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Assessing spatial and social dimensions of shared bicycle use in a Southern European island context: The case of Las Palmas de Gran Canaria

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A R T I C L E I N F O

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A B S T R A C T

The 21st century has seen a cycling renaissance across Europe with many cities moving away from the car-centric infrastructure, urban design and planning policies prevalent since the 1950s. Southern European island cities, which exhibit certain characteristics considered as barriers to cycling, such as hot summers and high humidity, hilliness, and car-oriented culture and infrastructure however, have been lagging behind in this resurgence of cycling. Despite this, bicycle sharing systems (BSS) and policies promoting cycling have emerged in this region. These have the potential to provide alternatives for those marginalized by car-based mobility and to reduce traffic related diseases and injuries, noise and air pollution, which can contribute to an improved quality of life for all citizens.

Using the coastal city of Las Palmas de Gran Canaria (Canary Islands, Spain) as a case study, the utilization of bike-sharing is investigated through a questionnaire to users of the shared bicycles, as well as through spatial analysis of the BSS trip data. The analysis of the survey, through descriptive and inferential statistics, allows for an understanding of the demographic and socio-economic characteristics of the users, and the inter- and intra-personal factors influencing the choice to use a shared bicycle as a mode of transport. Results show that distance to nearest station, money-saving and environmental concerns, satisfaction with the operating system, and provision of safe cycling infrastructure significantly influence BSS use. A regression model is constructed to assess the influence of spatial factors such as land use, socio-economic characteristics and network variables on the use of the BSS. From the regression model it appears that the presence of cycling infrastructure, proximity to a bus station and the density of tourism accommodation, and by proxy, the number of cafes and restaurants, near bicycle sharing stations positively influences frequency of use. These insights contribute to a deeper understanding of the role of the BSS in the promotion of cycling and the transition to sustainable and inclusive mobility policies, which are still contested in the car-centric transport system currently dominating the city.

1. Introduction

Cycling is being promoted in cities across the globe as part of a shift towards more sustainable mobility, and particularly more

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active transport, because of its potential to contribute to meeting public health, environment, climate, transport and other socio-economic policy goals (Goodman et al., 2013; Handy et al., 2014; Sallis et al., 2016). Cycling offers people a mode of transport that is healthy, highly autonomous, flexible and accessible (Efthymiou et al., 2013). Due to its relative low cost to users, cycling is also an economical choice, and because of its affordability it is one of the most equitable forms of transport (Pucher and Buehler, 2008). In car-dependent societies, road infrastructure caters mostly for those opting to use a private vehicle, but there are many members of society who cannot or do not drive, such as youths, elderly, people with a disability or those who cannot afford to drive (Litman, 2017). The rise of bicycle sharing systems (BSS) has been shown to have positively contributed to the promotion of cycling as a transport mode. They provide for lowered barriers for urban cycling through the provision of bicycles, contributing to increased access to bicycles (Médard de Chardon et al., 2017) with the advantage of renting over owning (Efthymiou et al., 2013), but also through normalising the image of cycling, by "increasing the number and diversity of cycling role models visible" (Goodman et al., 2014), and through "safety in numbers" (Elvik, 2009).

Southern European island cities have been selected as the area for investigation, as their transport systems and infrastructure are under notable pressure due to a heavy reliance on private car transport, with the addition of a seasonal influx of tourists, especially during their high season (Cavallaro et al., 2017). There are barriers to cycling in Southern European island cities, such as their climate with high temperatures and humidity (Médard de Chardon, 2016), hilliness and elevation patterns that present a challenging topography (Heinen et al., 2010), car-oriented culture and infrastructure (Cavallaro et al., 2017), and economic and social peripheralization, as a result of their insularity (Deidda, 2016). At the same time, there is also evidence to support the contrary: low rainfall and lack of sub-zero temperatures can provide a more attractive climate for cycling (Fishman, 2016), investment in cycling infrastructure and facilities can create a notable increase in the cycling modal share, as evidenced by the example of Seville (Marqués et al., 2015), and increased availability of electric bicycles can neutralize the effect of steep inclines and warm weather (Shaheen et al., 2010). A question put forward in the literature, and one that is specifically relevant in cities with a minimal modal share of cycling and a budding bicycle sharing system, is "who uses bicycle sharing systems and why?" (Clark and Curl, 2016; Fishman, 2016). This research aims to contribute to the research field by providing a better understanding of who the users of the BSS in Las Palmas de Gran Canaria are, what their socio-economic characteristics are, what motivations they have for using BSS, and how their BSS use is influenced by the (objective and perceived) physical environment.

2. Literature review

Bicycle sharing systems, or BSS, are shared bicycle fleets allowing short-term public use (Shaheen et al., 2010). Since the late 1990s, when only a handful of bicycle sharing systems existed, the number of BSS around the world has spread rapidly across the globe, growing to over 1000 active systems in 2016 (Médard de Chardon, 2016). BSS can be broadly classified in two different categories: those based on docking stations, where users rent and return the bicycles (most often at any available station, but in some cases bicycles have to be returned to the same station), and dockless free-floating systems, where users find, rent and return a bicycle through an app within a defined area (DeMaio, 2009; Fishman, 2016). BSS are operated by different type of actors: privately owned and operated, publicly owned and operated (by either a local government or transport authority), publicly owned and contractor operated, companies (e.g. advertising agencies or dedicated bicycle sharing system provider), third-party operators with a street furniture contract, non-profit organisations, universities or vendor operated (DeMaio, 2009; Shaheen et al., 2013; Médard de Chardon et al., 2017).

Shared bicycle use, as other types of travel behaviour, is affected by multiple levels of factors, ranging from individual factors to social and spatial factors (Handy et al., 2010; Heinen et al., 2010; van Acker et al, 2010). Individual factors include socio-demographics characteristics, attitudes, preferences, habits and self-efficacy. Social factors refer to social influences and cultural norms. Spatial factors include both built environment characteristics (e.g. land use patterns, transport system) and natural environment characteristics (e.g. elevation, scale, weather). Together such factors form a socio-ecological model of travel behaviour. Handy et al. (2010) applied such a socio-ecological travel behaviour model to bicycling behaviour specifically, upon which this study's framework is based (Fig. 1). In this study, the influence of individual and social factors is assessed through a BSS user survey. The influence of spatial factors, as well as certain individual and social factors at an aggregate level (e.g. socio-economic data at census tract and

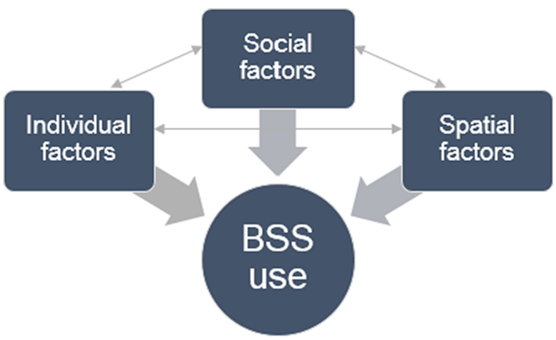

Fig. 1. A socio-ecological model of shared bicycle use (adapted from Handy et al., 2010).

neighbourhood level), are investigated through analysis of the BSS trip data.

In principle BSS are often presented as a public service, and are available to almost anyone, with generally the only limitation being the necessity of using a bank or credit card for payment (Beroud and Anaya, 2012). BSS users can be divided into two market segments: registered members who obtain a subscription on a monthly, semester or yearly basis, and casual users, who pay for a short term (e.g. per day, or up to a week) or on a pay-as-you-go basis (Gauthier et al., 2013; Jain et al., 2018). However, despite the premise of being accessible to (almost) all, evidence from a number of different cities show that bicycle sharing users tend to be predominantly white, male, with relatively high income and education, and engaged in full-time or part-time work (Fishman, 2016; Médard de Chardon et al., 2017), for example in London (Morton, 2018), Dublin (Murphy and Usher, 2015) and Chicago (Faghih-Imani and Eluru, 2015). There are however also studies showing no significant difference between male and female use of BSS, such as in Montréal (Fuller et al., 2011) and amongst students in Valencia (Molina-García et al., 2013). Furthermore, in a study assessing the difference between regular cyclists and BSS users in Washington D.C., BSS users were found to be more likely to be female, younger and own fewer cars and bicycles when compared to regular cyclists in the same city, indicating that BSS in a city may be appealing to different user groups than private cycling (Buck et al., 2013).

