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Exploring the Influences of Safety and Energy Expenditure Parameters on Cycling

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Abstract: Several determinants affect the reason to cycle or not, and some of them are described in a detailed way in the current technical literature review. The recent spread of new modes of active mobility brings up questions for urban transport planners on how to foresee future demand and assess safety conditions; from this comes the need to explore the relationships among several determinants. In this paper, after the collection of the main data required, three Regression Models are proposed, which demonstrate evidence for the role of safety and energy expenditure issues as important predictors. The method is applied to a dataset of 90 Italian cities selected according to their class of dimensionality and geographical position. The three models for each class of dimensionality (50,000–100,000 no. of inhabitants, 10,000–50,000 no. of inhabitants, and 0–10,000 no. of inhabitants) show a good accuracy (in terms of adj-R^2 values of 0.6991, 0.7111, and 0.6619, respectively). The results show that energy expenditure, which is related to the terrain characteristics of an urban area and individual aerobic abilities, and safety perception, which is related to cycle network extensions, appear to be significant determinants in predicting bicycle modal share. The aim is to provide a useful and simplified tool, when only aggregated-type data are available, to help urban road designers and city planners in identifying and forecasting bike-sharing.

Keywords: sustainable mobility; modal split; energy expenditure parameters; safety; e-bike; c-bike; cycling models

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1. Introduction

Sustainable mobility is commonly considered to be a very hot topic due to its complexity and its multidisciplinary nature. This has generated debates in international and national institutions and policies thanks also to the increased active modality and the interests of governments to increase active mode share [1].

The world is growing at an unsustainable pace. In the early 2000s, 193 UN member states launched the Millennium Development Goals (MDGs), which were a chance to hear about environmental sustainability for the first time [2].

In the past years, the same governments approved Agenda 30 for Sustainable Development to achieve the Sustainable Development Goals (SDGs) [3], with a focus on sustainable mobility that falls under goals 3 (health and well-being), 9 (business, innovation, and infrastructures), and 11 (sustainable cities and communities).

Cycling is a common way to reduce traffic congestion in urban areas and improve environmental conditions, safety conditions, and sustainability. How to evaluate and forecast cycling demand is an early-stage challenge due to the complexity of the problem and the many variables that affect the decision to cycle or not. Aggregate-level methods and discrete choice models are the two main approaches that are often used to assess cycling demand [4].

An important aspect of this type of model is that it could be used to design measures, as shown in the study of Hitge et Joubert [5], where an example of this method is proposed to estimate potential demand. The aim is to quantify a potential market for utility cycling by ranking the most attractive mode of the City of Cape Town, South Africa, to allow authorities to design interventions and change behavioral attitudes. In another work [5], the authors estimate a range of the number of bicyclists currently riding in a given geographic area using available data from CTPP (U.S. Census Bureau) and a national household travel survey.

Despite the simplicity of this type of model, it cannot explain how the main variable will influence cycling demand. Several studies consider demand as a choice behavior and focus primarily on quantifying the factors that influence the choice between cycling and other transport modes. There is also another difference between these two types of methods, which consists of the type of data available; to create a discrete choice model, a survey is needed and must be organized at a disaggregate level [6–8].

Several studies tend to summarize and classify in specific determinants the reason why movements are undertaken with a bike or with another mode of transport [1,9]. With the spread of discrete choice models, the utility of using a selected mode of transport is strictly related to the disadvantages of the alternative one. The choice also depends on variables that could influence commuting the most, thereby only exploring the relation that exists and not the reason behind it. In this study, particular attention is paid to cycle lane equipment and energy expenditure.

Cycle lanes are the main infrastructure dedicated to cyclists (and sometimes also to pedestrians in shared spaces), and they must be safe, direct, cohesive, attractive, and comfortable [10]. In a systematic review carried out by Thomas et al. [11], the authors show that a different configuration of the cycle lane may not be beneficial for reducing cycling crashes; bicycle lanes marked with painted lines are more effective than painted-arrow cycle lanes [12]. Another aspect is related to roadway conditions; the protection of cycle lanes increases when there is a higher difference between cyclists' and motor vehicles' speeds [13]. Morrison et al. [14] state that cycle lanes "*that provide greater separation between cyclists and vehicular traffic are most consistently protective*".

According to Nurse et al. [15], the main problem for cycle lanes is pushback from car users' space despite the benefits for the environment [16], health [17], and the economy [18]. But, on the other hand, as shown by Loyola et al. [19] by analyzing the results of a survey, there are some countries, such as the Netherlands, where people show greater recognition of having space to implement cycle lanes compared with other respondents in other countries (the U.K. and Australia).

In the Italian national context, some sources [20] show that Italy is one of the most motorized cities in Europe, and the costs of congestion are about EUR 142 billion. According to the Italian Report drawn up by the Italian Federation of the Environment and Bicycle (FIAB) [21], the density of cycle lanes from 2008 to 2016 increased from 13.7 to 21.1 m/inhabitants. In 2020, the number of cycle lanes increased by 5%, with a critical difference between Southern and Northern Italy (5.8 km/100 km^2 and 61 km/100 km^2, respectively) according to the Italian report of Isfort [22]. Despite the lack of cycle lanes, it is crucial to create methods to assess the effectiveness of cycle lanes [23].

In a study on cycle street safety conducted in the urban Rhine-Main metropolitan region in Germany, Müggenburg et al. [24] found that the participants of the survey attribute more importance to a pleasant environment and fast travel than to safety conditions, and the reason is that, according to the authors, traveling is not considered as a risk. While safety conditions can be measured objectively, it is essential to consider subjective perceptions as follows: a light and clean urban space [25,26] and the presence of commercial activities [27], which show a high likelihood of feeling that the urban space is safe. In the study by Marquez et al. [28], it is shown that people who use bikes for training and not for commuting are also more concerned about bicycle theft, and public transport users are more concerned about theft risks. So, the perception of safety depends on the reason for the travel and the type of movement (for recreational purposes and commuting)

Although perceived safety is an important aspect of a user's decision process, according to the evidence provided by the scientific community, the quantifiable and objective evaluation of safety plays a key role [29]. According to Elvik [30], the major problem is the lack of a strong theoretical basis for road safety, and this does not encourage or promote measures in the direction of sustainable mobility. When the problem of safety is addressed, the interaction between motorized traffic and non-motorized traffic needs to be analyzed. According to Parking et al. [31] and Franklin [32], with the presence of many cycle lanes, drivers tend to overtake cyclists in a faster and closer way, and unsuitable cycle lanes encourage cyclists to adopt inappropriate behaviors [32]. Stewart et al. [33] concluded that in the urban context, there are a lot of significant factors other than the presence of cycle lanes during overtaking; therefore, it is difficult to predict travel behaviors. But in general, beginner cyclists prefer segregated facilities and quiet roads compared with the most frequent cyclists who have few safety concerns [34].

Another aspect to bear in mind is the effort that a cyclist needs to exert, which can be regarded as an indicator to predict travel choice behavior. The human body, as it is constituted, is not a system isolated from its surroundings according to the thermodynamic principles. When work (or any other activity) is performed, the energy required is provided by different chemical reactions and adenosine triphosphate (ATP) hydrolysis for muscular contraction. This reaction allows the human body to release energy, but a percentage of this is transformed into work or activity, while another part (which depends on low human body efficiency) is transformed into heat [35]. Cycling has the main advantage that cycling activity power can be measured in a very specific way, for example, by following Hook's law, strain gauges are attached to areas where consistent deformation of the material is expected (for instance, the most used sensors are located on the pedals due to their low-cost solution) [36]. And, by knowing the power required for a specific activity, it is possible to retrieve energy expenditure parameters and the intensity of the activity.

The best way to assess the energy expenditure of a certain activity is to collect data on several subjects, as was performed by de Geus et al. [37] in one of the first studies in which the activity intensity of commuter riders was directly measured. From a group of 80 participants, 10 men and eight women were selected to follow a specific protocol, by performing some Maximal Tests (MTs). By making use of these tests, several types of data were collected that gave information on commuting speed, heart rate, travel distance, travel time, power, and perceived effort. Although the study had an innovative aspect (not conducted on elite athletes), it is possible to highlight two main limitations. The first one is that only the usual route to reach a work destination was analyzed and not the other un-chosen alternatives. The second one is that such a study is very difficult to execute, given the demanding analysis tools to be employed and the amount of data available for each single participant. Therefore, enlarging this study to a greater number of participants will be complicated. Although it is difficult to replicate this experiment, analytic instruments could be useful [38].

