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Abstract

Bike-sharing systems allow occasional and regular users to move by replacing other transport modes for the same trip or generating a new journey. Our research assesses the demand for Lisbon's public dock-based bike-sharing system (BSS) users named after GIRA. This paper aims to identify the determinant factors that influence the potential of the BSS to generate new trips or replace previous modes using a binary logit model based on a survey of 3112 BSS users. The survey results indicate that GIRA generated approximately 20% of the BSS trips, i.e., they would not have been realized if GIRA did not exist. The remaining BSS trips replaced other motorized (55%) and non-motorized (25%) trips. The main determinants explaining a higher likelihood of replacing other modes are having a yearly GIRA pass and a bike-sharing station within a 5-min walking distance. In contrast, regular car users are more likely to generate new trips, suggesting they use bike-sharing for recreational purposes. The findings provide policymakers with an assessment of the determinants that can influence bike-sharing users to generate or substitute trips from other modes for bike-sharing and, consequently, give policies to potentially increase bike-sharing mobility share.

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Generating or replacing trips with bike-sharing systems: the case-study of GIRA, Lisbon

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Bike-sharing systems allow occasional and regular users to move by replacing other transport modes for the same trip or generating a new journey. Our research assesses the demand for Lisbon's public dock-based bike-sharing system (BSS) users named after GIRA. This paper aims to identify the determinant factors that influence the potential of the BSS to generate new trips or replace previous modes using a binary logit model based on a survey of 3112 BSS users. The survey results indicate that GIRA generated approximately 20% of the BSS trips, i.e., they would not have been realized if GIRA did not exist. The remaining BSS trips replaced other motorized (55%) and non-motorized (25%) trips. The main determinants explaining a higher likelihood of replacing other modes are having a yearly GIRA pass and a bike-sharing station within a 5-min walking distance. In contrast, regular car users are more likely to generate new trips, suggesting they use bike-sharing for recreational purposes. The findings provide policymakers with an assessment of the determinants that can influence bike-sharing users to generate or substitute trips from other modes for bike-sharing and, consequently, provide policies to potentially increase bike-sharing mobility share.

Keywords: Bike-sharing; Modal shift; Cycling; Built environment; Travel Behavior; Latent demand

1. Introduction

The adoption of Bike-sharing systems (BSS) has grown widely in many cities worldwide. They are a mode of public transport that allow citizens to pick up and drop off bikes in different locations throughout the city. The main advantage of BSS is to use a bicycle without the responsibility and cost of owning one. Although the international market for bike-sharing is relatively recent, this mobility service appeared in the 1960s (Shaheen, Guzman, & Zhang, 2010). BSS can operate with fixed docks at stations or dockless. Even though dockless systems allow more flexibility for users since there is no specific location for bicycle drop-off, public policymakers tend to avoid them. The main reason is that bicycles are often left on sidewalks and have a higher rate of breaking (Wei, Luo, & Nie, 2019). People typically use this system for short-distance trips, and when integrated adequately with transit, it can potentially offer a solution for the "first-and-last mile" dilemma (Fan, Chen, & Wan, 2019; Wang & Zhou, 2017). Based on the experience of European and Japanese cities, bike-sharing policies may promote public transportation and diversify transport modes shares, reducing car dependence (Fan et al., 2019).

However, since BSSs are very recent in many regions, there is a lack of research analyzing the demand patterns of modal shift or trip generation in an already operating system. Few studies examine the expansion of existing BSS (Hsieh et al., 2021; Zhang et al., 2016), and others consider latent (or potential) demand only when planning for a new BSS (Frade & Ribeiro, 2014; Krykewycz et al., 2010). Therefore, little has been done on the usage and behavior of current users of an already operating system (Zhang et al., 2016). Policies favoring BSS expansion should be based on an already functioning system's existing and latent demand. In this context, we evaluate the demand of regular and occasional bike-sharing users, i.e., whether they generate new trips or replace previous modes in an operating system. We also aim to provide insights to support the planning of BSS expansion. We evaluate the case study of Lisbon's public dock-based BSS based on a travel survey.

We begin with a literature review in section 2, followed by the description of the research design, the survey, and the modeling framework, in section 3. Section 4 presents the model results, followed by the corresponding discussion in section 5. Finally, section 6 presents the conclusions.

