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Research Article

A multinomial logistic regression model for public transportation use in a medium-sized Brazilian city

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Abstract

Paper aims: This paper addresses the influence of socioeconomic, quality, built environment, and safety variables on the demand for public transportation service.

Originality: This study covers a differentiated and little explored analysis in the literature on the frequency of use of public transport, using different exploratory variables and characteristics of the urban environment.

Research method: A sample of 274 bus users was obtained and the multinomial logistic regression method was performed to analyze how different variables impact frequency of use public transportation.

Main findings: The use of public transportation to work and study, transportation vouchers, distance traveled to central business and accessibility were strongly associated with more frequency of public transportation use. Owning a vehicle, and dissatisfaction with fare and bus schedules led to less frequent use.

Implications for theory and practice: This study corroborate with literature, where the public transportation is not the main mode of transportation due: private vehicle ownership; dissatisfaction with the public transportation; very low household income; no tariff subsidy; and difficulties in accessing bus stops. In practice, it can aid public transport providers to promote strategies to increase demand and improve service. It also advises government bodies on encouraging sustainable mobility, bringing benefits to society.

Keywords

Sustainability. Users' satisfaction. Public transport service. Demand promotion strategies. Increased frequency of use.

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1. Introduction

The growing activities of transport worldwide have increased sector-related problems, e.g., traffic deaths and injuries, congestion, noise, and air pollution (Ribeiro et al., 2007; Silva et al., 2015; Zailani et al., 2016). The main cause attributed to these problems is the rapid growth of private vehicles and social habits in their favor, reducing the use of sustainable transport, such as public transportation (Vij et al., 2013; Chiou et al., 2015; Zailani et al., 2016).

Lima & Machado (2019) state that cities must be well planned to guarantee equal access to all people and seeking sustainable efficient urban mobility solutions. Several challenges are involved in the process of moving people safely and comfortably to their desired destinations (Brunoro et al., 2015). Given technological advancements, there are now more mobility options, e.g., on-demand transportation and micro-mobility options (Meng et al., 2020; Davies et al., 2020). Nonetheless, public transportation is still one of the most sustainable modes of mass mobility transportation over long distances.

Public Transportation (PT) provides affordable and sustainable mobility solutions, and is essential for economic interests and societal well-being (Kaeoruean et al., 2020), especially in promoting social equity (Zuo et al., 2020).

Adequate PT infrastructure alleviates transportation problems, and ensures daily urban operations (Sun & Cui, 2018). However, there has been a decrease in PT demand in several countries (Chakrabarti 2017; Tembe et al., 2019; Liu et al., 2019). In Brazil, the main mode of public transportation is the bus and, in the recent decades, it has experienced drops in its demand. There was a sharp decline (26.1%) among paying bus users from 2013 to 2019, and in 2020, this decline increased to 51.1%, mainly due to social distancing restrictions in light of the Covid-19 pandemic (Associação Nacional das Empresas de Transportes Urbanos, 2021). Private transportation use in 2018 accounted for 30.5% of all daily trips, while 28% of all trips were conducted using public transportation (Associação Nacional de Transportes Públicos, 2020).

Given the importance of public transportation and recurring demand losses, PT use needs to be promoted to increase customers and travel frequencies (Ekinci et al., 2018). Demand, users, and satisfaction characteristics need to be considered to attract also non-users (Yu et al., 2018). Literature has addressed variables that encourage or restrict use of PT, e.g., economic, geographic, or sociological factors (Arana et al., 2014), including spatial analyses for built environment and public and road safety (Yu et al., 2018; Liu et al., 2019). Perception factors on the level of service quality have also been studied to understand user perspectives (Diez-Mesa et al., 2016).

These aspects have been modeled together or separately in transport mode choice studies (e.g., Chakrabarti, 2017; Sarkar & Mallikarjuna, 2017; Han et al., 2018; Yang et al., 2018; Yang & Wang ,2018). Other studies developed models with some this variables to represent the demand in function of the number of passengers (e.g., Aljoufie 2014; Chiou et al., 2015; Nazem et al., 2015; Liu et al., 2019). Gascon et al. (2020) stated that, despite extensive literature on the matter, these factors still need to be evaluated to understand the frequency of PT use, given variations in different regions. Therefore, a lack of studies involving the frequency of PT use was identified, mainly considering it as a dependent variable. Thus, the research gap addressed in this study is the need to explore how different exploratory variables, significant in mode choice and PT demand, can influence the frequency of PT use. The research is also important because it represents cities where public transportation by bus is the only mode of mass transport available, without availability of PT with greater capacity, such as subway or BRT (bus rapid transit).

In the literature, some studies were identified that addressed the frequency of PT use, but in relation to specific objectives, such as the frequency of PT use among the elderly (Truong & Somenahalli, 2015). Others based only on the perceived quality of the services provided (Birago et al., 2017), different geographic locations (Chiou et al., 2015) or security (Delbosc & Currie, 2012; Verma et al., 2020). However, no studies were identified in the researched literature that performed analyzes of frequency of PT use using different exploratory variables and city characteristics such as the one presented in this paper.

Thus, the objective of this study is to analyze the influence of socioeconomic variables, modes of transportation, quality perceptions, built environment, and safety on PT demand by using frequency-of-use as a dependent variable. We study PT bus users in a medium-sized Brazilian city. Built environment and safety variables are addressed and analyzed using the Geographic Information System (GIS). We use Multinomial Logistic Regression to analyze the association between relevant variables and their influence on the frequency of using PT. This study contribute companies providing PT services to promote strategies to increase demand and improve the service. It also aid government agencies in urban planning for sustainable mobility by identifying barriers and ways for encouraging public transportation.

2. Determining factors for Public Transportation

In relation to transportation planning, understanding different factors must be integrated to better understand individual commuting behavior needs (Haslauer et al., 2014; Vij et al., 2013). Socioeconomic characteristics, mode of travel, built environment, and safety are significant in determining modes of transportation, particularly public transportation. Some researches, among the many in the study area, address different variables for understanding the choice and use of transport modes, but we highlight relevant studies that resulted in the identification of determinant variables in the choice and use of public transport, specifically. These are compiled and shown in Table 1.

Socioeconomic characteristics must also be evaluated. In general, they are motivated by cultural inequalities (Han et al., 2018). Built environment also need to be assessed since they also contribute to understanding choices and behaviors surrounding modes and frequency-of-use of transportation (Ewing & Cervero, 2010; Wang & Zhou, 2017; Yu et al., 2018; Liu et al., 2019; Ko et al., 2019). This can be described using five dimensions, i.e., the 5D's (density, diversity, design, distance to transportation, and destination accessibility) (Yu et al., 2018; Lima et al., 2019). A sixth dimension can also be added to assess traveler demographic characteristics (Liu et al., 2019).

