Journal of Infrastructure, Policy and Development 2024, 8(8), 5452.
https://doi.org/10.24294/jipd.v8i8.5452

Article

Patronage loss and bicycles: Factors influencing mode transition from a strategic digital city perspective

Luis André Wernecke Fumagalli[1,2,*], Denis Alcides Rezende[1], Thiago André Guimarães[3,4]

[1] Master's and Doctoral Program in Urban Management, Strategic Digital City Research Group (CNPq), Pontifícia Universidade Católica do Paraná (PUCPR), Curitiba 80215-901, Brazil
[2] MBA Department, FAE Business School (FAE), Curitiba 80010-100, Brazil
[3] Business School, Federal University of Paraná (UFPR), Curitiba 80215-901, Brazil
[4] Technical and Technological Education Department, Federal Institute of Science and Technology of Paraná (IFPR), Curitiba 80230-150, Brazil
*** Corresponding author:** Luis Andre Wernecke Fumagalli, luis.fumagalli@fae.edu

CITATION

Fumagalli LAW, Rezende DA, Guimarães TA. (2024). Patronage loss and bicycles: Factors influencing mode transition from a strategic digital city perspective. Journal of Infrastructure, Policy and Development. 8(8): 5452. https://doi.org/10.24294/jipd.v8i8.5452

ARTICLE INFO

Received: 26 March 2024
Accepted: 16 May 2024
Available online: 15 August 2024

Abstract: Sustainability is a top priority for municipal administrations, particularly in large urban centers where citizens rely on transportation for work, study, and daily errands. Public transportation faces a significant challenge beyond availability, performance, safety, and comfort: balancing the cost for the city with fare attractiveness for passengers. Meanwhile, bicycles, supported by public incentives due to their clean and healthy appeal, compete with public transit. In Curitiba, the integrated transport system has been consistently losing passengers, exacerbated by the pandemic and the rise in private vehicle usage. To address this, the city is expanding bicycle infrastructure and electric bike rental services, impacting public transit revenue, and prompting the need for financial compensation to maintain affordable fares for those reliant on public transport. Therefore, this study's objective is to analyze the bicycle's impact on public transportation, considering the impact of public policies on economic and social efficiency, not just ecological and environmental factors. Data from six main bus lines were collected and analyzed in two separate linear regression models to verify the effects of new bicycles in circulation, bus tariffs, and weather conditions on public transportation demand. Research results revealed a significant impact of bus tariffs and fuel prices on the number of new bicycles that are diverting passengers from public transportation. The discussion may offer a different perspective on public transport policies and improve city infrastructure investments to strategically change the urban form to address social and economic issues.

Keywords: city administration; transport policy; sustainability in public transportation; bicycles impact

1. Introduction

Public transportation continues to lose passengers to other modes of transportation, particularly private vehicles. Automobiles and motorcycles provide a combination of convenience, flexibility, comfort, perceived safety, and economic and social factors, contributing to their widespread use compared to other transportation modes in various contexts. Public transport should be more supported, with attention given particularly to buses for urban transport (Spreafico and Russo, 2020). The socio-technical approach recognizes the interconnectedness of social, technical, and institutional aspects in shaping transportation systems (Brand et al., 2018). Transitioning from public transportation to bicycles, for instance, requires not only infrastructure advancements but also changes in social practices, institutional frameworks, and policy environments.

Brazilian municipalities, particularly in large metropolitan areas, are increasingly investing in alternative transportation modes, with bicycles and electric bicycles emerging as favored options. However, the necessary infrastructure and electric bicycle docks are predominantly concentrated in downtown areas or affluent neighborhoods (Fontoura et al., 2019). This situation disproportionately affects the less affluent citizens, who constitute a significant portion of the population in these cities. Many of them reside in areas distant from schools and job centers, thus relying heavily on public transportation. Unfortunately, public transit often falls short in terms of affordability, security, punctuality, and comfort, primarily due to congestion and overcrowding (Cats et al., 2016).

Curitiba, the State of Paraná capital in Brazil is internationally recognized for its efficiency by using buses on its transportation system. Since 1970s, the city started with the innovative Bus Rapid Transit (BRT) system that served as a model to be followed by many other cities worldwide due to its high service level, quality, comfort, agility, and sustainability. The exclusive bus lanes crossing the city in the most important directions gave significant contributions to residents' quality of life and changed the city's shape and its urban development through the last 50 years (URBS, 2023).

The Curitiba BRT system reached its highest number of transported passengers' number in 2007, with 1.68 million passengers, but it decreased in the last seven years, with 28.1% (URBS, 2023) accumulated lost in this period, not taking into consideration the slump that occurred in 2020 due to the COVID-19 outbreak. The city administration is making many efforts to increase comfort and safety on buses, terminals, and bus stations and is currently testing 70 full electrical cars in the transport system. However, the system loses around 70 thousand passengers per day every year (URBS, 2023) to other transport modes, including bicycles introduced by the municipality.

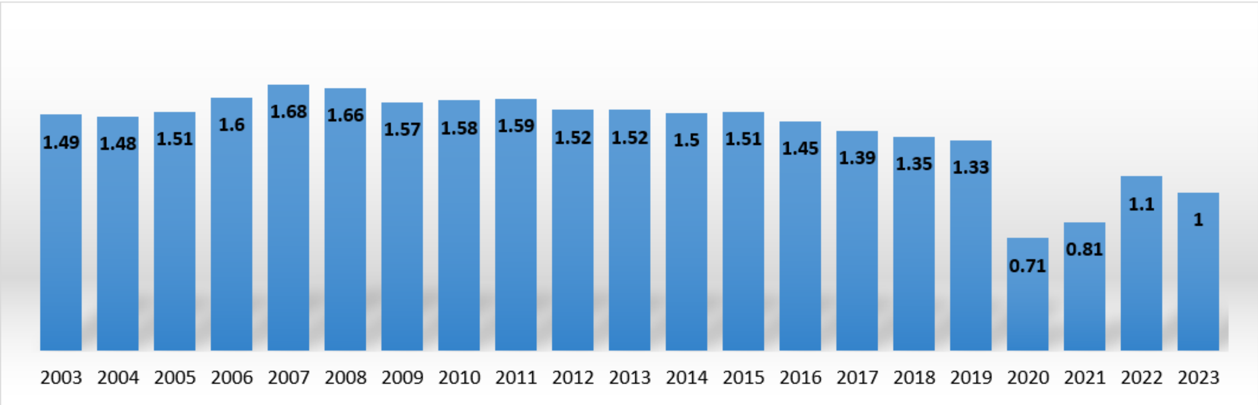

Figure 1. Average daily transported passengers in Curitiba over the years (in millions) (URBS, 2023).

Previous research observed that the patronage loss started in 2016 and accelerated in 2020 during the COVID-19 lockdown. Even with some recovery since 2021, those numbers never returned to normality, and 2023 showed a new decrease. Many passengers changed to private transportation, causing systemic losses to the public transport system, traffic jams, and accidents, especially with motorcycles. Every extra car on the road displaces 25 passengers (or BRT tickets) from the system, while each additional motorcycle in circulation removes 201 passengers (or BRT tickets) (Fumagalli et al., 2022). These findings correlate with the average number of passengers recorded during the same studied period, as depicted in **Figure 1**.

