Comparative Analysis of the Predictive Performance of an ANN and Logistic Regression for the Acceptability of Eco-Mobility Using the Belgrade Data Set

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Abstract: To solve the problem of environmental pollution caused by road traffic, alternatives to vehicles with internal combustion engines are often proposed. As such, eco-mobility microvehicles have significant potential in the fight against environmental pollution, but only on the condition that they are widely accepted and that they replace the vehicles that predominantly pollute the environment. With this in mind, this study aims to elucidate the main variables that influence the acceptability of these vehicles, using prediction models based on binary logistic regression and a multilayer artificial neural network—a multilayer perceptron (ANN). The data of a random sample obtained via an online questionnaire, answered by 503 inhabitants of Belgrade (Serbia), were used for training and testing the model. A multilayer perceptron with 9 and 7 neurons in two hidden layers, a hyperbolic tangent activation function in the hidden layer, and an identity function in the output layer performed slightly better than the binary logistic regression model. With an accuracy of 85%, a precision of 79%, a recall of 81%, and an area under the ROC curve of 0.9, the multilayer perceptron model recognized the influential variables in predicting acceptability. The results of the model indicate that a respondent’s relationship to their current environmental pollution, the frequency of their use of modes of transport such as bicycles and motorcycles, their mileage for commuting, and their personal income have the greatest influence on the acceptability of using eco-mobility vehicles.

Keywords: artificial neural network; multilayer perceptron; binary logistic regression; eco-mobility; environmental pollution

1. Introduction

The increased use of internal combustion passenger cars and their growing number contribute to our dependence on fossil fuels and exhaust gas emissions. The majority of greenhouse gas emissions from transportation are carbon dioxide (CO₂) emissions that result from the burning of petroleum-based fuels, such as gasoline and diesel, in internal combustion engines [1]. According to a USEPA report [2], the percentage of CO₂ in the total emissions of greenhouse gases in the USA in 2020 was 78.8%, while the percentage of CH₄ was 10.9%, and that of N₂O was 7.1%. Other gases participated with a share of 3.2%.

Taking this breakdown into account, emissions from the transportation sector accounted for the largest share (27.2%) of the US’s total greenhouse gas emissions in 2020. On the other hand, looking at cities in Europe, from 2014 to 2020, slightly less than two-thirds of all reported exceedances of air quality standards were related to higher traffic intensities in urban areas and near major roads, most often due to nitrogen oxide (NOₓ) emissions. Road traffic was the key source of air pollution in Western and Northern Europe, in six countries, namely Austria, Denmark, Finland, the Netherlands, Portugal, and the United Kingdom, which highlighted road traffic as the only source exceeding the mentioned standards [3].

It is predicted that emissions of harmful greenhouse gases, which arise as a result of transport, will almost barely decrease by 2030 [4]. The polluting particles that are emitted
in higher concentrations due to transport are NO\textsubscript{X} and PM\textsubscript{2.5}, which can be very harmful to public health [5,6]. According to estimates, by 2050, as much as 68% of the world’s population will be concentrated in urban areas, while their transportation requirements will double. In the Republic of Serbia, according to the annual report of the Environmental Protection Agency [7] for 2021, road traffic had a share of 38% in the country’s total emissions of nitrogen oxides, while the share of traffic in the emission of PM\textsubscript{2.5} particles was 8%. Belgrade, the capital and, at the same time, one of the largest cities in Europe, had excessively polluted air during 2021, mainly due to increased concentrations of PM\textsubscript{10}, PM\textsubscript{2.5}, and NO\textsubscript{2} particles from road traffic. Because road traffic causes such an important part of urban emissions and the economic losses from congestion are significant, cities face the challenge of designing transport policies to reduce the externalities of pollution and traffic congestion [8,9].

Until now, various strategies have been proposed to reduce the emission of polluting substances, among which are the redistribution of surface uses and the promotion of more energy-efficient and environmentally sustainable vehicles [10–12]. Electric vehicles, being more energy efficient and environmentally friendly than vehicles with internal combustion engines, are still not widely accepted by users due to their high initial costs. In this regard, many European countries are increasingly turning to providing financial incentives for them, primarily through the provision of purchase subsidies, or a full or partial exemption from taxes [13,14]. However, it seems that eco-mobile vehicles of smaller dimensions with an electric drive (in the following, microvehicles) represent a more desirable mode of transportation for individuals with low incomes, taking into account the more affordable price of the vehicle and the costs of its use [15,16].

In this regard, the use of micromobility vehicles, such as e-scooters, e-bikes, and e-mopeds, is often proposed as one of the possible solutions to reduce environmental pollution by many researchers, taking into account their characteristics, such as zero-emission and problem-solving the “first and last kilometer”. The environmental benefit of micromobility vehicles is that they emit no or limited direct CO\textsubscript{2} emissions to air, when viewed from a tank-to-wheel perspective, and they emit relatively fewer other air pollutants compared to combustion engine vehicles [17]. In other words, these vehicles do not emit polluting substances from the exhaust pipe of their electric motor, which makes them sustainable and more environmentally friendly compared to other modes of transport (passenger cars, public transport, etc.). However, even though these vehicles are characterized by zero emissions of pollutants during trips, it is important to look at their impact on the environment from all aspects, from the very process of their production and use to recycling itself [18,19]. Also, many studies indicate that changing the mode of transportation to electric-powered microvehicles can contribute to reducing environmental pollution if people replace the trips of vehicles that emit the most pollutants [20,21].

Bearing in mind the above, this work aims to analyze the influence of certain factors and predict the acceptability of the use of this form of mobility to the public in Belgrade (Serbia). Current road regulations in the Republic of Serbia still do not recognize microvehicles and their participation in traffic, nor has the appropriate infrastructure been defined for these means of transport. Accordingly, the focus of this paper is on understanding the attitudes of respondents who do not use electric-powered microvehicles and examining the reasons for their non-use and the environmental pollution in Belgrade (Serbia) caused by vehicles in road traffic. Using the data obtained from this research, it is possible to determine how binary logistic regression algorithms and artificial neural networks can contribute to assessing the importance of the mentioned impacts, as well as the respondents’ attitudes regarding the use of microvehicles. The contribution of this work is reflected in its comprehensive data analysis, which can be a useful basis for decision-making when defining strategies for reducing environmental pollution.

This work consists of seven chapters, namely the introductory chapter, which indicates the basic idea and goal of this work; a literature review, which includes the most significant and interesting findings of the application of classification algorithms; the methodology,
through which the method and analysis used in this work are explained; an overview of the analyzed results; a discussion of the obtained results; and a conclusion.

2. Literature Review

Artificial neural networks have found wide-ranging applications in many scientific fields in recent years. In contrast to conventional calculation models, artificial neural networks (ANNs) have been proven to significantly reduce the time, cost, and complexity of pollutant emission analyses [22,23]. Well-trained artificial neural network models have proven to be an effective tool for predicting noise and exhaust gas emissions with high accuracy, which is confirmed by the results of the scientific papers presented below.