2. Literature Review

2.1 Studies with bike-sharing modal choice

BSS investment can provide various social, economic, environmental, and public health benefits. Shaheen et al. (2010) enumerated the principal ones: flexible mobility, reducing congestion and emissions, user cost savings, increasing public transportation use, promoting physical activity, and providing a mobility option for the "first-and-last mile" dilemma. Nonetheless, a few studies empirically validate the benefits of BSS claimed by Shaheen et al. (2010) (Fishman, Washington, & Haworth, 2013). Furthermore, the benefits of installing such a system cannot be taken strictly into account since promoting cycling through other measures can achieve the same benefits (Handy, Wee, & Kroesen, 2014; Wang & Zhou, 2017). Therefore, it is not clear if the bike-sharing program or other measures were more significant in promoting cycling in some cases.

Investments in BSS can promote better access to public transportation and perform longer distances than walking (Hamidi, Camporeale, & Caggiani, 2019). BSS is arguably a public transport, but few studies address BSS design integrated with the existing transit system (Wu, Gu, Fan, & Cassidy, 2020). In practice, BSSs are implemented lacking or having minimum adjustments in the current public transportation system.

Most public bike-sharing programs aim to not only promote cycling but also to substitute car use. However, according to Fishman et al. (2013), studies demonstrate that people are more likely to shift from walking and transit than from automobiles. Evidence from Washington, Minnesota, Lyon, and Dublin confirm a very low modal shift from car to bike-sharing (Fishman et al., 2013). The ease of access to a bike-sharing station is a relevant factor that can impact the number of people that use the system. In a study developed in London, low levels of income and education tend to have lower rates of using bicycle sharing programs (Ogilvie & Goodman, 2012). However, this may be since the home zones of this portion of the population may lack or have high distances to a bike-sharing station (Fishman et al., 2013; Ogilvie & Goodman, 2012). According to Ogilvie and Goodman (2012), even though people from low-income zones use less the BSS than high-income zones, they are more likely to adopt this mode due to the low levels of bicycle ownership and lack of bicycle storage facilities at home. Therefore, a better distribution of bicycle stations could provide better access to the latent demand of this population.

2.2 Factors impacting bike-sharing choice

Most studies demonstrate that hilliness and slopes negatively influence bicycle use on home-work trips, having less impact or even none on experienced cyclists (Heinen, van Wee, & Maat, 2010). However, electric bicycles (E-bikes) require less physical effort and overcome problems related to topography, increasing the number of bike riders and trips by bicycle (Popovich et al., 2014). As a result, E-bikes overcome common barriers for all types of cyclists (Dill & Rose, 2012). In the case of Lisbon, 66% of the public bike-sharing fleet are E-bikes. Thereby, a public BSS that offers E-bikes should have a higher utilization rate than a system that lacks this technological improvement.

People who lack bicycle storage at home are less likely to use bicycles (Fernández-Heredia, Jara-Díaz, & Monzón, 2016). BSS can motivate this portion of the population to use bike sharing in daily commuting if docks have short distances to the origin and destination of the trip (Fishman et al., 2013). Users of bike-sharing avoid problems related to bicycle robbery and hold a more on-demand transportation mode than regular bicycles (Fan et al., 2019). In the case of Lisbon, the housing conditions are not homogeneous, and, in some districts, leaving a bicycle at home is impractical, namely in older buildings (Félix, 2019). Another issue is that it is rare to detect bicycles parked on sidewalks (bike racks and parking) at night due to the risk of theft in Lisbon (Félix, 2019). However, this is not the case in cities with a higher bicycle modal share than Lisbon, although it is a moderately safe city (Félix, 2019; Pucher & Buehler, 2008).