In this paper, the role of safety (related to the cycle network extension and cyclists' perceptions of this infrastructure) and the energy expenditure parameters (related also to several main factors, such as slope) during cycling activity will be explored. Three different Regression Models are proposed that forecast the bike share according to several explanatory parameters. Finally, the results of this study are shown, and how to use this type of tool to assess the modal split to another mode of transport is explained.

2. Methodology

The basic aim of the proposed methodology is to explore the main relationship among variables that have the most influence on the choice to cycle or not. According to this essential aim, in Figure 1, a flowchart of the proposed methodology is represented to better explain and highlight the main steps.

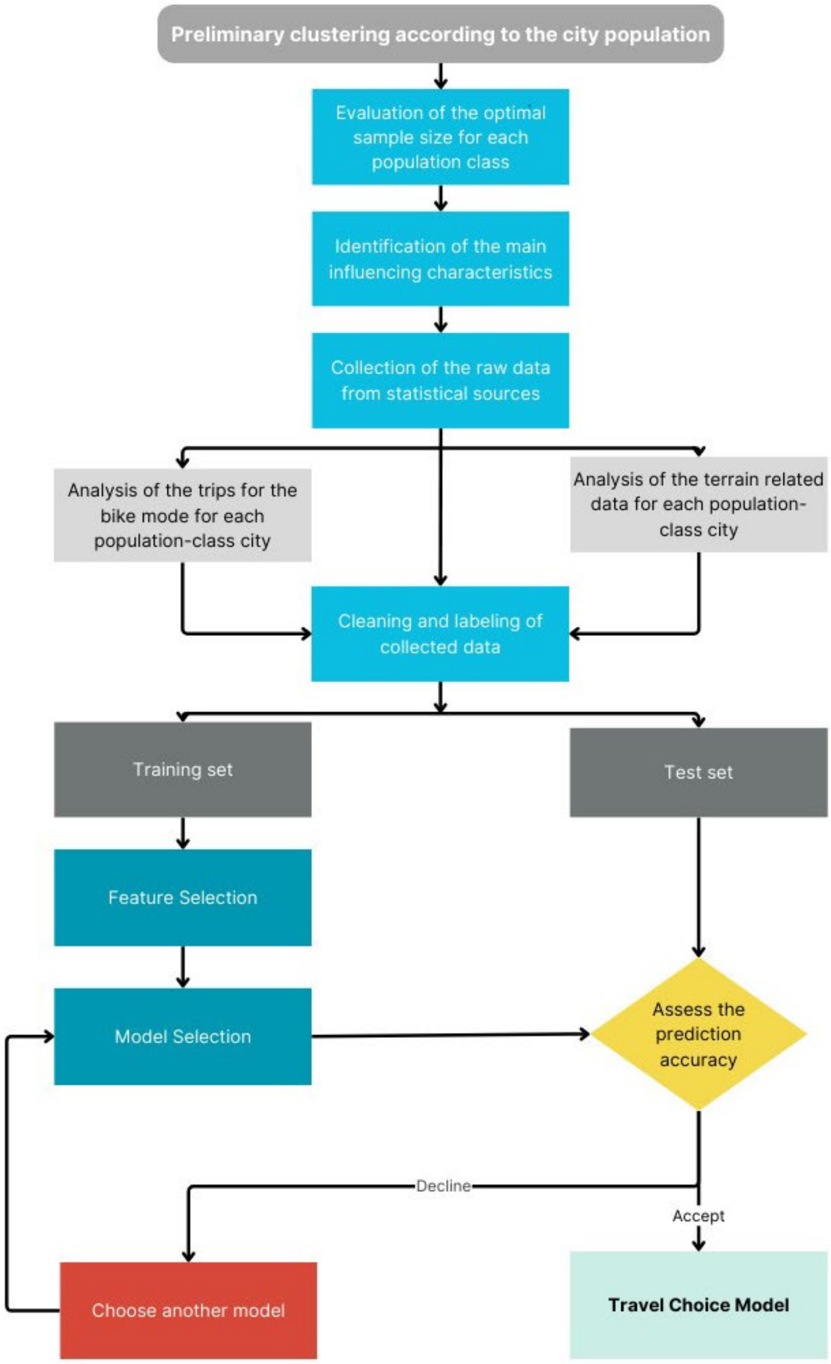


Figure 1. Flowchart of the proposed methodology.

According to the literature review, several determinants affect this choice. The first step is identifying an optimal sample size of cities to distinguish regional and socio-economic differences.

After the first phase regarding the collection of the main data needed for the sequential analysis, for each population-class city, it is essential to analyze the total number of trips with the studied mode of transport and the terrain-related characteristics of the cities. For a detailed overview of this part, see Section 2.2, where the methodology to process the data is proposed. As the last part of the methodology, emphasis is put on the relationship between the terrain-related parameter and the energy expenditure parameters, also bearing in mind the need to evaluate in some way the importance of safety issues when planning on soft mobility is performed. The proposed output of the methodology is a model that forecasts the cycling demand according to safety and metabolic aspects.

2.1. Assessment of Energy Expenditure: Theoretical Framework

Whether a cyclist decides to move is constantly subjected to the following three types of resistances: aerodynamic, rolling, and gravity resistance, as described in the well-known equation of motion (Equation (1)) described below [38]:

$$W = \frac{C_v}{\eta_{bike}}\left\{\sum mg\left[C_R + \frac{s}{100} + \frac{a}{g}\left(1 + \frac{m_w}{\sum m}\right)\right] + 0.5C_D A\rho(C_v + C_w)^2\right\} \tag{1}$$

where:

W: is the power expressed during cycling activity [W];
C_v: bicycle speed [m/s];
η_{bike}: mechanical efficiency;
m: mass of the cyclists, bike, and accessories [kg];
C_R: rolling resistance coefficient [dimensionless];
g: gravity acceleration [m/s^2];
s: road gradient [%];
a: acceleration [m/s^2];
m_w: rotational mass of wheels and tires [kg];
C_D: drag coefficient;
A: frontal area of cyclists and bikes [m^2];
ρ: air density [kg/m^3];
C_w: headwind [m/s].

As expressed in Equation (1), some of the variables are very related. For example, bicycle speed depends on the road gradient and on the headwind, but it also depends on heart rate and VO_2max (maximum oxygen volume), which are not possible to see in the equation.

As is mentioned in the scientific literature [39], speed is related to infrastructure layout and topology. Following a large-scale collection of GPS data in the Oslo area, some differences in speed behavior between men and women were detected as follows: the men cycled faster than the women, but the difference was less significant in the case of e-bike use.

In a study on cycling GPS survey data conducted in England [40], speeds and accelerations on different gradients were studied. Sixteen cyclist volunteers were provided with a handle-bar mountable GPS, which collected information on x, y, and z coordinates, and a chest-worn monitor, which collected heart rate data. Volunteers collected data on their commuting trips for 100 min in a week, and the average trip time amongst them was 26.8 min (within a range from 15 to 50 min). The authors developed two linear models for the main two dependent variables of speed and acceleration with an independent variable related to the route gradient. According to the study, on flat terrain, the mean value of the speed was 21.6 kph, and for every additional 1% of uphill gradient, the mean speed reduced by 1.44 kph.

Slope influences not only the speed but also the choice to cycle or not. According to Ardigò et al. [41], there is a "critical slope" above which walking is less expensive, metabolically speaking, than running and/or cycling. After some tests on seven amateur cyclists, during which they were asked to walk, run, and ride on a treadmill at different gradients with a speed set to maintain the metabolic demand constant, the critical slope reached a value of 13–15%. The main drawback of their study is that the participants were amateur cyclists and not commuters, so the resultant critical slope may be higher than that pertaining to non-cyclists or commuters.

Speed is related to slope according to some physiological variables. When a road is steep enough, the power required according to the equation of motion increases due to the gravitational resistance the cyclists will face. As seen before, power is an objective way to measure cycling activity, but, on the other side, it is related to human metabolic and physiological variables and capabilities. According to Atkinson et al. [42], the main physiological variables that are crucial for cyclists' performances are VO_2max, lactate threshold, and cycling efficiency, and in this study, VO_2 (the total oxygen cost of the cycling activity) is related to the oxygen cost to overcome rolling resistance, air resistance, and gravity (as described by the equation of motion).

2.2. Analysis and Processing of Terrain-Related Data

Once it has been acknowledged that slope plays a critical role in cyclists' speed behavior and choice, it is necessary to investigate candidate explanatory variables that can capture the main terrain properties of examined urban areas.

Although few studies address the role of the terrain-related configuration [43], according to the current literature, the slope may play a key role in the cycling decision process for commuting purposes, and it is configured as an important variable to describe the route choice model and the choice to follow a particular route rather than another [44]. In this study, for each examined urban area, after the preliminary clustering according to the city's populations, data about the elevation of specific points were collected. For this purpose, a grid with a given number of nodes and a dimension proportional to the extension of the cities analyzed was needed. In the figure below (Figure 2), there is an example of a grid.