Cai et al. (2009) [24] have developed artificial neural network models to predict the hourly concentrations of air pollutants (carbon monoxide, nitrogen dioxide, particulate matter, and ozone) near a traffic artery in Guangzhou, China. Their results show that the models are able to produce accurate predictions of hourly air pollutant concentrations more than 10 h in advance. Similarly, Jaikumar et al. (2016) [25], in their work, developed an ANN model of real-time passenger car exhaust emissions under heterogeneous traffic conditions. Similar to previous research, the authors of this paper used data such as engine speed, acceleration, and passenger-car-specific power as inputs to their neural network to predict NO\textsubscript{x}, CO, and HC emissions. The results showed that the actual emissions were several times higher than conventional emission factors.

Fontes et al. (2013) [26] researched the impact of air quality on human health, using only traffic and meteorological data and a multilayer perceptron. The results of the study indicate that the application of MLP neural networks with one hidden layer can predict air quality with good accuracy when using only traffic and meteorological data. Similarly, E. Agirre-Basurko et al. (2006) [27] used a multilayer perceptron model and multiple linear regressions to predict ozone (O\textsubscript{3}) and nitrogen dioxide (NO\textsubscript{2}) levels in real time in Bilbao (Spain). The results showed the improved performance of models based on a multilayer perceptron compared to their multiple linear regression model. The same results were obtained by the author Capilla (2016) [28], who considered the application of multiple linear regression models and neural networks to forecast the ozone level of the urban area of the eastern coast of the Iberian Peninsula. A comparison of multiple linear regressions and multilayer perceptron networks indicates that the second approach allows for the obtaining of a more accurate forecast for three prediction intervals. Similarly, a comparative analysis of regression models and a multilayer perceptron was applied in research on the prediction of GHG emissions arising from passenger and freight road transport in Canada by Khan et al. (2021) [29]. The study’s results indicate that the multilayer perceptron artificial neural network model showed a better predictive performance than other models. That a multilayered perceptron can give better results compared to logistic regression models is also indicated by the work of Shams et al. (2020) [30]. Namely, their study aimed to forecast CO concentrations in Tehran. This research showed that the error of the neural network model is smaller than that of the linear regression model, while indicating significant indicators that contribute to air pollution such as hot/cold season parameters. Similarly, authors Shams et al. (2021) [31], in their research, were concerned with comparing the performance of multiple linear regressions (MLRs) and a multilayer perceptron (MLP) in predicting the CO\textsubscript{2} concentration in the air of Tehran. Like the results of their previous study, the results of this research indicated the importance of applying the multilayer perceptron model, which this time also gave more accurate results.

In addition to predicting pollutant emissions from vehicles with the help of neural networks, many authors have also dealt with predicting traffic noise. Traffic noise is characterized as an equally important factor representing the negative impact of traffic. The first traffic noise prediction (TNP) models date back to the early 1950s. Since then, a large number of methods and models for predicting traffic noise have been developed. Most of the TNP models presented in previous research are based on linear regression analyses.
However, more advanced models involving artificial neural networks (ANNs) [32] and genetic algorithms are increasingly being used [33].

By reviewing the previous literature, a significant number of applications of logistic regression and neural networks in the matter of predicting the emissions of polluting substances and noise by road vehicles with an internal combustion engine could be seen. However, when it comes to micromobility, numerous works refer to the spatiotemporal demand for micromobility vehicle services (e.g., refs. [34,35]) both shared and personal, the classification of electric scooters and scooters with the help of smartphones [36], the estimation of the time and cost of the services provided by electric scooters [37], and similar.

3. Research Methodology

Data analysis was carried out using the standard methods of descriptive and analytical statistics, logistic regression, and artificial neural network modeling, using IBM SPSS version 21 software. The binary logistic regression model and artificial neural network model were used to predict the acceptability of microvehicle use to users. The main goal was to compare the performance of a widely used logistic model and a machine learning model that is increasingly preferred due to its accurate and precise results. The formation of a binary logistic regression model was conducted to evaluate how well the observed predictors predict or explain the dichotomous dependent variable—the acceptability of microvehicle use. Similarly, the artificial neural network model was designed to enable measurements that minimize error when predicting acceptability, that is, “Yes” and “No” responses. In this study, a multilayer perceptron (MLP) model was developed. The architecture of the neural network model included three different layers, commonly known as the input layer, hidden layer, and output layer. The input layer inputs attribute values in the form of nodes (neurons), which refer to independent variables. The hidden layer includes radially symmetric functions and unsupervised learning to describe the hidden neurons. Finally, the output layer, with the final values of the model’s classification in the form of nodes, allows for the calculation of the weighted sums from the output of the hidden layer and allows for the calculation of the index class of the input pattern. Model formation is based on experimenting with different combinations of nodes in one and/or two hidden layers. During model development, a data set split of 60% training, 20% testing, and 20% holdout was determined, with randomly assigned values from the entire database. Considering that the neural network builds the model by learning from the potential correlation between independent and dependent variables, it can justify the final results of the model, relating the predicted values to existing values. In this regard, models such as neural networks can be said to be better able to approach problem-solving than standard computer systems.

3.1. Development of a Binary Logistic Regression Model

The prediction of the dependent variable is carried out within the logistic regression (LR) analysis using independent (predictor) variables. Although the independent variables can be continuous or categorical, the dependent variable in LR must be categorical. In cases where the dependent variable is categorical, an LR analysis is preferred over a multiple regression analysis [38]. What also characterizes an LR analysis is the fact that the predictor variables do not have to be normally distributed [39]. These variables can be continuous, categorical, or mixed. However, while a negative predictor value can be produced in a multiple regression analysis, LR does not produce negative values [40].

In cases where the dependent variable has two categories, binary logistic regression (BLR) is applied. In BLR, the independent variables are determined by logarithmic operations. A BLR with one independent variable can be defined by Equation (1):

\[
\pi(x) = \frac{\e^{\beta_0 + \beta_1 x}}{1 + \e^{\beta_0 + \beta_1 x}}, \quad \beta_0, \beta_1 \in \mathbb{R}, \beta_1 \neq 0
\]
where \( \beta_0 \) is the constant in the regression and \( \beta_1 \) is the regression coefficient that specifies the effect of the independent variable on the dependent variable. In cases where there are more independent variables, the binary logistic regression model can be represented by Equation (2):

\[
\pi(x) = \frac{e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p}}{1 + e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p}}
\]  

(2)

Since the displayed function is not linearized by the parameters \( \beta_i, i = 0 \ldots p \), it can be linearized using the corresponding logistic transformations, shown by Equations (3) and (4):

\[
1 - \pi(x) = \frac{1}{1 + e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p}}
\]

(3)

That is:

\[
\ln \left( \frac{\pi(x)}{1 - \pi(x)} \right) = e^{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p}
\]

(4)

This equality represents a logit transformation, where the value of \( \pi \) varies between 0 and 1, and the logit can be in the range of \(-\infty \) to \( \infty \) and can also be continuous. To implement any logistic regression model, one needs to choose \( \beta_1, \ldots, \beta_p \) values based on a given training set [41].