Table 1. Variables related to choosing and using Public Transportation.

			Authors												
			Badoe & Yendeti (2007)	Delbosc & Currie (2012)	Truong & Somenahalli (2015)	Chiou et al. (2015)	Wang & Zhou (2017)	Sarkar & Mallikarjuna (2017)	Han et al. (2018)	Sarker et al. (2018)	Yu et al. (2018)	Ko et al. (2019)	Tembe et al. (2019)	Liu et al. (2019)	Verma et al. (2020)
Variables	*Socioeconomics and mode of transportation*	Gender	✓		✓			✓	✓		✓	✓	✓		
		Age	✓			✓		✓	✓		✓	✓	✓	✓	
		Level of Education			✓			✓							✓
		Employment/Occupation	✓								✓	✓	✓		
		Income				✓		✓	✓		✓	✓	✓		
		Car ownership	✓	✓		✓		✓	✓	✓	✓		✓		
		Bicycle ownership						✓			✓				
		Main travel mode				✓				✓					
		PT payment type								✓				✓	
		PT Frequency-of-Use		✓	✓				✓						✓
	Built environment	Jobs-housing relationships	✓				✓							✓	
		Land Use				✓	✓	✓			✓	✓			
		Residential Location			✓		✓						✓		
		Accessibility by PT	✓		✓	✓	✓			✓	✓	✓		✓	
		Distance to CBD		✓	✓									✓	
		Population Density				✓	✓			✓	✓			✓	
	Safety	Index or perception of crimes		✓				✓	✓	✓		✓			✓
		Index or perception of accident road traffic		✓				✓	✓						✓

Note: PT = Public transportation; CBD = Central Business District.

Use of public transportation is also directly associated with the quality of services provided (Soltanpour et al., 2020). Currently, quality improvement objectives are more directed towards service users than towards transport companies (Barabino et al., 2013). The authors cite standards, such as the European standard EN 13816 (European Committee for Standardization, 2002), which seek to ensure higher levels of quality and attractiveness of the PT and reduce operating costs. Thus, many attributes are used to measure the quality of the PT, which can be quantitative, more objective, or qualitative, influenced by personal opinions (Barabino et al., 2020).

The Transit Capacity and Quality of Service Manual (National Academies of Sciences, Engineering, and Medicine, 2013), among other guidelines, reports techniques for capacity calculations and other operational characteristics of bus, train and other services. Despite the relevance of quantitative indicators, it is also important to assess perceived quality. Santos & Lima (2021) points out an extensive list of qualitative indicators that evaluate the PT system in relation to operational, human, environmental and infrastructure characteristics of the system.

Thus, user perception of latent variables e.g., flexibility, comfort, safety, convenience, and reliability, need to be assessed. Latent variables represent subjective elements in user choice behavior, and have intangible characteristics (Han et al., 2018). They are used to assess the perceived public transportation quality (Han et al., 2018; Yang et al., 2018; He & Thøgersen, 2017). Quality is assessed based on user perceptions and expectations, considering a service provider's capacity for offering good services (Maraglino et al., 2014; Diez-Mesa et al., 2016; Weng et al., 2018; Senne at al., 2021).

3. Research Methodology

This study was developed in three stages, as per Figure 1. The first stage, conception, evaluated existing literature, and selected potential variables that could influence the use of PT. It also included data collection from users and secondary sources.

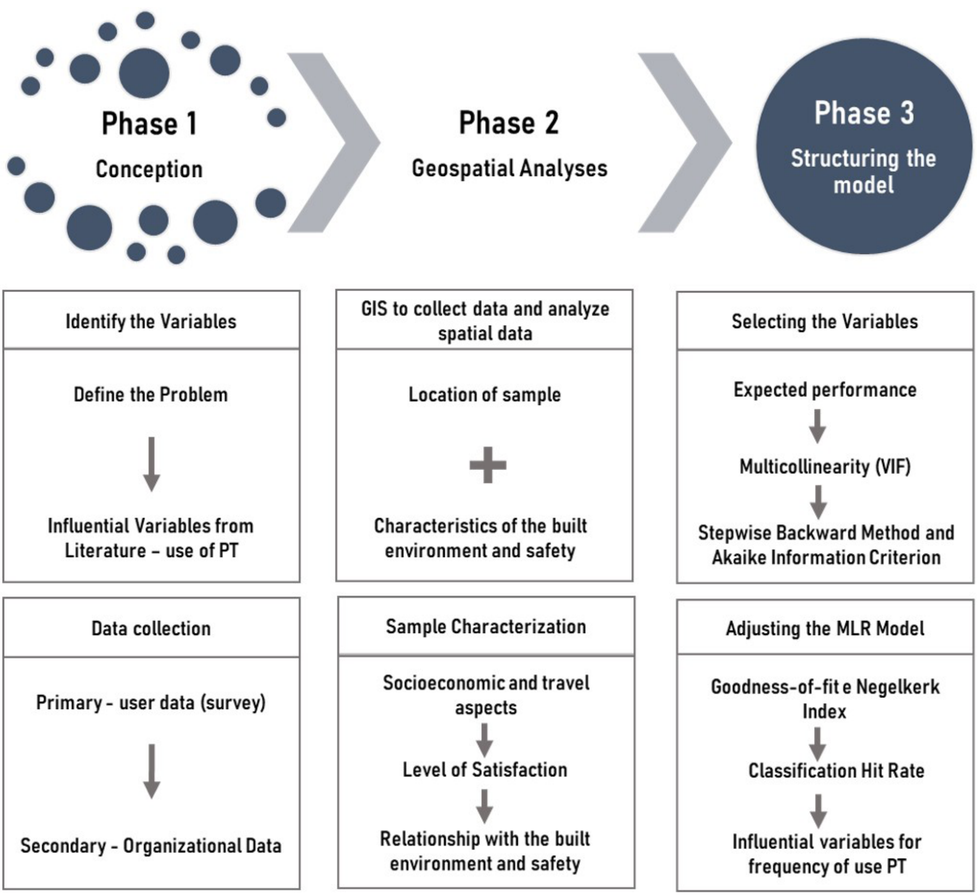


Figure 1. Methodological process. Note: PT = Public Transportation; VIF = Variance Inflation Factor; MLR = Multinomial Logistic Regression.

The GIS was used in the second stage to survey and analyze the relationships between respondent residential location, and built environment and safety, using the ArcGis® software program (ESRI, USA). The samples were characterized with respect to socioeconomic aspects, and level of satisfaction with PT services provided.

