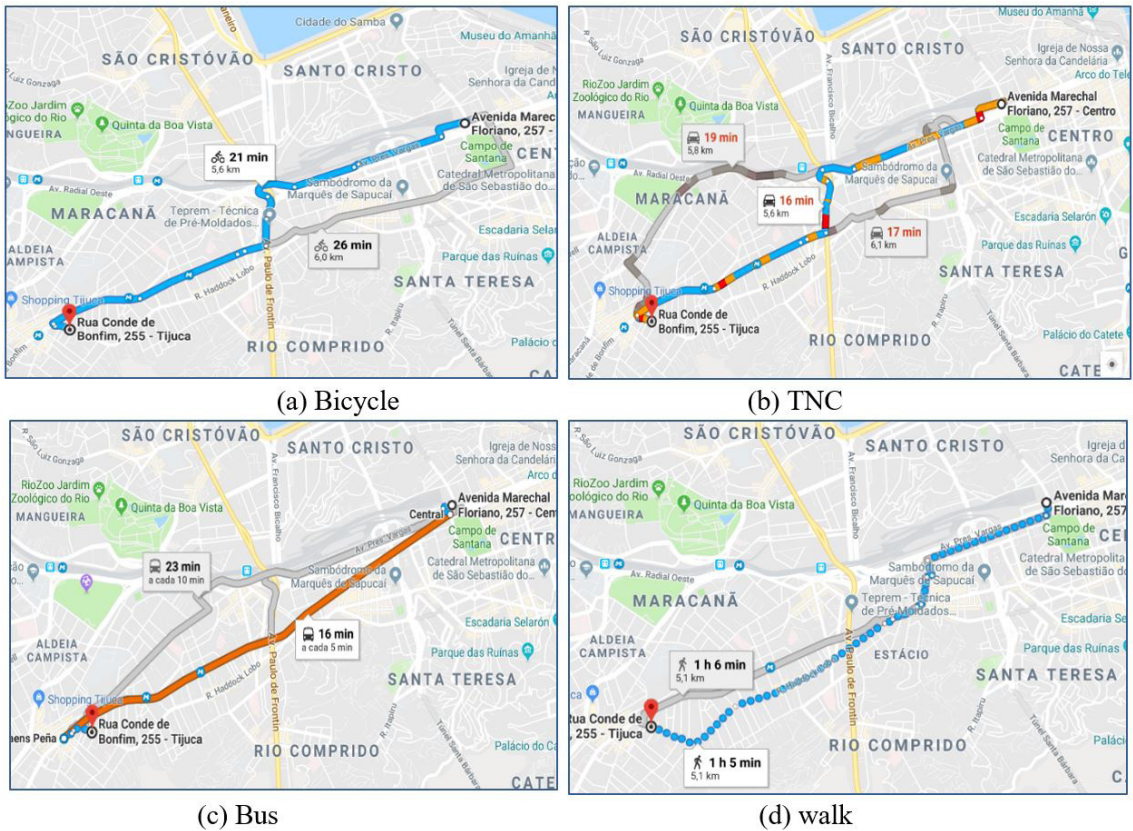
(a) Bicycle

(b) TNC

(c) Bus

(d) walk

Figure 3. Travel modes and its corresponding calculated time and distances.

Table 2. GHG and pollutant emission factors by vehicle category.

Categories	Fuel		Specific consumption Km/l (km/m³ for CNG)	% of fleet	Age of Fleet (years)	NO_x (g/km)	CO_2 (kg/l)	CO (g/km)	PM (g/km)
Light vehicles	Ethanol		6.9	1	25	0.03	1.457	4.2	–
	Gasoline		10.4	19	17	0.02	2.212	0.48	1.56
	Flex	*	8.6	60	4.4	0.03	1.457	0.47	–
		**	12,2			0.03	2.212	0.27	13.37
	CNG		12	20	11	0.29	1.999	0.56	–
Urban Buses	Diesel		2.5	100	4.7	2.103	2.603	0.27	262.76

*: ethanol use hypothesis by Flex vehicles; **: gasoline use hypothesis by Flex vehicles; CNG: compressed natural gas; CO: Carbon monoxide; PM: Particulate matter.