3.2. Development of an Artificial Neural Network Model

The basic concept of the artificial neural network (ANN) is a simulation of the way data are processed in the natural neurons of the nervous system, and not the psychology of solving problems found in intelligent beings. ANNs are usually designed as three-layer network models (see Figure 1a) of interconnected artificial neurons (an input layer, hidden layer, and output layer). Accordingly, artificial neural networks, like natural ones, consist of a large number of simple processing units—neurons that are highly interconnected, thus using all the power of highly parallel data processing. On the other hand, like the nervous system, artificial neural networks have the ability to learn based on solved examples from the domain of the problem thanks to the flexible connections between the neurons, which tend to adapt to the problem as best as possible in the learning process.

![Figure 1](https://via.placeholder.com/150)

**Figure 1.** Structure of an artificial neural network: (a) description of the architecture of an artificial neural network: Y—output layer; (b) description of an active neural network node: Sum—sum of the weighted input.

In this regard, neurons are interconnected by connections (branches), along which certain signals are sent. Each connection that exists between neurons has a certain strength associated with it. Depending on the input signals it received and the strength of the connections along which the signals travel, each neuron sends an output signal of a certain strength. Input signals \( (x_1, x_2, x_3, \ldots, x_n) \), which represent output signals from other neurons, are multiplied by their corresponding connection strengths \( (w_1, w_2, w_3, \ldots, w_n) \). The output signal is equal to the weighted sum of the input signals. Within an artificial
neural network, each neuron has a corresponding activation function, which is usually a non-linear, continuous, monotonically increasing, bounded, and differentiable logistic function. Its main goal is to use the “S” curve to transform the weighted sum of its input signals (Sum) into the values of the variable y, which take relatively small values regardless of the values of the variable sum (see Figure 1b).

In summary, the net sum of the weighted input values that enter node j is put through an output activation function that converts the neuron’s weighted input to its output activation (most often a sigmoid function). After the formation of the network architecture, the ANN neurons begin the training process. During the training process, data sets with authentic inputs and outputs are included as examples to train the model to predict outputs. Network training means determining the network weights with the aim of making the desired decisions in certain situations. On the other hand, a neural network is trained by constantly adjusting the strength of the connections between its branches during training in order to detect the relationships that exist between its input and output data [42].

This supervised learning starts with random weights and uses algorithms that continuously modify the weights of the branches of the network. The changes between the output target measures and the obtained measures are used by the error function to control learning. That is, the error function belongs to the weights, which must be improved to reduce the error. In the training process, each weight is transformed by adding an amount to its previous value. After a data set with respectable weights has been created, the neural network model can take an alternative set with unidentified output measures and automatically predict its corresponding outputs.

Development of a Multilayer Perceptron Model (MLP)

The previously described model is quite limited, considering that it is based on only one perceptron, which is only suitable for linearly identifiable data. Due to the existence of non-linear data sets, a model whose construction is extended to several layers is in use, which is better known as a multilayer perceptron (MLP) [43,44]. In other words, a multilayer perceptron can be defined as a neural network with layers of neurons that are interconnected, so that the output of a neuron in a layer is only allowed to be an input for the neurons in the upper layer. The power of the multilayer perceptron comes precisely from its nonlinear activation functions. Currently, the most commonly used functions today are the unipolar (or logistic) [45] sigmoid shown in Equation (5):

$$f(s) = \frac{1}{1 + e^{-s}}$$  \hspace{1cm} (5)

And the bipolar sigmoid (hyperbolic tangent) function, when \(a = 2\), is shown by Equation (6):

$$f(s) = \frac{1 - e^{-as}}{1 + e^{-as}}$$  \hspace{1cm} (6)

As such, the MLP neural network is capable of capturing the high non-linearity of the data set, proving that it is possible to approximate any continuous function with a small random error by applying sufficiently complex MLPs. The connection weight from the \(i\)-th neuron in the \(l\)-th layer to the \(j\)-th neuron in the \((l+1)\)-th layer, or \(l+1\), can be used to confirm the \(i\)-th neuron in the \(l\)-th layer, which can be described by Equation (7):

$$y_{li} = f_{li}(z_{li}); \quad z_{li} = \sum_{j=1}^{n_{l-1}} w(l-1)_{ij} \cdot Y(l-1)j + b_{li}$$  \hspace{1cm} (7)

where \(y_{li}, f_{li}, \) and \(b_{li}\) are the output, activation function, and bias, respectively, and \(n_l\) is the number of neurons in the \(l\)-th layer. For simplicity, a neuron is activated by the sum of the weighted outputs of the neurons in a lower layer. The training procedure of the MLP network is used to minimize the objective function in terms of its criteria (i.e., weight and
bias), which is associated with the task for which the MLP is being used. In this regard, the objective function shown in Equation (8) can generally be used for binary classifications:

$$E(\theta) = \frac{1}{n} \sum_{(x,y) \in D} (y - \hat{y})^2$$

(8)

where $D$ is the training data set, $\hat{y}$ can represent the MLP output of the preordered input $x$, and $\theta$ is its weights and biases data set. In the case of a need to reduce the objective function $E(\theta)$, the gradient method can be used, which states that the sum of updates for a parameter is negatively proportional to the gradient at its current value [42].

This artificial neural network algorithm changes the weights to reduce the root mean square error between the required and actual network outputs (a forward propagation algorithm) [46]. Such neural network models are based on supervised learning, where the neural network is trained using a set of data for which the inputs are known, as are the desired outputs. After the training process, the network weights are identified and then used to calculate the output measurements of the original input samples.

4. Data Description

4.1. Sample and Data Collection

Users’ attitudes were collected through an online questionnaire from October 2023 to January 2024. The questionnaire was sent to individual companies and faculties, students, pensioners, and users of social networks in Belgrade to obtain a representative sample of the population. The target group consisted of all inhabitants of Belgrade. As micromobility vehicles are mostly used in the central city zone, the research area included a targeted narrower central zone, including other parts of the wider area of Belgrade (a radius of 20 km from the center), to encourage other users to switch to the use of more environmentally friendly vehicles such as microvehicles. After incomplete questionnaires with illogical answers were removed from the total sample, the valid sample used for further analysis consisted of 615 respondents. Control questions determined illogicality.

To obtain authoritative research results, the target group consisted of respondents who had the opportunity to see and face the problems of environmental pollution in the territory of the city of Belgrade. During the research, the respondents were not presented with any additional information regarding the problem of environmental pollution. Respondents gave answers to the questions based only on their perceptions of the environmental problems caused by road vehicles in the territory of Belgrade.