The exploratory variables and expected associations with the dependent variable were presented in the third stage. The software SPSS® (IBM, USA) was used for statistical analyses. First, multicollinearity between continuous variables was verified to select the variables and adjust the model. The "stepwise backward" method was used to adjust and reduce the model to significant variables by analyzing the Akaike Index Criterion (AIC) for each proposed variable reduction. Model selection by the AIC occurs when reducing more variables in the model do not significantly *improve fits (Fávero et al., 2009).

Subsequently, a Multinomial Logistic Regression (MLR) model was developed and adjusted to examine the relationship between the dependent variable and the selected exploratory variables (Hosmer & Lemeshow, 2013). Logistic regression is used when dependent or response variables have two or more categories (Fávero et al., 2009; Hamid et al., 2017). It has been applied with positive results when investigating mode of transportation relationships with built environment and travel behavior (e.g. Etminani-Ghasrodashti et al., 2018; Keyes & Crawford-Brown, 2018).

Thus, a MLR was used to explore factors that affected frequency of PT use among occasional, and rare users, in relation a frequent users, using the following Equations 1 and 2:

$$Z = \mathrm{Ln}\left[\frac{Probability\left(Ocassional\ PT\right)}{Probability\left(Frequent\ PT\right)}\right] = \alpha_{1,0} + \sum_{i=1}^{k} B_{1,i}.X_i \tag{1}$$

$$Z = \mathrm{Ln}\left[\frac{Probablity\left(\mathrm{R}are\ PT\right)}{Probability\left(Frequent\ PT\right)}\right] = \alpha_{2,0} + \sum_{i=1}^{k} B_{2,i}.X_i \tag{2}$$

Where:

a) Xi are the independent variables that predict the frequency of PT use;

b) Bji are the estimated regression coefficients for category j of the dependent variable; and

c) α is the intercept.

Adjustment parameters like Goodness-of-fit, the Negelkerk index, and the classification hit rate were used to corroborate the developed model.

3.1. Study area

We studied the city of Itajubá, which is located in southern Minas Gerais state, Brazil, focusing on empirical PT by bus. The city has about 97,782 inhabitants, and a population density of 307.49 inhabitants/km^2 (Instituto Brasileiro de Geografia e Estatistica, 2022). Figure 2 shows the location of the city, and identifies the urban perimeter, i.e., the area studied here. Urbanization areas are especially important, where travel demands are higher and more complex, meaning that effective measures are needed to encourage more sustainable modes of transportation and reduce car use (Yu et al., 2018).

The characteristics of Itajubá are similar to small and medium-sized Brazilian cities, which had accelerated expansion from a single economic center without adequate planning and management (Felix et al., 2019). PT is provided in Itajubá by buses only, via a single contracted company, which has 19 bus lines. Most trips are destined for the economic center.

PT is essential and one of the main priorities of the National Plan for Urban Mobility (PNMU), which was established in Brazil in 2012. This plan seeks to prioritize non-motorized modes of transportation over motorized ones, and public transportation over individual motorized transportation, while also integrating various transportation modes (Brasil, 2012), among other things.

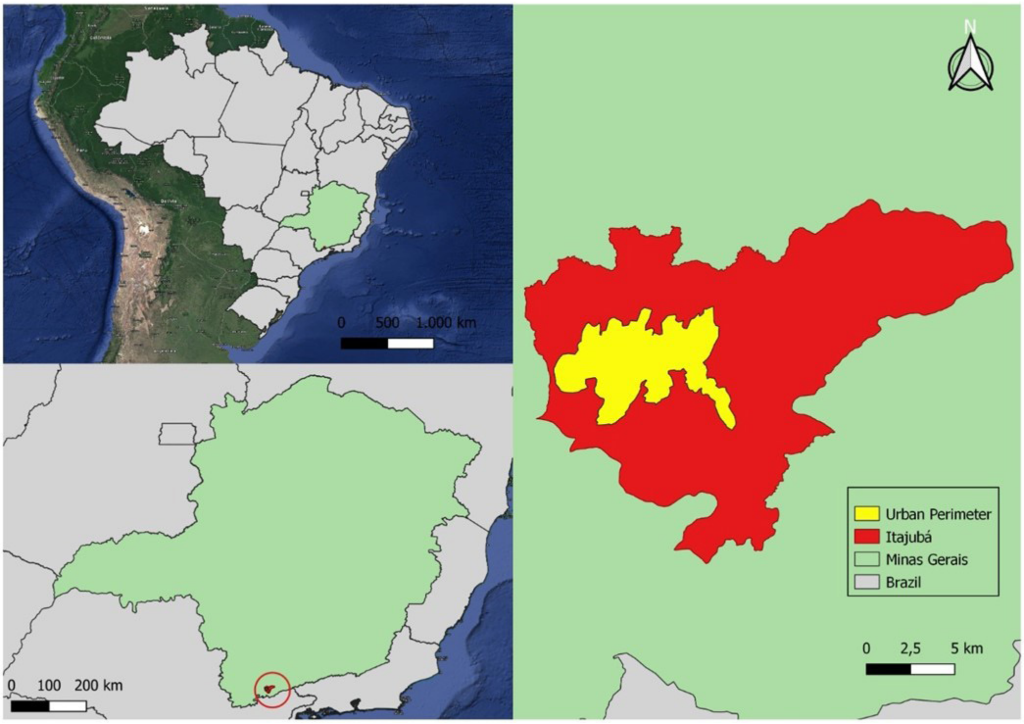


Figure 2. City location and urban perimeter limits.

3.2. Data collection

We conducted face-to-face interviews via questionnaire to obtain primary data on PT bus users in Itajubá. This data collection approach, despite communication clear and efficient with the interviewee, it has high cost and time of application, in addition to the low sample reach. So, The questionnaire was also made available in digital format, through the GoogleForms platform. The initial condition to respond to questionnaire was to be a user of the local PT. The face-to-face questionnaire were applied randomly, at different times and days of the week, and also in different places in the city, in order to obtain a heterogeneous sample. The places where the questionnaires were applied include schools, universities, supermarkets, general stores and city hall, in addition to some more remote neighborhoods and a housing complex.

The online questionnaire was disseminated in institutional e-mails and social networks of PT in the city, aiming at making it ease of access to the sample. This data collection method has strengths and weaknesses to be highlighted (Evans & Mathur, 2018). It are considered positive: global reach; ease of constructing a questionnaire in online survey programs; speed and punctuality; technological innovations; ease of data compilation and analysis; diversity of issues; low cost; ease of access to the sample, despite the low response rate; among others. Of the disadvantages presented, the following stand out: perception as electronic waste; exclusion of the population without access to the internet; distortion in understanding; unclear response instructions; impersonality; low response rate and privacy issues, mainly issues associated with information vulnerability.