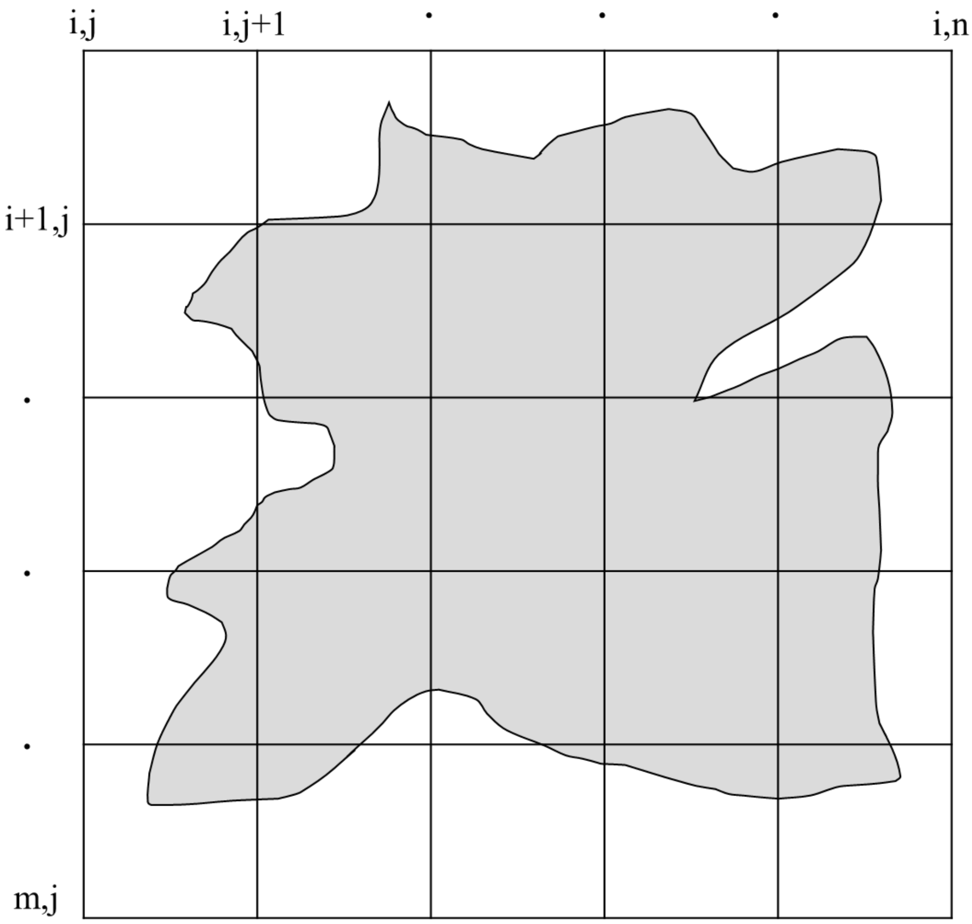


Figure 2. An example of a grid that can be used in the collection phase to collect elevation data and to elaborate data to retrieve information about the slope among the O/D pairs.

By knowing the relative distances among the nodes of the grid and the related elevation, a diagonal matrix that contains information on the relative slope among the nodes of the grid can be obtained. The fundamental idea behind this is that the different nodes represent the origin and the destination of a movement. In this way, bypassing the problem of defining specific traffic zones, it is possible to simulate casual routes that have a specific distance and a specific value of the slope parameter (Figure 3).

O/D	i	i+1	i+2	n
j		$\frac{\Delta h_{i+1,j}}{d_{i+1,j}}$	$\frac{\Delta h_{i+2,j}}{d_{i+2,j}}$	$\frac{\Delta h_{n,j}}{d_{n,j}}$
j+1			$\frac{\Delta h_{i+2,j+1}}{d_{i+2,j+1}}$	$\frac{\Delta h_{n,j+1}}{d_{n,j+1}}$
j+2				$\frac{\Delta h_{n,j+2}}{d_{n,j+2}}$
m				

Figure 3. An example of the matrix used to elaborate data to retrieve information about the slope among the O/D pairs.

3. Case Study

3.1. Description of the Analyzed Cities

Although recent surveys carried out at the national level investigated Italian attitudes toward bicycling in urban areas, the most comprehensive dataset reporting mobility patterns at the municipal level is the Italian Census dataset that was released in 2011. The mobility information reported in this dataset focused on commuting activities, yielding the distribution of trips according to travel mode, starting time, and trip duration and presenting figures aggregated at the municipal level.

Based on these data, a preliminary development of distance decay functions for active (soft) mobility has been proposed in past studies [43,44]. Therefore, the dependent variable, i.e., the proportion of trips carried out by cycling (namely, the *bike share*) can be derived from data extracted from the aforementioned Italian Census database.

On the other hand, as just previously discussed, there are several explanatory variables affecting cycling are several, which are very different. To summarize these into categories, three classes were identified as follows:

1. Land use variables, such as cycle lane equipment and other types of facilities (according also to the mode of transport analyzed).
2. Terrain-related variables, such as elevation gain or the slope parameter.
3. Socio-economic variables (average income, amount of car insurance, and parking fees).

After a preliminary clustering according to the city population (to obtain an idea of the main Italian cities to analyze), the optimal sample size for each population class was identified. By this preliminary analysis, excluding huge metropolitan areas (with a population higher than 100,000 inhabitants), three classes of population were identified as follows:

1. Cities with less than 10,000 inhabitants;
2. Cities with between 10,000 and 50,000 inhabitants;
3. Cities with between 50,000 and 100,000 inhabitants.

The need to identify three population ranges for the examined urban areas is due to the inherently different mobility needs, traffic patterns, and socio-economic and urbanistic conditions that may be experienced according to the different city sizes, thus yielding a different mobility background for the cycling attitude of urban commuters.

For each population class, according to the number of inhabitants, thirty (30) cities were selected (with an overall amount of ninety, 90, urban areas) across the Italian territory, bearing in mind the principle of heterogeneity behind this choice, based on terrain and socio-economic characteristics and historical and cultural conditions that are not trivial to collect and evaluate. The average values of the main characteristics collected (mean income, car insurance, parking fee, income, cycle lane supply, mean slope value, and bike proportion) are shown in Table 1 below. As it can be easily observed, differences in most of the collected values between northern central and southern cities are quite remarkable, reflecting the different economic development characterizing these areas.

Table 1. Mean value of the main attribute in cycling choice: the mean slope value was obtained according to the procedure described in Section 2.2.

City Size	0–10,000 Inhabitants			10,000–50,000 Inhabitants			50,000–100,000 Inhabitants		
Mean Value	**North**	**Centre**	**South**	**North**	**Centre**	**South**	**North**	**Centre**	**South**
Car insurance [EUR]	292	357	364	290	351	363	299	353	330
Parking fee [EUR]	0.93	-	1.25	1.21	1.01	0.89	1.27	1.01	1.15
Income [EUR]	19,992	16,145	14,503	21,872	18,815	17,469	21,326	21,009	18,164
Cycle lane [m/Inhab.]	0.022	0	0	0.012	0.004	0	32.59	21.12	8.48
Mean slope [%]	2.55	4.32	6.35	3.33	3.19	3.85	0.56	0.81	2.10
Bike share [%]	2.43	0.46	0.71	5.15	1.99	1.15	10.45	5.11	1.05

3.2. Bike Regression Models

As highlighted earlier, experimental investigations on professional athletes and also on commuters (although fewer references are available on this specific topic) have been carried out, and several relationships among the different variables that describe the effort exerted in cycling have been obtained. As it was mentioned, this type of study is very difficult and needs a high control of the procedure implemented and the measurements to be undertaken; therefore, replicating such type of study on a high number of urban areas would require a considerable amount of resources. However, since cycling (similar to rowing) is a "power"-based sport or activity, the equation of motion (Equation (1)) seems to be a useful tool to describe the phenomenon and the relationships among the several variables that could play a fundamental role.

According to recent studies [43,44], it was suggested that the decision to cycle or not depends on terrain-related characteristics, leaving aside other important aspects such as individual aerobic abilities required to complete a bicycle trip. The fundamental purpose of this paper is to take into account both terrain-related aspects and energy expenditure considerations. To achieve this objective, the first step in this procedure is to define the speed of a bicycle trip. As suggested by Liu et al. [27], speed can be determined as follows [45] (Equation (2)):

$$v = 20 - 4.3\, s^{0.5} \tag{2}$$

where:

v is the average cycling speed [km/h];

s is the slope [dimensionless].