At the beginning of the questionnaire, a general definition of the concept of micromobility was given to the respondents, highlighting it as one of the possible measures to solve the problem of environmental pollution while defining the existing types of microvehicles that this measure entails. In this way, the respondents were familiar with the term micromobility as well as the basic characteristics of microvehicles. The questionnaire combined questions about Revealed preference, about the actual behavior of users when moving, and questions about Stated preference, used to analyze user preferences regarding the use of microvehicles. The questionnaire is divided into four parts. The first part contained questions about the socio-demographic and economic characteristics of users, while the second part focused on trip characteristics. The third part dealt with the examination of user attitudes regarding environmental pollution, while the fourth aimed to determine user attitudes regarding the use of microvehicles, taking into account both respondents who use and respondents who do not use this mode of transportation. Finally, the respondents were asked about the reasons why they use/do not use microvehicles and whether, in the end, with a solution to the problem mentioned as the reason, they would accept the use of microvehicles for the sake of reducing environmental pollution. All questions in the questionnaire were closed. A five-point scale was used for certain questions.
4.2. Data Preparation for Model Development

The preparation of data for predicting the acceptability of the use of microvehicles from an ecological aspect was also carried out to create data sets for both considered models (LR and MLP). The observed data related to the questions and answers of only those users who do not currently use microvehicles. During the creation of the data sets, 27 attributes were defined which were considered to be important in terms of evaluating the views of respondents when accepting the use of microvehicles from an ecological aspect. The first 4 attributes refer to the socio-demographic characteristics of the respondents, such as their gender, age, employment, and personal income, while the next 14 refer to their trip characteristics in terms of the frequency of their use of a certain mode of transport when going to work/school/college (commuting trips), and for other trip purposes such as entertainment/recreation/shopping, and average mileage (one-way) for both stated trip purposes. Respondents had the opportunity to answer whether they use a certain mode of transportation for the stated purposes daily, several times a week, monthly, or annually, as well as never. The mileage covered included the possibility of choosing one of the 8 offered mileage ranges, from <0.5 km to 30 km. Then, the next group of attributes (4 attributes) refers to respondents’ views on the general pollution of Belgrade from the aspects of noise and emissions of pollution, as well as the impact of road traffic on environmental pollution in Belgrade from both mentioned aspects. Respondents were offered a five-point scale, which includes answers indicating the extent to which they believe that Belgrade is polluted, where 1 indicated to very large extent, 2—to a large extent, 3—to a medium extent, 4—to a small extent, and 5—to a very small extent. The last group of attributes (5 attributes) includes the reasons that influence the attitude of respondents regarding their previous non-use of microvehicles. These reasons include the lack of infrastructure, no safety during the use of such vehicles, the prices of microvehicles, unfavorable types of terrain, and undefined legal regulations. Respondents had the task of using a five-point scale to evaluate which of the reasons they consider 1—most significant, 2—significant, 3—moderately significant, 4—less significant, and 5—least significant.

All 27 attributes were independent variables when creating the binary logistic regression model and input neurons within the input layer of the artificial neural network. The dependent variable represented the acceptability of the use of microvehicles as a possible solution for reducing environmental pollution. The respondents’ possible answers were “Yes” and “No”, and, in addition to the two classes of the dependent variable of the binary logistic regression model, they represented two neurons in the output layer of the neural networks.

5. Results

5.1. Descriptive Statistics and the Application of the Chi-Square Test of Independence

The sample consisted of 615 residents of Belgrade. Of the total number of respondents, 49.6% were women, while 50.4% were men. When it comes to the age of the respondents, most of them were between 18 and 25 years old (35.6%), followed by 26 to 35 years old (21.3%). The largest number of respondents were in permanent employment (57.2%). Also, the largest number of respondents belonged to the group with a monthly income of EUR 501 to EUR 750 (28.6%), followed by those with an income of less than EUR 250 (24.6%) per month, and those in the range from EUR 750 to EUR 1000 (20.0%). The average mileage traveled in one direction of a trip, in most cases, was in the range of 5 km to 8 km (41.5%) for commuting trips and from 2.5 km to 5 km (42.0%) when the trips were for other purposes such as entertainment, recreation, and shopping. When taking commuting trips, respondents most often choose a passenger car for daily trips (39.7%), public transport for trips several times a week (14.8%) and several times a month (14.0%), and other modes of transport (such as taxis, car sharing, etc.) for trips several times a year (23.7%). On the other hand, for trips with other purposes, respondents mostly use a passenger car daily (43.6%), walk several times a week and several times a month (36.7% and 30.4%, respectively), and other modes of transportation several times a year (27.6%). Environmentally friendly and
sustainable modes of transportation such as electric bicycles and electric scooters are rarely used for commuting or other purposes.

Of the total number of respondents who believe that measures should be taken to reduce environmental pollution (90.1%), 9.2% use electric microvehicles such as electric bicycles (51.0%) and electric scooters (39.2%). The most frequent use of microvehicles for other purposes is several times a month (63.2%), while commuting trips use them every day (53.8%). As the most important reason for their use, the respondents, in addition to the shorter travel time (29.4%), also cited the reduction of environmental pollution as a significant (31.4%) and moderately significant reason (37.3%).

The remaining respondents (503; 90.8%) do not use these vehicles for their trips and they were considered for further analysis to predict their acceptability. To a very large and large extent, they believe that Belgrade is polluted by emissions (36.6% and 34.6%, respectively), while Belgrade is moderately more polluted by noise (44.9%). In their opinion, road traffic contributes to a very large and large extent to environmental pollution through the emission of pollutants (46.3% and 38.0%, respectively), while, to a large and medium extent, it contributes more to noise pollution (34.8% and 33.2%, respectively). Also, as the most important reason for not using microvehicles, respondents state that the lack of infrastructure (39.6%) and (lack of) safety during trips (42.9%) have the greatest influence.

Out of 90.8% of respondents, 69.6% would change their attitude and accept the use of microvehicles to reduce pollution, while the other 30.4% of respondents would not. First, a chi-square test of independence was conducted to determine the association between the various factors and respondents’ attitudes toward the use of microvehicles. Above all, the influence of socio-demographic characteristics on the respondents’ attitude towards the use of microvehicles was examined. The association of the use of microvehicles with the respondent’s gender ($\chi^2 = 11,082; p = 0.001$), age ($\chi^2 = 27,224; p = 0.001$), employment status ($\chi^2 = 28,797; p = 0.001$), and income ($\chi^2 = 22,943; p = 0.001$) is statistically significant. Also, the results indicate that there is a statistically significant relationship between the frequency of the use of almost all types of transport, except the use of motorcycles, when commuting ($\chi^2 = 4089; p = 0.394$) and when making trips for other purposes ($\chi^2 = 6161; p = 0.187$), as well as public transport when the trips are for other purposes ($\chi^2 = 6818; p = 0.146$). According to respondents’ answers, the average mileage traveled during a trip can have an impact on the acceptance of the use of microvehicles. A statistically significant correlation between the mileage traveled in one direction on the way to work ($\chi^2 = 36,493; p = 0.001$) and trips for other purposes ($\chi^2 = 16,846; p = 0.018$) proves this. Also, respondents’ views on environmental pollution in Belgrade, from the aspect of noise pollution ($\chi^2 = 26,088; p = 0.001$) and pollutant emissions ($\chi^2 = 16,890; p = 0.002$), have a significant statistical relationship with microvehicles’ acceptability. Namely, respondents who think that Belgrade is moderately polluted by noise (37.4%) and to a very large extent (50.9%) polluted by emissions of polluting substances are, to the greatest extent, ready to accept the use of microvehicles.