However, the increasing number of cars and motorcycles does not fully account for the continual and significant decline in public transport ridership. Factors such as fare pricing, weather conditions (temperature and precipitation), and recent incentives for bicycles warrant particular attention from city transportation policies. Their impacts are resulting in more social and economic drawbacks than ecological and environmental benefits, as they are diverting passengers from the system, thereby increasing costs for the remaining passengers (Fumagalli et al., 2022). The promotion of bicycles, renowned for their sustainability, minimal pollution, and reduced space requirements, necessitates investments in circulation infrastructure. Moreover, such infrastructure must be seamlessly integrated with public transport to mitigate further passenger loss (Hu and Schneider, 2015). Thus, public transport, urban mobility, and municipal investments in these domains are interconnected municipal priorities that require a comprehensive transportation plan encompassing municipal strategy, information systems, public services, and the utilization of information technology resources (Rezende et al., 2024).

Based on this context, the objectives of this study were to investigate the effects of tariffs, weather conditions, and bicycles on the behavior of public transport users in Curitiba, alongside the previously studied effects of cars and motorcycles (Fumagalli et al., 2022). The aim was to evaluate the extent of natural substitution between different modes of transportation and public transport. By understanding these parameters, it will be possible to develop a Strategic Digital City (SDC) project that supports decision-making for municipal administrators, as the definition of the four subprojects within the SDC should stem from this study. These subprojects encompass city strategies, city information, public services for citizens, and the application of information technology resources in cities (Rezende et al., 2024).

To achieve the objectives of the article, data were collected from the main six express lines of Curitiba's BRT system, which cover at least one-third of the entire city, spanning from January 2010 to December 2019, excluding the period affected by the pandemic outbreak. Passenger numbers were analyzed using two statistical regression models, incorporating variables such as the number of bicycles sold, fare prices, average temperature, and cumulative atmospheric precipitation for each respective month.

2. Literature review

Understanding transportation's role in a city's economic sustainability entails recognizing it as both a product and a driver of the economy, as well as acknowledging its associated costs. When these components are quantified, any imbalances can be identified as areas ripe for potential innovation, whether political or technological. However, delineating the relative contributions of capital, labor, and infrastructure to the economy is challenging, as is separating the impacts of public and private transportation, given their integration. The use of one mode of transportation often alleviates congestion on the other (Kennedy, 2002).

In recent decades, environmental and global warming concerns have influenced people's transportation choices, leading them to seek alternatives that do not rely on fossil fuels. The onset of the pandemic in 2020 intensified this trend, with passengers increasingly avoiding shared, confined spaces. This shift in public transportation behavior has led to persistent congestion, even outside of peak hours, and a rise in accidents involving motorcycles and bicycles, particularly in the absence of dedicated lanes for their circulation (Hasani et al., 2019), as observed on most bus routes across the city. Attitudes and other psychological factors significantly influence individuals' decisions to commute by bicycle, with safety, direct benefits, comfort, and time savings playing prominent roles (Fu and Farber, 2017; Heinen et al., 2011).

The relationship between micro-mobility and public transportation is complex. While micro-mobility can complement public transportation in underserved areas, it also appears to substitute for public transportation on some trips. This suggests that people may prioritize the flexibility and speed of micro-mobility over public transportation or walking, even when viable alternatives exist. Given this dynamic, it underscores the importance of implementing appropriate regulations and policies to ensure the sustainability of micro-mobility services (Schwinger et al., 2022).

Public policy plays a crucial role in promoting cycling. To significantly increase cycling rates, a comprehensive approach is necessary, encompassing infrastructure development, pro-bicycle programs, supportive land use planning, and restrictions on car use (Pucher et al., 2010). Attitudinal factors such as convenience, personal safety, modal comfort, service environment, and waiting feelings also influence cycling behavior, as observed in a survey of 570 citizens in Chengdu, China (Chen and Li, 2017). Similarly, in Sydney, Australia, policies aimed at promoting active travel, such as cheaper public transport and segregated bicycle paths, received strong support among residents (Rissel et al., 2018).

Direct benefits such as time savings and comfort significantly impact bicycle use, while convenience and external constraints such as danger, vandalism, and infrastructure availability play pivotal roles in shaping attitudes towards cycling (Fernández-Heredia et al., 2014). Enjoyment and fitness improvement are key motivators for cycling, particularly among regular cyclists, although weather and safety concerns pose significant obstacles (Swiers et al., 2017).

Weather conditions, particularly temperature, precipitation, and road conditions, greatly influence cycling behavior. Precipitation, in particular, has a significant negative impact on cycling flows, with its effect intensifying with rain intensity (Bergström and Magnusson, 2003; Nosal and Miranda-Moreno, 2014). Weather impacts vary across seasons and regions, highlighting the diverse challenges faced by cyclists (Liu et al., 2015).

Finally, individuals who perceive travel as burdensome are more inclined to use personal vehicles and micro-mobility, while showing less intention to use public transportation. This preference for personal vehicles and micro-mobility stems from a desire to minimize travel time (Koo and Choo, 2022). Public transportation usage, on the other hand, is positively associated with factors such as being female and residing in urban areas with high population density, but negatively correlated with age and income (Emond et al., 2009; Swamni et al., 2010; Yazdanpanah and Hosseinlou, 2017). Cycling is positively related to being male (Emond et al., 2009) and negatively related to age (Roos et al., 2020).

Many cities have advocated for cycling as a mode of urban transport, yet few have succeeded in integrating it as a significant transport mode within their urban traffic systems. Despite the existence of numerous cycling paths, cycling remains predominantly a leisure activity rather than a daily transportation option in urban settings. To promote cycling as a viable urban transport mode, an integrated approach to transport policy that incorporates cycling planning is essential. Alongside the promotion of urban mobility, it is crucial to raise public awareness regarding the benefits of utilizing public transport and to encourage behavior change. Combining bicycle traffic with public transport represents one of the most significant sustainable approaches to achieving acceptable levels of citizen mobility and fostering the sustainable development of cities (Dimter et al., 2019).

In efforts to enhance the sustainability and livability of urban environments, cycling and public transport, known for their low energy consumption and minimal pollution, have been strongly advocated for in metropolitan areas worldwide (Bordagaray et al., 2013; Moreno Gonzalez et al., 2012). The whole population should also have equitable opportunities to access public services coverage, including transportation, which also has an instrumental value with respect to education, health services, and employability. Inclusive transport policies must improve environmental aspects in big cities, and public transportation policies must include economic and social issues in decision-making. And the SDC can help the city administrators in a more comprehensive direction to better respond to all citizen’s needs.

Unlike the conventional concepts of digital city and smart city, the strategic digital city (SDC), a term introduced by Rezende (2024), can be viewed as the application of information technology resources in city management and the provision of information and services to citizens, guided by the city’s management strategies. It encompasses a broader scope than merely providing internet access to citizens through conventional telecommunication resources, extending to the digital inclusion of citizens in the global computer network (Rezende et al., 2024).

The SDC is grounded in the city’s strategies aimed at fulfilling the objectives of various public thematic or municipal functions. These functions represent macro activities present in all cities (or municipalities) and should not be confused with city areas or municipal departments. Examples of such functions include agriculture; science, technology, and innovation; marketing or commerce; culture; education; sports; housing; industry; legal affairs; leisure; logistics or materials; environment; health; sanitation; security; social services; transportation or mobility; tourism; urban planning; and rural development. Each of these functions can be further divided into modules or subsystems, also referred to as municipal affairs, subjects, themes, or issues that are systematized and integrated (Rezende et al., 2024).