The research took place before the COVID 19 pandemic, verifying that it was not influenced by changes in transport during the pandemic. In fact, the public transport service has already been re-established and continues to be provided by the same carrier and under the same service conditions.

The sample calculation was performed using Equations 3 and 4 below (e.g. Barcelos et al., 2017), and resulted in the need for at least 270 samples. The sample error considered was 6% and the population size adopted was the average daily demand of 9,411 users, according to data from the PT service provider in Itajubá.

$$N0 = 1 / \varepsilon^2 \quad (3)$$

$$n = N0.N / N0 + N \quad (4)$$

Where:

a) N0: first approximation of the minimum sample size;

b) ε: tolerable sampling error;

c) N: population size; n: sample size.

The sample consisted of 328 valid questionnaires. Four questionnaires answered online were excluded due to incomplete and/or inconsistent completion. The t test was applied to two samples and no inconsistencies were found between responses. Also, each answer leads to a different home address. Subsequently, 54 questionnaires were excluded, as the respondents were located outside the urban perimeter. The final validated sample consisted of 274 users. The internal reliability of the questionnaire was verified using Cronbach's alpha test (α), which varies between 0 and 1. The minimum acceptable value is 0.70 (Weng et al., 2018). Our results gave an alpha at 0.75, confirming the reliability of the questionnaire.

The questionnaire was designed focusing on socioeconomic, location of residence, and mode of transportation preference questions. Users were also asked about why they used public transportation, and their level of satisfaction relative to 11 quality of service indicators. The indicators were selected based on relevance in literature, and their importance relative to Itajubá (Santos & Lima, 2021). In general, the indicators assessed the characteristics of the bus stops, the services provided, and aspects related to employee behavior and safety factors. Evaluations were made using a satisfaction survey. The main methodology was collecting user opinions (De Oña & De Oña, 2015), which were measured using a Likert scale, which is used in satisfaction surveys (Guirao et al., 2016). This study, a scale ranging from 1 (poor) to 5 (excellent) was adopted. We emphasize that the measure of the general quality of a transport system must be evaluated by objective and subjective measurements. However, in this study, was evaluated only the level of user satisfaction, where the focus on the perceived quality of the PT system.

Secondary data were obtained from organizations that register information on built environment and public and road safety. This included the Brazilian Institute of Geography and Statistics (IBGE), the Military Police of Minas Gerais (PMMG), City Hall, and the public transportation service company.

4. Results and discussions

4.1. Determining the socioeconomic variables and perceived quality

The first data collection stage involved applying a questionnaire to 274 PT users. The sample showed that 62% of all respondents used bus frequently, 17.9% used bus occasionally, and 20.1% used rarely. The ratio of women to men was 74.8:25.2, and 71.5% of all respondents were aged between 20 and 59 years old. Most respondents had a high school and university education. Occupations were mainly divided between work and study. Regarding household income, 74% of all respondents reported income between 1 and 3 minimum Brazilian wages (BRL$1,212.00 in 2022), highlighting the need for government subsidies to make these services accessible to low-income individuals. The results also showed that 56% of the respondents possessed motor vehicles, and 49% possessed bicycles. Figure 3 shows the spatial distribution of the residential locations of the respondents and the sample density. One can see greater user concentration in areas marked in red. These locations are populated districts in the city, far from the center, which has more PT users.

The questionnaire also addressed questions on why respondents chose PT, travel times, and modes of transportation for work and study. Most respondents cited distance-to-destination, PT as being the only available mode of transportation, the weather (rain, sun, cold, or heat), and less physical wear, at 55%, 47%, 42%, and 34%, respectively, in their responses. Bus was the main mode of transportation for 80% of all work trips, and 46% of all study trips. Bus was preferred for trips longer than 30 minutes and, active transportation was used more for faster trips up to 10 to 20 minutes. Ko et al. (2019), also highlighted that people who commute less than 16.5 minutes tend to rely on active modes of transportation more, and preferred public transportation for trips longer than 42 minutes.

The PT satisfaction level results presented in Figure 4 show that users are more satisfied with aspects related to employees and safety. Fares, bus schedules, and factors related to the bus stops were the most unsatisfactory indicators.

According to Figure 4, 72% of the respondents in Itajubá stated that fares were poor or bad. Despite the importance attibuted that some authors, Birago et al. (2017) highlight that fare value alone is insufficient in guaranteeing increased demand. Bus stop characteristics were also viewed negatively. Trimet (2010) emphasized the importance of offering easily identifiable, safe, accessible, and comfortable bus stops to promote public transportation. Employee-related aspects were well evaluated and corroborated results from Maraglino et al. (2014), and Guirao et al. (2016).