Also, respondents with the same preferences think that road traffic greatly affects the pollution of Belgrade from the aspect of noise (37.7%) and, to a very large extent, from the aspect of exhaust gas emissions (51.4%). This indicates a statistically significant association with the acceptability of microvehicles ($\chi^2 = 19,811; p = 0.001$ and $\chi^2 = 21,594; p = 0.001$, respectively). After that, reasons why the residents of Belgrade do not use microvehicles in realizing their trips, such as a lack of infrastructure ($\chi^2 = 11,206; p = 0.024$), the price of microvehicles ($\chi^2 = 16,254; p = 0.003$), and unfavorable terrain ($\chi^2 = 25,575; p = 0.001$), also have a significant statistical association with their acceptability.

5.2. Binary Logistic Regression

In the developed model, the dependent variable related to the acceptability of the use of microvehicles from the aspect of reducing environmental pollution is classified as dichotomous. Independent variables such as gender, age, employment, income, mileage, and frequency of use of the considered modes of transport (passenger car, motorcycle,
public transport, bicycle, walking, and other modes), when commuting and trips for other purposes, are classified as categorical. Other independent variables are classified as continuous.

The model of the acceptance of the use of microvehicles has a higher predictive power than the null model, and this difference is statistically significant ($\chi^2 = 350.204$, df = 87, $p = 0.000$, pseudo $R^2 = 58.4\%$). The most statistically significant independent variables that have the greatest influence on the predictive power of the model, as well as their coefficients and Wald values, are shown in Table 1. The most significant results of the model indicate that respondents who use a passenger car several times a year ($p = 0.001$) for commuting trips and when making trips for other purposes ($p = 0.005$) have a higher chance of accepting the use of public transport compared to other modes and their frequencies. In addition to the above, the views of these respondents in terms of the pollution of Belgrade by road vehicles, from the aspect of pollutant emissions ($p = 0.001$), as well as the lack of infrastructure ($p = 0.004$), which was the reason for them not using microvehicles so far, have a significant role in the acceptability of microvehicles. It can be concluded that the passenger car, as the most dominant form of transportation in Belgrade, plays a significant role in changing behaviors during a trip.

Table 1. Binary logistic regression model.

<table>
<thead>
<tr>
<th>Predictors</th>
<th>B</th>
<th>S.E.</th>
<th>Wald</th>
<th>df</th>
<th>Sig.</th>
<th>Ex (B)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender (Female)</td>
<td>0.65</td>
<td>0.32</td>
<td>4.09</td>
<td>1.00</td>
<td>0.043</td>
<td>1.92</td>
</tr>
<tr>
<td>Trip with other purposes</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use of a passenger car</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use of a passenger car several times a year</td>
<td>−1.92</td>
<td>0.68</td>
<td>7.93</td>
<td>1.00</td>
<td>0.005</td>
<td>0.15</td>
</tr>
<tr>
<td>Never use the passenger car</td>
<td>−1.36</td>
<td>0.62</td>
<td>4.85</td>
<td>1.00</td>
<td>0.028</td>
<td>0.26</td>
</tr>
<tr>
<td>Use of bicycles</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use of bicycles several times a year</td>
<td>3.07</td>
<td>1.34</td>
<td>5.26</td>
<td>1.00</td>
<td>0.022</td>
<td>21.56</td>
</tr>
<tr>
<td>Motorcycle used several times a week</td>
<td>−4.36</td>
<td>2.09</td>
<td>4.35</td>
<td>1.00</td>
<td>0.037</td>
<td>0.01</td>
</tr>
<tr>
<td>Commuting trip</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use of a passenger car</td>
<td>−2.29</td>
<td>0.68</td>
<td>11.24</td>
<td>1.00</td>
<td>0.001</td>
<td>0.10</td>
</tr>
<tr>
<td>Never use a passenger car</td>
<td>−1.48</td>
<td>0.63</td>
<td>5.51</td>
<td>1.00</td>
<td>0.019</td>
<td>0.23</td>
</tr>
<tr>
<td>Use of walking</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Use of public transport several times a week</td>
<td>−1.56</td>
<td>0.71</td>
<td>4.85</td>
<td>1.00</td>
<td>0.028</td>
<td>0.21</td>
</tr>
<tr>
<td>Use of public transport several times a year</td>
<td>−1.40</td>
<td>0.71</td>
<td>3.92</td>
<td>1.00</td>
<td>0.048</td>
<td>0.25</td>
</tr>
<tr>
<td>Mileage</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mileage (0.5 km–2.5 km)</td>
<td>−2.53</td>
<td>0.98</td>
<td>6.61</td>
<td>1.00</td>
<td>0.010</td>
<td>0.08</td>
</tr>
<tr>
<td>Pollution of Belgrade by the emission of pollutants from road traffic</td>
<td>0.73</td>
<td>0.19</td>
<td>13.98</td>
<td>1.00</td>
<td>0.001</td>
<td>2.07</td>
</tr>
<tr>
<td>Non-existence infrastructure</td>
<td>0.49</td>
<td>0.17</td>
<td>8.18</td>
<td>1.00</td>
<td>0.004</td>
<td>1.63</td>
</tr>
</tbody>
</table>

* <0.001.

According to the binary logistic regression model, it was determined that all predictor variables can distinguish between users who would and would not agree to use microvehicles for the sake of reducing environmental pollution. When the accuracy of user classification was analyzed, it was found that a very good classification was achieved by all independent variables. Namely, the model can correctly classify 84.7% (85%) of all cases, that is, 90.9% of users who accepted the use of microvehicles and 70.6% of those who did not (see Table 2). Higher prediction success refers to number of users who will first accept microvehicles, compared to those who do not belong to that group.
Table 2. Prediction of microvehicle acceptability using binary logistic regression.

<table>
<thead>
<tr>
<th>Observed Values</th>
<th>Existing Values</th>
<th>Classified Instances</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Classified Instances</td>
<td></td>
</tr>
<tr>
<td>Acceptability</td>
<td>Yes</td>
<td>318</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>Incorrectly</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>Incorrectly</td>
<td>108</td>
</tr>
<tr>
<td>Overall (%)</td>
<td>72.0%</td>
<td>28.0%</td>
</tr>
</tbody>
</table>

The precision and sensitivity of the model in predicting the acceptability of microvehicles were subjected to the detailed analysis shown in Table 3. The binary logistic regression model has a significant precision that, in both cases of the classification of answers, has a higher percentage of correct positive values, giving preference to the answer “Yes” (0.91). Also, its sensitivity values indicate that the model predicts the given values very well (>0.8), which affects the higher precision of the model.