As expressed by this equation, a base value of 20 km/h is reached when the road is flat (according to other experimental evidence). Once the value of speed is defined, it is possible to use Equation (1) to retrieve the power needed on a particular gradient. Terms related to resistance to motion such as cyclists' weights, bike weight, and so on can be derived from technical and scientific literature [46]. Once the power has been evaluated, the oxygen consumption, expressed as the volume of oxygen utilized in a minute, can be obtained as follows (after a re-arrangement of the original equation reported in [46]):

$$VO_2 = \frac{450 + 9.7067W}{m} \tag{3}$$

where:

VO_2 is the oxygen consumption during the activity [$mLO_2/min/kg$];

W is the power expressed during the cycling activity [W];

m is the total mass of the cyclist, bike, and accessories [kg].

By knowing the oxygen uptake required, it is possible to retrieve energy expenditure expressed as metabolic equivalents (METs) during the cycling activity (it is essential to remember that, by definition, the MET unit is equal to 3.5 $mLO_2/min/kg$), as expressed in Equation (4):

$$EE = \frac{VO_2}{3.5} \tag{4}$$

where:

EE is the energy expenditure during the cycling activity [MET];

VO_2 is the oxygen consumption during the activity [$mLO_2/min/kg$].

Given this relationship among the main variables that can be observed in Equation (1), by knowing the speed of a rider on a particular gradient and the strong relationship between cyclist motion and VO_2, it is possible to retrieve the energy expenditure of a determinate activity (Equation (4)).

4. Results and Discussion

As demonstrated and suggested by the scientific literature in this regard [1,9], several determinants affect bike share in a certain area. From Figures 4–15, the main relationships between variables are proposed while, in Figure 16, it is possible to notice that bike share is not normally distributed. To approach a normal distribution, the logarithm transformation is applied to the dependent variable bike share as it is possible to see in Figure 16.

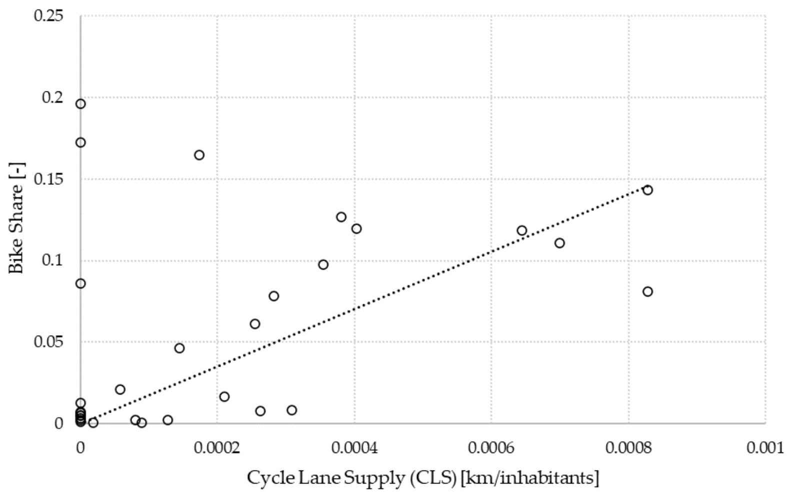


Figure 4. Relationship between cycle lane supply and bike share (50,000–100,000 inhabitants).

However, it has to be highlighted that simplified tools need to be actually simple, and considering all the determinants in the same model is quite complex. Furthermore, a simplified model also has the merit of drastically reducing overfitting. In a dataset where the number of the independent variables p is quite comparable with the number of samples (or observation n), the target is to reduce the number of the variables [47,48].

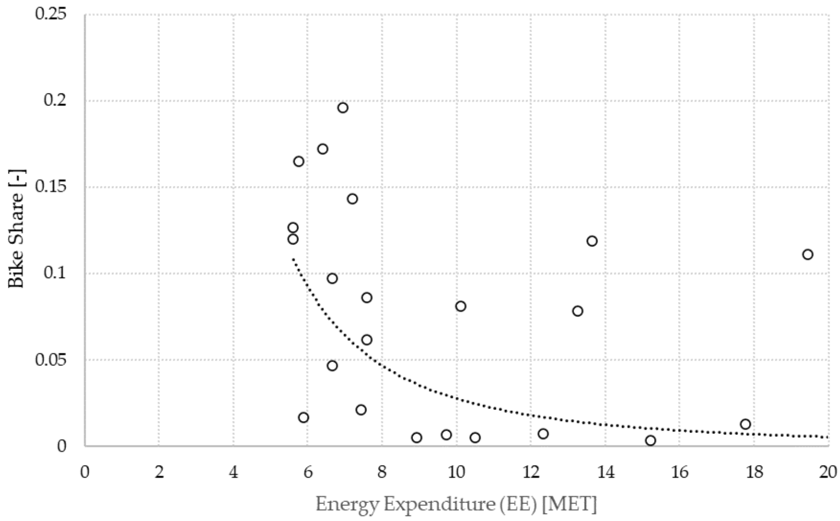


Figure 5. Relationship between energy expenditure and bike share (50,000–100,000 inhabitants).

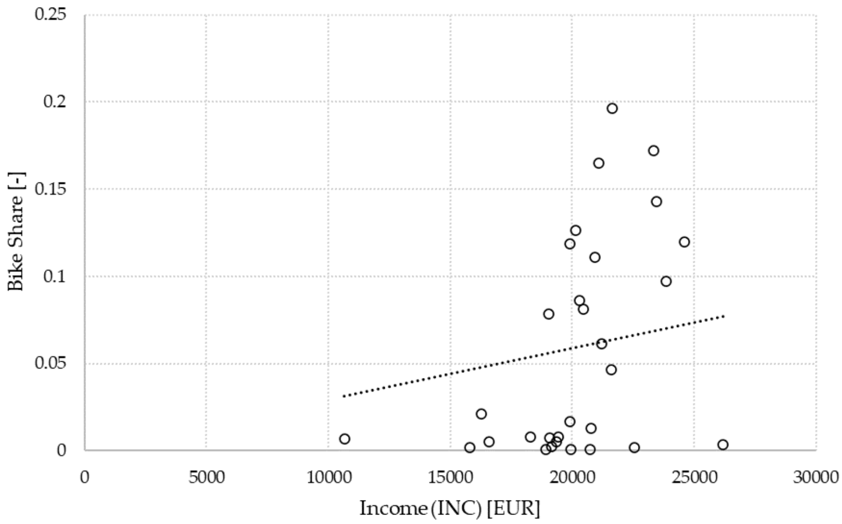


Figure 6. Relationship between Income and bike share (50,000–100,000 inhabitants).

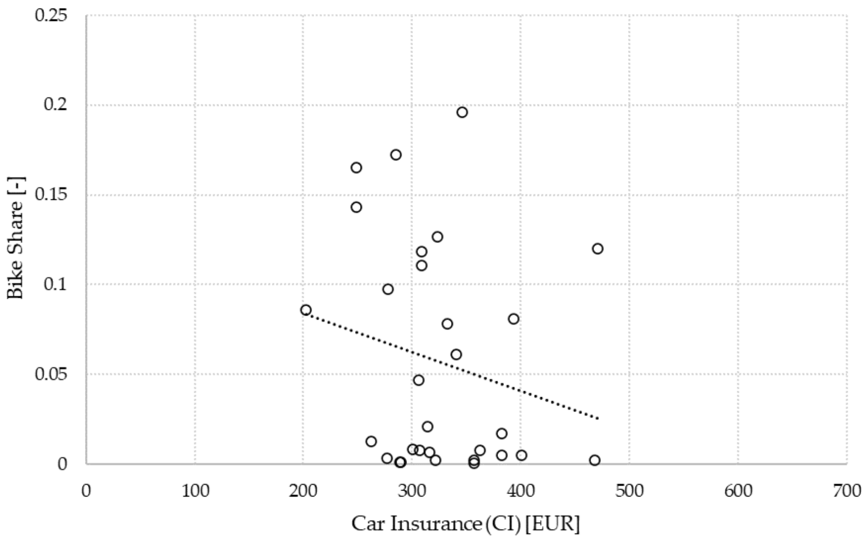


Figure 7. Relationship between car insurance and bike share (50,000–100,000 inhabitants).