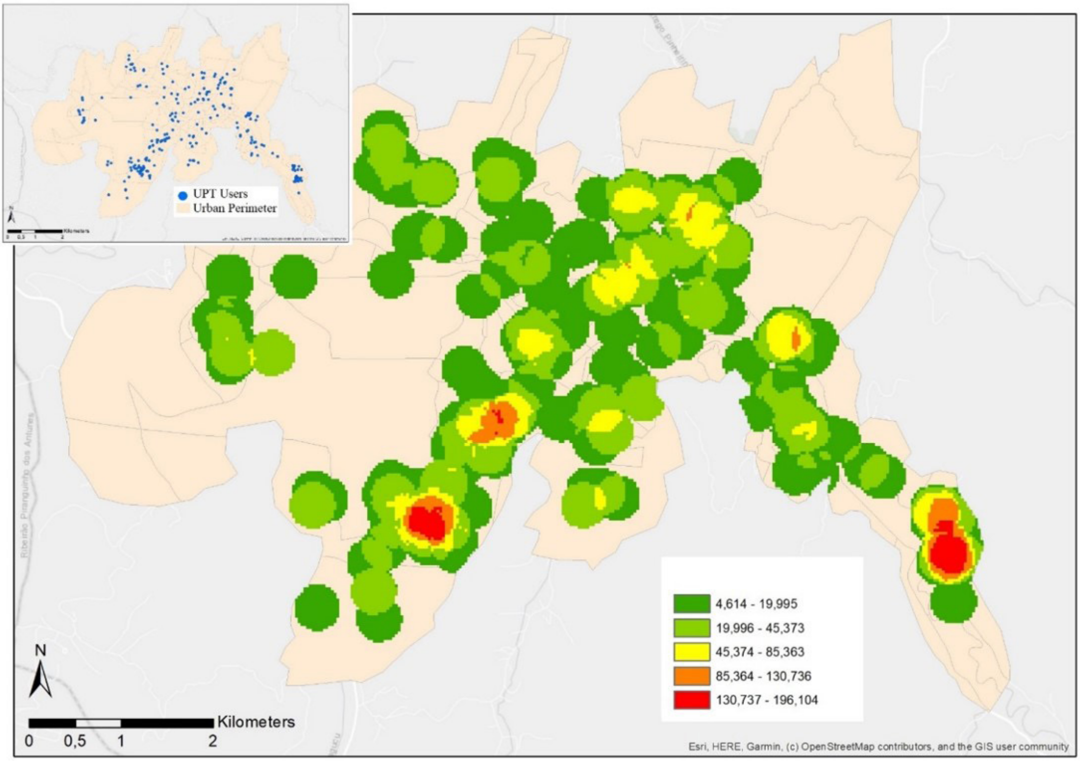


Figure 3. Respondents sample density within urban perimeter.

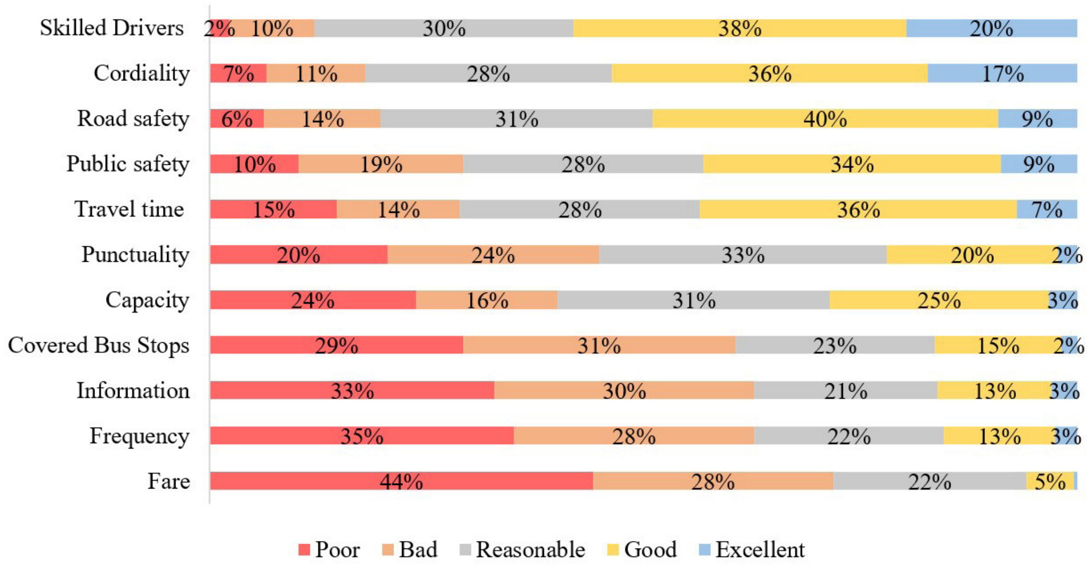
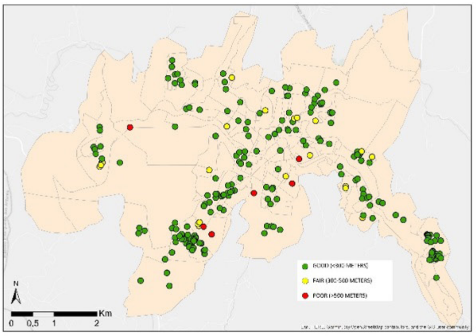


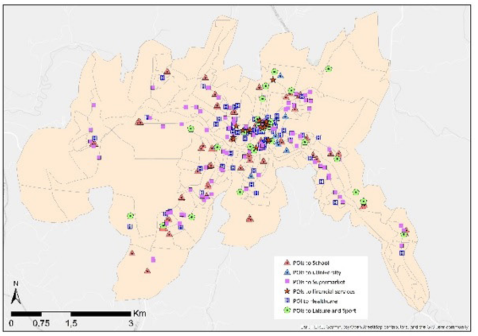
Figure 4. Levels of satisfaction for quality indicators.

4.2. Determining building environment and safety variables

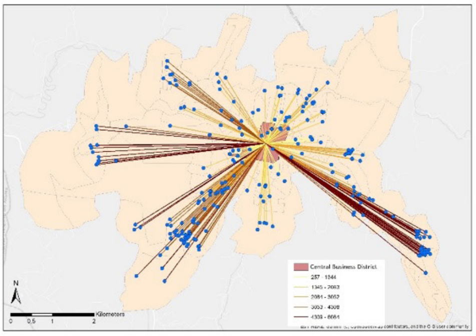
We analyzed georeferencing data to obtain variables on built environment and safety, as shown in Figures 5 and 6, respectively. The variables were related to the residential locations of the respondents, characterizing the aspects related to the origin of their trips.



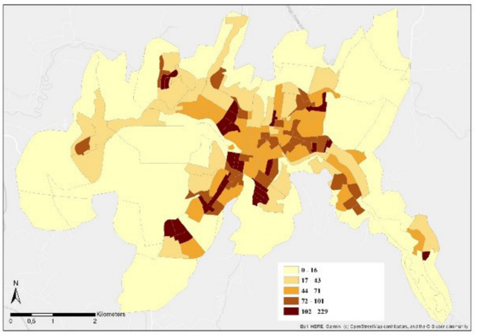
a) Users accessibility to Public Transportation



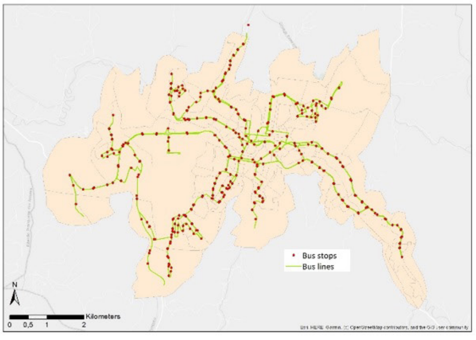
b) Urban points of interest



c) User distance relative to center of CBD

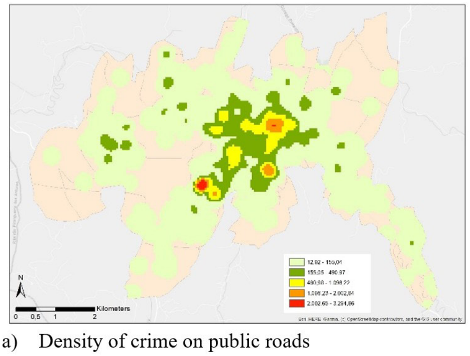


d) Population density per sector

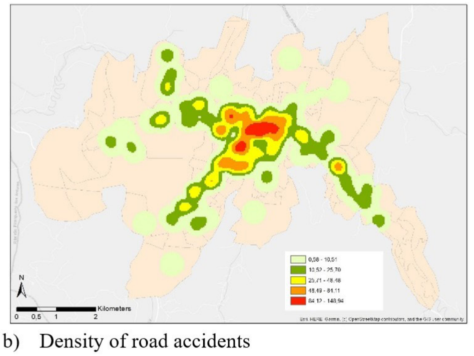


e) Bus lines and stops

Figure 5. Maps of the built environment variables related to accessibility, points of interest, distance to CBD, population density, and bus lines and stops.