SDC is divided into four subprojects: city strategies (to achieve the city’s objectives); city information (to assist in the decisions of citizens and city managers); public services (to increase the citizens’ life quality); and information technology resources applied in cities. For the adequate implementation of the SDC model (Rezende et al., 2024) is necessary to elaborate on four projects: city strategic planning with objectives and strategies covering all city public thematic or municipal functions; city information planning; city public service planning; and city information technology planning, also considering the municipality, prefecture and municipal public organizations involved (Rezende et al., 2024).

To make the SDC concept and project viable, it is necessary to divide the city into municipal themes and public issues, including mobility and cycling in cities. The City Hall's efforts are in this direction, where the strategies are planned, and public services relevant to bicycles are made available to citizens, considering peculiar public roads (cycle paths), traffic facilities, and mobility software.

In this study, the following two additional models that were not considered in the previous article (Fumagalli et al., 2022) are applied. The first point is the introduction of bicycles into the system in the same observed period (Jan/2010 to Dec/2019). As the number of bikes increases, passengers on public transportation may reduce, and the performance of the existing transportation system may be negatively affected, impacting over tariffs. The second model includes weather conditions (rain and temperature) and public transport tariffs to investigate how they affect passengers' preference between cycling and public transportation.

3. Research methodology

The Curitiba BRT system integrates various components, like dedicated bus lanes, faster boarding on terminals and stops, and prepaid fares, that create a seamless and efficient transport experience, reducing travel times significantly. The system allows passengers to pay a flat fare to travel in all transport network without transfers. Bus stations are wheelchair accessible, making the entire system more inclusive. The fleet comprises bi-articulated buses capable of accommodating up to 250 passengers and powered with biodiesel and many others are hybrids and electrics in certain lines. These features reduce the number of circulating vehicles, alleviate traffic jams and pollution, and promote a greener and sustainable urban environment.

The city's commitment to sustainability and cost-effective pricing on transport tariff try to encourage more people to use public transportation as their primary travel choice. However, despite all thoughtful urban planning, infrastructure, and accessible and environmentally friendly transport system, it still loses passengers every month to other transport modes. Recently, the city administration introduced new investments in exclusive cycling paths, shared reduced-speed streets with other vehicles in parallel with the main bus lines, and new rental e-bike docks introduced in strategic points around the city center.

Therefore, the bicycle's impact on public transportation is evaluated with weather and tariff prices, in two statistical models. The number of passengers in the main BRT express lines (203, 303, 502, 503, and 602) were analyzed with the number of bicycles sold in Curitiba, the tariff nominal price, the temperature, and the precipitation average in the period between January 2012 and December 2020, recorded monthly, in 120 periods (T), with no gaps. Formally, there are monthly periods between January 2010 and December 2019, where $|T| = 120$.

Data is collected from public official sites. It means that the information gathered originates from sources that are accessible to anyone and are considered legitimate or authoritative. These sources include government websites, public databases, official publications, and other similar platforms that provide reliable and verified information about the studied variables in the present study.

In order to obtain greater representativeness of the use of the system, six-line passenger records were grouped, defining the set Λ, as: set of aggregate lines for analysis, where $|\Lambda| = 6$. The dependent variable y_i^t with $i \in \Lambda, t \in T$, represents the number of passengers on the line *i* at period *t*. This representation produces a matrix of records with 720 elements, described in **Table 1**.

Table 1. Analyzed periods.

Line	*t* = 1 (Jan/2010)	*t* = 2 (Feb/2010)	...	*t* = 120 (Dec/2019)
i = 1 (203)	y_1^1	y_1^2		y_1^{120}
i = 2 (303)	y_2^1	y_2^2		y_2^{120}
i = 3 (502)	y_3^1	y_3^2		y_3^{120}
i = 4 (503)	y_4^1	y_4^2		y_4^{120}
i = 5 (602)	y_5^1	y_5^2		y_5^{120}
i = 6 (603)	y_6^1	y_6^2		y_6^{120}

Finally, the dependent variable aggregate for each analyzed period is obtained by directly adding the observed values in each line, as shown in Equation (1).

$$Y^t = \sum_{i \in \Lambda} y_i^t = y_1^t + y_2^t + y_3^t + y_4^t + y_5^t + y_6^t \quad (1)$$

To explain passengers' demand, four independent variables were tabulated, as detailed below:

- X_{bic}^t : number of bicycles sold in Curitiba in period *t*. Due to the substitution relation with the use of public transport, the hypothesis is that the impact is negative.
- X_{tar}^t : tariff nominal price in period *t*, measured in R$. Due to the income effect, the hypothesis is that the impact is negative.
- X_{temp}^t : month temperature average in Curitiba, measured in degrees Celsius. As the seasonality cycle of demand coincides with the cycle of climatic seasons, the hypothesis is that the relationship is reversed, that is, higher temperatures have a negative impact on the demand for public transport.
- X_{rain}^t : month precipitation average in Curitiba, measured in millimeters. Rainier periods imply greater demand for covered means of transport. The hypothesis, therefore, is that the relationship is direct, that is, the greater the rainfall, the greater the demand for public transport.

Regression models are employed in this study to understand the relationship between continuous variables. In this approach, one variable, termed the independent variable or predictor variable, is used to predict the values of another variable, known as the dependent variable or response variable. The simple linear regression model assumes a linear relationship between the independent variable and the dependent variable. The objective of the model is to determine the best-fitting line through the data points, minimizing the difference between observed values and those predicted by the line.

To achieve this, simple linear regression calculates the slope and intercept of the line that best fits the data. The slope represents the change in the dependent variable for a one-unit change in the independent variable, while the intercept represents the value of the dependent variable when the independent variable is zero. Consequently, the regression line can be used to predict the values of the dependent variable for new values of the independent variable not included in the original dataset. This predictive capability makes simple linear regression a valuable tool for understanding and forecasting relationships between variables.

The Analysis of Variance (or ANOVA) assesses whether there are differences in means between groups, while the F-test within ANOVA determines if these differences are statistically significant. If the F-statistic exceeds a critical value based on the chosen significance level (usually 0.05), then the null hypothesis, which states that there are no significant differences between group means, is rejected, and it is concluded that at least one group mean is significantly different from the others.

The absence of tools for detecting outliers, histograms, and P-P plots hindered the ability to visualize outliers in the dataset and assess the normality of its distribution. These graphical representations typically display the frequency or proportion of observations within different intervals or bins, providing valuable insights into the shape, central tendency, and spread of the data distribution. Additionally, P-P plots are instrumental in evaluating normality by comparing the observed cumulative distribution function (CDF) with the theoretical CDF of a normal distribution. Any deviations from a straight line in a P-P plot may suggest departures from normality.

4. Regression models and results

Based on demand dynamics, data was operated in two modal replacement models. This analysis objective is to verify if there is a fact of the mode of transport substitution and, additionally, to detect which one is capturing systems passengers. A simple linear regression model was operated separately for bicycle and tariff and weather conditions to investigate how it affects the system demand. The first analysis model verifies the relationship between the number of purchased bicycles and the bus system demand, shown in Equation (2):

$$M1: Y^t = \beta_0 + \beta_1 X^t_{\text{bic}} \qquad (2)$$

There is required $n \geq 20$ for each predictor variable. A single predictor variable and 120 ($|T| = 120$) observations satisfy this requirement, consequently. The linear relationship between the independent (X^t_{bic}) and dependent (Y^t) variables is observable in **Figure 2**.