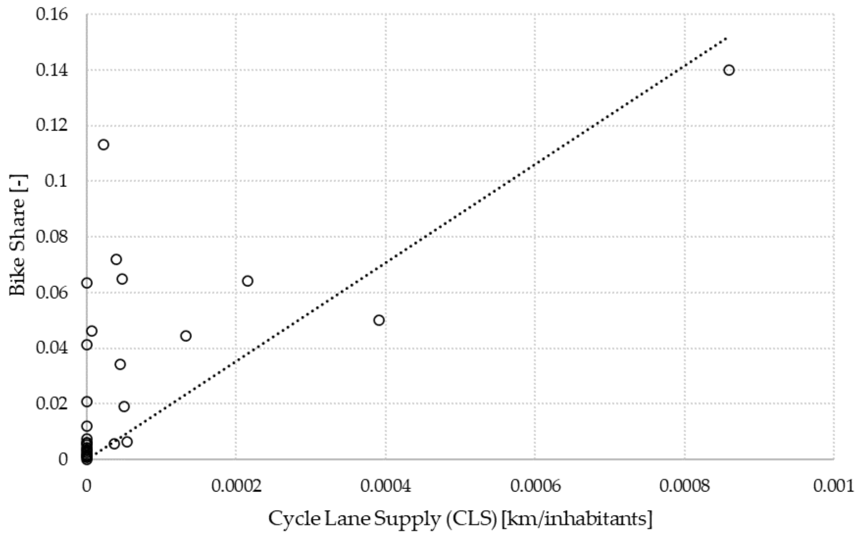


Figure 8. Relationship between cycle lane supply and bike share (10,000–50,000 inhabitants).

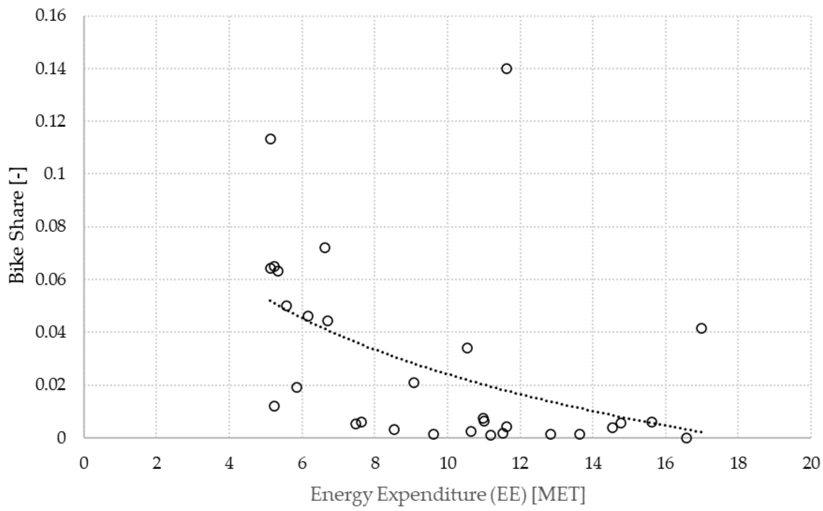


Figure 9. Relationship between energy expenditure and bike share (10,000–50,000 inhabitants).

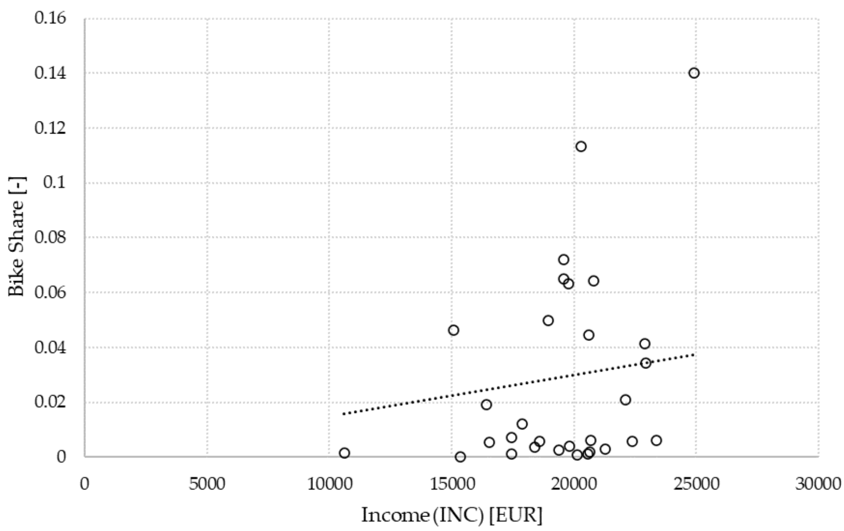


Figure 10. Relationship between income and bike share (10,000–50,000 inhabitants).

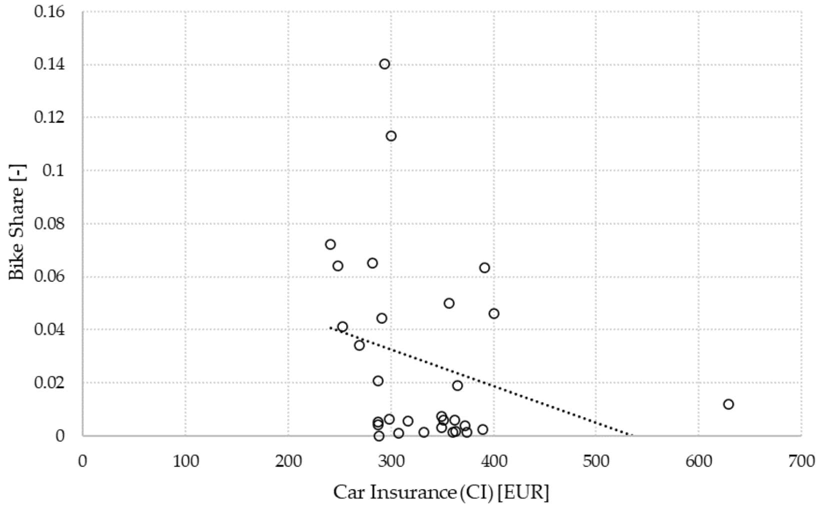


Figure 11. Relationship between car insurance and bike share (10,000–50,000 inhabitants).

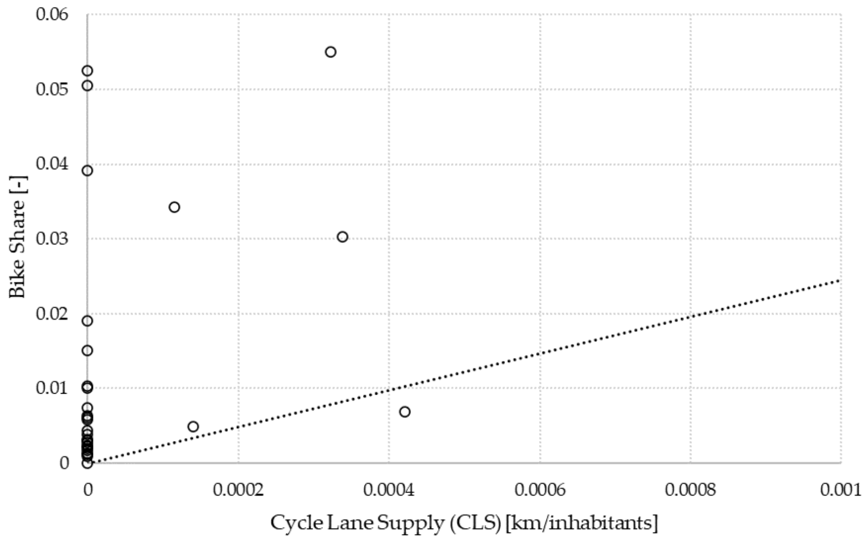


Figure 12. Relationship between cycle lane supply and bike share (0–10,000 inhabitants).

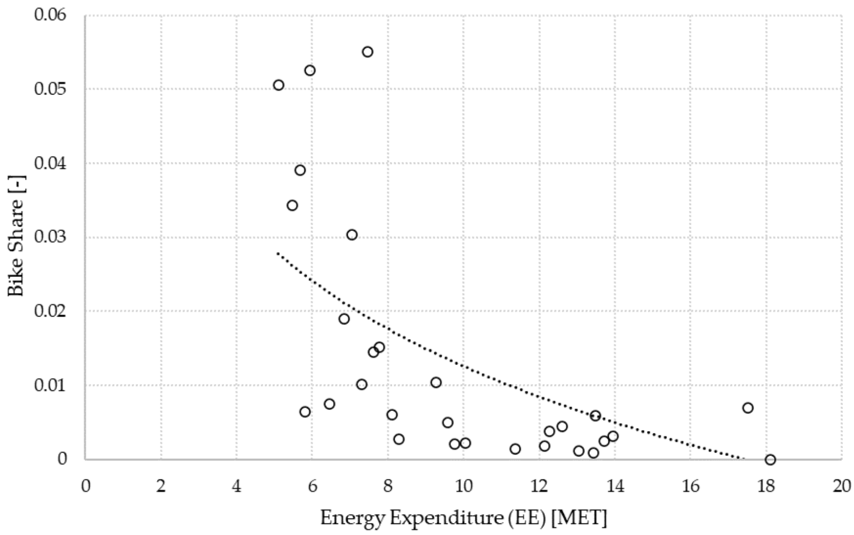


Figure 13. Relationship between energy expenditure and bike share (0–10,000 inhabitants).