Some barriers faced by bike-sharing users for daily commuting are like those faced by private bicycles users. They are usually related to the built environment, transportation policies, socio-demographics, and travel time-related aspects (Chen, Zhou, & Sun, 2017). The built environment factors that influence bicycle use are usually related to travel distance (Cervero, 1996; Heinen et al., 2010; Pucher & Buehler, 2006); density (Heinen et al., 2010; Saelens, Sallis, & Frank, 2003; Vale, Saraiva, & Pereira, 2015); land-use diversity (Heinen et al., 2010; Saelens et al., 2003; Vale et al., 2015); connectivity between bike-routes (Heinen et al., 2010; Muhs & Clifton, 2016); accessibility (Vale et al., 2015); the presence of segregated bike lanes (Dill & Carr, 2003; Félix, Moura, & Clifton, 2019; Pucher, Dill, & Handy, 2010); and the availability of a BSS (Félix, Cambra, & Moura, 2020).

Furthermore, some studies demonstrate how demographic characteristics influence people using a bike, such as age, gender, and physical ability (Akar & Clifton, 2009; Ma & Dill, 2015). Female and elderly populations are less likely to use a bike than male or young users. Furthermore, people with children are less likely to cycle than others who don't have them. According to Heinen et al. (2010), bicycle use may vary during hours of the day, weekdays, seasons, and weekends. For this reason, it is necessary to take this into account when implementing pro-cycling policies.

3. Research Design

Lisbon's public BSS is our case study to evaluate how trips were generated or substituted for occasional and frequent bike-sharing users. This study assesses choice preferences and sociodemographic characteristics through a travel survey of GIRA's users (3112 valid responses). It was necessary to treat most of the collected data due to the lack of patterns or incomplete home addresses answered by the users. Furthermore, we estimated each respondent's routes and corresponding distances, costs, and trip duration, for each mode. After analyzing the correlation and collinearity between variables, we used a binary logit model to evaluate which sociodemographic, trip characteristics, and build environment variables can influence the generation or the substitution of trips with Lisbon's BSS GIRA.

3.1 Case-study

We studied the case of Lisbon, Portugal. According to the Census 2011, 48% of Lisbon's population used a car to commute; 34% used public transportation; 17% commuted by foot, and only 0.2% cycled to work daily (Instituto Nacional de Estatística, 2011). The last mobility survey of Lisbon's metropolitan region (Instituto Nacional de Estatística, 2018) shows that the modal share for commuting did change significantly, apart from the increase of the bicycle modal share to 0.6% in 2018. The recent rise of bicycle users is partly explained by the expansion of the cycling network and other significant investments in pro-cycling policies. In 2021, segregated bicycle lanes reached an extension of 150 km (Câmara Municipal de Lisboa, 2021).

Lisbon's *GIRA* began with ten stations in June 2017 during the pilot project and expanded to 74 stations in December 2018, having a fleet of 10 bicycles per station. A first phase expansion of at least 140 stations and 1400 bicycles operating in the system is undergoing. The second expansion phase will have 3,000 bicycles and 300 stations, resulting in better city coverage. Consequently, Lisbon is a good case study since the BSS is not yet completed, and expansion projects are still undergoing. The stations have adaptable bicycle racks that can be changed depending on different demands, but not in a dynamic form (during the day, week, etc.). In addition, each station has a wi-fi connection, where the smartphone app is necessary to use the system (Pincha, 2018). In 2018, roughly one million trips were registered in the system (Moura & Félix, 2019). GIRA users pay 25 euros/year to use the system with no limitations and 2 euros for a daily pass[1].

The stations are distributed in four areas: *Eixo Central*, *Parque das Nações*, *Telheiras* and *Frente Ribeirinha*, as illustrated in Figure 1. The *Eixo Central* is the city's Central Business District with the highest employment and economic activity concentration. The average distance between stations is 200m to 300m depending on the zone. Still, the lack of stations between the zones served by the network may result in low adoption of bike-sharing in these unserved zones. Each station has docks for 10 to 40 bicycles (18 on average).