It was verified that the behavioral changes regarding the choice of transport mode is related to the distances presented in the questionnaire and their consequent variations of travel time and cost. As shown in Figure 5, as distances increase the motorized travel mode choice is preferred in relation walking. In the selected regions, respondents answered that the trips up to 1.4 km occur predominantly by walking. However, in trips with distances equal or greater than 1.9 km, both TNC and bus are the transport alternatives most adopted. In order to extend the modal repartition analysis to the 193 Tembici stations system, the Logit calibration was carried through the stated preference surveys, applying the Forward Wald Stepwise method, and by estimating parameters of maximum likelihood to evaluate the quality of the calibrated models. It should be emphasized that the models were generated including several different combinations of the explanatory variables and, therefore, the presented results include the models and variables that present greater significance. The level of significance was set at 5%. Results are presented in Table 3. After the iterations, four of the five independent variables presented significance to compose the final model.
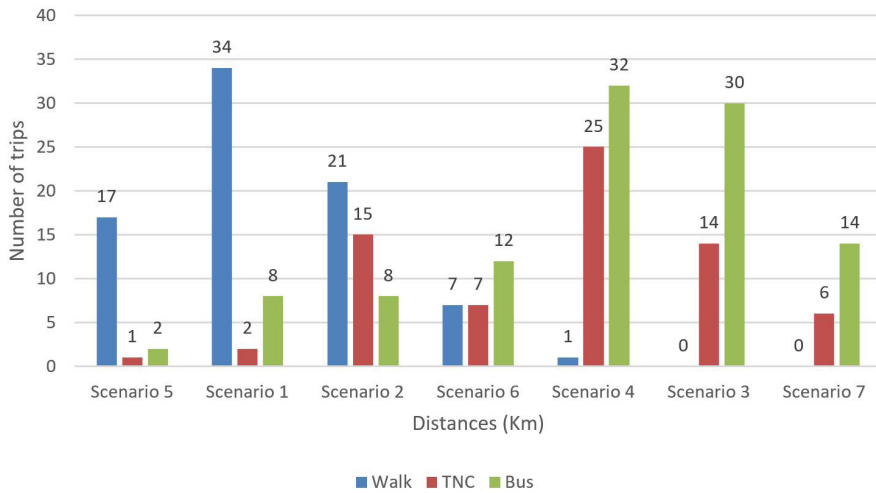
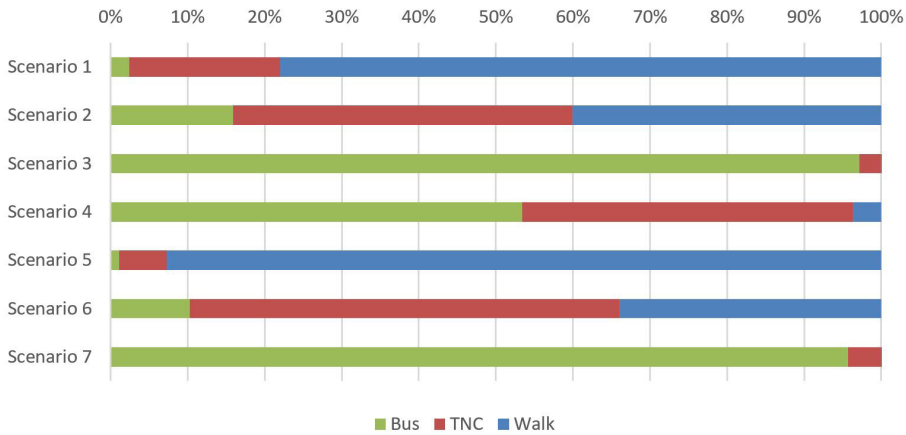**Figure 4.** Travel quantities declared by mode and distance.

Figure 5. Modal replacement according to transport mode and scenario.

Table 3. The model estimation results.

Mode choice	Equation terms	B	S.E	W	df	Sig	Exp(B)	Cox & Snell's R-Square	Nagelkerke's R-square
Walk	twalk	−0.247	0.034	53.707	1	0	0.781	0.462	0.62
	Constant	4.449	0.636	48.883	1	0	85.545		
TNC	ctnc	−0.295	0.093	10.169		0.001	0.74	0.06	0.097
	Constant	1.916	0.908	4.448	1	0.035	6.791		
	ttnc	−0. 243	0.085	8.217	1	0.004	0.784		
	tbus	0.133	0.066	4.109	1	0.043	1.142		
Bus	twalk	0.109	0.025	19.787	1	0	1.115	0.321	0.428
	Constant	−2.475	0.531	21.755	1	0	0.084		

B=Estimated parameters; S.E=standard error; W=Wald statistic; df=degrees of freedom; Sig= Significance of Wald statistics; Exp(B)=ODDS; TNC= Transportation Network Company.