Previous studies have looked at the influence of several spatial factors on BSS use, e.g. land use (Faghih-Imani et al., 2014; Wang et al., 2016), cycling infrastructure (Buck and Buehler, 2012; Rixey, 2013; Mateo-Babiano et al., 2016), socio-economic variables (Rixey, 2013; Wang et al., 2016) and network variables (Rixey, 2013; Wang et al., 2016). Buck and Buehler (2012) used a simple multiple regression model to analyse the influence of different factors on BSS use in Washington D.C. at station level and found that cycling infrastructure and retail near the stations, as well as higher population density and households without a car positively affected BSS use. In their research, Faghih-Imani et al. (2014) extended their enquiry into the analysis of both spatial and temporal factors on the use of the BSS in Montréal in a linear mixed model, and found that warmer weather, bicycle infrastructure, presence of restaurants and metro stations, and distance to the central business district all positively influence station use. Rixey (2013) assessed the influence of socio-economic, land use and network variables across three BSS systems in the US using a multivariate linear regression model, and found network variables, higher median income, population density, job density, as well as other socio-demographic factors, to be positively associated with BSS use at station level across different systems. In a study of the BSS in Minneapolis-St. Paul, Wang et al. (2016) found socio-demographics (age, race), proximity to the central business district, water, trails and other BSS stations to be positively correlated with BSS use in both a log-linear OLS and a negative binomial regression model. Mateo-Babiano et al. (2016) used a linear regression model to analyse the influence of cycling infrastructure, land use and topography on BSS use in Brisbane, and found that dedicated cycling infrastructure influences the use positively, and elevation negatively.

Bicycle sharing systems are geographically limited, often focused in the city centre, and on destinations such as business districts and university campuses (Fishman et al., 2015; Ricci, 2015), which can explain at least part of the observed demographic bias of BSS users (Fishman, 2016). The equity and accessibility implications of BSS for different groups of people have been addressed in a number of BSS studies. In their study of BSS membership in three US cities, Gavin et al. (2016) found that the gender, ethnicity and socio-economic status of BSS users does not reflect the population characteristics of the communities in which they are operating. BSS generally serve only a small section of a city's population; in the case of Glasgow only 9% of the city's population lives within a 400 m radius of a BSS station (Clark and Curl, 2016). Other parts of the city, especially less affluent areas, are often not effectively served by BSS. Evidence from the London BSS has shown that when adjusting for distance to the nearest BSS station, residents of more deprived neighbourhoods actually make more trips per month than those from wealthier areas (Ogilvie and Goodman, 2012), and the expansion of the London BSS eastward into more deprived areas demonstrated an increase in shared bicycle use by residents of these parts of the city (Goodman and Cheshire, 2014). In their study of the Dublin BSS, Murphy and Usher (2015) found that modal shift among higher income earners was more likely to be from car or rail to bicycle, while modal shift of those in lower income groups was more likely to occur from bus or walking to bicycle, indicating increased mobility and efficiency for low-income earners. Providing good accessibility to the BSS, while ensuring affordability, can enable equal opportunities and improved mobility for everyone.

3. Case study

Las Palmas de Gran Canaria is the largest city and capital of the island Gran Canaria, located on the North-Eastern coast, with almost 380,000 inhabitants living in the wider metropolitan area in 2018 (Ayuntamiento de Las Palmas de Gran Canaria, 2018). The city has a challenging topography, due to its linear development along the coast, the presence of an isthmus and peninsula within the urban perimeter, and elevation differences of up to 300 m between sea level and the highest located neighbourhoods, colloquially dividing the city into the lower city and the upper city (Ayuntamiento de Las Palmas de Gran Canaria, 2015).

Fig. 2 presents a land use map of the city, including the BSS station locations, the existing and proposed bicycle network and some key neighbourhoods indicated. Fig. 3 presents the spatial distribution of main Points-of-Interest, such as the locations of the bus stations (the two main bus stations at Santa Catalina and San Telmo, and two other bus stations, at the port and to the south of San Telmo), the location of the main university campus (*Universidad de Las Palmas de Gran Canaria*, ULPGC), and the location of hotels, clothing shops and café's/restaurants. The city has two areas that can be defined as the city centre: the area around Santa Catalina park and the Las Canteras beaches, and the historic centre around San Telmo, Triana and Vegueta. Contour lines illustrating the elevation differences in the city show how the majority of the Points-of-Interest are located in the lower part of the city, whereas the upper city is more residential in nature. The study area is confined to the near vicinity of the network of BSS stations, indicated by the 300 m buffers around the stations, a common metric for the direct catchment area of a BSS station. However, when looking at areas that the BSS does not currently serve, the study looks at the city as a whole, defined by the perimeter of the urban area (i.e. the residential area, industrial / commercial, sports facilities and parks, as indicated in Fig. 2), as well as nearby facilities such as the

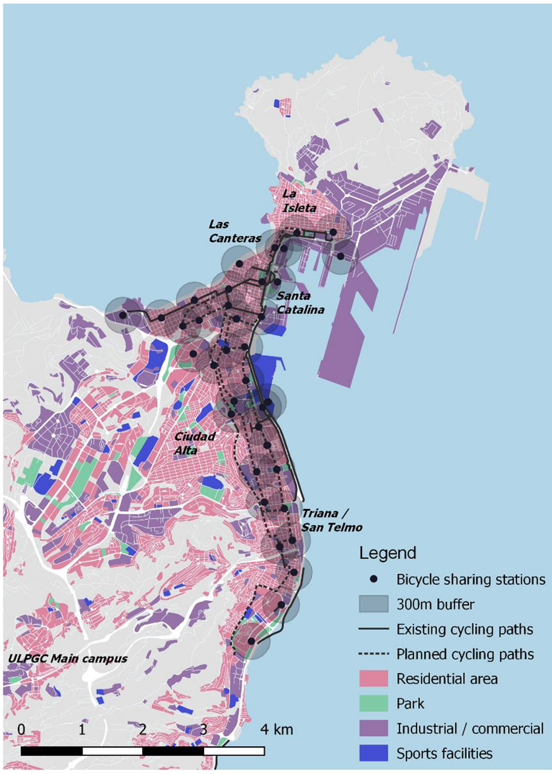

Fig. 2. BSS stations, (existing and planned) cycling paths and land use in Las Palmas de Gran Canaria. (Drawn by author, based on EEA, 2012; Estudio Manuel Calvo, 2016; Sítycleta, 2019).

university main campus (ULPGC).

In a study as part of the Sustainable Urban Mobility Plan (SUMP) modal share in the city was determined, which found that of all trips, 67% are done by private car, 13% by bus, 15% on foot and < 1% by bicycle (Ayuntamiento de Las Palmas de Gran Canaria, 2015). In 2016, the municipality published the Bicycle Master Plan (*Plan Director de la Bicicleta,* Estudio Manuel Calvo, 2016), an updated version of a previously issued plan in 2013, which proposes a plan for promoting cycling as a mode of transport, defines a cycling network for the city and sets out design principles for the proposed cycling infrastructure. The Bicycle Master Plan identifies five main axes that together will create an integrated bicycle network (included as 'planned cycling paths' in Fig. 2), the first parts of which started being implemented in summer 2019.

SAGULPA, the municipal company responsible for parking management, introduced the bicycle sharing system *Sítycleta* in April 2018, with around 375 bicycles and 37 stations, all located within the lower part of the city (situation up until March 2019 is shown in Fig. 2). After the first year of operation, in March 2019, the BSS had close to 24,000 registered users and nearly 11,000 active users (SAGULPA, 2019). Las Palmas de Gran Canaria receives tourists all year round, but especially in the winter season, when temperatures are still pleasant on the island. The percentage of BSS users with a foreign phone number (indicating tourists or temporary residents) ranged from 5 to 15% in spring and summer to 15–25% of users in autumn and winter, based on data from the first year of operation (SAGULPA, 2019). Extension of the system up to the part of the city at higher elevation is foreseen, with the first two e-bicycle docking stations installed and a fleet of 20 electric bicycles inaugurated in April 2019. There are no plans to move to a (partially) dockless system, but there are plans to further densify the system, with a station every 200 m, rather than the current 400 m (C. García, SAGULPA, personal communication, July 24, 2019). The system is open daily throughout the year from 07:00 until 23:00. There are weekly (€15), monthly (€20), and yearly memberships (€40 for one person, €72 for a two-person membership and €102 for a three-person membership), which gives a user unlimited free 30-minute use of the system, and a pay-as-you-go rate of €1.50 for every 30 min. The electric bicycles are also free for the first half hour for subscription users, or €2.50 per 30 min for casual users. The yearly membership fees are relatively low compared to other BSS, as the system is subsidized through income generated from municipal parking fees (C. García, SAGULPA, personal communication, July 24, 2019).