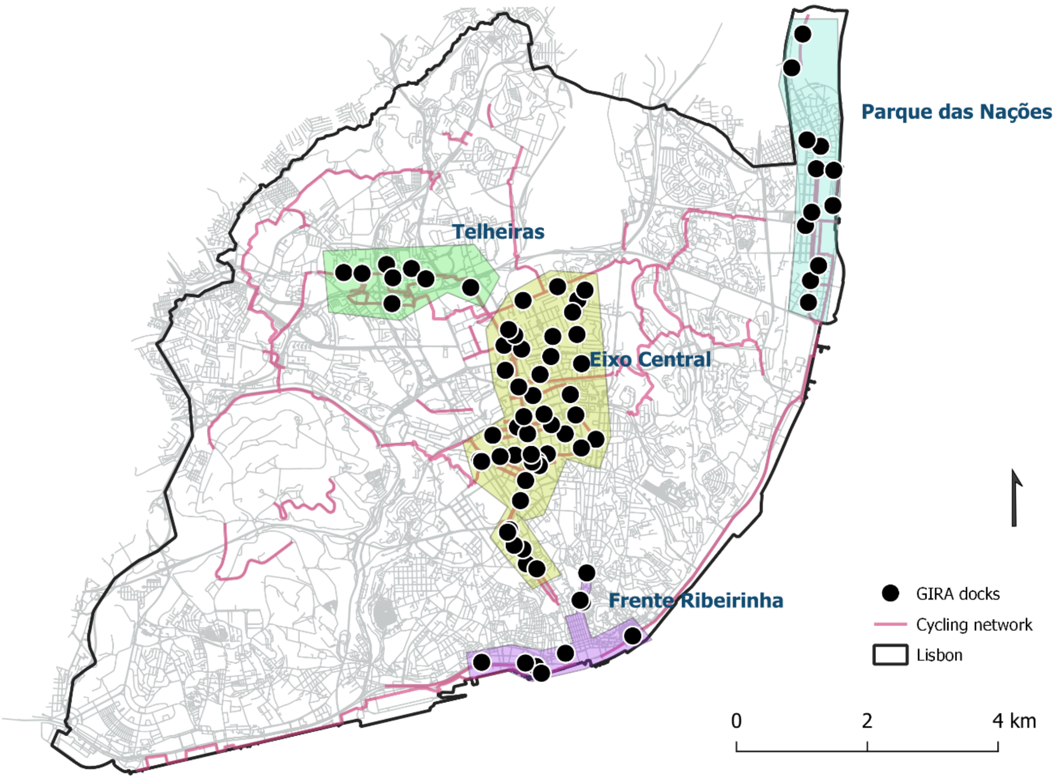

Figure 1: Distribution of GIRA stations in Lisbon's municipality at the time of the survey

[1] GIRA subscription plans: https://www.gira-bicicletasdelisboa.pt/passes-e-tarifarios/

3.2 Survey design

An online survey was sent by e-mail to all *GIRA* subscribers living in Portugal. The survey was open from January 28th to February 22nd, 2019. From a universe of 25,465 users that have used it for at least one trip, the survey collected 5,053 answers. We excluded respondents who reported they never used *GIRA* or used it in 2017. We also eliminated observations with missing values of critical variables, ending up with 3,112 valid answers. Table 1 shows the descriptive statistics of the survey and compares them with the GIRA user's dataset (Moura & Félix, 2019) to validate the sample.

Table 1: Descriptive statistics and comparison between GIRA and survey datasets

	***GIRA* dataset**	**Survey**
Total № of users	25465	4970
№ residents of Lisbon	16029 (63% of users)	3527 (70.9% of users)
№ of residents within 10 min walk to a station	12578 (78,5% of residents)	2734 (77,5% of residents)
№ of residents within 5 min. walk to a station	9999 (62,4% of residents)	2196 (62,3% of residents)
Age (average)	35	36.5
Female users	37.0 %	33.0 %
Users with an annual pass	77.3 %	90.5 %
Frequent users	24.0 %	63.3 %
Home-work trip users	-	45%

The survey aimed to estimate which trips GIRA has generated and which modes it has substituted. We divided GIRA users into frequent and occasional users. We considered a frequent user to use GIRA at least once a week. Frequent users were asked about their most frequent trip origin and destination (OD pair) and which mode they substitute when using the BSS. Similar questions were addressed to occasional users, focusing on their GIRA's last trip. Table 2 presents the distribution of responses per type of trip (generated or replaced and the corresponding mode) and per type of user (frequent or occasional).