Table 3. Accuracy of microvehicle acceptability classification.

<table>
<thead>
<tr>
<th>Data Set</th>
<th>TP Rate</th>
<th>FP Rate</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>MCC</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing</td>
<td>0.876</td>
<td>0.229</td>
<td>0.909</td>
<td>0.876</td>
<td>0.892</td>
<td>0.631</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>0.777</td>
<td>0.124</td>
<td>0.706</td>
<td>0.777</td>
<td>0.740</td>
<td>0.635</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>0.826</td>
<td>0.176</td>
<td>0.807</td>
<td>0.826</td>
<td>0.816</td>
<td>0.633</td>
<td>Avg.</td>
</tr>
</tbody>
</table>

5.3. Multilayer Perceptron Model (ANN)

For the network training process, a maximum time of 15 min was set, while the time for testing was automatically determined by the software. The manually created MLP network architecture with nine neurons in the first and seven neurons in the second hidden layer gave the best results. Different functions were used for different layers of the MLP network, i.e., in the hidden layer it was a hyperbolic tangent, and in the output layer it was an identity function.

After determining its basic characteristics, the network was trained and then tested, after which its basic characteristics were again determined, indicating that the MLP network requires a minimum training time of 0.012 s. The error function values indicate that the MLP network, during testing, has smaller sum-of-squares error values (13,633) compared to its error values during training (31,882), which indicates that the MLP model has smaller deviations in its predicted values during both training and testing compared to the real deviations.

Taking into account the large number of attributes and the size of the sample, the neural network model, in its training phase, gives very good results in predicting users who would agree to use microvehicles to reduce environmental pollution (94.6%), which is not the case for users who do not would use these vehicles (65.9%). In addition to the above, Table 4, which also represents the confusion matrix, indicates the final prediction results observed after testing. The final results indicate that the model can classify users into two groups with high accuracy, taking into account all the attributes that contributed to their final answer, similar to its results during training. In this regard, the model predicted a significantly worse number of users who would not be willing to use microvehicles (65.4%), which may indicate its worse dependence on attributes (independent variables) in its final response, which additionally harmed both training and test data.

The precision of the model during the classification of true positive values, when tested, indicates its high accuracy at predicting acceptability among those users who would agree to use microvehicles (0.92) (see Table 4). On the other hand, the precision of the model in the classification of respondents with the opposite attitude is significantly worse (0.65). That the model can find a large number of instances of the “Yes” class in the test data set is also indicated by its sensitivity, which is 0.88. Compared to this, the precision of the model indicates, the sensitivity of the model regarding the “No” class is significantly lower.
In addition to the above, other performances of the model such as F1 indicate its significant predictive power, in the form of precision and data memory, when it comes to the responses of users who would use micromobility vehicles (0.90), while this is not the case for those who would not (0.69). Finally, the value of Matthew's correlation coefficient formula (MCC), which includes all values from the confusion matrix (Table 5), indicates that the MLP model can predict and classify instances into both given classes relatively well.

Table 4. Prediction of microvehicle acceptability using multilayer perceptron (ANN).

<table>
<thead>
<tr>
<th>Sample</th>
<th>Existing Values</th>
<th>Correctly Classified Instances</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>192</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>31</td>
<td>60</td>
</tr>
<tr>
<td>Overall (%)</td>
<td>75.9%</td>
<td>24.1%</td>
</tr>
<tr>
<td></td>
<td>77.0%</td>
<td>23.0%</td>
</tr>
<tr>
<td></td>
<td>62.4%</td>
<td>37.6%</td>
</tr>
<tr>
<td></td>
<td>65.9%</td>
<td>65.4%</td>
</tr>
<tr>
<td></td>
<td>75.9%</td>
<td>24.1%</td>
</tr>
<tr>
<td>Training</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>192</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>31</td>
<td>60</td>
</tr>
<tr>
<td></td>
<td>94.6%</td>
<td>65.9%</td>
</tr>
<tr>
<td></td>
<td>91.9%</td>
<td>65.4%</td>
</tr>
<tr>
<td></td>
<td>77.0%</td>
<td>23.0%</td>
</tr>
<tr>
<td></td>
<td>75.3%</td>
<td>63.9%</td>
</tr>
<tr>
<td></td>
<td>85.7%</td>
<td>85.0%</td>
</tr>
<tr>
<td></td>
<td>85.7%</td>
<td>85.0%</td>
</tr>
<tr>
<td>Holdout</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>55</td>
<td>18</td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>75.3%</td>
<td>63.9%</td>
</tr>
<tr>
<td></td>
<td>62.4%</td>
<td>37.6%</td>
</tr>
</tbody>
</table>

Table 5. Prediction of microvehicle acceptability using multilayer perceptron (ANN).

<table>
<thead>
<tr>
<th>Data Set</th>
<th>TP Rate</th>
<th>FP Rate</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>MCC</th>
<th>Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td>0.861</td>
<td>0.155</td>
<td>0.946</td>
<td>0.861</td>
<td>0.901</td>
<td>0.654</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>0.845</td>
<td>0.139</td>
<td>0.659</td>
<td>0.845</td>
<td>0.741</td>
<td>0.654</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>0.853</td>
<td>0.147</td>
<td>0.803</td>
<td>0.853</td>
<td>0.821</td>
<td>0.654</td>
<td>Avg.</td>
</tr>
<tr>
<td>Testing</td>
<td>0.883</td>
<td>0.261</td>
<td>0.919</td>
<td>0.883</td>
<td>0.901</td>
<td>0.597</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>0.739</td>
<td>0.117</td>
<td>0.654</td>
<td>0.739</td>
<td>0.694</td>
<td>0.597</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>0.811</td>
<td>0.189</td>
<td>0.787</td>
<td>0.811</td>
<td>0.798</td>
<td>0.597</td>
<td>Avg.</td>
</tr>
<tr>
<td>Holdout</td>
<td>0.809</td>
<td>0.439</td>
<td>0.753</td>
<td>0.809</td>
<td>0.780</td>
<td>0.381</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>0.561</td>
<td>0.191</td>
<td>0.639</td>
<td>0.561</td>
<td>0.597</td>
<td>0.381</td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>0.685</td>
<td>0.315</td>
<td>0.696</td>
<td>0.685</td>
<td>0.689</td>
<td>0.381</td>
<td>Avg.</td>
</tr>
</tbody>
</table>