4. Methodology

In this study a combination of two quantitative approaches in BSS research is used. Revealed usage through BSS trip data is analysed to understand "how much", "when" and "where" the bicycle sharing system is used, and how they are influenced by spatial factors such as land use and socio-economic variables. Self-reported data provided through user surveys is analysed to understand

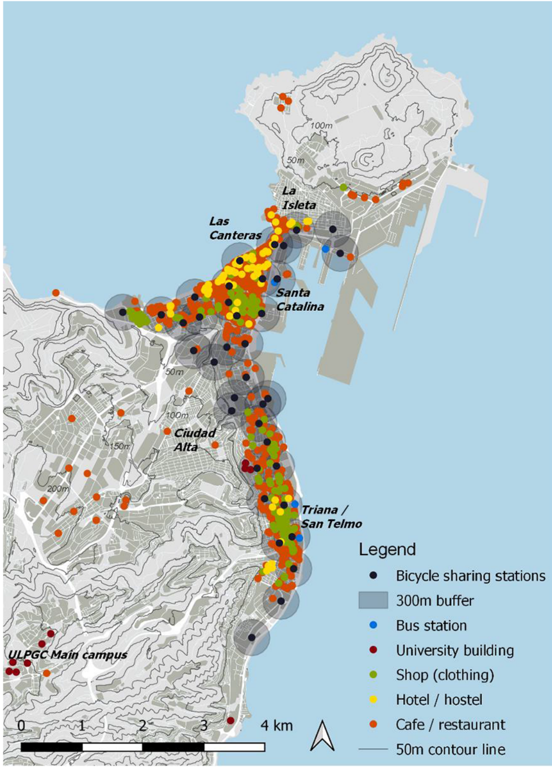

Fig. 3. BSS stations, Points-of-Interest and elevation (contour lines) in Las Palmas de Gran Canaria. (Drawn by author, based on EEA, 2012; OSM, 2019; Sítycleta, 2019).

"who" the users are, and "why" they use the BSS; to assess how intra- and inter-personal factors, such as socio-demographic characteristics, personal attitudes, and the influence of their peers and wider social norms influence their use of the BSS. This study builds and expands on previous research with BSS users and spatial analysis of BSS use, by assessing one system from both perspectives to understand both social and spatial influences, in a city with a different context, where several identified barriers to cycling are present. Results can be used to better understand to what extent the BSS serves the city's population, what motivates current users, how to attract other user groups, and ultimately, how to promote (shared) bicycle use in a city with a low cycling modal share.

4.1. BSS user survey

The BSS user survey is a self-administered revealed preference survey with a cross-sectional design, using Google Forms, a web-based platform to collect questionnaires. In order to reach both registered users that have a subscription, as well as casual users using the pay-as-you-go tariff, the survey was distributed in different ways: through intercept surveys at the stations during a 3-week fieldwork period in July 2019 where users were handed a free reflective wristband with the link to the survey, through a newsletter sent out by the BSS operator to their database of registered users, and through different social media channels. As an incentive for participation, respondents were offered a free gift provided by the operator of the BSS. Using different methods to distribute an online survey allows for broader exposure and can aid in minimizing the bias associated with these types of surveys (Bachand-Marleau et al., 2012). The survey contains three sections: 1) demographic and socio-economic characteristics; 2) mobility practices and travel habits; and 3) attitudes and perceptions, with a total of 34 questions. Questions about frequency of use of different transport modes (e.g. walking, cycling, public transport, car) and frequency of use of BSS for different purposes (e.g. commuting, shopping, fun) are measured through a five-point Likert scale ranging from 'daily' to 'never'. Attitudes and perceptions, e.g. motivating factors, satisfaction with the service, encouraging and discouraging factors, are measured through five-point Likert scales ranging from 'completely agree' to 'completely disagree'. A total of 491 survey responses were collected. The margin of error is 4.4% at a 95% confidence level. The survey responses were analysed using R. Chi-square tests were performed to analyse the relationship between nominal and ordinal variables, and the Kruskal-Wallis test to analyse the relationship between age (quantitative variable) and the other variables. For any pairs of variables that showed an association (p-value < 0.05), a Spearman's correlation test was performed to understand the strength and direction of the association, and to determine whether the association is significant. For the quantitative variable, the Dunn test was used to analyse the significance of associations.

Table 1
Dependent and independent variables in the regression model.

Variable	Definition	Unit; range	Median (SD)
Dependent variables			
COUNTO	Count of station location as a trip origin	Discrete number; 32–12,529	3,987 (3148)
COUNTD	Count of station location as a trip destination	Discrete number; 17–13,862	3900 (3528)
Independent variables			
Land use variables			
LU_RES	Percentage of residential land use in 300 m buffer	Percentage points; 0.00–0.81	0.57 (0.22)
LU_COM	Percentage of commercial/industrial land use in 300 m buffer	Percentage points; 0.00–0.73	0.11 (0.17)
LU_TOUR	Count of hotels/hostels within 300 m buffer	Discrete number; 0–15	0 (3.76)
LU_CAFE	Count of café's/bars/restaurants in 300 m buffer	Discrete number; 0–134	20 (30.54)
LU_BEACH	Presence of beach/promenade in 300 m buffer	Dummy variable; 0–1	–
LU_PARK	Percentage of park land use in 300 m buffer	Percentage points; 0.00–0.28	0.04 (0.06)
LU_BUS	Presence of bus station in 300 m buffer	Dummy variable; 0–1	–
LU_UNI	Presence of university building in 300 m buffer	Dummy variable; 0–1	–
LU_SHOP	Count of clothes shops in 300 m buffer	Discrete number; 0–40	3 (11.68)
LU_LEN_CYC	Length of cycling paths in 300 m buffer	Length in meters; 0.00–1,486.32	520.95 (457.30)
LU_DIST_CY	Distance from station to nearest cycling path	Distance in meters; 0.96–769.52	135.74 (178.94)
LU_DISTSEA	Distance from station to nearest coastline	Distance in meters; 33.76–927.94	217.55 (206.35)
LU_DISTBUS	Distance from station to nearest bus station	Distance in meters; 68.69–2,540.29	859.84 (645.57)
LU_DISTUNI	Distance from station to nearest university building	Distance in meters; 109.00–4,182.91	2135.00 (1140.39)
LU_NODES	Count of nodes in transport network in 300 m buffer	Discrete number; 114–550	324 (110.52)
ELEV	Elevation in meters above sea level at station location	Elevation in meters; 2.25–66.15	6.69 (12.04)
Socio-economic variables			
POP_DENS	Inhabitants/km^2 (2011) in census tract at station location	Inhabitants/km^2; 371.6–64,031.60	13,998.00 (13547.96)
PERC_EDU3	Percentage of residents with tertiary education (2011) in census tract at station location	Percentage points; 0.02–0.60	0.32 (0.13)
GEND_RATIO	Percentage of M in M/F quotient (2018) in neighbourhood at station location	Percentage points; 0.83–1.00	0.91 (0.05)
AGING_POP	Percentage of population over 65 years of age (2018) in neighbourhood at station location	Percentage points; 0.07–0.25	0.21 (0.03)
FORGN_POP	Percentage of foreign population (2018) in neighbourhood at station location	Percentage points; 0.02–0.22	0.09 (0.06)
AVG_AGE	Average age (2016) in census tract at station location	Discrete number; 37–47	44 (2.20)
AVG_INC	Average income in €/year (2016) in census tract at station location	Amount in €; 6,217–20,336	12,931 (3807.33)
Network variables			
DIST_MEAN	Station distance from centre of the BSS	Distance in meters; 72.97–4,318.37	1556.08 (979.23)
COUNT_STAT	Number of stations in 600 m buffer around station	Discrete number; 2–12	7 (2.53)

Data sources: Land use variables (EEA, 2012; Estudio Manuel Calvo, 2016; IGN, 2018; OpenStreetMap contributors, 2019); Socio-economic variables (INE, 2011, 2016; Ayuntamiento de Las Palmas de Gran Canaria, 2018);
Network variables (Sítycleta, 2019).