a) Density of crime on public roads



b) Density of road accidents

Figure 6. Maps on public and road safety.

The accessibility to PT variable was calculated as a function of the distance between the location of residence to the nearest bus stop (Langford et al., 2012). Similar accessibility analyses can be found in Cervero et al. (2010), and Sarker et al. (2018). Accessibility to PT was classified as either good (<300 meters), fair (300-500 meters), or poor (>500 meters) (Ferraz & Torres, 2004; Aljoufie, 2014). Figure 5a shows user location and their accessibility levels to bus stops. The results show that most respondents have good accessibility to PT (88.69%). Only 8.76% and 2.55% of the sample had either regular or poor accessibility, respectively.

Points of interest (POIs), e.g. education, health, leisure, financial services and shopping malls, were collected for the urban perimeter for measure accessibility to destinations, as shown in Figure 5b (Thao & Ohnmacht, 2019; Saghapour et al., 2019). Similar to the PT accessibility variable, we calculate the distance to the nearest POI. Respondents were, on average, closer to supermarkets and schools, and further away from universities and financial institutions (banks). The distance to the CBD (Central Business District) was obtained by taking the Euclidean distance from the user to the center of the CBD (Liu et al., 2019). This is an important variable that is correlated with reduced motorized travel (Ewing & Cervero, 2010). Figure 5c shows that the majority of respondents (63%) lived more than two kilometers from the CBD.

The variable on number of routes was measured by taking the number of route segments available to the user within a 500-meter buffer zone. We took this value considering the distance that people would willing to walk to access PT (Aljoufie, 2014). Available PT routes within the urban perimeter are shown in Figure 5e. More routes were found in the center and in neighborhoods with higher PT demands.

Finally, population density was obtained from a census (Instituto Brasileiro de Geografia e Estatistica, 2010). Figure 5d shows how the population density in the city is inherently distributed in the data according to the “Natural Breaks” classification from the ArcGis software program. The percentage of users in low-density sectors (up to 43 inhabitants/ha) was 41%, 38% for medium-density sectors (from 44 to 101 inhabitants/ha), and 21% for high-density sectors (from 102 to 229 inhabitants/ha).

The safety variables addressed evaluated crimes on public roads, and road accidents involving cyclists and pedestrians in the vicinity of the residence. Security aspects can influence which routes users take to access PT, including walking and waiting times. We considered a 500-meter buffer zone for this analysis. Figures 6a and 6b show the occurrence densities from 2018 to 2020 that affected public and road safety, respectively.

4.3. Defining the dependent and exploratory variables

The independent variables were developed according to relevance in literature, and data availability. Altogether, 34 variables that could influence PT frequency were considered. Frequency-of-use was set as a dependent variable, and classified into three categories: frequent users (from 3 to 7 days a week); occasional users (1 or 2 days a week); and rare users (up to 3 days per month).

Table 2 shows the exploratory variables and gives the expected performance relative to the dependent variable.

A direct influence (+) is expected, i.e., contributing to frequency of PT use, for the following characteristics: being female, having a free transportation voucher, using PT as one’s main mode of transportation, having access to more bus lines, and being located further from the CBD, POIs, and denser areas. Inverse relationships (-) are expected for the following characteristics: having a higher level of education, being unemployed or retired, having a higher monthly household income, owning private transportation, having low access to PT, being located closer to locations of crimes and road accidents.

Regarding PT quality indicators, higher levels of satisfaction are expected the greater the frequency of PT use (Han et al., 2018). Age group was undefined (*), as more active PT users tended to belong to the middle age group (Badoe & Yendeti, 2007).

Some categorical variable classes were grouped to improve occurrence frequencies in each category. Variables like occupation, PT as one’s main mode of transportation, and accessibility to PT did not permit grouping into categories, and may contribute to sample bias, with few samples in some categories. Nonetheless, they can be included in the regression model when testing the influence of covariates, and when interpreting the coefficients (Vittinghoff & McCulloch, 2007).

4.4. The Multinomial Logistic Regression Model

This step selected the variables in the Multinomial Logistic Regression (MLR) model. First, we verified multicollinearity among the continuous variables via Variance Inflation Factor (VIF) analysis. The POIs to bank, and to university variables were removed, since they showed high correlation with distance to the CBD.

Part of this can be explained by the city's characteristics, since these activities are generally located within or close to the CBD. The POIs to healthcare variable, and road accident variable were also removed because they had VIFs greater than 5.

Then we used the "stepwise backward" computational method to select significant variables for the model. The Akaike Index Criterion (AIC), was used to compare the model fit by reducing the suggested variables considering the model with the lowest AIC value.

Finally, 13 variables were selected to comprise the final MLR model using the logit function, which provides a natural interpretation of estimated coefficients. The results are shown in Table 3.

Where: Bi = the regression coefficient; EP Bi = the standard error of the coefficient; Z = the Wald test; and p-value = the significance level.

Table 2. Independent variables and expected performance relative to the dependent variable.