There is a single predictor variable, and the number of observations is met. It was possible to observe that the relationship is not perfectly linear between the variables, although there is a visual relationship. The correlation test between the variables shown that Pearson's coefficient is moderate to strong (−0.875) and in fact negative, that is, as the number of registered bicycles increases, the number of passengers decreases. The correlation e is statistically significant ($p = 0.000 < 0.005$) (**Table 2**).

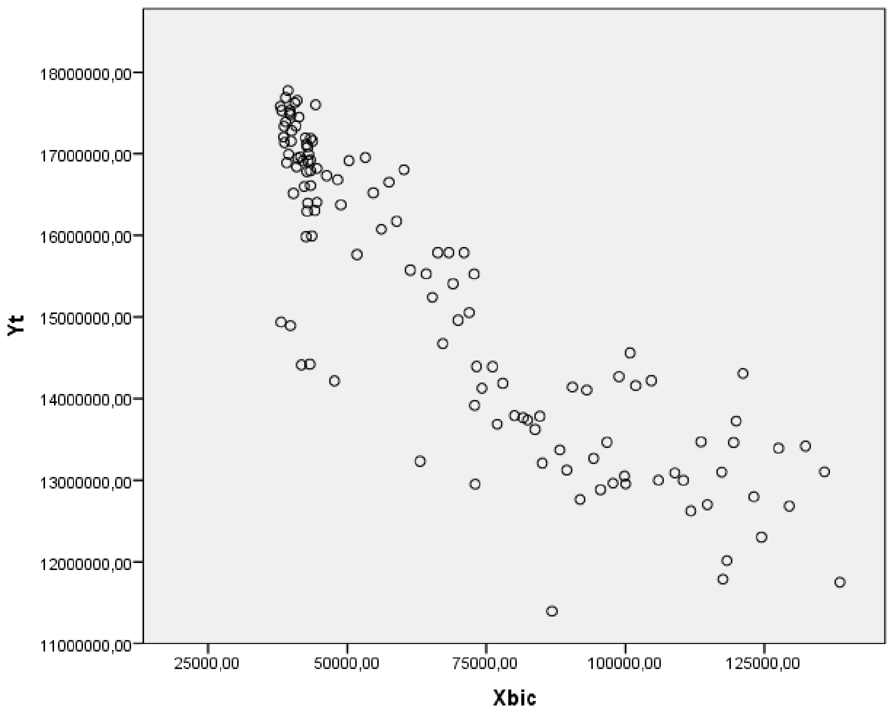

Figure 2. Linear relationship between independent variable (X_{bic}^{t}) and dependent variable (Y^{t}).

Table 2. Correlation analysis results.

		Y^t	X_{bic}
Pearson Correlation	Y^t	1.000	**−0.875**
	X_{bic}	**−0.875**	1.000
Sig. (1-tailed)	Y^t		0.000
	X_{bic}	0.000	
N	Y^t	120	120
	X_{bic}	120	120

In this case, the Durbin-Watson test should have a value between 1.0 and 2.5, and the closer to 2.0, the better. The analyzed data shows that the *R*-squared is 0.766 (**Table 3**). This means that 76.67% of the variation in the number of passengers is explained by the purchased bicycles number. The value of the Durbin-Watson test was 1.629 (**Table 3**), within the range [1.0; 2.5], which precludes autocorrelation.

Table 3. Model tests summary.

Model	*R*	*R*-square	Adjusted *R*-square	Std. Error of the Estimate	Durbin-Watson
1	0.875[a]	**0.766**	0.764	868,497.16233	**1.629**

Data from the ANOVA show that the *F* test of the model is statistically significant ($F = 385.51$ and $p = 0.000 < 0.005$ in bold) (**Table 4**), that means, the model with the predictor by the number of bicycles purchased can predict the demand for passengers.

Table 4. ANOVA results.

Model	Sum of Squares	df	Mean Square	*F*	Sig.
Regression	290,788,708,690,476.800	1	290,788,708,690,476.800	**385.515**	**0.000**[b]
Residual	89,005,903,874,953.020	118	754,287,320,974.178		
Total	379,794,612,565,429.800	119			

It was possible to observe that the coefficients are significant ($p = 0.000 < 0.005$ in bold) (**Table 5**), both for the intercept and for the slope of the independent variable.

Table 5. Coefficients.

Model		Unstandardized Coefficients		Standardized Coefficients	*t*	Sig.
		B	Std. Error	Beta		
1	(Constant)	**18,842,035.924**	200,570.994		93.942	**0.000**
	X_{bic}	**−52.475**	2.673	−0.875	−19.635	**0.000**

The absence of outliers was verified and occurs when the minimum and maximum range for standardized residues must be between [−3; +3]. From the values obtained, it was observed that there is the presence of outliers in the model for the residues, although this does not compromise the analysis and the results (**Table 6**).

Table 6. Residuals statistics.

	Minimum	Maximum	Mean	Std. Deviation	*N*
Predicted Value	11,571,036.0000	16,849,018.0000	15,224,644.9500	1,563,202.67209	120
Residual	−2,892,457.00000	1,822,166.75000	0.00000	864,840.31593	120
Std. Predicted Value	−2.337	1.039	0.000	1.000	120
Std. Residual	**−3.330**	2.098	0.000	0.996	120

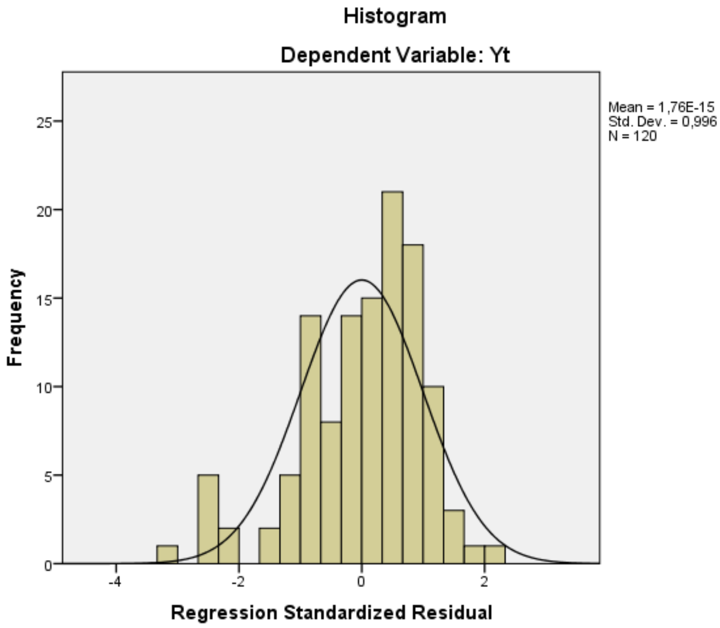

Figure 3. Histogram.

Data normality was checked graphically by the histogram (**Figure 3**) and the P-P plot (**Figure 4**). The independent variable frequency analysis must be close to the normal curve in the histogram, which occurs in fact.