4.2. BSS trip data

Trip data refers to the data pertaining to the bicycle trips made from origins (O) to destinations (D), including the location of the stations, the date and time when the bicycle was rented and returned, the bicycle number and an anonymised user ID, which has been shared by the operator following the signing of a data sharing agreement. The dataset used for the analysis in this paper pertains to the period 9 April 2018 (the start of the BSS) until 31 March 2019. Descriptive statistics of the dataset, such as trip duration and time series, are presented to get a basic understanding of the BSS trip patterns and dynamics (Mateo-Babiano et al., 2016). To prepare the trip data for analysis, entries with a missing origin or destination station, as well as those pertaining to a temporary station on to a station outside of the city were removed. In line with the literature, any trips with a duration under 2 min were removed as these are likely the result of a mistake or malfunctioning bicycle (Fishman et al., 2014), as well as trips with a duration of longer than 500 min (Bordagaray et al., 2016). Data cleaning resulted in the removal of 7.84% of the initial 176,731 trips in the dataset, with 162,871 trips remaining. The data was analysed and the regression model constructed using R. From the literature, several independent variables were identified that may influence the frequency of use of the BSS: land use, socio-economic, infrastructure and network variables (Buck and Buehler, 2012; Rixey, 2013; Faghih-Imani et al., 2014; Mateo-Babiano et al., 2016; Wang et al., 2016). In order to understand which of these variables explain variation in the dependent variables in the case of Las Palmas de Gran Canaria's BSS, a regression model was constructed including the dependent and independent variables listed in Table 1.

Two dependent variables were included, COUNTO and COUNTD, the total aggregated counts of trip origins and trip destinations respectively at a station location, to see if there is any difference in the factors influencing the frequency of use of a station as a trip origin and as a trip destination. Data from different secondary sources was collected based on the station location (Sítycleta, 2019). The station location was used to determine the specific value of a variable at that location (e.g. the population density in the census tract, or the elevation at that location), within a 300 m buffer around the station location (e.g. count of the presence of Points-of-Interest) or to calculate the distance from the station location to a specific feature (e.g. to the nearest bus station or the coastline). All

Table 2
The socio-demographic profile of the survey sample (n = 491).

	Sample specifics		Sample specifics		
				Permanent resident (1 year +):	85%
Gender	Female:	37.3%	Residency	Temporary resident (< 1 year):	6%
	Male:	62.3%		Visitor (for work/education):	4%
	Non-binary:	0.04%		Visitor (for leisure/tourism):	5%
Age	< 18:	1%	Employment status	Full-time employed:	68%
	18-24:	9%		Part-time employed:	6%
	25-34:	29%		Housewife/husband:	1%
	35-44:	29%		Retired/pensioner:	4%
	45-54:	23%		Student:	10%
	55-65:	7%		Unemployed:	8%
	65+:	2%		Self-employed:	3%
				Other:	1%
Nationality	Spanish:	87%	Highest completed education	None:	0%
	Italian:	3%		Primary school:	1%
	British:	1%		Secondary school:	12%
	French:	1%		Undergraduate degree (college, bachelor degree):	49%
	Dutch:	1%		Postgraduate level (Master's degree, PhD):	38%
	Finnish:	1%		Less than €10.000/year:	20%
	German:	1%	Gross annual Income	Between €10.000 and €20.000/year:	27%
	Polish:	1%		Between €20.000 and €30.000/year:	21%
	Venezuelan:	1%		Between €30.000 and €40.000/year:	15%
	Other:	4%		Between €40.000 and €50.000/year:	7%
				More than €50.000/year:	10%

measures of distance are based on the Euclidian distance between the station location and a specific feature. Data on land use was extracted from the Copernicus Land Monitoring Service - Urban Atlas (UA) 2012 dataset (EEA, 2012) and the OpenStreetMap (OSM) dataset (OpenStreetMap contributors, 2019). A buffer of 300 m, was used around the stations, as it is the most commonly used measure for a walkable distance to BSS stations (e.g. Sun et al., 2017; Zhang et al., 2017; Jain et al., 2018). Based on the UA dataset, the percentage of land use (e.g. residential, commercial/industrial, park) within the station buffer was calculated. The presence of restaurants/café's, hotels, university, city centre, parks, promenade/beach and bus stations within the buffer was obtained from the OSM dataset. The road network was extracted from the OSM dataset and the number of nodes within the buffer around the stations was calculated. The distance to the nearest cycling path and the length of cycling path within the 300 m buffer was based on the location of existing cycling infrastructure (Estudio Manuel Calvo, 2016). Elevation was extracted from the Digital Elevation Model (IGN, 2018). Population density, percentage of population with tertiary education level, average age and average income values per station location were obtained by intersecting the point location of the station with a dataset of these socio-economic variables by census tract (INE, 2011, 2016). Values for the gender quotient, the percentage of population over 65 years, and the percentage of foreign population per station location were obtained by intersecting the point location of the station with a dataset of these socio-economic variables by neighbourhoods *(núcleos)* (Ayuntamiento de Las Palmas de Gran Canaria, 2018). Network variables were included to control for the influence of the system design and interaction.

5. Results

5.1. Analysis of the survey

Table 2 presents the socio-demographic profile of the respondents from the survey responses (n = 491). The gender balance shows that 37.3% of respondents are female and 62.3% male. In line with most BSS, especially in cities without a strong cycling culture, an initial predominance of male users is expected (Murphy and Usher, 2015; Faghih-Imani and Eluru, 2015).

The mean age of respondents is 39, with a minimum of 17 and maximum of 73. Surprisingly, the age distribution shows that the main age groups using the BSS are those within the 25–34, 35–44 and 45–54 age brackets, as opposed to the age distribution observed in many other BSS, which follow a more right-skewed curve where the majority of users is in the 18–34 age bracket (Murphy and Usher, 2015; Fishman et al., 2015). The users are highly educated, with 87% of respondents having an under- or postgraduate level education, in line with user characteristics of other BSS, where the majority of users are highly educated and in employment (Fishman, 2016; Médard de Chardon et al., 2017).

The frequency of the use of the BSS for different trip purposes is presented in Fig. 4. Respondents were asked how often they use the BSS for commuting purposes (*commute*), for business/work travel (*business*), to go shopping (*shopping*), to go out for food or drinks (*food*), for touristic sightseeing (*tourism*), for fun (*fun*), for exercise (*exercise*) and for visiting friends and family (*friends*). The possible answers were presented on a Likert scale consisting of the options 'daily', 'often' (a few days per week), 'sometimes' (about once every 2 weeks), 'rarely' (less than once a month), and 'never'. The most popular uses for the BSS are for commuting (29% of respondents use it for this purpose daily or often) and for fun (27% of respondents use it for this purpose daily or often). The least common use is for

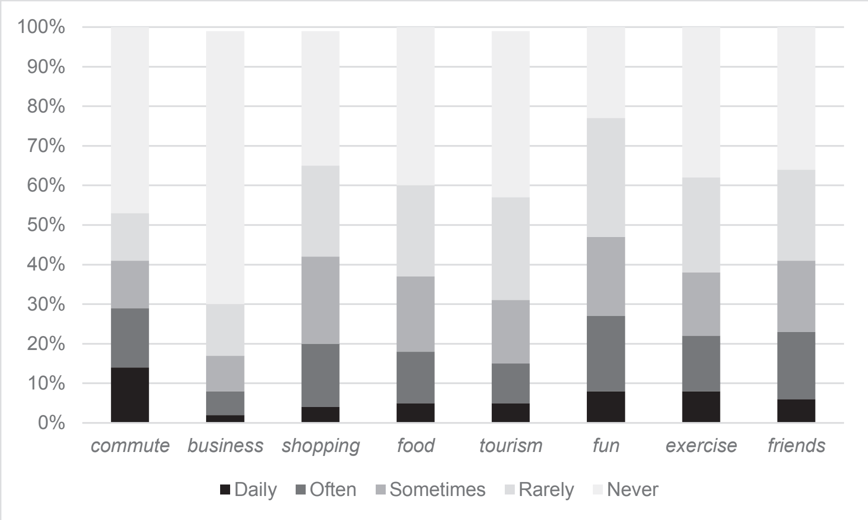

Fig. 4. Frequency of use of BSS for various trip purposes (n = 491).

business/work travel.