Table 2: Answers' distribution according to types of trips and users

Type of trip	Frequent	Occasional
Generated trip	595 (20 %)	196 (13 %)
Replacing trip previously done by:		
Foot, bicycle	591 (20 %)	490 (32 %)
Motorcycle	45 (2 %)	37 (2 %)
Metro	893 (30 %)	330 (21 %)
Train	19 (1 %)	6 (1 %)
Bus	272 (9 %)	83 (5 %)
Car	518 (18 %)	402 (26 %)
Total	2934 (66 %)	1544 (34 %)

Approximately 20% of the frequent user trips were generated, meaning that previously the users did not perform the journey and would not do it if they would not have access to a GIRA. Thus, the generated trips satisfy a latent demand for new and previously unrealized activities (Clifton & Moura, 2017). The remaining trips replaced other modes, i.e., shifting away from active or motorized modes. Other studies have evaluated that bike-sharing replaces more walking and public transit trips (Chen, van Lierop & Ettema, 2022; Teixeira, Silva, & Moura e Sá, 2021). Although our results demonstrate that bike-sharing replaced previous trips by foot considerably, we observed that the types of public transport had different results. Metro had many replaced trips, while train and bus had few. This fact may be explained by the Lisbon BSS stations being overlapped by the metro lines. Therefore, the BSS is not serving as a first-and-last mile for metro service, conversely to other studies (Ashraf et al., 2021). Furthermore, the number of trips replaced by car is also significant, especially for the occasional users (second-highest number of trips replaced). In the case of occasional users, potentially, bike-sharing can replace ride-hailing services.

3.3 Trip-related variables estimation

The trip-related variables were estimated based on Origin - Destination coordinates. These were geocoded with GoogleMaps API based on the participant's revealed home and work seven-digit Zip Codes or closest Point-of-Interest. The trip distances and travel times were computed using Google maps API for the following transportation modes: walking, car, and public transit. Cycling distances and travel times were calculated using the Open Route Service API for each OD pair (between two stations). This method considers the route with the minimum travel time and not necessarily the most direct path.

We estimated car travel costs based on the 2018 average fuel price and parking costs. Public transit costs were calculated with the operator's average one-trip fares, distinguishing urban and suburban trips (under and above 20 km).

3.4 Dataset descriptive statistics

Table 3 and Table 4 present the descriptive statistics of our final dataset. The *cycling network dependence* variable translates how the participants are dependent on the existence of segregated cycling infrastructure for bicycles, as they were asked to classify their dependence from 0 (not dependent at all) to 100 (totally dependent).

Table 3: Descriptive statistics – categorical variables.

Variable	%
Type of trip (Frequent / Occasional)	68.7/31.3
Gender (Female/Male)	33.2/66.8
Trip replacement	
Generated	21.1
Walk	21.9
Bike	2.0
Car	23.1
Public Transit	31.8
Children in the household (< 12 years/ >= 12 years/ No)	11.8/26.9/61.3
Education level (Higher/ Other)	83.4/16.6
Employment condition (Job with the fixed place/ No job or no fixed place)	67.1/32.9
Self-assessment of income status	
Live without difficulties	39.4
Live with moderate ease	48.4
Live with difficulties	4.9
No income	7.3
Usual transportation mode	
Walk	10.5
Bike	14.0
Public Transit	25.4
Car	27.6
PT + Car	2.6
PT + Bike	13.3
Bike + Car	6.5
Transit pass monthly holder (Yes/no)	40.7/59.3
BSS pass holder (Annual/ Other)	94.6/5.4
Car in the household (Yes/ No)	82.9/17.1
Owns a bicycle (Yes/ No)	49.9/50.1
Room to park a bike at Work (Yes/ No)	55.7/44.3
Bicycle proficiency	
Experienced	33.3
Somewhat experienced	49.0
Beginner	17.1
Inexperienced	0.6
Helmet wearing when using BSS (Yes/ No)	7.9/92.1
Rides BSS when raining (Yes/ No)	50.9/49.1
GIRA dock at 5 minutes from home (Yes/ No)	55.5/44.5
Gave up GIRA to use her bicycle (Yes/ No)	2.2/97.8

Table 4: Descriptive statistics – continuous variables.