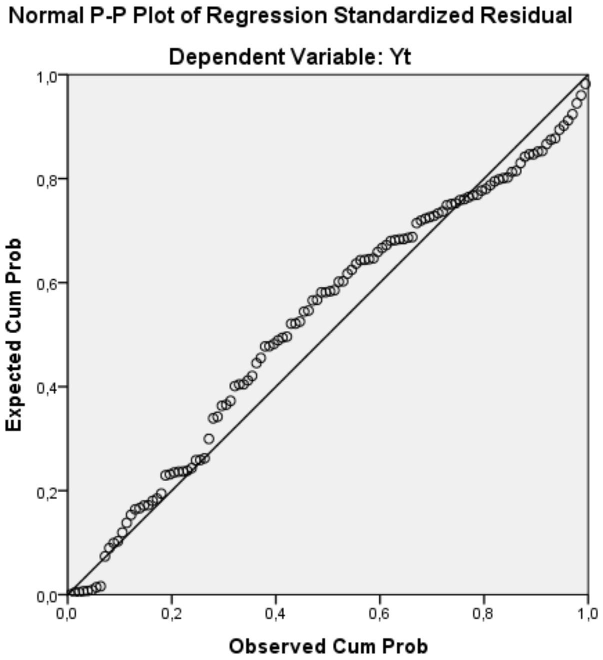

Figure 4. P-P Plot graphic.

The P-P plot can verify the residual's normality when the residual's cumulative probability equals the observed cumulative probability, which represents the bisector line of the even quadrants. There is an overlap observed, and the residuals are normal.

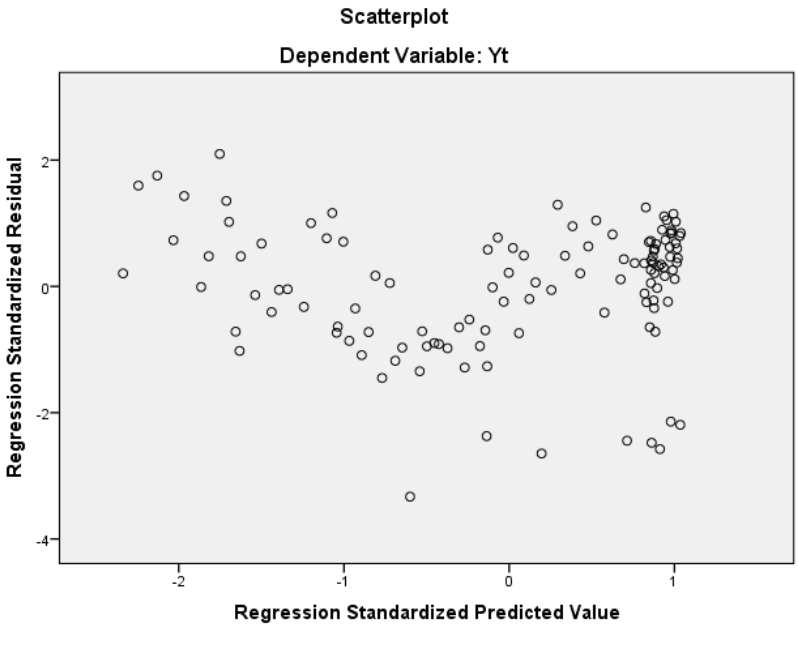

Figure 5. Homoscedasticity graph.

The last prerequisite of the regression model is that the error variance is constant.

If this occurs, the model is said to be homoscedastic. Graphically, the error dispersion distribution must be similar to a rectangle. If a conic figure appears, then the model is heteroscedastic. The graph (**Figure 5**) shows that the homoscedasticity requirement is not guaranteed, as the figure is distinct from a rectangle.

The model obtained is, therefore, $Y^t = 18{,}842{,}035.92 - 52.475 \times X_{\text{bic}}^t$. The angular coefficient shows that with each new bicycle in the city, the number of passengers reduces by approximately 52.48, which confirms the hypothesis of a negative impact on the variable.

The second model intends to verify the effect of fare prices and temperature over system's demand. The purpose of this analysis is to verify the effect of the tariff and temperature, which coincides with seasonal aspects of demand. The hierarchical regression model is used, in which the variable X_{tar}^t is added first Equation (3), followed by the variable X_{temp}^t in Equation (4).

$$M2: Y^t = \beta_0 + \beta_1 X_{\text{tar}}^t \tag{3}$$

$$M3: Y^t = \beta_0 + \beta_1 X_{\text{tar}}^t + \beta_2 X_{\text{temp}}^t \tag{4}$$

In the correlation between the variables, it is important to note that the fare has a strong correlation with the number of passengers (−0.901), while the temperature has a weak correlation (−0.077), but still negative (**Table 7**). At the same time, there is no correlation between the independent variables. The correlation between demand and tariff is significant and the correlation with temperature is not significant.

Table 7. Correlation analysis results.

		Y^t	X_{tar}	X_{temp}
Pearson Correlation	Y^t	1.000	**–0.901**	**–0.077**
	X_{tar}	**–0.901**	1.000	–0.034
	X_{temp}	**–0.077**	–0.034	1.000
Sig. (1-tailed)	Y^t		**0.000**	0.200
	X_{tar}	**0.000**		0.355
	X_{temp}	0.200	0.355	
N	Y^t	120	120	120
	X_{tar}	120	120	120
	X_{temp}	120	120	120

Table 8. Model summary.

Model	***R***	***R*-Square**	**Adjusted *R* Square**	**Std. Error of the Estimate**	**Change Statistics**					**Durbin-Watson**
					***R*-Square Change**	***F* Change**	**df1**	**df2**	**Sig. *F* Change**	
1	0.901[a]	**0.811**	0.810	779,138.27	0.811	507.633	1	118	0.000	
2	0.907[b]	**0.823**	0.820	757,643.354	0.012	7.790	1	117	0.006	2.215

The value of the Durbin-Watson test was 1.629, within the range [1.0; 2.5], which precludes autocorrelation in errors. Analyzing the *R*-square of the Model 1, which considers only the fare, explains 81.1% of the variation in the number of passengers. When the temperature variable is added, this explanation increases to 82.3%, and this change is statistically significant (Sig F Change). **Table 8** summarizes this test results.

Data from the ANOVA show that the F test of Model 1 is statistically significant (F = 507.633 and p = 0.000 < 0.005 in bold), that is, the model with the fare-based predictor is capable of predicting passenger demand. When adding the temperature to the model, it maintains statistical significance (F = 272.31 and p = 0.000 < 0.005 in bold). The coefficients are shown in the **Table 9**. It is possible to observe that the coefficients are significant (p = 0.000 < 0.005 in bold), both for the intercept and for the slope of the independent variable.

Table 9. ANOVA results.

Model		Sum of Squares	df	Mean Square	*F*	Sig.
1	Regression	308,161,951,955,340.800	1	308,161,951,955,340.800	**507.633**	**0.000**
	Residual	71,632,660,610,089.000	118	607,056,445,848.212		
	Total	379,794,612,565,429.800	119			
2	Regression	312,633,868,738,431.100	2	156,316,934,369,215.560	**272.318**	**0.000**
	Residual	67,160,743,826,998.670	117	574,023,451,512.809		
	Total	379,794,612,565,429.800	119			

The coefficients are presented in the **Table 10**. It is possible to observe that the coefficients are significant (p = 0.000 < 0.005 in bold), both for the intercept and for the angular coefficient of the independent variable.

Table 10. Coefficients.

Model		Unstandardized Coefficients		Std Coeff	*t*	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	21,967,117.25	307,593.087		71.416	**0.000**		
	X_{tar}	−20,866.452	926.134	−0.901	−22.531	**0.000**	1.000	1.000
2	(Constant)	23,213,671.315	537,518.547		43.187	**0.000**		
	X_{tar}	−20,953.016	901.117	−0.905	−23.252	**0.000**	0.999	1.001
	X_{temp}	−73,482.396	26,326.994	−0.109	−2.791	**0.006**	0.999	1.001

Note: The Variance Inflation Factor (VIF) measures the severity of multicollinearity in regression analysis.