The relationship between the socio-demographic variables included in the survey (see the variables presented in Table 2) and variables describing and measuring travel behaviour and BSS use were explored using the Kruskal-Wallis test (for the quantitative socio-demographic variable 'age') and Pearson's Chi-squared tests (for the categorical socio-demographic variables). The results section primarily focuses on the relationships that showed a significant association (p-value < 0.05), but some non-significant results are highlighted where there is an expected effect based on findings from the literature. Significant associations were further analysed through a Spearman's correlation test for the categorical variables and Dunn's test for the quantitative variable, to understand the strength and direction of the association.

Socio-demographic variables have a clear relationship with car ownership and use. Younger respondents are less likely to own a car, to have a driving license or to use the car (as a driver) frequently. Conversely, respondents with a higher income are more likely to own a car, have a driving license and use the car (as a driver) more frequently. Respondents with a lower education level are more likely not to have access to a car and/or use the car (as a driver). Whereas these socio-demographic variables are at least partly multicollinear, in the sense that with an increase in age, there is usually also an increase in average income, there is also a trend for younger generations to be less attracted by car-oriented lifestyle, where the car is seen as a marker of progress (Woodcock and Aldred, 2008), and more attracted to shared mobility options (Martin and Shaheen, 2011; Clark and Curl, 2016). There was no significant association between ownership of a private bicycle and BSS use in terms of frequency of use or purpose of use. However, respondents that own a private bicycle were found to be significantly more experienced cyclists and more likely to indicate they like cycling; results that are expected as they are directly linked with the motivation to cycle and the frequency of cycling. Respondents that own a private bicycle differ from the other respondents as they most frequently cycle on a bicycle lane on the road rather than on a separated cycling path as the other respondents indicate. This shows how BSS users without a private bicycle take a more cautious approach and prefer separated cycling infrastructure, potentially also because on the whole they are less experienced cyclists. Lastly, respondents with a private bicycle were more likely to drive a car more frequently.

Younger respondents are more likely to use public transport on a daily basis, and are also more likely to use the BSS in conjunction with public transport to complete their trips. The mean age of respondents that use the BSS 'daily' to go out for food or drinks, for fun, and for touristic purposes is significantly lower than the mean age for those who 'rarely' or 'never' use the BSS for these purposes. Those who 'completely agree' that money-saving is a motivating factor to use the BSS are significantly younger than those who disagree or agree to a lesser extent.

In terms of gender differences, females self-report to be less experienced cyclists than males, with more females indicating they are 'not experienced' or 'moderately' experienced cyclists, and more males indicating they are 'very experienced'. There is a significant difference in the trip duration between females and males, with the median of trips by females in the category 20–30 min, and that of males in the category 10–20 min. In terms of motivation, female respondents are more motivated by money-saving and by fun than male respondents. When respondents were asked about their feeling of safety in different road environments (on separated bicycle paths, on bicycle lanes on the road, on the road without infrastructure, and on pedestrian spaces such as pavements and promenades), all respondents indicated that they feel safest on separated bicycle paths and least safe on the road, but females indicate feeling more unsafe than males on the road. This gender difference is generally observed in cities with a low modal share for cycling, where cycling is generally less safe and/or perceived as less safe, as women are more risk-averse in general (Pucher and Buehler, 2008). Looking specifically at the age variable for women in relation to their BSS use showed that the more frequent the BSS use, the lower the median age (median age for different frequency of use: 'never': 38; 'rarely': 37; 'sometimes': 35; 'often': 32.5; 'daily': 32). However, the Kruskal-Wallis test for the association between these variables did not confirm the differences between the categories as significant. When analysing specific trip purposes of BSS use by women, only BSS use ‘for fun’ showed a significant association: female users who ‘never’ or ‘rarely’ use the BSS for fun are significantly older than those who use the BSS for fun ‘sometimes’, ‘often’ or ‘daily’.

Residency status, whether a respondent identified as a permanent resident, temporary resident (< 1 year), or a visitor (for work / education; or for tourism / leisure), shows a significant relationship with the frequency of BSS use. The median varied between the different classes of residency, with temporary residents indicating the most frequent use (median: ‘often’, a few days per week). Permanent residents and visitors (for work / education) had a median value of ‘sometimes’, about once every 2 weeks. Visitors (for tourism) used the BSS least frequently (median: ‘rarely’, less than once a month), which can be explained by the temporality of their visit and most likely only using the shared bicycle as a one-off experience rather than as a mode of transport during their stay. Results for the association with BSS use by trip purpose shows similar results. Temporary residents use shared bicycle most frequently for commuting purposes, as well as to visit touristic sites (in both cases, median: ‘sometimes’, about once every 2 weeks). Permanent residents and visitors (both for work / education, and for tourism) use the BSS less frequently for these purposes. Temporary residents are less likely than permanent residents to own a car: 58% versus 70% of respondents in that category. Chi-squared tests of the relationship between nationality and the use of BSS (frequency of use, and use for different trip purposes) found no significant associations.

Income as a variable did not generate many significant associations, despite the association having been found by e.g. Rixey (2013). The only significant relationships found were (i) that those respondents with a higher income have a higher level of cycling experience (confounded by the age factor), and (ii) that users with a higher level of income are less motivated to use the BSS for money-saving purposes. Employment status did not show any association with either the frequency of the use of the BSS, nor with BSS use for specific work related purposes (e.g. ‘for commuting’ or ‘for business/work travel’).

Finally, the relationship of the dependent variable, the frequency of the use of the BSS, with the variables that showed a significant association was further explored through correlation analysis. The frequency of BSS use was measured on a Likert scale consisting of the options ‘daily’, ‘often’ (a few days per week), ‘sometimes’ (about once every 2 weeks), ‘rarely’ (less than once a month), and ‘never’. For any pairs of variables that showed an association (p-value < 0.05) in the Pearson’s Chi-squared test, a Spearman’s correlation test was performed to understand the strength and direction of the association, and to determine the significance (see Table 3). From Table 3 the following factors have a negative influence on the frequency of BSS use: the frequency of use of a car (as a driver), an increase in the distance between a respondent’s residence or most frequent destination and the nearest BSS station, and agreement with the statement that one needs a car to perform daily tasks. Saving money and the bicycle being an environmentally friendly mode of transport are motivating factors that positively influence the frequency of BSS use. Satisfaction with the operation and design of the system, the availability and comfort of the bicycles and the marketing of the brand all positively influence the frequency of use of the BSS, highlighting the importance of providing a high level of service, maintenance, and customer service. The feeling of safety on separated bicycle paths and dedicated bicycle lanes on the road is also positively correlated with frequency of BSS use, giving an indication of the importance of the creation of safe cycling infrastructure for increasing BSS use and cycling. There is also a positive relationship between the frequency of BSS use and a higher agreement with finding cycling a convenient mode of transport, and feeling supported in their cycling behaviour by friends and family. The normality of cycling, both in terms of it being an accepted form of transport by an individual, as well as by wider society, is an important driver for cycling behaviour (Goodman et al., 2014).

5.2. Analysis of the trip data

Fig. 5 presents the histogram of trip duration, which shows a right-skewed frequency distribution, indicating the majority of trips

Table 3
Bivariate Spearman’s correlation with dependent variable ‘frequency of BSS use’

Variable	Definition (scale)	Correlation coefficient*
Use_cardriver	Frequency of use of car as a driver (Likert 5-point scale)	−0.201
Dist_home	Walking distance from residence to nearest station (ordinal scale, 6 categories)	−0.175
Dist_dest	Walking distance to frequent destination from nearest station (ordinal scale, 6 categories)	−0.292
Mot_money	Money-saving as a motivating factor (Likert 5-point scale)	0.294
Mot_env	Environmentally friendly as a motivating factor (Likert 5-point scale)	0.120
Sat_regist	Satisfaction with sign-up / registration process (Likert 5-point scale)	0.243
Sat_loc	Satisfaction with locations of the stations (Likert 5-point scale)	0.155
Sat_avail	Satisfaction with availability of bicycles (Likert 5-point scale)	0.172
Sat_rent	Satisfaction with renting/returning bicycles (Likert 5-point scale)	0.151
Sat_comf	Satisfaction with comfort of the bicycles (Likert 5-point scale)	0.195
Sat_brand	Satisfaction with BSS brand / marketing (Likert 5-point scale)	0.206
Safe_path	Perceived safety on separated bicycle paths (Likert 5-point scale)	0.167
Safe_lane	Perceived safety on bicycles lanes on road (Likert 5-point scale)	0.211
Conv_cycling	Attitude towards the convenience of cycling as a mode of transport (Likert 5-point scale)	0.261
Need_car	Attitude towards the need for using a car for daily tasks (Likert 5-point scale)	−0.234
Friends	Perception of support of cycling behaviour by friends and family (Likert 5-point scale)	0.261

* All coefficients significant at the 1% level; n = 491.