In addition to the presented analysis, IBM SPSS version 21 software enables the display of the predicted pseudo-probability of the MLP model with respect to the two perceived classes (responses) of microvehicle acceptability in a box plot diagram. This graph specifically illustrates the model’s predictions for two classes of the dependent variable, acceptability (answers “Yes” and “No”). Also, it is important to point out that this graph shows box plots that categorize the predicted pseudo-probabilities based on the entire analyzed data set. As a rule, for each box plot in each different class, values above 0.5 can confirm correct predictions. In this regard, the box plot graph developed for the MLP model showed the predicted probability of the observed acceptability class being correct. The first box plot on the left indicates the answer “Yes”, while the second box plot shows the probability that “No” will be classified as a “Yes”, even though it belonged to the answer “No”. In this case, incorrectly predicted answers are marked with the symbol “*”. These results indicate that the MLP model correctly classified the answers in the “Yes” class better than it did for the “No” class (see Figure 2a).
That is, they use a piece of data to give a clear insight into the benefits of using a model. Potential to bias, as seen in the lift plot. This indicates that the model is performing well, population, growth curves only evaluate model performance in a subset of the population. This shows the model's correct classification of training users who answered “No” was 29%/10% = 2.9, while the increase of 14% for the group of users who answered that they would accept the use of microvehicles. Similarly, looking at the first point of the gain plot (see Figure 3a) illustrates that the "No" class, in terms of the first point, was at (10%, 29%), which indicates that the first 10% covers a little less than 30% of all users who answered that they would not accept the use of microvehicles. Similarly, looking at the first point of the "Yes" class (10%, 14%), it indicates that the first 10% covers a little less than 15% of all users who answered that they would accept the use of microvehicles.

The lift curve is a basis for evaluating the performance of a classification model (see Figure 3b). However, unlike a confusion matrix, which evaluates the model for the entire population, growth curves only evaluate model performance in a subset of the population. That is, they use a piece of data to give a clear insight into the benefits of using a model as opposed to not using a model. The values from the gain graph (Figure 3a) were used to calculate the lift value (i.e., benefit). In this regard, the 29% increase for the group of users who answered “No” was 29%/10% = 2.9, while the increase of 14% for the group of users who answered “Yes” was 14%/10% = 1.4 (Figure 3b). The slopes shown in Figure 3 decrease steadily as fewer records are classes of interest to add and the model has less potential to bias, as seen in the lift plot. This indicates that the model is performing well, providing a significant “boost” for a relatively small fraction of the ranked data.
Table 6 indicates the importance of the evaluation of independent variables in the formed neural network model of the multilayer perceptron. The table includes all the values of the independent variables, whose importance and normalized importance (NI) are ranked from the highest to the lowest. The conducted analysis indicates that user awareness of the impact of road traffic on environmental pollution in terms of exhaust gas emissions has the greatest importance of all observed independent variables (NI = 100%). This was confirmed by the answers of the respondents, which indicated that those with the greatest willingness to use microvehicles from an environmental point of view are those users who believe that the environment is polluted to a very large extent by road traffic in terms of emissions (51.4%). The other variables with the highest values were the frequency of using bicycles when making trips for other purposes (NI = 90.74%), followed by the mileage of trips when commuting (NI = 84.02%). Analogous to this result are the responses of the respondents, indicating that the greatest acceptability of electric-powered microvehicles is by those respondents who never use bicycles when making trips for other purposes (35.4%), and who cover a distance of 5 to 8 km when commuting (43.7%). In addition to the above, the frequency of the use of motorcycles and bicycles when commuting (NI = 73.91% and 71.35%, respectively) has a significant role in respondents’ willingness to use these eco-mobility vehicles. As in the previous case, users who would accept the use microvehicles currently never make trips by bicycle (71.7%) or motorcycle (93.1%) when commuting. The user’s monthly personal income, as one of their socio-economic characteristics, stood out as a significant variable that has an impact on the acceptability of microvehicles (NI = 66.66%). According to the results of these responses, users with incomes of less than EUR 250 per month (30.6%), and from EUR 501 to EUR 750 (25.4%), are the most willing to use microvehicles, which demonstrates the affordability of the vehicles’ prices and their lower travel costs, in addition to their ecological benefits. The frequency of trips made by walking when commuting (NI = 66.36%), is also significant when it comes to the willingness of users to accept moving by microvehicle, which is also indicated by the large number of respondents who commute by other modes of transport and rarely exclusively by walking (46.6%). Age can also, in addition to a user’s income, have a significant impact on their willingness to accept the use of a microvehicle (NI = 56.99%). In this regard, users between the ages of 18 and 25 will mostly decide to use a microvehicle (44.0%).

Figure 3. Presentation of the correct classifications obtained by the model in relation to classifications without the use of the model, and measurement of its classification performance on part of the population: (a) gain curves and (b) lift curves.
Table 6. Independent variables’ importance.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Importance</th>
<th>Normalized Importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pollution of Belgrade by pollutant emissions from road vehicles</td>
<td>0.0766</td>
<td>100.00%</td>
</tr>
<tr>
<td>Frequency of bicycle for trips for other purposes</td>
<td>0.0695</td>
<td>90.74%</td>
</tr>
<tr>
<td>Mileage when commuting</td>
<td>0.0643</td>
<td>84.02%</td>
</tr>
<tr>
<td>Frequency of motorcycle for commuting trips</td>
<td>0.0566</td>
<td>73.91%</td>
</tr>
<tr>
<td>Frequency of bicycle for commuting trips</td>
<td>0.0546</td>
<td>71.35%</td>
</tr>
<tr>
<td>Monthly personal income</td>
<td>0.0511</td>
<td>66.66%</td>
</tr>
<tr>
<td>Frequency of walking for commuting trips</td>
<td>0.0508</td>
<td>66.36%</td>
</tr>
<tr>
<td>Age</td>
<td>0.0436</td>
<td>56.99%</td>
</tr>
<tr>
<td>Frequency of walking for trips with other purposes</td>
<td>0.0402</td>
<td>52.55%</td>
</tr>
<tr>
<td>Frequency of other modes of transport for commuting trips</td>
<td>0.0401</td>
<td>52.33%</td>
</tr>
<tr>
<td>Frequency of public transport for commuting trips</td>
<td>0.0359</td>
<td>46.88%</td>
</tr>
<tr>
<td>Pollution of Belgrade by emissions</td>
<td>0.0355</td>
<td>46.37%</td>
</tr>
<tr>
<td>Pollution of Belgrade by noise</td>
<td>0.0325</td>
<td>42.42%</td>
</tr>
<tr>
<td>Unfavorable type of terrain</td>
<td>0.0320</td>
<td>41.74%</td>
</tr>
<tr>
<td>Mileage for trips with other purposes</td>
<td>0.0311</td>
<td>40.63%</td>
</tr>
<tr>
<td>Frequency of passenger car use for commuting trips</td>
<td>0.0306</td>
<td>40.02%</td>
</tr>
<tr>
<td>Frequency of motorcycles for trips with other purposes</td>
<td>0.0306</td>
<td>39.97%</td>
</tr>
<tr>
<td>Non-existent infrastructure</td>
<td>0.0288</td>
<td>37.59%</td>
</tr>
<tr>
<td>Frequency of passenger car use for trips with other purposes</td>
<td>0.0287</td>
<td>37.53%</td>
</tr>
<tr>
<td>Price of e-microvehicle</td>
<td>0.0280</td>
<td>36.51%</td>
</tr>
<tr>
<td>Employment</td>
<td>0.0261</td>
<td>34.15%</td>
</tr>
<tr>
<td>Gender</td>
<td>0.0252</td>
<td>32.92%</td>
</tr>
<tr>
<td>(No) safety during the trip for e-microvehicle users</td>
<td>0.0246</td>
<td>32.09%</td>
</tr>
<tr>
<td>Frequency of use of other transport modes for trips with other purposes</td>
<td>0.0193</td>
<td>25.19%</td>
</tr>
<tr>
<td>Frequency of public transport for trips with other purposes</td>
<td>0.0153</td>
<td>20.04%</td>
</tr>
<tr>
<td>Pollution of Belgrade by noise from road vehicles</td>
<td>0.0146</td>
<td>19.01%</td>
</tr>
<tr>
<td>Absence of legislations</td>
<td>0.0137</td>
<td>17.89%</td>
</tr>
</tbody>
</table>