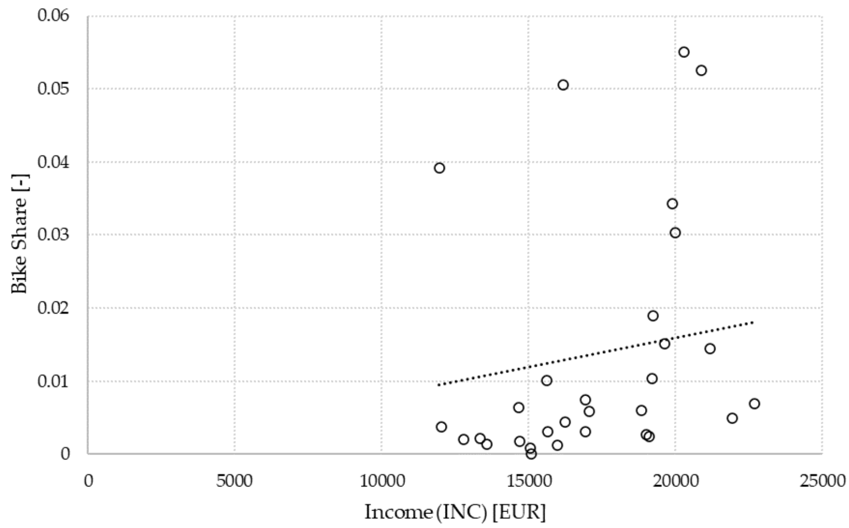


Figure 14. Relationship between income and bike share (0–10,000 inhabitants).

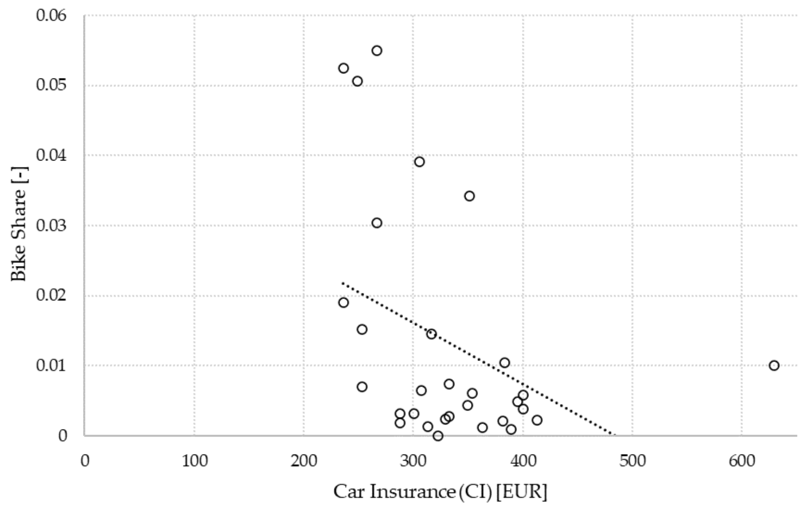
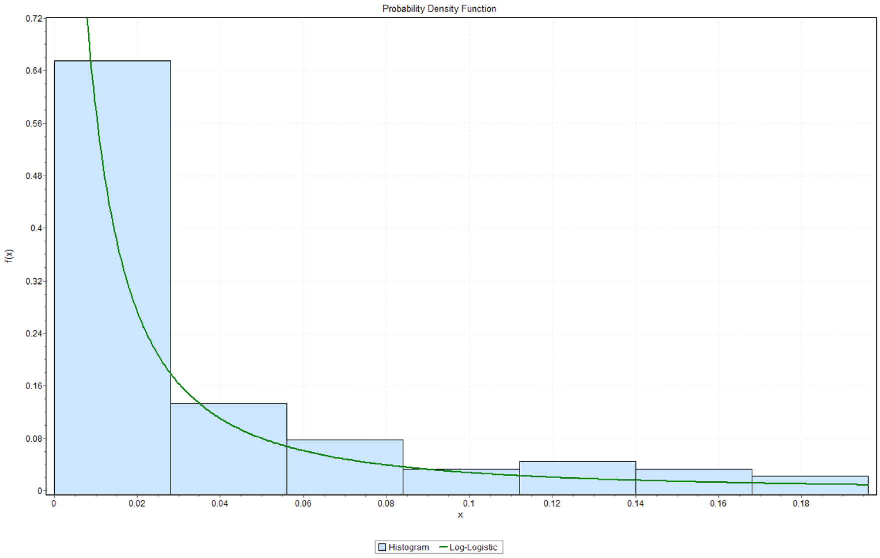


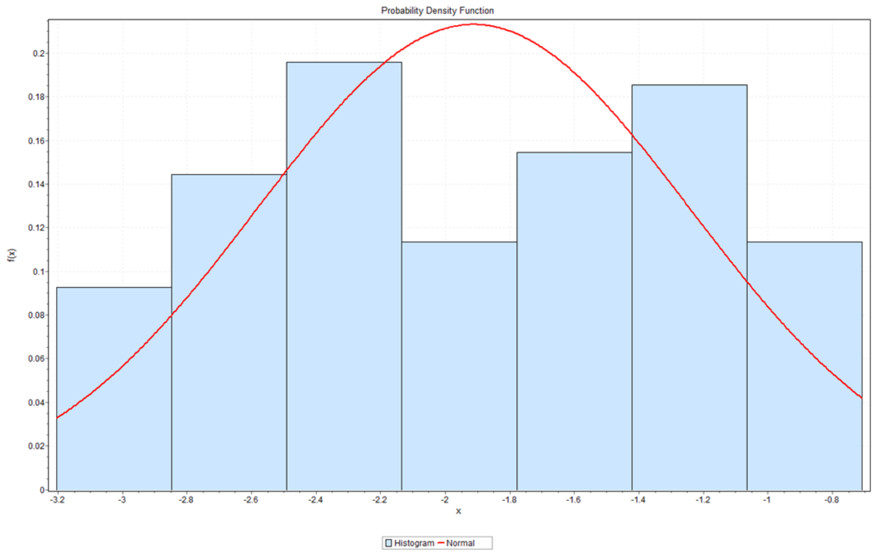
Figure 15. Relationship between car insurance and bike share (0–10,000 inhabitants).

When p is too large, reducing the number of features is important to ensure good prediction accuracy (avoiding overfitting problems), but it is also essential for interpretability. By removing irrelevant features, a model that is easier to interpret is obtained. Usually, in order to optimize the number of explanatory variables, three important classes of methods can be employed as follows:

- Subset Selection: with this method, the aim is to identify a subset of the p predictor. The outcome is several p^* (predictor) values that are $p^* < p$. The two problems with this method are essentially how many and which variables to select.
- Shrinkage Method: the complexity of the model is reduced by shrinking the Least Square Estimates toward zero. Subset Selection and Shrinkage Methods can also be used in nonlinear problems (for instance, Logit and Probit models). By making use of these methods, the increase in interpretability is not always reported, but an increase in prediction accuracy is generally obtained because by reducing the size of the coefficients, the variance in the model is reduced.
- Dimension Reduction: these models are based on reducing the space of the variable p in a subspace M of variable p, with the condition that $M < p$.



(**a**)



(**b**)

Figure 16. Histogram for (**a**) the dependent variable bike share and (**b**) the logarithm of the dependent variable and corresponding best-fitting probability density function.

In Table 2, different Feature Selection Methods are compared as follows:

Table 2. Selected features (identified with the "*") according to the city size and the Features Selection Method.

City Size	Features Selection Method	Cycle Lane Supply	Energy Expenditure	Inhabitant Density [inhab./km^2]	Inhabitant Centre [km^2]	Income [EUR]	Car Insurance [EUR]	Parking Fee [EUR]
50,000–100,000	BSS	*	*					
	FwSS	*	*					
	BwSS	*	*					
10,000–50,000	BSS	*	*				*	*
	FwSS	*	*				*	*
	BwSS	*	*				*	*
0–10,000	BSS		*			*		
	FwSS		*			*		
	BwSS		*			*		

- Best Subset Selection (BSS);
- Forward Stepwise Selection (FwSS);
- Backward Stepwise Selection (BwSS).

The aim is to highlight the reason why the energy expenditure parameter and cycle lane supply may play an important role, according to the main techniques used to select the most important features. Among the variables selected with the methods described above, by applying the BIC criterion (Bayesian Information Criterion), which penalizes more effectively the complexity of the models, it is found that EE and CLS are often chosen as relevant variables.