Independent Variables	Expectation.	Description	
Socioeconomic			
1 Gender	+	0 = male; 1 = female	
2 Age Group	*	1 = 15 - 19; 2 = 20 - 35; 3 = 35 - 59 ; 4 = >60	
3 Level of Education	-	1 = grade school; 2 = high school; 3 = college	
4 Occupation	-	1 = worker; 2 = students; 3 = retired; 4 = unemployed	
5 Type of Payment	+	1 = normal; 2 = transport vouchers; 3 = free	
6 Average Household Income	-	1 = < $185.00; 2 = $186.00 - $553.00; 3 = > $553.00	
7 Possessing a Vehicle	-	0 = Do not have; 1 = have	
8 Possessing a Bicycle	-		
PT as a main mode of transportation			
9 Work	+	0 = no; 1 = yes	
10 Study	+		
11 Daily Routines	+		
Level of Satisfaction			
12 Covered Bus Stops	+	1 unsatisfied 2 neutral 3 satisfied	Bus Stop Availability
13 Information	+		Bus Stop Availability
14 Travel Time	+		Time Spent to Destination
15 Frequency	+		Time Between Two Busses
16 Punctuality	+		Compliance with the established time
17 Capacity	+		Number of Passengers Aboard
18 Public Safety	+		Crime Safety
19 Road Safety	+		Traffic Accident Safety
20 Fare	+		Cost of Trip
21 Cordiality	+		Employee Attitudes
22 Skilled Drivers	+		Driver Performance
Built environment			
23 PT Accessibility	-	1 = <300m (good); 2 = 300-500m (regular); 3 = >500m (bad)	
24 Population Density	+	Inhabitants/Hectare	
25 Distance to the CBD	+	Euclidian Distance in meters	
26 Number of Lines	+	Number of Bus Lines (buffer 500m)	
27 POIs to School	+	Distance in meters to Points of Interest (POIs)	
28 POIs to University	+		
29 POIs to a Supermarket	+		
30 POIs to a Bank	+		
31 POIs to Healthcare	+		
32 POIs to Leisure and Sport	+		
Safety			
33 Crime	-	Number of crimes occurring within the 500m buffer zone	
34 Accidents	-	Number of accidents involving cyclists and pedestrians withing the 500m buffer zone	

Note: PT = Public Transportation; CBD = Central Business District; POIs = Points of interest; m= unit for meters.

The model was significant at a p-value <0.01, a -2 likelihood log at 179.41, and a final AIC at 279.41. The model significance was supported by the Goodness-of-fit test, where the model is adequate in representing the data, with no significant difference between predicted and observed values. We also used the classification hit rate parameter, with assertive predictions 87.6% of the time. Frequent PT use had the highest explanatory power, and the highest classification hit rate was 95.9%. The hit rate for occasional PT use was lower (67.3%), implying that the behavior of these users may not be easily explained by the selected variables. The Negelkerke index value was analyzed at the level of interpretation for model data variation. The index ranges from zero to one, where closer to one the better. The results were satisfactory (0.828).

Frequent users were used as a reference for the dependent variable, and the references for the exploratory categorical variables were: age group (36-59), education (university), income (< $185.00), occupation (work), payment type (transport vouchers), satisfaction levels (satisfied), and accessibility (poor).

The current investigation found that gender was significant for rare and frequent use with a negative coefficient, indicating that women tend to use PT more frequently. This corroborates previous studies that showed that women are more likely to use public transportation (Badoe & Yendeti, 2007; Pitombo & Costa, 2015; Ko et al., 2019), inclusive more frequently (Truong & Somenahalli, 2015).

Regarding age group, we noticed that younger users (15-19 years old) prefer to use PT occasionally, compared to the 36 to 59 year-old age group (p<0.05). This was more significant (p<0.01) for the 20 to 35 year-old age group for both occasional and rare use.

Users with monthly household income greater than 3 Brazilian minimum wages (>$553.00) were more likely to use PT frequently than occasionally, compared to users with an income up to 1 minimum wage (p<0.01). Very low-income users may be unable to afford fares for public transportation frequently, and prefer using active transportation, for example. Previous studies contradictorily state that lower-income users are more likely to use public transportation (Chakrabarti, 2017; Yang & Wang, 2018). However, fares may exclude very low-income individuals, or individuals who do not receive transportation vouchers. Tariff policies like integration policies can help disadvantaged passengers benefit from PT.

Compared to workers, students tended to rarely use PT (p<0.01), and retirees did so more often than rarely (p<0.05). Part of this can be explained by the fact that retirees choose not to drive vehicles and use PT (Bocker et al., 2017). PT is crucial for maintaining elderly lifestyles, since they are increasingly active. It is important to quality-of-life, a sense of freedom, and independence (Shrestha et al., 2017). A German survey found that as people aged, they started to walk more, drive less, and use PT more (MiD, 2008).

Table 3. Multinomial Logistic Regression - Significant results in bold.

	Occasional				Rare			
	B1	EP B1	Z	p-value	B2	EP B2	Z	p-value
Constant	-4.21	3.23	1.70	0.19	-10.02	3.78	7.04	0.01
Female	-0.51	0.75	0.45	0.50	-2.03	0.92	4.88	**0.03****
Age Group (15-19)	3.67	1.71	4.62	**0.03****	1.91	1.91	1.01	0.32
Age Group (20-35)	3.74	1.29	8.44	**0.00*****	3.43	1.38	6.14	**0.01*****
Level of Education (High School)	-1.59	0.94	2.88	**0.09***	-0.18	1.09	0.03	0.87
Household Income (>$553.00)	-3.24	1.17	7.68	**0.01*****	-2.07	1.33	2.41	0.12
Occupation (Retired)	-0.39	1.95	0.04	0.84	-4.55	2.24	4.11	**0.04****
Occupation (Unemployed)	-1.30	1.22	1.13	0.29	-2.43	1.41	2.98	**0.08***
Occupation (Student)	1.48	1.20	1.51	0.22	2.71	1.45	3.51	**0.06***
Payment (Normal)	7.07	1.48	22.78	**0.00*****	8.17	1.74	21.99	**0.00*****
Payment (Free)	7.68	2.36	10.61	**0.00*****	10.97	2.73	16.19	**0.00*****
Automobile/Motorcycle	2.28	0.83	7.59	**0.01*****	3.57	0.93	14.72	**0.00*****
PT to Work	-5.26	1.16	20.65	**0.00*****	-7.37	1.45	25.68	**0.00*****
PT to Study	-6.19	1.45	18.29	**0.00*****	-10.30	2.56	16.24	**0.00*****
Punctuality (Neutral)	2.29	1.10	4.34	**0.04****	3.93	1.29	9.27	**0.00*****
Fare (Unsatisfied)	5.94	2.06	8.31	**0.00*****	6.43	2.15	8.93	**0.00*****
Fare (Neutral)	7.39	2.29	10.42	**0.00*****	9.01	2.39	14.22	**0.00*****
Accessibility (Good)	-6.07	2.55	5.68	**0.02****	-3.78	2.75	1.89	0.17
Accessibility (Regular)	-8.29	3.01	7.59	**0.01*****	-6.69	3.27	4.19	**0.04****
Distance to CBD	-0.17	0.22	0.63	0.43	-0.52	0.27	3.62	**0.06***
POI to a Supermarket	2.26	1.36	2.73	0.10	6.02	1.78	11.41	**0.00*****

Note: *Significance Level 0.1; ** Significance Level 0.05; *** Significance Level 0.01.