The collinearity statistics indicate that there is no multicollinearity in the model since the tolerance values are all greater than 0.1. The model obtained is shown in Equation (5).

$$Y^t = 23{,}213{,}671.31 - 20{,}953.01 \times X^t_{\text{tar}} - 73{,}485.4 \times X^t_{\text{temp}} \quad (5)$$

The angular coefficient shows that at every R$1.00 increase in the fare, the number of passengers falls by approximately 20,953. Likewise, with each additional Celsius degree in the average temperature of the month, the number of passengers decreases by 73,482. It is It is important to highlight that this result reflects the seasonality in demand, given that there is a sharp drop in the months of December, notably warmer.

The absence of outliers was verified and occurs when the minimum and maximum range for standardized residues must be between [−3; +3]. From the values presented, it is observed that there are no outliers in the model for the residues (**Table 11**).

Table 11. Residuals statistics.

	Minimum	Maximum	Mean	Std. Deviation	*N*
Predicted Value	12,838,992.0000	17,722,220.0000	15,224,644.9500	1,620,856.36857	120
Residual	−2,240,890.75000	1,648,288.00000	0.00000	751,249.62466	120
Std. Predicted Value	**−1.472**	**1.541**	0.000	1.000	120
Std. Residual	**−2.958**	**2.176**	0.000	0.992	120

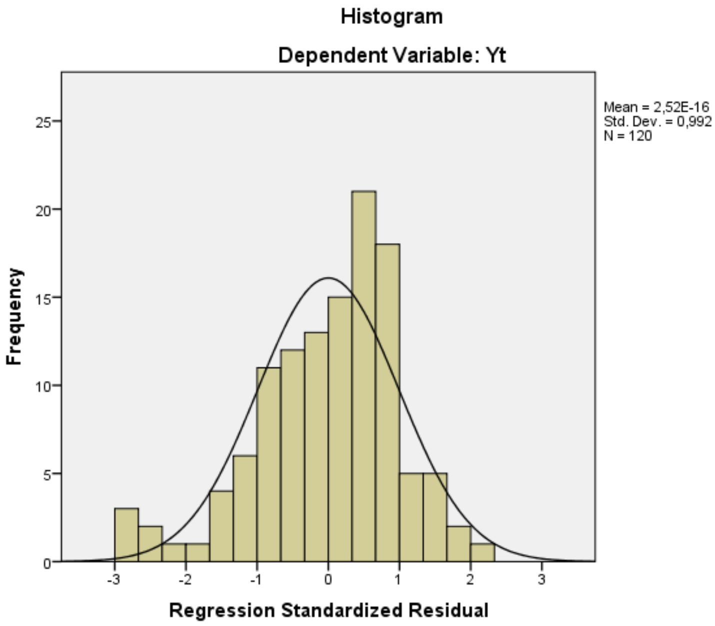

Figure 6. Histogram.

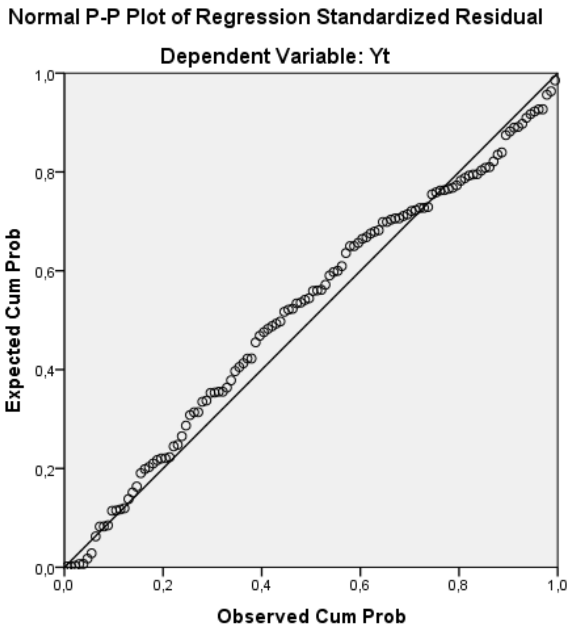

Figure 7. P-P Plot graphic.

The normality of the data is checked graphically by the histogram (**Figure 6**) and the P-P plot (**Figure 7**). It is observed that the overlap is not perfect, but it is still possible to accept the normality of the residues.

The P-P plot can verify the residual's normality when the residual's cumulative probability equals the observed cumulative probability, which represents the bisector line of the even quadrants. There is an overlap observed even if it's not perfect, and the residuals are normal (**Figure 7**).

The last prerequisite of the regression model is that the error variance is constant. If this occurs, the model is said to be homoscedastic. The graph (**Figure 8**) shows that the requirement of homoscedasticity is guaranteed, since the shape of the figure approaches a rectangle with random dispersion.

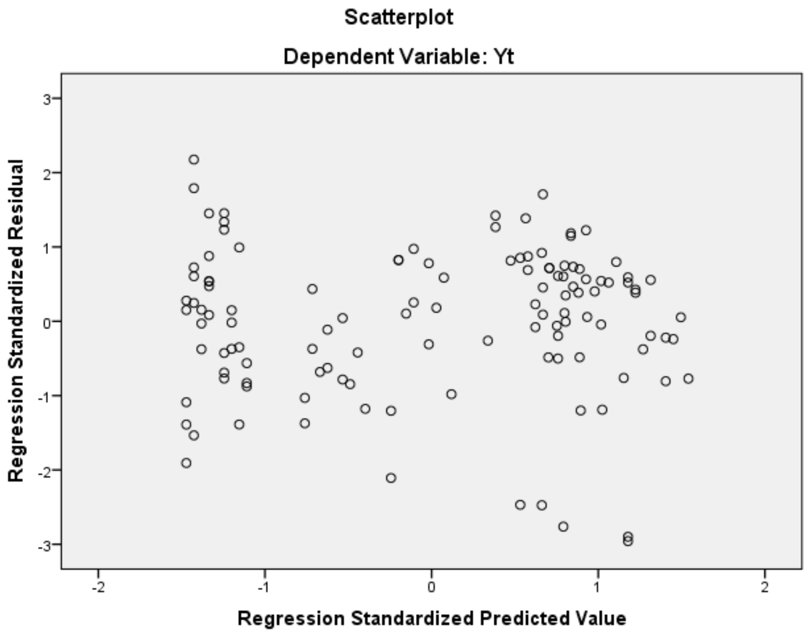

Figure 8. Homoscedasticity graph.

5. Discussion

In the context of structural change in urban mobility, the strongest effect comes from bicycles. In this case, a simple model was employed to measure the direct effect. The model passed all tests and showed significance. As a result, each new bicycle in the city decreases the number of passengers (or bus travels) by approximately 52 per month. This reduction tends to be long-lasting (unlike fluctuations in fuel prices). It is possible to assert that when former passengers opt for a bike, they rarely revert to using the bus. For city administration, this holds significance in terms of transport policy because incentives on bike prices, taxation, investments in bike-exclusive lanes, and the recent introduction of e-bike docks can be decisive factors for passengers to switch from motorized vehicles and public transportation.

The research findings offer valuable insights into the ongoing decline of the Curitiba RIT system's passenger numbers each month, complementing prior research on the impacts of cars and motorcycles. Specifically, bicycles emerge as a significant factor contributing to this trend, exerting a stronger influence on public transportation compared to cars (resulting in an estimated loss of 25 tickets per car) and a somewhat weaker influence compared to motorcycles (equating to approximately 201 tickets per motorcycle), as highlighted in a previous study (Fumagalli et al., 2022).