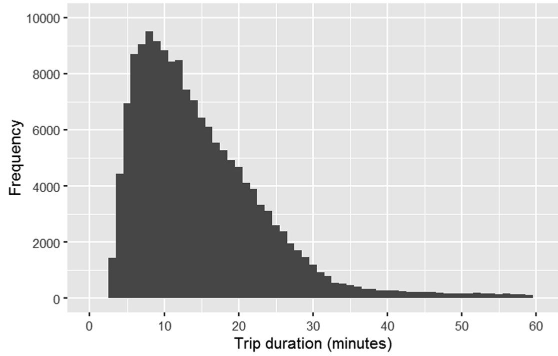

Fig. 5. Histogram of aggregated trip duration (in 1 min increments).

constitute short trips. The histogram includes only the observations in the first hour (from 3 to 60 min), when the majority of trips take place. The propensity for short trips is governed by the pricing structure, based on incremental price increases which encourages short journeys: a 30-minute flat fee interval for casual users, and free rental time for subscribed users (Bordagaray et al., 2016; Pfrommer et al., 2014). Based on the full dataset, with observations between 3 and 500 min, the median trip duration in Las Palmas de Gran Canaria is 13 min, and the average trip duration is 20 min. These findings are in line with average trip duration observed in other BSS, e.g. an average trip duration between 16 and 22 min in Melbourne, Brisbane, Washington D.C., Minnesota and London (Fishman, 2016).

The hourly time series of aggregated weekday and weekend day trips, based on the starting time of the trip at the origin (Fig. 6) shows that weekdays exhibit a triple peak, in the morning between 07:00–08:00, around 14:00 and between 17:00–19:00. These observations are concurrent with observations in other Southern European cities, where next to the morning and evening commuting peaks, a lunch hour or afternoon peak can be observed, e.g. in Lyon and Seville (Borgnat et al., 2011; Castillo-Manzano and Sánchez-Braza, 2013). The weekend peaks (between 11:00–13:00, and between 16:00–18:00), are less pronounced. This is in accordance with commuting patterns during the week and a flatter curve related to leisure activities in the weekend (Pfrommer et al., 2014; Fishman, 2016).

Fig. 7 lists and visualises the top 5 most frequently used stations (as origin, COUNTO, and destinations, COUNTD), their location and their spatial characteristics. A cluster of 4 popular stations is located near the area with most tourist accommodation and attractions, around the areas of Santa Catalina and Las Canteras. This area is one of the centres of Las Palmas de Gran Canaria, with shops, cafés, restaurants and the majority of hotels and hostels in the city. Two stations that feature in both the Origin and Destination top 5, Parque Santa Catalina and San Telmo, are located near the city's two main bus stations. The San Telmo station is near the shopping street Triana, with many shops, cafés and restaurants. All station locations are directly connected or near to the bicycle network.

When looking at the distribution of the BSS stations throughout the city, it can be noted that not the entire city is served by the system. From the distribution of the population in terms of population density (Fig. 8) and average income (Fig. 9), it is clear that there are parts of the city with high population density and low average incomes, in the higher parts of the city (*Ciudad Alta* and other neighbourhoods in the upper city), as well as on the peninsula (*La Isleta*), that are currently not being served by the BSS. Using a buffer around the stations, it was calculated that in Las Palmas 33% of the city's population lives within a 400 m radius of a BSS station, and 28% live within a 300 m radius of a BSS station. However, although that means that the BSS reaches a much larger portion of the population than in the aforementioned example for Glasgow, where 9% of population live within a 400 m buffer (Clark and Curl, 2016), there is still a large part of the city that is currently not served by the BSS.

Bivariate regression was used to determine the relationship strength and direction between the dependent variable and each independent variable on its own, in order to determine which variables should be included in the regression model. At the 0.01 (***),

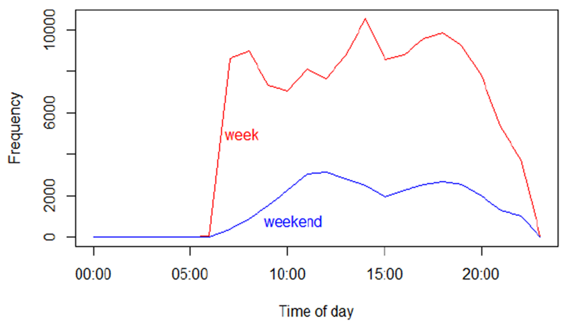

Fig. 6. Hourly time series of aggregated weekday and weekend day trips.

Fig. 7. Location and spatial characteristics of top 5 COUNTO and COUNTD stations.

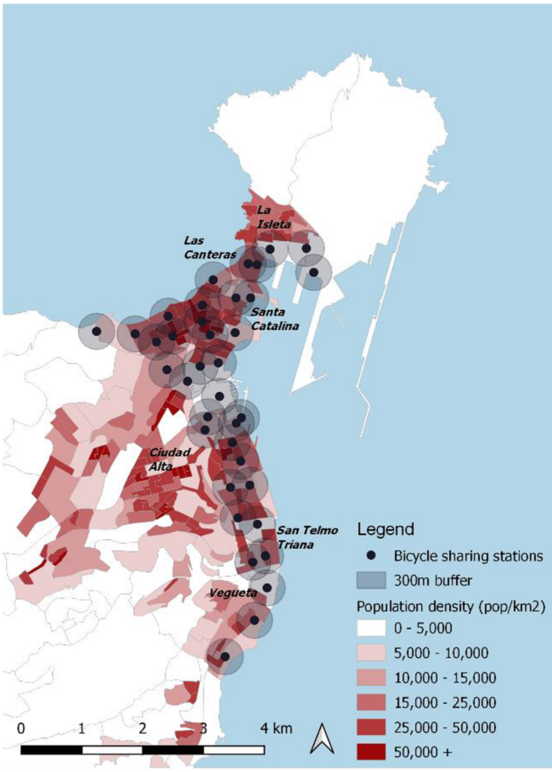

Fig. 8. The population density in Las Palmas de Gran Canaria (INE, 2011).

0.05 (**) or 0.1 (*) significance level for the COUNTO variable, the number of restaurants and cafés (LU_CAFE,***), the number of hotels/hostels (LU_TOUR,***), the distance to (LU_DIST_CY,**) and length of the cycling infrastructure within the buffer (LU_LEN_CYC,***), the distance to the bus station (LU_DISTBUS,**), the presence of coastline in the buffer (LU_BEACH,*), the gender quotient (GEND_RATIO,*), the percentage of foreign population (FORGN_POP,**), and the population density (POP_DENS,*) showed a significant impact on BSS use. For the COUNTD variable, the same variables showed significance as for the COUNTO variable, with the addition of the number of clothing shops (LU_SHOP,*), the average age in the census tract (AVG_AGE,*) and the elevation (ELEV,**). The other variables considered, including network variables, were not of significant influence on the use of stations either