Users who received transport vouchers or student vouchers were more likely to use PT more often. Encouraging PT via more affordable prices could contribute to increased demand (Arana et al., 2014) and users satisfaction with the fare, since it is an important attribute in the general satisfaction of the quality of the service provided (Oliveira et al., 2022). Furthermore, PT as a main mode of transportation for work or study showed a tendency towards frequent use with significant results (p-value<0.01), and negative coefficients.

It is generally agreed upon that motor vehicle ownership (cars and/or motorcycles) negatively affects PT use (Badoe & Yendeti, 2007; Vij et al., 2013; Chiou et al., 2015; Yang & Wang, 2018; Tembe et al., 2019). The results of this study show, quite significantly (p<0.01), that there is a tendency for less frequent PT use among those who own vehicles. He and Thøgersen (2017) state that after owners purchase vehicles usage trends are almost inevitable, and are not influenced by PT systems, no matter how efficient and convenient they are. Restrictive measures should be taken, e.g., limiting vehicle ownership, reducing road speeds, reducing car access to city centers, and increasing infrastructure and access for walking, bicycles, and PT.

Another important finding is that regarding level of satisfaction. The greater the dissatisfaction and/or neutrality relative to fare and bus punctuality, the less the PT use. It is clear that latent variable perception is significant in choosing a mode of transportation (Sarkar & Mallikarjuna, 2017). According to Diez-Mesa et al. (2016), good cost perceptions promote subway use, even among higher-income individuals. One possible intervention measure would be reducing fare prices via government subsidies, to aid with transportation costs. For example, in Europe 74%, 68%, and 60% of transportation costs are paid for by government subsidies in Prague, Turin, and Warsaw, respectively (IPEA, 2013). In São Paulo, only 20% of transportation costs are subsidized. During the Covid-19 pandemic several Brazilian cities undertook initiatives to partially or fully subsidize fares to ensure service continuity.

Regarding the variables on built environment, PT accessibility proved to be significant, and is fundamental in encouraging PT (Langford et al., 2012; Sarker et al., 2018). Distances up to 500 meters promote more frequent PT use. Accessibility in the first and last mile has been linked to PT (Zuo et al., 2020), especially in the form of ride-sharing, bike-share, and using e-scooters, which can improve accessibility and PT demand, while also reducing social inequality (Meng et al., 2020).

User location relative to the CBD was also significant (p<0.05), showing a direct relationship for greater distances and more frequent PT use. Tembe et al. (2019), stated that PT choices may vary according to PT services in areas further away from the CBD, and the need for PT in central areas.

Finally, regarding POIs destinations, only the distance to supermarkets proved to be relevant for frequency-of-use. The greater the distance, the less frequent the PT use. This may be due to supermarket choices varying beyond required distances, e.g., preferring certain supermarkets based on the weight of to-be-purchased goods. Users can also take advantage of work or study trips to make purchases.

Other variables related to built environment were irrelevant in the model, along with other variables related to public and road safety. Similar results were found in a study by Thao & Ohnmacht (2019), who concluded that population density and POIs did not significantly impact travel frequency. Ko et al. (2019), emphasized that variable insignificance can also be attributed to the measurement methods used.

5. Conclusions

Public transportation (PT) systems, particularly buses, have suffered from falling demand. Many studies propose adequate systems, but do not attract enough demand to ensure efficient urban mobility by using sustainable transportation. There is growing private vehicle use and serious transportation infrastructure inadequacies in developing countries, in addition to a need for substantial improvements to public transportation systems.

This study identified influential variables for the frequency-of-use for PT, like user socioeconomic aspects, quality-of-services provided, and built environment. We studied bus users in a medium-sized Brazilian city and we applied a multinomial logistic regression model to assess differences in frequency of use.

The results for this application corroborate the results from literature, that state that PT is not the main mode of transportation, or is used rarely due to: private vehicle ownership; dissatisfaction with the public transportation services; very low household income; no transportation voucher or tariff subsidy assistance; male preferences for other modes of transportation; and, difficulties in accessing bus stops.

This work contributes to existing knowledge about public transport demand by providing a perspective on the frequency of PT use. This was the research gap observed, in which important variables in determining the frequency of PT use had still been little explored so far. A selection of variables, among the study of several classes of variables (such as socioeconomic, level of satisfaction, built environment and safety) was performed to understand the frequency of PT use. Others works evaluated only one or two classes of variables or specific user segments (eg, elderly people (Truong & Somenahalli, 2015)). However, it is pertinent to consider the ownership of vehicles and the quality of the PT services provided, as well as the characteristics of users and the city.

This new understanding provides model to aid decision-making to attracting customers, through comprising its main characteristics, level of satisfaction, and, travel needs, related with your frequency of PT use. In addition, this study contributes to the understanding of the PT's demand for buses, in the context of small and medium-sized cities, which generally have a single business center, the destination of most trips.

The regression method used here for the variables that influence frequency-of-use was satisfactory, allowing us to identify and explore the relationships between the variables. Multinomial Logistic Regression was effective insofar as the dependent variable was multi-categorical, and because similar studies have successfully used this technique to meet similar objectives (Truong & Somenahalli, 2015; Etminani-Ghasrodashti et al., 2018; Keyes & Crawford-Brown, 2018).

Variables like the frequency of provided services, built environment at destinations, travel characteristics (distance, time, and origin/destination), and competition with other modes of transportation all limit the explanatory power of this study, given the importance of choice in modes of transportation (Wells & Thill, 2012; Nazem et al., 2015; Yu et al., 2018). This could be addressed by future studies. This study was also limited in that the sample size was relatively small for some variable categories, which could cause sample bias. Additionally, the COVID-19 pandemic has been shown to negatively influence public transportation demand (Chen et al., 2020). Future studies could consider pandemic-induced changes, or post-pandemic scenarios.

Finally, the results have policy implications in terms of: urban planning, directing the government guidelines and service providers based on proposal that can help improve PT demand and use more frequently; and urban mobility, encouraging sustainable modes of transport and help develop mobility policies. We can highlight (i) offering financial subsidies to reduce fares, (ii) increasing inspections of companies operating the public transportation system, and (iii) limiting purchases and access to individual vehicles in urban centers. It is also important to improve service-related aspects, e.g., real-time access to information, and facilitated payment systems in the form of smart cards. These technological resources can make public transportation more attractive and efficient, and facilitate fare integrations with other modes of transportation.

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