Bicycles and motorcycles exhibit greater space efficiency than cars within urban infrastructure, allowing them to navigate congested areas more effectively. However, motorcycles maintain their allure due to several advantages, including higher speeds, greater convenience, extended range capabilities, adaptability to various terrains, enhanced comfort during adverse weather conditions, and the availability of secure parking facilities and dedicated cycle tracks. In essence, while bicycles and motorcycles offer compelling alternatives to traditional car-based transportation, the superior speed and versatility of motorcycles continue to make them a preferred choice for many commuters, despite the space-saving benefits and environmental advantages associated with bicycles. Bicycles also may not be suitable for individuals with disabilities or the elderly.

Given the significance of bicycles in the model, attempts were made to estimate which factors best determine their usage. After adjustments, the best model considers the effect of replacing the bus (by increasing the fare) and motorized vehicles (by increasing fuel prices). Additionally, there is a positive effect on the presence of cycle tracks. In numerical terms, for every R$0.10 increase in the fare, the number of bicycles increases by 1068 units. For every R$0.10 increase in fuel prices, the number of bikes increases by 1520, indicating a greater migration from cars to bikes than from buses to bikes. Finally, for every additional kilometer of cycle lane, the number of bicycles increases by 333 units. These variables were analyzed simultaneously to ensure the consistency of the conclusion.

These findings also reinforce what was deduced in the very first demand prediction study, which states that people continue to use public transportation for two main reasons: (i) it is cheaper compared to other transport options, and/or free; (ii) and/or because there are no other options available for certain users (Fumagalli et al., 2022). People who live far from their points of interest lack the financial means for motorized vehicles and do not have the time or safety conditions to cycle such distances daily.

This conclusion can be positively explored by the city in terms of public policy if it aims to alleviate the burden on the system and reduce traffic congestion, especially during rush hours. Investing in bike lanes is preferable to expanding roads, as the impact of bicycles is more than twice that of cars. Other positive effects include environmental benefits contributing to the reduction of greenhouse gas emissions; improvements in well-being and health, thereby alleviating strains on healthcare systems; efficient utilization of urban space and enhanced accessibility, reducing the space required for cars and other motorized vehicles, particularly for parking; integration of modal shifts, cost savings, and economic opportunities, such as serving as a complementary mode to public transportation for the first and last mile, requiring minimal infrastructure investment and creating new businesses through bike-sharing, e-bike docks, and other opportunities along the system.

On the contrary, negative impacts on urban planning and public policies include the need for infrastructure investments in bike lanes, racks, parking, and secure storage facilities at bus stops and terminals. There may be concerns regarding cyclists sharing busy streets with other vehicles and pedestrians in crowded areas, along with other challenges related to mixed traffic. Social and economic equity issues arise, as cycling infrastructure is often unavailable in suburban areas, hindering individuals living at greater distances from work and school from accessing this option and fostering dependence on public transport. Integrating public transport with micro-mobility presents significant complexities in terms of pricing, scheduling, and availability.

As evidenced in a prior study (Fumagalli et al., 2022), micro-mobility options are primarily utilized by affluent individuals who reside near downtown areas and key destinations, mirroring the preferences of private car and motorcycle owners. This socioeconomic dynamic creates a segment of the population that largely bypasses public transportation, thereby undermining its overall efficiency and affordability.

To address this issue and promote a more balanced and inclusive transportation ecosystem, it is necessary to integrate various modes of transport and implement targeted public policies. By adopting a holistic approach that incorporates buses, cars, motorcycles, bicycles, and other modes of transportation, cities can create a more interconnected and accessible mobility network. For instance, enhancing bus services with expanded routes and increased frequency can provide viable alternatives for individuals who currently rely solely on private vehicles or micro-mobility options.

Moreover, the establishment of dedicated lanes for buses and bicycles can improve traffic flow and safety, encouraging more sustainable modes of travel. Additionally, incentivizing carpooling and ride-sharing initiatives can reduce single-occupancy vehicle trips, alleviate congestion, and reduce emissions. Furthermore, promoting the adoption of electric motorcycles and bicycles can offer environmentally friendly alternatives to traditional gas-powered vehicles, further reducing pollution and carbon emissions.

In essence, by integrating diverse transportation modes and implementing targeted public policies, cities can create a more efficient, equitable, and sustainable mobility system that meets the diverse needs of their residents while addressing socioeconomic disparities in access to transportation in accordance with the SDC subprojects (Rezende et al., 2024).

6. Conclusion

Bicycles are significantly diverting passengers from public transportation, and whether consciously or not, the city administration is contributing to this trend through investments in dedicated cycling lanes, e-bike sharing services, and bike docks across the city center. Warmer temperatures tend to incentivize more passengers to opt for cycling over buses. As public transit sees fewer passengers but maintains its infrastructure (reductions in transport infrastructure do not align linearly with demand), tariff prices rise, further promoting the modal shift towards bicycles. If fuel prices also increase simultaneously, it could create a perfect storm for the city's transportation system.

Residents living in remote areas continue to rely on public transportation as their sole option, if its price and service level remain below a certain threshold. In addressing this scenario, transportation policies should not solely prioritize environmental concerns but should also consider the needs of citizens compelled to utilize public transport for long-distance travel. These policies ought to foster a multi-modal approach, enhancing overall efficiency and ensuring inclusive accessibility of transport systems, particularly public ones.

There is an infinite and intricate array of factors and variables currently impacting public transport systems, and future policies must strive to encompass them as comprehensively as possible to avert imminent collapses. In conclusion, Strategic Digital City (SDC) initiatives can mitigate these effects, rendering them more sustainable, equitable, efficient, and inclusive, thereby enhancing the quality of life for citizens. SDC can harness data to assist authorities in decision-making processes, traffic management, and optimization of public transportation, facilitating the integration of multiple transport modes and enabling demand-responsive transport services. Moreover, SDC can integrate considerations of infrastructure, budget efficiency, and environmental impact across transportation and other public service domains, aligning with population needs and striving to achieve desired outcomes aimed at improving people's lives.

These research fills a gap in the literature by providing empirical evidence of the substantial influence of bicycles on public transportation systems. By quantifying the effect of bicycles on passenger demand for public transit, our findings offer a new perspective on the complex interactions between different modes of transportation within urban environments. This novel understanding of urban mobility dynamics is essential for transportation researchers seeking to develop more comprehensive models and theories that accurately capture the intricacies of modern transportation systems.

Future studies could focus on longitudinal research to find possible changes over time, comparative analyses to identify best practices, qualitative methods to understand individuals' experiences, multi-modal approaches to consider interactions between different modes, and policy evaluation to assess effectiveness. These new possibilities of research can inform evidence-based decision-making and contribute to the development of sustainable and equitable transportation systems.

While the study provides valuable insights into the dynamics of urban transportation in the study area, it is important to recognize the limitations inherent in the analysis, including the complexity of variables, data limitations, contextual factors, challenges in generalizability, and the scope of analysis. These limitations should be considered when interpreting the results and drawing comparisons with other cities and transport systems.