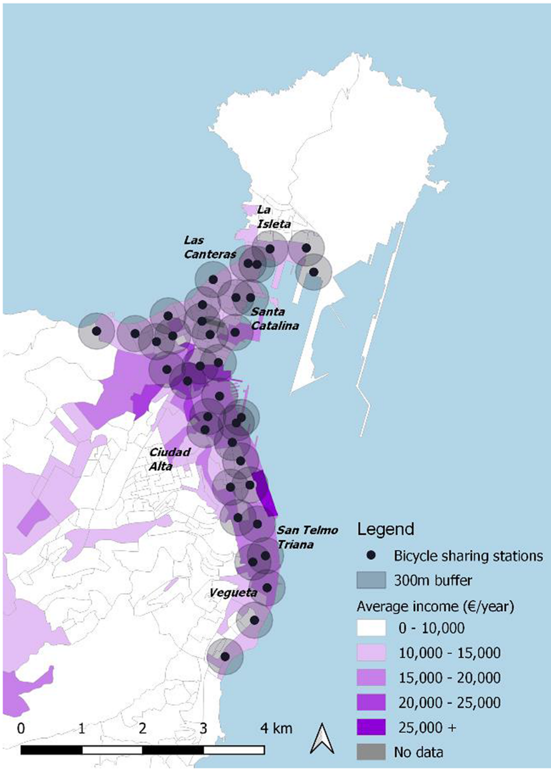

Fig. 9. The average income in Las Palmas de Gran Canaria (INE, 2016).

as an origin or a destination. A correlation plot was created to examine the collinearity between independent variables, to avoid including two or more multi-collinear variables in the different variations of the regression model, before settling on the best model fit. Based on a threshold of ± 0.7 to indicate multi-collinearity, several instances of multi-collinear variables were found, e.g. between LU_COM and LU_RES, and between LU_TOUR and LU_CAFE.

To create the regression model, a traditional Ordinary Least Squares (OLS) regression model was the starting point, after confirming the assumptions for an OLS model were met (Frost, 2019). Regression diagnostics of the fitted models confirmed assumptions of normality of the residuals, linearity in the coefficients and error term, and examination of the residuals confirmed homoscedasticity. The VIF values (ranging between 1.18 and 1.51) indicate the absence of collinearity in the data. Plotting the residuals against the independent variables confirmed independence of errors. Some outliers were present, but their limited number was acceptable and Cook's distance statistics (all values < 0.20) did not give an indication of influential cases. Various regression models were built and tested, based on different combinations of the variables that showed the strongest influence and significance in the bivariate regression, aiming to balance the maximum predictive power of the model (as measured by Adjusted R^2) with a parsimonious design, while ensuring variables follow the expected direction of influence, and are all statistically significant at the 0.05 level (or support the model to maintain significance of other variables).

Since BSS station use is typically not normally distributed, but right-skewed (with few stations with a lot of use, and many stations with little use), several other authors that have used regression models for assessing the influence of land use and socio-demographic characteristics on BSS use have transformed their dependent variable to better fit under a normal curve, e.g. by using a log transformation on the dependent variable 'station activity' (sum of count trip origin and destination) by Wang et al (2016), or on the average monthly rentals by Rixey (2013). However, when comparing model fit of the dependent variables (COUNTO; COUNTD), with a log transformation and the square root of the values, it turned out that model fit was best for the untransformed variable, and interpretation of the results was also more intuitive. Furthermore, in an OLS model there is no need for the dependent or independent variables to be normally distributed, as long as the residuals are normally distributed (Frost, 2019). Since the regression model deals with spatial variables, Moran's I and the Lagrange-Multiplier tests were used to check for spatial autocorrelation in the dataset, in order to determine whether using a Spatial Autoregressive (SAR) model would be a better fit for the data rather than the OLS model. Using different spatial criteria, e.g. the distance between points, *n* nearest neighbours, and the Rook and Queen criteria after creating Voronoi polygons around the station point dataset (Borgnat et al., 2011), several spatial weights matrices were created to test for autocorrelation (Anselin and Bera, 1998; Sarmiento-Barbieri, 2016). However, the results of neither the Moran's I test, nor the Lagrange-Multiplier test, confirm the presence of spatial autocorrelation, and thus there is no justification for using a SAR model instead of OLS model.

The results of the best fitted OLS model (p-value < 0.000***) for both dependent variables (COUNTO, the total counts of trip

Table 4
OLS regression results of best fitted models.

	COUNTO model				COUNTD model			
Variable	*Coefficient*	*Standard error*	*Standardizedcoefficient*	*p-value*	*Coefficient*	*Standard error*	*Standardizedcoefficient*	*p-value*
(Intercept)	27,870	7368		0.001***	34,540	8162		0.000***
LU_TOUR	371.4	105.3	0.443	0.001***	369.2	119.5	0.393	0.004***
LU_DISTBUS	−0.9337	0.595	−0.192	0.127	−1.049	0.664	−0.192	0.124
LU_DISTSEA	3.963	2.073	0.260	0.065*	–	–	–	–
LU_LEN_CYC	3.914	0.894	0.569	0.000***	3.478	0.892	0.451	0.000***
GEND_RATIO	−29,110	8148	−0.430	0.001***	−34,750	9210	−0.458	0.001***
Adjusted R^2	**0.559**				**0.542**			

(n stations = 37; n trips = 162,871; – = variable not included in this model; significant at: * 10%; ** 5%; *** 1% level).

origins per station; and COUNTD, the total counts of trip destinations per station) are presented in Table 4. The standardized coefficients are included too, to be able to compare the relative impact of the independent variables on the dependent variable.

The presence of tourist accommodation has a positive effect on the station use, in both models. The length of dedicated cycling infrastructure (bicycle paths and lanes) in a 300 m buffer around the station is also positively correlated with station use, in accordance with results found by Buck and Buehler (2012), Faghih-Imani et al. (2014) and Mateo-Babiano et al. (2016). In terms of socio-economic variables, only the gender quotient was found to have a significant impact on station use. The direction of the effect shows that a lower percentage of males in the M/F ratio is associated with higher station use, which is somewhat contrary to results found in the literature, as well as the predominance of male BSS users as found through the user survey. The distance to the nearest bus station was included to support the model, as without it other variables were not found to be significant. Although it is not significant, the direction of the effect shows that the further away from a bus station, the less station use, in accordance with other findings showing the positive relationship between BSS use and public transport. Distance to the coastline was only included in the COUNTO model and was significant only at the 0.10 level, but indicates that for stations as an origin, further distance from the coastline is associated with more use. Other factors found in the literature were also included in the model, such as residential land use, population density, median income and network variables. Such as distance from the centre of the BSS and the count of nodes within the 300 m buffer around the stations. These however were not found to have significant relationships with the dependent variables. While in some cities the university campus and the university population (students and staff) have contributed to the spread and success of the BSS (e.g. in Seville, Castillo-Manzano and Sánchez-Braza, 2013), in Las Palmas de Gran Canaria the university campus is situated outside of the city centre, at the edge of the metropolitan area at higher elevation (see Fig. 2). Although there are a few university buildings closer to the city centre, there is no observable effect on BSS use.

6. Discussion

6.1. Limitations of the study

Self-reported data obtained through voluntary-based survey responses is subject to a number of possible biases, such as social desirability bias and participation bias. The support from the operator in sharing the survey and offering a free gift in exchange for participation could lead respondents to give socially desirable answers. To minimize social desirability bias, the survey was kept anonymous. The short timeframe in which the survey responses were collected (a three-week period in July 2019) could give rise to further bias, as a result of the type of users using the system at that time. However, the percentage of permanent residents of all respondents (85%) is in line with what has been recorded as characteristic for the BSS for that period of the year (foreign users around 15%; SAGULPA, 2019). Furthermore, in an effort to address participation bias, the survey was shared through different channels (i.e. online, through email list, in-person, through freebie left on the bicycles), thus reaching different types of users: casual and subscribed users, frequent and occasional users. A certain level of bias is still expected in any self-report survey study (Bachand-Marleau et al., 2012; Bryman, 2016).

Differences between the trip duration of male and female users, for example in their different median trip time (10–20 min versus 20–30 min), can potentially be explained by the fact that women tend to make more complex trips, being more frequently responsible for tasks such as shopping and taking care of children (Heinen et al., 2010). Combining several trip purposes (trip-chaining) can lead to longer average trips. Another factor that could influence this difference is that women prefer separated cycling infrastructure (Pucher and Buehler, 2008), and thus perhaps opt for longer, but safer routes to reach their destinations. Over- or under-estimation of the trip duration by male and/or female respondents can also be a cause of bias, as could be the relatively large size of classes in the question about trip duration (10-minute bins, where 5-minute bins may have provided more accurate results). Although the survey included a question on the size of the respondent's household, information on whether respondents have children or other dependent family members was not included in the survey. As this is a potential explanatory factor, it should be included as a variable in future or follow-up studies.