The different classes identified and the different models aim to highlight the main characteristics that influence the use of bikes as a mode of transport. This is also a reflection of the needs that different cities have and the different countermeasures that can be applied to encourage the use of bikes.

Although energy expenditure is a fundamental term of the equation, it is also correct to consider *cycle lane supply* (CLS) as one of the main determinants of cycling choice commuting, due to its relationship with safety level and safety perception. Based on these aforementioned assumptions, a Regression Model for each class analyzed is here proposed by collecting the information required for the three classes of the size of urban areas considered in this study. For a city size of 50,000–100,000 inhabitants, the best model is described by means of the following relationship (Equation (5)):

$$\log(BS) = a + b * \frac{1}{EE} + c * CLS \tag{5}$$

where:

BS is the bike share, expressed as the number of cyclists that use bikes for commuting over the total number of users that use other modes of transport for commuting purposes [dimensionless];

EE is the value of the energy expenditure [MET];

CLS is cycle lane supply [km/inhabitants];

a, *b*, and *c* are the estimated parameters of the model.

For the city size of 10,000–500,000 inhabitants, the best model is proposed below (Equation (6)):

$$\log(BS) = a + b * CLS + c * \frac{1}{EE} + d * CIns + e * PFee \tag{6}$$

where:

BS is the bike share, expressed as the number of cyclists that use bikes for commuting over the total number of users that use other modes of transport for commuting purposes [dimensionless];

EE is the value of the energy expenditure [MET];

CLS is cycle lane supply [km/inhabitants];

CIns is the mean value of car insurance [EUR];

PFee is the mean value of parking fee [EUR];

a, *b*, *c*, *d*, and *e* are the estimated parameters of the model.

While for the smallest class of city size, the model that best fits the data is the following (Equation (7)):

$$\log(BS) = a + b * \frac{1}{EE} + c * INC \tag{7}$$

where:

BS is the bike share, expressed as the number of cyclists that use bikes for commuting over the total number of users that use other modes of transport for commuting purposes [dimensionless];

EE is the value of the energy expenditure [MET];

INC is the mean value of the income [EUR];

a, b, and c, are the estimated parameters of the model.

According to the city size, as it is possible to see in Table 3, the variables that influence bike share usage are not always the same, but CLS and EE seem to influence the demand. For a city size of 50,000–100,000 inhabitants, bike share is proportional to the increase in the mean income. Car insurance, mainly for the classes of 10,000–50,000 and 0–10,000, is negatively related to bike demand while, for the smallest class, cycle lanes seem not to play a favorable incentive, probably due to the low presence of cycle paths (Figure 12).

Table 3. Estimated parameters, main statistics of interest, and prediction accuracy of the models (Adj-R^2) for each city size.

City Size	Model	Parameter	Value	Std. Error	t-Value	Pr(>t)	Adj-R^2
50,000–100,000	$\log(BS) = a + b * \frac{1}{EE} + c * CLS$	a	−3.055	0.184	−16.606	1.07×10^{-15}	0.6991
		b	10.521	1.631	6.452	6.49×10^{-7}	
		c	1397.647	323.536	4.320	1.89×10^{-3}	
10,000–50,000	$\log(BS) = a + b * \frac{1}{EE} + c * CLS + d * PFee + e * CIns$	a	−2.521	3.595×10^{-1}	−7.014	2.98×10^{-7}	0.7111
		b	9.376	1.504	6.235	1.92×10^{-6}	
		c	1.4043×10^{3}	3.987×10^{2}	3.522	1.75×10^{-3}	
		d	4.530×10^{-1}	1.314×10^{-1}	3.446	2.10×10^{-3}	
		e	-3.051×10^{-3}	9.70×10^{-4}	−3.146	4.38×10^{-3}	
0–10,000	$\log(BS) = a + b * \frac{1}{EE} + c * INC$	a	−4.223	3.556×10^{-1}	−11.878	5.26×10^{-12}	0.6619
		b	8.868	1.371	6.468	7.44×10^{-7}	
		c	6.069×10^{-5}	1.918×10^{-5}	3.164	3.94×10^{-3}	

Deepening the results of the Best Subset Selection Method, as shown in Table 4, cycle lane supply and energy expenditure are often selected as important features when the dimension of the model is equal to two. The only exception is for the smallest city class, as already defined.

For this purpose, much attention is given to the role of energy expenditure and cycle lane supply, by comparing models with different dimensions, from the simplest to the most complex (including the variable in Table 2).

As it is possible to see from Tables 5–7, the models that contain only the variables cycle lane supply and, especially, energy expenditure, have good accuracy in terms of Adj-R^2. Moreover, the increase in the complexity of the model does not lead to an increase in predictive capabilities.

Table 4. Selected features (identified with the "*") according to the city size, Best Subset Selection Method, and the dimensionality of the model.

City Size	Model Dimension	Cycle Lane Equipment	Energy Expenditure	Inhabitant Density [Inhab./km^2]	Inhabitant Centre [km^2]	Income [EUR]	Car Insurance [EUR]	Parking Fee [EUR]
50,000–100,000	1		*					
	2	*	*					
	3	*	*		*			
	4	*	*		*	*		
	5	*	*		*	*		*
	6	*	*		*	*	*	*
	7	*	*	*	*	*	*	*
10,000–50,000	1		*					
	2	*	*					
	3	*	*					*
	4	*	*				*	*
	5	*	*		*		*	*
	6	*	*	*	*		*	*
	7	*	*	*	*	*	*	*

Table 4. *Cont.*

City Size	Model Dimension	Cycle Lane Equipment	Energy Expenditure	Inhabitant Density [Inhab./km^2]	Inhabitant Centre [km^2]	Income [EUR]	Car Insurance [EUR]	Parking Fee [EUR]
0–10,000	1		*					
	2		*			*		
	3		*			*	*	
	4		*			*	*	*
	5		*	*		*	*	*
	6	*	*	*		*	*	*
	7	*	*	*	*	*	*	*

Table 5. Estimated parameters, main statistics of interest, and prediction accuracy of the models (Adj-R^2) for the city size of 50,000–100,000 inhabitants, by increasing the complexity of the models.

Model	Parameter	Value	Std. Error	t-Value	Pr(>t)	Adj-R^2
$\log(BS) = a + b * \frac{1}{EE}$	a	−2.8652	0.2281	−12.559	5.05×10^{-13}	0.5092
	b	11.4987	2.0621	5.576	5.76×10^{-6}	
$\log(BS) = a + b * \frac{1}{EE} + c * CLS$	a	−3.055	0.184	−16.606	1.07×10^{-15}	0.6991
	b	10.521	1.631	6.452	6.49×10^{-7}	
	c	1397.647	323.536	4.320	1.89×10^{-3}	

The three models, as previously described in Equations (5)–(7), show a strong and good relationship between energy expenditure (EE) and bike share (BS), expressed as the proportion of cyclists according to the total number of road users (especially for the medium and large city class). By knowing the terrain-related characteristics (expressed as a mean or a max value of the slope parameter), the speed, the power required to travel, and the VO_2 consumption during cycling activity (from Equation (1) to Equation (3)), an estimated value of the energy expenditure parameter is obtained. For a steeper route, more energy needs to be used. With elevated values of the slope parameter, the energy cost of cycling increases to a higher degree than that pertaining the use of an e-bike. Based on these results, municipality and mobility managers could evaluate which sustainable mobility solution may lead to a higher bike share and thus gain points in favor of design services of bike or e-bike sharing (and other form of transport). For the smallest class analyzed, the importance of the energy expenditure parameter is even more predominant than the presence of the cycle lane: within very small cities, the cycle lane supply parameter appears to be somehow negligible.

It could be argued that in such small cities, bike lanes are still not as widely diffused as in the other more crowded urban areas that have been examined. Therefore, this parameter appears to be statistically poorly significant.

Table 6. Estimated parameters, main statistics of interest, and prediction accuracy of the models (Adj-R^2) for the city size of 10,000–50,000 inhabitants, by increasing the complexity of the models.