Variable	Mean	sd.	Median
Age	35.7	10.9	35
Cycling network dependence [0-100]	55.1	33	61
Frequency of BSS usage [times per month]	14.5	13.2	10
Estimated commuting trip duration [minutes]			
Walk	75.2	70.7	52.0
Bike	23.2	22.6	15.8
Public Transit	29.3	18.4	24.9
Car	13.7	6.7	12.8
Estimated commuting trip distance [km]			
Walk	5.969	5.746	4.094
Bike	6.691	6.488	4.594
Public Transit	6.969	7.107	4.747
Car	7.388	0.708	5.017
Estimated commuting trip cost [€]			
Public Transit	0.777	0.138	0.723
Car	2.400	1.200	2.000
Estimated distance from Home to … station			
Metro	5.797	23.573	0.603
Train	1.697	1.149	1.420
Bus	0.176	0.162	2.152
Ferry	6.731	4.575	5.896
Estimated distance from Work to … stations			
Metro	1.780	10.913	0.349
Train	1.286	0.800	1.251
Bus	0.160	0.134	0.126
Ferry	5.000	3.203	4.206

3.5 Binary logit model

A binary logit model was used to estimate the effects of sociodemographic and trip-related variables for each type of GIRA trip – generated or replacing other modes. We used open-source *PandasBiogeme* software for the model estimation (Bierlaire, 2018).

We consider two discrete outcomes: i) GIRA trip j generated (it would not occur if the BSS would not exist), and ii) a GIRA trip j replacing other modes. The model's framework considers the choice of a person i in performing the discrete outcome j, based on a linear function, T (Washington, Karlaftis, & Mannering, 2011):

$$T_{ij} = \beta_j X_{ij} + \varepsilon_{ij}$$

(1)

, where $\beta_j X_{ij}$ is the systematic component of the model; β_j is a vector of coefficients of j that is estimated through the calibration; X_{ij} is a vector of explanatory variables and ε_{ij} is the random component of the model, assumed to have a Gumbel distribution (Generalized Extreme Value distribution – Type 1).

Thereby, the probability (P_{ij}) of a trip i being generated or substituting another mode is calculated with the following equation (Washington et al., 2011):

$$P_{ij} = \frac{EXP\,[\beta_j X_{ij}]}{\sum_j \quad EXP\,[\beta_j X_{ij}]} \qquad (2)$$

, where j corresponds to two alternative outcomes.

Binary logit models require the independence of observations and little or no multicollinearity among the independent variables and assume linearity of independent variables (Washington et al., 2011).

For the maximum likelihood estimation, goodness-of-fit statistics were computed. The McFadden adjusted ρ^2 statistic was selected to quantify the explained variance of the fitted models (Hensher, Rose, & Greene, 2005). Where LL^0 and $LL^*$are the Log-likelihood of the base and the estimated models, respectively. The ρ is related to the number of parameters used in the predicted model and making sure that overfitting does not occur, and the model is parsimonious.

4. Results

4.1 Significant variables

We analyzed a set of variables that we categorized into five dimensions:

sociodemographic (SDC), mobility options and travel habits before shifting to bike-sharing (MTH), cycling habits and expertise attributes (CHE), access to cycling facilities and infrastructures (CFI), and built-environment attributes (BE). Twenty-two parameters were calibrated to identify the potential effects of each independent variable. We calibrated the model with a random selection of 80% of the sample, while 20% was used for validation.

Final models considered only statistically significant explanatory variables, with a minimum confidence level of 85% (except for the variable "Cycling network dependence "- refer to table 5). When using discrete choice models for explanatory purposes (within the range of observed values), higher p-values are acceptable (Washington et al., 2011).

4.2 Model and interpretation

Table 5 shows the results of the binary logit model's parameters that estimate the probability of the BSS generating new trips or replacing other modes. Variables with high correlation and collinearity were not included in the model. All the variables were included in the utility function of the alternative "*Generated trips"* to simplify the results' interpretation. The alternative specific constant (ASC) was fixed for the alternative "Replacing trips " and, consequently, the "*Replacing trips"* alternative's utility function includes only the specific constant (ASC_REP). ASC_REP is negative, suggesting that BSS are more likely to replace trips previously made by other modes than generate new trips (although the parameter is not statistically significant).

Table 5: Binary logit model parameters: generating vs. replacing.