A limitation of the study is the quality of the spatial data from secondary sources included in the spatial regression modelling. Effort was made to obtain data at the finest-grain level possible, as well as data that was collected in recent years. However, some datasets from recent years were found to be incomplete, e.g. population figures from the 2016 census, and therefore an older dataset from 2011 was used. In addition, while some data was available at the census tract level (e.g. population density, average age, median income), other data was only available at a coarser spatial scale (e.g. gender quotient, foreign population). This spatial level may be less suitable to adequately capture spatial characteristics that contribute to variations in frequency of station use, as observed in the counterintuitive result of the impact of the gender quotient on the dependent variables (negative influence of higher M/F quotient).

The use of stations as origins (COUNTO) or destination (COUNTD) were included in the OLS model based on their aggregated counts over the period of study; the first year of operation of the BSS. While useful to understand the overall popularity of stations as origins and destinations and the factors influencing their use, certain temporal influences, such as weather factors and the availability of bicycles or free docks, are not taken into account in an aggregated approach, even though the literature suggest they can influence the use of the system and variation in use of specific stations (e.g. Borgnat et al., 2011; Pfrommer et al., 2014). Another factor that may be of influence is the station size, i.e. the number of docks/bicycles per station (Rixey, 2013). Analysis of such shorter term temporal variations and station-level effects are a potential avenue for further research.

In this research, the influence of spatial factors on the dependent variables was assessed by using a simple OLS model. While this is a common and useful approach, other models might be more suitable for the type of data and lead to better fitting models. For example, other authors have indicated that negative binomial regression models (Wang et al., 2016), or a Poisson regression model can be more suitable for count data (Frost, 2019). Furthermore, the addition of temporal variables to the models can enable the influence of the time of the year: the influence of differences in terms of weather and tourism numbers. Further analysis of the data will compare the results obtained through the OLS model with those obtained from other models in order to explore the relationship between independent and dependent variables more deeply.

6.2. Implications of the study

Both the survey results as well as the trip data analysis showed the relevance of public transport (bus use and the location of bus stations) to BSS use. The complementary relationship between (shared) bicycle use and public transport and the promotion of multi-modal travel have started to receive more research interest in the past two decades, and results show they can provide an avenue for growth for cycling modal share and bicycle sharing use (van Nes, 2002; Handy et al., 2014; Heinen and Bohte, 2014; Olafsson et al., 2016). Results from a survey with BSS users in Dublin showed that 40% of trips are made in conjunction with another mode of transport, of which over 90% constituted public transport (Murphy and Usher, 2015). Although a number of BSS stations in Las Palmas de Gran Canaria are already located in the vicinity of the bus stations and Park & Ride locations, further integration in terms of real-time information provision and integrated payment options can promote more multi-modal use (van Nes, 2002). Survey results show that younger respondents are more likely to use public transport on a daily basis and in combination with the BSS. The benefits of the combination between bus and bicycle, and the alternative it provides to private car use, could be further promoted, especially amongst the older demographics.

The survey results clearly show a skewed demographic of the current users, in line with results from other BSS around the world, where users are predominantly male and highly educated. The age distribution in Las Palmas de Gran Canaria was however less skewed towards the younger age brackets. The results provide some clear avenues for promoting the BSS with currently under-represented user groups, most notably those people in the 18–24 age group and people from lower socio-economic classes (in terms of median income and level of education). As found in other research, current users are motivated by the dominant social norms, and specifically the influence of their friends and family. Schoner et al. (2016) suggest the creation of "take your friend on a bike ride" types of marketing schemes to promote BSS use. The expansion of the system, and the provision of electric bicycles can play a role in encouraging uptake among the student population, seeing as the university campus is located relatively far from the city centre and at a higher elevation. Ensuring that the system is expanded to also serve lower income neighbourhoods, and creating a dedicated outreach campaign, potentially including discounted memberships could encourage people on lower incomes to use BSS as an affordable mode of transport (Rixey, 2013). To promote shared bicycle use for commuting and for work / business purposes, the BSS operator can seek collaborations with companies, businesses and (public) authorities, to promote bicycle use for their staff, as it can provide economic benefits for the employer, in terms of reduced health costs and sick leave days and reduced need for parking (Handy et al, 2014). In return, employers need to then consider providing lockers, showers and changing facilities, as research has shown these are important for employees considering utilitarian cycling to work (Heinen et al., 2010).

Density of tourism accommodation near bicycle sharing stations emerged as a significant positive influence on BSS use, even though the majority of users are local residents. This can partly be explained by the fact that the area with most tourism accommodation (the area around Las Canteras and Santa Catalina) is an area with many leisure, entertainment and shopping facilities, and thus draws both local residents as well as tourists to enjoy the beach and city life. It is not the tourist accommodations themselves that have a positive effect on BSS use, but rather their location in an area with many leisure and entertainment opportunities, as also shown by the multi-collinearity between the count of tourist accommodations (LU_TOUR) and the number of cafes and restaurants (LU_CAFE). From the analysis of the survey results, it appears tourists use the BSS only infrequently and there is scope for promoting the system as a mode of transport during their stay, for example through direct promotion and collaboration with hotels and hostels, and through the provision of a dedicated subscription option for tourists (e.g. a multi-day or week pass). The BSS appears to be most attractive to temporary residents, as these are looking for affordable and reliable transport to move around the city, and are perhaps less likely to make the investment in private transport, as shown by their lower car ownership.

The importance of dedicated cycling infrastructure, including separated cycling paths, is evident from both the OLS model of the trip data, as well as from the responses to the user survey. The growth in cycling modal share in Seville (Marqués et al., 2015), another Southern European city that has promoted cycling in recent years through the creation of a connected network of separated bicycle infrastructure and the introduction of a BSS, highlights the potential for Las Palmas de Gran Canaria. The creation of dedicated cycling infrastructure on arterial roads, reduction of speed limits on residential and rural roads, and awareness raising among all road users are proven strategies to improve road safety for cyclists and promote cycling (Heinen et al., 2010; Handy et al., 2014). The municipality of Las Palmas de Gran Canaria has designed an integrated bicycle network and has started implementation in 2019. Further efforts can be made in the next step to connect this (proposed) network with the areas currently not served by the BSS, including on the peninsula and the upper city, as well as to connect to the university campus outside of the city.

7. Conclusion

Bicycle sharing systems have been introduced in cities around the world. Even cities that lack a strong cycling culture and thus far have a low cycling modal share are now implementing BSS as part of a set of cycling promotion policies. This study investigated the BSS in Las Palmas de Gran Canaria, which started operation in April 2018. The research looked at social and spatial factors influencing the use of the system, through the analysis of results from a user survey, as well as a spatial analysis using trip data provided by the operator and spatial datasets from secondary sources. A new finding, specific to the tourist destination context, was the significant influence of tourist accommodation on the frequency of use of the BSS, next to proximity to cycling infrastructure and a bus station. From an analysis of the distribution of the BSS and its ability to serve the city's population, it was found that although a third of the population lives within a 400 m radius of a BSS station, there are parts of the city, especially certain neighbourhoods with high population density and low average incomes, that are currently not being served by the BSS. Results from the user survey show that distance to nearest station, money-saving and environmental concerns, satisfaction with the operating system, and provision of safe cycling infrastructure significantly influence BSS use.

The results found in this study can guide future policy for the promotion of cycling and shared bicycle use, by focusing efforts on connecting the cycling infrastructure and the provision of the BSS between the lower and upper city and to extend BSS to reach population currently not served in addition to serving the main city centres. Opportunities for further promotion of the BSS can be found in collaborations with employers, hotels and hostels, and with public transportation providers.

Further work will include a deeper analysis of the BSS use over a 2-year period, to assess the influence of temporal variables such as weather and tourist arrival numbers, as well as the impact of the creation of new cycling infrastructure, which was installed in summer 2019. There is further scope for analysis of the dataset presented in this paper, by classifying BSS trip data based on frequency of users by different users, or setting up different regression models for clusters of stations with similar characteristics.

CRediT authorship contribution statement

Suzanne Maas: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Maria Attard:** Conceptualization, Methodology, Supervision, Writing - review & editing, Funding acquisition. **Mark Anthony Caruana:** Formal analysis, Investigation, Writing - review & editing.

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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