Author contributions: Conceptualization, LAWF; methodology, LAWF and TAG; software, TAG; validation, LAWF, DAR and TAG; formal analysis, LAWF; investigation, LAWF; resources, LAWF; data curation, TAG; writing—original draft preparation, LAWF; writing—review and editing, LAWF; visualization, LAWF and TAG; supervision, DAR; project administration, LAWF; funding acquisition, LAWF. All authors have read and agreed to the published version of the manuscript.

Conflict of interest: The authors declare no conflict of interest.

References

Bergström, A., & Magnusson, R. (2003). Potential of transferring car trips to bicycle during winter. Transportation Research—Part A Policy and Practice, 37, 649–666. https://doi.org/10.1016/S0965-8564(03)00012-0

Bordagaray, M., dell'Olio, L., Ibeas, A., et al. (2013). Modelling user perception of bus transit quality considering user and service heterogeneity. Transportmetrica A: Transport Science, 10(8), 705–721. https://doi.org/10.1080/23249935.2013.823579

Brand, C., Anable, J., & Morton, C. (2018). Lifestyle, efficiency and limits: modelling transport energy and emissions using a socio-technical approach. Energy Efficiency, 12(1), 187–207. https://doi.org/10.1007/s12053-018-9678-9

Cats, O., West, J., & Eliasson, J. (2016). A dynamic stochastic model for evaluating congestion and crowding effects in transit systems. Transportation Research Part B: Methodological, 89, 43–57. https://doi.org/10.1016/j.trb.2016.04.001

Chen, J., & Li, S. (2017). Mode Choice Model for Public Transport with Categorized Latent Variables. Mathematical Problems in Engineering, 2017, 1–11. https://doi.org/10.1155/2017/7861945

Dimter, S., Stober, D., & Zagvozda, M. (2019). Strategic Planning of Cycling Infrastructure Towards Sustainable City Mobility—Case Study Osijek, Croatia. IOP Conference Series: Materials Science and Engineering, 471, 092022. https://doi.org/10.1088/1757-899x/471/9/092022

Emond, C. R., Tang, W., & Handy, S. L. (2009). Explaining Gender Difference in Bicycling Behavior. Transportation Research Record: Journal of the Transportation Research Board, 2125(1), 16–25. https://doi.org/10.3141/2125-03

Fernández-Heredia, Á., Monzón, A., & Jara-Díaz, S. (2014). Understanding cyclists' perceptions, keys for a successful bicycle promotion. Transportation Research Part A: Policy and Practice, 63, 1–11. https://doi.org/10.1016/j.tra.2014.02.013

Fontoura, W. B., Chaves, G. de L. D., & Ribeiro, G. M. (2019). The Brazilian urban mobility policy: The impact in São Paulo transport system using system dynamics. Transport Policy, 73, 51–61. https://doi.org/10.1016/j.tranpol.2018.09.014

Fu, L., & Farber, S. (2017). Bicycling frequency: A study of preferences and travel behavior in Salt Lake City, Utah. Transportation Research Part A: Policy and Practice, 101, 30–50. https://doi.org/10.1016/j.tra.2017.05.004

Fumagalli, L. A. W., Rezende, D. A., & Guimarães, T. A. (2022). Data Intelligence in Public Transportation: Sustainable and Equitable Solutions to Urban Modals in Strategic Digital City Subproject. Sustainability, 14(8), 4683. https://doi.org/10.3390/su14084683

Hasani, M., Jahangiri, A., Sener, I. N., et al. (2019). Identifying High-Risk Intersections for Walking and Bicycling Using Multiple Data Sources in the City of San Diego. Journal of Advanced Transportation, 2019, 1–15. https://doi.org/10.1155/2019/9072358

Heinen, E., Maat, K., & Wee, B. van. (2011). The role of attitudes toward characteristics of bicycle commuting on the choice to cycle to work over various distances. Transportation Research Part D: Transport and Environment, 16(2), 102–109. https://doi.org/10.1016/j.trd.2010.08.010

Hu, L., & Schneider, R. J. (2015). Shifts between Automobile, Bus, and Bicycle Commuting in an Urban Setting. Journal of Urban Planning and Development, 141(2). https://doi.org/10.1061/(ASCE)UP.1943-5444.0000214

Kennedy, C. A. (2002). A comparison of the sustainability of public and private transportation systems: Study of the Greater Toronto Area. Transportation, 29(4), 459.

Koo, J., & Choo, S. (2022). Identification of Causal Relationship between Attitudinal Factors and Intention to Use Transportation Mode. Sustainability, 14(24), 16806. https://doi.org/10.3390/su142416806

Liu, C., Susilo, Y. O., & Karlström, A. (2015). The influence of weather characteristics variability on individual's travel mode choice in different seasons and regions in Sweden. Transport Policy, 41, 147–158. https://doi.org/10.1016/j.tranpol.2015.01.001

Moreno Gonzalez, E., Romana, M.G., & Martinez Alvaro, O. (2012). Bus Dwell-Time Model of Main Urban Route Stops Case Study in Madrid, Spain. Transportation Research Record, 2274(1), 126–134. https://doi.org/10.3141/2274-14

Nosal, T., & Miranda-Moreno, L. F. (2014). The effect of weather on the use of North American bicycle facilities: A multi-city analysis using automatic counts. Transportation Research Part A: Policy and Practice, 66, 213–225.

Pucher, J., Dill, J., & Handy, S. (2010). Infrastructure, programs, and policies to increase bicycling: An international review. Preventive Medicine, 50, S106–S125. https://doi.org/10.1016/j.ypmed.2009.07.028

Rezende, D. A., Almeida, G. G. F., & Fumagalli, L. A. W. (2024). Strategic Digital City: Multiple Projects for Sustainable Urban Management. Sustainability, 16. https://doi.org/10.3390/su16130000

Rissel, C., Crane, M., Standen, C., et al. (2018). Public support for bicycling and transport policies in inner Sydney, Australia: A cross-sectional survey. Australian and New Zealand Journal of Public Health, 42(3), 309–314.

Roos, J. M., Sprei, F., & Holmberg, U. (2020). Sociodemography, geography, and personality as determinants of car driving and use of public transportation. Behavioral Sciences, 10(6), 93. https://doi.org/10.3390/bs10060093

Swamni, V., Chamorro-Premuzic, T., Snelgar, R., et al. (2020). Egoistic, altruistic, and biospheric environmental concerns: A path analytic investigation of their determinants. Scandinavian Journal of Psychology, 51, 139–145. https://doi.org/10.1111/j.1467-9450.2009.00760.x

Schwinger, F., Tanriverdi, B., Jarke, M. (2022). Comparing Micromobility with Public Transportation Trips in a Data-Driven Spatio-Temporal Analysis. Sustainability 2022, 14. https://doi.org/10.3390/su14148247

Spreafico, C., Russo, D. (2020). Exploiting the scientific literature for performing life cycle assessment about transportation. Sustainability, 12(18), 7548. https://doi.org/10.3390/su12187548

Swiers, R., Pritchard, C., & Gee, I. (2017). A cross sectional survey of attitudes, behaviours, barriers and motivators to cycling in University students. Journal of Transport & Health, 6, 379–385. https://doi.org/10.1016/j.jth.2017.07.005

URBS. (2023). Urbanization of Curitiba S. A. (Portuguese). Available online: https://www.urbs.curitiba.pr.gov.br/ (accessed on 5 May 2023).

Yazdanpanah, M., & Hadji Hosseinlou, M. (2017). The Role of Personality Traits through Habit and Intention on Determining Future Preferences of Public Transport Use. Behavioral Sciences, 7(4), 8. https://doi.org/10.3390/bs7010008