Model	Parameter	Value	Std. Error	t-value	Pr(>t)	Adj-R^2
$\log(BS) = a + b * \frac{1}{EE}$	a	−2.9942	0.2854	−10.493	5.01×10^{-1}	0.3413
	b	8.7191	2.2143	3.938	5.22×10^{-4}	
$\log(BS) = a + b * \frac{1}{EE} + c * CLS$	a	−3.0440	0.2463	−12.357	2.18×10^{-12}	0.5111
	b	8.2416	1.9134	4.307	2.09×10^{-4}	
	c	1639.7642	509.0337	3.221	3.417×10^{-3}	

Table 6. *Cont.*

Model	Parameter	Value	Std. Error	t-value	Pr(>t)	Adj-R^2
$\log(BS) = a + b * \frac{1}{EE} + c * CLS + d * PFee$	a	-3.4114	0.2583	-13.206	8.97×10^{-13}	0.6083
	b	8.4053	1.7137	4.905	4.77×10^{-5}	
	c	1645.2442	455.6252	3.611	1.34×10^{-3}	
	d	0.4162	0.1524	2.730	1.14×10^{-2}	
$\log(BS) = a + b * \frac{1}{EE} + c * CLS + d * PFee + e * CIns$	a	-2.521	3.595×10^{-1}	-7.014	2.98×10^{-7}	0.7111
	b	9.376	1.504	6.235	1.92×10^{-6}	
	c	1.4043×10^{3}	3.987×10^{2}	3.522	1.75×10^{-3}	
	d	4.530×10^{-1}	1.314×10^{-1}	3.446	2.10×10^{-3}	
	e	-3.051×10^{-3}	9.70×10^{-4}	-3.146	4.38×10^{-3}	

Table 7. Estimated parameters, main statistics of interest, and prediction accuracy of the models (Adj-R^2) for the city size of 0–10,000 inhabitants, by increasing the complexity of the models.

Model	Parameter	Value	Std. Error	t-Value	Pr(>t)	Adj-R^2
$\log(BS) = a + b * \frac{1}{EE}$	a	-3.2277	0.1913	-16.869	7.26×10^{-16}	0.5490
	b	9.3265	1.5746	5.923	2.59×10^{-6}	
$\log(BS) = a + b * \frac{1}{EE} + c * INC$	a	-4.223	3.556×10^{-1}	-11.878	5.26×10^{-12}	0.6619
	b	8.868	1.371	6.468	7.44×10^{-7}	
	c	6.069×10^{-5}	1.918×10^{-5}	3.164	3.94×10^{-3}	

To give an example of the reliability of the models, a further collection of data was carried out in cities other than those used to calibrate the model. Overall, and additional twenty cities belonging to the population class ranging from 50,000 to 100,000 inhabitants were examined, and relevant information on terrain and cycle lane extension was derived and analyzed. Moreover, to highlight the importance of CLS and EE, the model that contains only these two variables was tested (Equation (8)).

$$\log(BS) = a + b * CLS + c * \frac{1}{EE} \tag{8}$$

where:

BS is the bike share, expressed as the number of cyclists that use bikes for commuting over the total number of users that use other modes of transport for commuting purposes [dimensionless];

EE is the value of the energy expenditure [MET];

CLS is cycle lane supply [km/inhabitants];

a, *b*, and *c* are the estimated parameters of the model (references are made to Table 6).

The predicted bike share was compared with the actual bike share derived from census surveys, as reported in the figure below (Figure 17).

As it is shown, the proposed model seems to be reliable enough to predict the bike share on another dataset of cities selected as a validation set. However, it has to be highlighted that further analysis needs to be carried out, as it appears essential to enlarge the collection of cities for each class of the population and validate this methodology on other cities. The dataset specifically referred to the Italian context, and calibrated parameters for similar European cities may differ; nevertheless, the proposed methodology seems to highlight a significant relationship between bike share, on the one hand, and energy expenditure and safety, on the other. It is essential to highlight that the proposed methodology considers cities belonging to the population class ranging from 50,000 to 100,000 inhabitants. Further effort needs to be made to collect additional data on the other classes of cities.

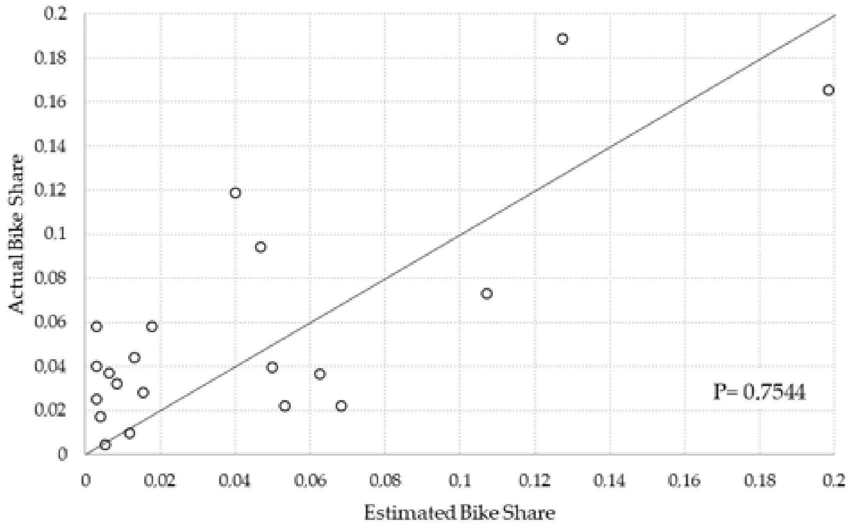


Figure 17. Results of the validation phase according to the Pearson coefficient for the cities expressing a population ranging from 50,000 to 100,000 inhabitants ($p = 0.7544$).

Energy expenditure is, in turn, related to the terrain characteristics of an urban area. Similarly, safety perception can be related to the cycle network extension, expressed in terms of kilometers of cycle lanes per inhabitant. In addition, this explanatory variable appears to be a significant determinant in predicting bike share.

According to the proposed models, the results show that generally, an increase in cycle lanes is beneficial to improve the attitude toward cycling. Energy expenditure, associated with terrain-related characteristics, human capabilities, and the type of mode used (c-bike and e-bike), could be a fundamental parameter in designing cycle lanes. The objective is to make cycling movement physically achievable and to select specific routes. Moreover, this parameter could be useful to explain the utility of using an e-bike rather than a C-bike. From a purely social–economic perspective, if the cost of car insurance increases, the modal share linked to the bike decreases. This is mainly because, in Italy, the cost of car insurance is much lower in cities where the use of bikes is greater. Conversely, a high mean income has a positive impact on bike share.

The tool described in this paper could be useful not only to identify critical areas for cycling safety but also to promote cycling by increasing cycle lanes and creating suitable paths and routes for everyone. In addition, it could be used to forecast the future cycling demand. In terms of future development, the methodology could be extended to a larger and richer dataset of information. This would allow for moving from a macroscopic point of view to a microscopic one, analyzing the individual movements made by bikes.

5. Conclusions

Among the several determinants that affect the choice to cycle or not, the role covered by safety issues and metabolic aspects is not considered much in the current scientific literature. According to the literature review, cycle lane network extension, and slope may have strong repercussions on the cycling demand. The presence of a cycle lane could influence the modal choice, based on a principle of perceived and quantifiable safety. Users will follow a route if they feel themselves in a safe condition, and so cycle lane extension plays a fundamental role in commuting choices.

On the other hand, slope could be related to “energetic issues” since a steeper road drains more energy than a flat one. The equation of motion gives, in this way, a detailed scenario of the power required by a cyclist to overcome all the forces.

Another aspect to consider in evaluating bike sharing is the different classes of cities according to their size in terms of city population since this explanatory variable may affect the overall traffic pattern of the examined urban area in terms of inner and exchanged commuting mobility.

In this study, the non-homogeneous Italian territory seems to deeply influence commuting choices and may offer an interesting "case study" if bike share determinants are to be investigated. Several cities are located in the Alps and Apennines Regions and although they are interested in very high tourism flows, people who choose bikes for recreational matters have different motivations than commuters. In addition, in a non-homogeneous territory such as the Italian one, it is essential to consider the different socio-economic conditions, the urban development, the public services provided, and cultural and historical matters, which are peculiar aspects within a single State. So, city size may also play a critical role in bike choice behavior since small cities are characterized by less critical traffic scenarios compared with bigger ones.

Based on these assumptions, a mathematical model able to predict bike share as a function of safety, terrain characteristics, and population class was developed. The model was calibrated and tested against Italian data collected in small and medium urban areas.

A further step forward was made in modeling terrain characteristics, proposing an original physics-based connection with metabolic parameters (namely, the energy expenditure that a commuter needs to spend to complete a trip). So, following the collection and analysis of land use, socio-demographic, cycle lane supply, and bike share data on 90 Italian cities according to three classes of populations, a Regression Model for each class (to highlight the inner characteristics) was obtained considering the cycle lane network extension (namely, the cycle lane supply, CLS) and the metabolic energy expenditure as main explanatory variables. Although further efforts should be focused on enlarging the size of the dataset used for the calibration and validation of the model and on extending the prediction range to higher-population cities, the preliminary results seem to confirm that these two parameters may influence the choice to cycle or not for commuting purposes.

It is hoped that this model will be of use to city administrators to help them in planning the upgrading of bicycle networks.

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