Group	Variable	Value	Std err	t-test	p-value		Aggregate Direct Elasticities
	ASC_REP	-0,019	0,282	-0,07	,945		
SDC	Gender (1: female)	-0,359	0,114	-3,14	,002	**	-0,086
MTH	Regular user of PT and Bike	-0,429	0,177	-2,42	,016	**	-0,033
	Regular cyclist	-0,860	0,232	-3,70	,000	**	-0,037
	Regular car user	0,282	0,117	2,41	,016	**	0,075
	Yearly BSS pass	-0,570	0,199	-2,87	,004	**	-0,392
CHE	Experienced cyclist	-0,231	0,120	-1,92	,055	*	-0,047
	User of BSS when raining	-0,339	0,108	-3,15	,002	**	-0,105
	Bike trip frequency	-0,021	0,005	-4,25	,000	**	-0,167
CFI	Bike parking at work	0,289	0,106	2,73	,006	**	0,130
	Cycling network	0,002	0,002	1,01	,313		0,072
	5-min access to BSS (home)	-0,359	0,105	-3,41	,001	**	-0,132
	5-min access to BSS (work)	-0,277	0,112	-2,47	,014	**	-0,131
BE	Distance to Bus stop (work)	0,558	0,379	1,47	,141		0,068
	Distance to Train station (work)	-0,141	0,067	-2,10	,036	**	-0,131

Goodness-of-fit indicators

Sample Size: 2489
Number of estimated parameters: 15
Init log-likelihood: -1945.96
Final log-likelihood: -1176.15
Likelihood ratio test for the init. Model: 1539.61
Rho-square for the init. Model: 0.396
Rho-square-bar for the init. Model: 0.388

Legend: sociodemographic attributes (SDC), mobility options and travel habits prior to shifting bike-sharing (MTH), cycling habits and experience (CHE), access to cycling facilities and infrastructures (CFI), and built-environment attributes (BE); ** p-value<0,05; * p-value < 0,1.

The model presents a rho square of 0.39, which is a good fit of the model to the data. Coefficients present logical signs, and all are significant with a *p-value* below 0,1, except for the variable "Cycling network" that had a *p-value* of 0,3. Although the confidence level is around 70%, we decided to keep the variable as it brings some explanation on the importance of having access to the cycle network of Lisbon.

The following table summarizes the contribution of each variable to increase the likelihood of the trips being generated after Lisbon's BSS began operating or substituting other modes.

Table 6: Determinants for generating new trips vs. replacing previous modes

Group	Variable	Generating trips	Replacing modes
SDC	Gender (1: female)	↓	↑
MTH	Regular user of PT and Bike	↓	↑
	Regular cyclist	↓	↑
	Regular car user	↑	↓
	Yearly BSS pass	↓	↑
CHE	Experienced cyclist	↓	↑
	User of BSS when raining	↓	↑
	Bike trip frequency	↓	↑
CFI	Bike parking at work	↑	↓
	Cycling network	↑	↓
	5-min access to BSS (home)	↓	↑
	5-min access to BSS (work)	↓	↑
BE	Distance to Bus stop (work)	↑	↓
	Distance to Train station (work)	↓	↑

Legend: ↓ - Decreases the likelihood; ↑ - increases the likelihood.

We highlight women have a lower probability of generating new trips with *GIRA*. Regular car users are more likely to generate new trips with *GIRA* than substitute car trips regarding mobility and travel habits. On the other hand, regular bicycle users or regular PT users combined with bicycles are less likely to generate new BSS trips. An explanatory variable that stands out in this model, in terms of magnitude, is the annual BSS subscription. *GIRA* subscribers are less likely to generate new trips and thus more likely to replace trips from other modes.

As for cycling habits, having a higher cycling experience, being a frequent cyclist, and using the BSS while raining, decreases the likelihood of generating new trips. Having access to bike parking at work is more likely to generate BSS trips. Notice that GIRA is a dock-based system that does not require parking spaces at work. Nonetheless, we acknowledge that parking spaces might attract trips from private bicycle users.

Having access to a *GIRA* station within a 5-min walk from home or work is less likely to generate new *GIRA* trips than to replace other modes. The availability of a cycling network was not a statistically significant variable for this model.