According to the parameters estimated in Table 3, the utility functions were obtained as follows:

$$V_{walk} = 4.449 - 0.247*twalk \; ; \tag{4}$$

$$V_{tnc} = 1.916 - 0.295*ctnc \tag{5}$$

$$V_{bus} = -2.475 + 0.109*twalk + 0.133*tbus - 0.243*ttnc \tag{6}$$

When analyzing the utility functions for walking trips (equation 4), the variable that was statistically significant to explain the choice of the interviewees for this mode was the time in which the trip would be done by walking (*twalk*). As for trips made by TNC (equation 5), the travel cost by TNC is considered (*ctnc*), and for the travel mode by bus (equation 6), all the three travel times are considered in the model (*twalk, ttnc* and *tbus*). ODDS corresponds to the odds ratio (Hosmer & Lemeshow, 2000), and is defined as the ratio between the probability for *x*=1 and *x*=0, of choosing between two alternatives for the Nested Logit Model. ODDS greater than 1 indicates that the variable concerned increases the probability of choosing the mode of transport analyzed, and ODDS less than 1 decreases the choice's likelihood.

The Wald (W) test is used to verify constraints imposed on the regression coefficients and computes a statistic that measures the estimate of the coefficients of the original regression to satisfy the constraints of the null hypothesis, thus testing the significance of each model coefficient (B). Cox & Snell's R-square and the Nagelkerke's R-square, whose values are less than or equal to 1, are pseudo statistical R^2 that represent a fraction of the variance that is shared between the variables and are calculated on the basis of the likelihood function (Hosmer & Lemeshow, 2000).

Therefore, by applying Equation 2, the probabilities of choosing walking, TNC and bus travel are defined according to Equations 7 to 9.

$$P(walk) = \left(\frac{e^{4.449-0.247*twalk}}{e^{4.449-0.247*twalk} + e^{1.916-0.295*ctnc} + e^{-2.475+0.109*twalk+0.133*tbus-0.243*ttnc}} \right) \tag{7}$$

$$P(TNC) = \left(\frac{e^{1.916-0.295*ctnc}}{e^{4.449-0.247*twalk} + e^{1.916-0.295*ctnc} + e^{-2.475+0.109*twalk+0.133*tbus-0.243*ttnc}} \right) \tag{8}$$

$$P(bus) = \left(\frac{e^{-2.475+0.109*walk+0.133*tbus-0.243*ttnc}}{e^{4.449-0.247*twalk} + e^{1.916-0.295*ctnc} + e^{-2.475+0.109*twalk+0.133*tbus-0.243*ttnc}} \right) \tag{9}$$

Figure 5 presents the results for the modal split obtained by the application of Equations 7 to 9, considering the 7 scenarios described in Table 1 (Section 3). Walking is the predominant choice in scenarios 1 and 2, which consider shorter travel distances. However, as walking time increases, this option becomes disadvantageous, which is translated by the negative coefficient of parameter B, equal to -0.247 in Table 3. The utility function for this travel mode assumes positive values for routes performed up to 18 minutes, which suggests this as the time limit that the individuals interviewed would predispose to walk, without opting for the adoption of a motorized travel mode.

Trips performed by TNC exceeds the number of trips performed by bus only in scenario 2, since the distances considered in these scenarios, result in the minimum fees charged for private transport applications, making it thus a viable option in comparison to bus. To the extent, however, that travel time per car increases, reflecting on higher service charges, bus transportation becomes more advantageous. This explains the negative sign of parameter B in the TNC utility function variable *ctnc* (Table 3). For scenarios 3, 4, 6 and 7, the bus option prevails in relation to other modes of transport. When comparing the interviews results (Figure 4) with the result of the utility functions application (Figure 5), it was verified that the model was able to determine the BSS users predominant choice between motorized and non-motorized transport for all seven scenarios, proving to be equivalent to all observed results in interviews.

Expanding this analysis to the total of 1,048,575 trips registered in the BSS of Itau Bike, the modal split model resulted in 283,220 foot trips (27.01%), 109,262 TNC trips (10.42%) and 656.093 bus trips (62.57%), indicating, therefore, that in the city of Rio de Janeiro most of the users would be replacing the walk and the public transit by the use of the bicycle, in accordance with the findings in the literature for other cities (Fishman et al., 2015; Zhu et al., 2012). As shown in Table 4, the modal replacement rates obtained from the proposed model for BSS of Rio de Janeiro are included among the values verified in other existing bicycle sharing systems in the world, indicating the validation of the calibrated model.

Table 5 shows the estimations of CO_2, CO, PM and NOx emission reductions due to the use of BSS. Estimations were made according to the methodology presented in Section 3, considering the number of trips made, the transportation mode employed, and the total distances traveled. Due to the greater transport capacity offered by these transport modes when compared to bicycles, the average occupancy factor adopted was: 1.3 people per vehicle for cars, and 35 people per vehicle for the urban bus, thus trips were grouped according to the offered transportation capacity. Both data obtained from the Energy Matrix Report of the State of Rio de Janeiro - 2017-2031 (Rio de Janeiro, 2018).

Table 4. Transport modes replaced by BSSs.

	Barcelona	Stockholm	Lyon	Paris	Milan	Rio de Janeiro
Users who have moved from motorized transport	73.56%	63.21%	56%	73%	77.42%	72.99%
Users who have transferred from non-motorized transport	26.54%	36.33%	44%	20%	22.58%	27.01%
Source	1	2	2	1	1	-

Source 1: OBIS (Intelligent Energy Europe, 2011); Source 2: Oliveira (2014).

Table 5. Estimated emissions reduction due the bike sharing in Rio de Janeiro.

Category	Number. of annual trips	Occupancy factor	Adjusted travels	Fuel	Travelled distance (Km)	CO_2 (ton)	CO (ton)	PM (ton)	NO_x (ton)
Light vehicles	655,782	1.3	504,448	Ethanol	11,187.43	2.36	0.047	-	0.001
				Gasoline	212,561.15	45.21	0.102	0.33	0.004
				Flex*	671,245.75	121.70	0.181	8.97	0.020
				CNG	223,748.58	37.27	0.125	-	0.065
Bus	3,936,390	35	112,468	Diesel	378,176.64	393.76	0.102	99.37	0.795
Total annual	4,592,172	-	616,916	-	1,496,919.55	600.30	0.557	108.67	0.884

*Assumption for exclusive use of gasoline. CNG: compressed natural gas; CO: Carbon monoxide; PM: Particulate matter.

Detailed interviews were conducted by Oliveira (2014) with BSS users in Rio de Janeiro and their results were checked for plausibility, comparing it with rates for transport modes replaced by BSSs collected in papers published for other cities (Intelligent Energy Europe, 2011; Zhu et al., 2012; Fishman et al., 2015). When comparing the CO_2 reduction results estimated in this paper with the analysis by Oliveira (2014), it is possible to verify that the BSS in the city of Rio de Janeiro has evolved in terms of the environmental benefits provided, since there was an increase in the gross reduction of CO_2 (ton CO_2/year). It is justified by the greater number of bicycles available, reflecting in the number of trips and kilometers traveled per year, as shown in Table 6. Average distances traveled per trip changed from 3.5 km in 2014 to 2.62 km in 2018, presenting an average reduction of 25.14%, which can be explained by the growing number of stations made available by the system. This figure went from 60 stations in 2014 to 193 in 2018.

Table 6. Quantitative evolution of the bicycle sharing system in the city of Rio de Janeiro.

Comparative	Oliveira (2014)	Observed scenario in 2018
Number of bicycles in the system	600	2600
Average distance per trip on Bike (Km)	3.50	2.62
Number of annual trips	1,288,215	6,291,450
Distance traveled per year (km)	4,510,852	16,509,063
Average daily trips per bike	3,531	17,476
% of bike trips replacing public transport	70%	62.57%
% of bike trips replacing individual transport	2%	10.42%
Reduction of CO_2 emissions (ton / year)	17.321	206.54*
Participation in the reduction of emissions of the road transport sector in the municipality	0.0035%**	0.0418%**

*Considered only emissions from individual transport; **Compared to the estimated for the year 2016, according to the Inventory and scenario of greenhouse gases emissions from the City of Rio de Janeiro (Instituto Alberto Luiz Coimbra de Pós-graduação e Pesquisa de Engenharia, 2011).

It can also be observed, from Table 6, changes in the percentage of BSS trips that replace the use of public and individual transport when comparing the research scenarios of 2014 and 2018. This fact is mainly due to the transportation alternatives considered in these two studies. In 2014, interviewees had the option to choose from individual motorized transportation by private cars, whereas in 2018 the alternative offered to the interviewees was the travel mode by cars offered by TNC services, through applications. Thus, it has been identified that, under certain conditions of time and cost, transport applications begin to compete with public transport modes, modifying the modal split between trips made by car and bus, particularly in last-mile travel scenarios. It is also suggested that the usage expansion of transport applications, especially to non-private car owners, justifies the higher adoption rate of individual transportation by the interviewees.