Finally, built-environment attributes (BE) had only a minor effect in the "generating versus replacing" binary logit model. Having a higher distance from the workplace to the train station decreases the probability of generating trips with *GIRA*.

5. Discussion of results

We found that bike-sharing users who subscribe to a yearly pass have a more significant influence in substituting modes than generating new trips, making sense from two perspectives. Frequent BSS users, who are more likely to use bike sharing for commuting trips, as suggested by the literature (Talavera-Garcia, Romanillos, & Arias-Molinares, 2021), are more likely to subscribe to a yearly pass and replace another mode for the same trip. For the occasional BSS users, who made the once-in-a-year decision to subscribe to an annual pass, it is more intuitive to consider bike sharing as a modal option with no extra costs when making an occasional trip. These are trips that often can be an alternative to a car, taxi, or ride-hailing. On the other hand, non-yearly pass subscribers are more susceptible to not considering bike-sharing as a mobility option for frequent or occasional trips. Promoting policy packages to increase access to yearly passes could potentially influence higher use of GIRA to replace frequent or occasional journeys, such as integration of GIRA's subscription to the public transit pass or other transportation services.

Regular car users are more likely to generate new bike-sharing trips since they are more likely to use BSS for recreational purposes. Regular cyclists are less likely to generate new trips with BSS. Instead, they tend to replace some of their usual trips with *GIRA*. However, the lack of bike-sharing stations near home makes it less likely for people to shift from regular commuting mode to bike-sharing. In this case, *GIRA*, when used, is mainly for recreational purposes. Our results confirm that implementing GIRA stations within 5min walking distances to home and work locations can attract users to shift their frequent or occasional trips to bike-sharing. This finding is in the same direction as Moura & Félix (2019), stating that GIRA subscribers are located close to a bike-sharing station. As such, planners should locate BSS stations close to high-density residential and working areas.

Income and trip-related variables such as trip distance, duration, and cost were not significant and thus not considered in this model, suggesting that they are not relevant for substituting modes or generating a new trip. The result is understandable since we include only the choice of respondents that already chose to use bike-sharing and are not comparing the alternative of using bike-sharing versus other modes. Furthermore, according to Wu et al. (2019), high costs and increasing subscription plans can reduce frequent users using BSS for short distances. Instead, these users will prefer an alternative mode choice for short-distance trips. In the case of GIRA, as income is not significant, this may suggest that the cost of using the GIRA is inclusive for both frequent and occasional users. Also, the high percentage of yearly pass subscription users compared to unique pass users confirms this fact (refer to Table 1). Policies favoring waiving or integrating the cost of public transit passes may influence a higher bike-sharing adoption.

6. Conclusions

This paper analyses which attributes are more relevant for Lisbon's BSS users (frequent or occasional) to generate a new trip or replace other modes in a previous trip. A survey collected answers from 5053 GIRA users, of which 3,112 were validated. The valid sample corresponded to approximately 20% of all GIRA's users. We used a binary logit model to determine the most relevant determinants. The results bring insights that support the definition of public policies to increase the impact of BSS on the generation of new trips (and thus satisfying an existing latent demand) or replacing other modes. We found that having a BSS station within a 5-min walking distance to home significantly influences frequent or occasional users to replace trips. Nonetheless, 62% of users from the sample are within a 5-min walking distance of a station (refer to Table 2), indicating a potential to expand the system in dense residential areas.

Additionally, citizens who subscribe to a yearly bike-sharing pass tend to substitute more trips than generate them for frequent and occasional users. While the literature indicates that frequent users usually use bike-sharing for commuting, occasional users are more likely to travel for recreational purposes. Thereby, replacing trips for both types of users can have short and long-term benefits in increasing cycling levels for recreational and home-work-based trips.

The results also demonstrate a challenge to substituting cars for bike-sharing for regular car users since they tend to use bike-sharing to generate new trips. If the policy goal is to reduce regular car trips, then it may be necessary to promote cycling policies and restrictions on car use. Although our initial findings suggest that bike-sharing replaces walking and the metro, it would be interesting to understand the determinants for substituting each transport mode in future studies. As a result, it is possible to analyze if the BSS promotes less car use and how municipalities and agencies can influence people to shift to BSS.

7. References

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