This change in modal replacement percentages significantly affects the calculated emission values. In fact, the average load factor of 1.3 passengers per vehicle adopted for the TNC exerts a greater environmental

impact than 35 passenger load factor per vehicle adopted for the bus, so that a higher percentage of car modal shift to bicycles directly influences emission reduction efficiency indicators by the BSS. In 2018, this system allowed a reduction of 0.0418% of the total emissions made by the road transport sector in the city of Rio de Janeiro, which was estimated for the year 2016 at 4,937.2 Gg CO_2, according to the Inventory and scenario of greenhouse gases emissions from the City of Rio de Janeiro (Instituto Alberto Luiz Coimbra de Pós-graduação e Pesquisa de Engenharia, 2011).

5. Conclusions, research constraints and recommendations for future research

The present paper aims to quantitatively explore the contribution of the bicycle sharing system in the reduction of CO_2, CO, MP and NO_x emissions to the city of Rio de Janeiro. In a first stage, we used actual travel data from the Tembici company the Google Maps APIs to estimate origin-destination matrices, constituted by distances, travel times and costs, to each considered alternatives. Then, we applied the preempted interviews to the users of the Tembici system, in order to allow the calibration of a modal split model that explains the choice behavior among the modes of transportation, for the scenarios evaluated. Finally, emissions were estimated in accordance to the information on the circulating fleet, vehicles occupancy rates and emission factors characteristic of each pollutant and GHG considered.

Results indicated a gross increase in CO_2 emission reductions, compared to the existing system in 2014, not only due to the increase in the service offer, but also due to a higher transfer rate from private motorized to bicycle trips.

The logistic regression models obtained, allowed us to identify BSS user's behavioral trends, and revealed that the variables travel time by walk, TNC and bus, as well as the travel cost by TNC, were the most statistically significant for the prediction of travel replacement models. Only the travel cost by bus was not incorporated into the model, since the fee charged is constant in all the routes studied. Hence, for the scenarios and distances assessed in the interviews the utility function for walking travel mode assumes positive values for the trips performed up to 18 minutes, whereas, for the TNC mode, the travel times results on the minimum fare charged by the transport applications, allowing favor to the use of this travel mode in relation to the bus one. As the price charged increases, bus trips become more advantageous, as verified in the utility function generated.

It was verified that the mode most substituted by BSS is public transport. Moreover, after introducing in questionnaires the transportation alternative by using TNC, it was observed a 7.43% reduction average net in public transport use among BSS users in Rio de Janeiro, comparing the research scenarios of 2014 and 2018. This phenomenon is in accordance to previous findings in major cities in the United States, where the average net change in public transport use suffered a 6% reduction (Clewlow & Mishra, 2017). It can be explained due to the increasing "technology-oriented" lifestyles: the degree of familiarity with modern technologies and their adoption in daily life is associated with a higher likelihood of adopting TNC services. Yet, many of the most fundamental changes occurred by these innovations – such as competitive travel – would seem to work in opposite directions, acknowledging concerns that "[...] every technological innovation has acted to increase demand rather than to reduce it [...]" (Gössling, 2018, p.157).

The net environmental benefits of bicycle sharing depend on whether the system is considered a good substitute for the ownership and use of private vehicles, and whether it is well integrated with public transport, cycling and pedestrian infrastructure, so that it improves rather than replaces walking and public transport (Fishman et al., 2015). Therefore, although the emission reduction contribution reveals a small influence on the total emissions generated by the road transportation system in the city of Rio de Janeiro, bicycle sharing should be understood as part of the multimodality adopting process, with effective reductions achieved by encouraging the behavioral change of the transport systems users. Thus, the increase in bicycle density provided by the BSS growth, integrated with other public transport options and associated with measures that make car traffic less attractive, are likely to trigger a much more significant reduction in GHG and air pollutant emissions.

Although this study provides innovative and quantitative estimations of the environmental benefits of BSS, there are some constraints. First, due to the privacy issue, the bike-sharing data obtained were preprocessed by Tembici. Each trip only contained a collection of chronologically unordered spatial locations, consequently, it was impossible to accurately retrieve a user's actual travel route from their travel information. It is suggested that in the future, the original trip data can be tracked by GPS. Based on this dataset, more accurate trips can be retrieved. Second, the survey relies on self-reported behavior and Some respondents may have provided information that did not reflect their real behavior, although there was little reason to do so knowingly. As a suggestion for future research, a larger sample size may help improve the degree to which the non-member sample represent the wider population.

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