The next group of moderately influential variables consists of the frequency of walking for other purposes (NI = 52.55%), as well as the use of other modes of transportation and public transportation when commuting (NI = 52.33% and 46.88%, respectively). In these cases, respondents who are more willing to use microvehicles from the aspect of less pollution, make trips several times a week, by walking, for other purposes (36.6%), never use other modes of transport (59.4%) when commuting, and commute every day using public transport (38.3%). The respondents’ awareness of the current environmental pollution in Belgrade in terms of emissions and noise has a medium impact on their choice (NI = 46.37% and 42.42%, respectively). In this regard, respondents who believe that Belgrade is polluted to a very large extent by emissions (50.9%), and to a large extent by noise (29.7%), are more willing to accept the use of microvehicles for the sake of reducing pollution. In addition to the above, the majority of users who declared that an unfavorable type of terrain is a less significant reason for their previous non-use of microvehicles (44.0%), indicated that an unfavorable type of terrain was a moderately important variable in their assessment of microvehicle acceptability (NI = 41.74%). Similarly, the average mileage when making trips for other purposes can be a moderately significant indicator in assessing the acceptability of the use of a microvehicle (NI = 40.63%), the influence of
which was mentioned by the largest number of respondents who, for the stated purposes, travel a distance of 2.5 to 5 km (40.3%). Finally, the respondents who never use a passenger car when commuting (32.0%) are more willing to use microvehicles, from the aspect of reducing pollution, and, in this regard, indicate that the frequency of using a passenger car when commuting is one of the moderately important variables determining acceptance (NI = 40.02%).

The frequency of using a motorcycle when making trips for other purposes (NI = 39.97%), especially for those users who rarely use it for trips for the stated purposes (92.0%), is one of the less significant variables influencing the decision of users to accept the use of microvehicles. In addition to the above, the lack of infrastructure (NI = 37.59%), as expected, is the most significant reason for not using a microvehicle (42.6%), compared to the price of a microvehicle (NI = 36.51%), which is quite affordable, considering that it is the least significant reason (43.4%) for not using these vehicles. Also, the frequency of using a passenger car when making trips for other purposes (NI = 37.53%) has less importance when accepting a microvehicle, especially for respondents who use a car for the stated purposes every day (34.6%). As expected, respondents who are permanently employed (53.4%) and female (58.6%) are more willing to accept the use of microvehicles, which the neural network ranks as not-so-significant indicators when choosing microvehicles (NI = 34.15% and 32.92%). Among the least significant variables, the lack of safety when using a microvehicle (a reason for current non-use) and the frequency of the use of other modes of transport and public transport for other purposes can be highlighted (NI = 32.09%, 25.19% and 20.04%, respectively). Accordingly, it is expected that the lack of safety will be a significant reason that people do not currently use a microvehicle (43.4%), including respondents who never use other types of vehicles (52.0%) but who use public transport every day (32.9%) for other purposes, when they are more willing to use microvehicles for environmental purposes. Finally, the noise pollution of Belgrade due to road traffic and the absence of legal regulations represent the least significant variables in deciding on the acceptability of these vehicles (NI = 19.01% and 17.89%). Although users who would accept the use of microvehicles consider noise pollution to be largely present (37.7%) in Belgrade, the absence of legal regulations is also one of the least significant reasons for the current non-use of microvehicles (31.1%); the neural network model does not take them into account as significant when making its final decisions.

6. Discussion

In addition to the fact that electric microvehicles are less harmful to the environment, from the aspects of noise and the emission of polluting particles, a large part of the population of Belgrade has not yet experienced their use. To consider in detail the reasons for their non-use and make decisions that will contribute to increasing support for them from the public, it is necessary to analyze the factors that influence the willingness of users to use electric-powered microvehicles. With this in mind, an analysis of the predicted acceptability of the use of microvehicles was carried out, including an analysis of the mentioned factors using an artificial neural network model and binary logistic regression.

The application of binary logistic regressions is found in a large number of traffic studies analyzing various factors of the acceptability of services offered by transport systems [47–49]. On the other hand, the application of artificial neural networks such as a multilayer perceptron is more based on the prediction of traffic protocols, traffic congestion, etc. [50–53]. When it comes to microvehicles, research focuses on the spatiotemporal demand for micromobility vehicle services (e.g., refs. [34,35]) both shared and personal, then classification of electric scooters and scooters with the help of smartphones [36], the estimation of the time and cost of the services provided by electric scooters [37], and so on. Bearing in mind that the spread of the application of both prediction models is wide, indicating their good predictive power, this paper aimed to reveal the most significant findings regarding the use of electric-powered microvehicles by applying both models.
Using IBM SPSS version 21 software, two models were developed with the 27 most significant independent variables as input, including socio-demographic characteristics, trip characteristics, attitudes about environmental pollution in Belgrade, and reasons for not using microvehicles. The acceptability of using a microvehicle was a dependent output variable with the possibility of the answer “Yes” or “No”.

To develop a model based on the performance of a neural network in the classification of users who accept and do not accept electric vehicles, it was necessary to create and develop several ANN models with an MLP structure to find the ideal number of neurons, hidden layers, and transfer functions, as evidenced by other studies [42,54]. In this regard, the results of this study indicate that the most adequate network model was the MLP trained with 27 input neurons, 9 hidden neurons in the first layer, 7 hidden neurons in the second layer, and 2 output neurons. The results of the MLP model in which the data are split into training, testing, and holdout sets containing 60%, 20%, and 20% of the data, respectively, with the hyperbolic tangent function as the activation function in the hidden layer and the identity function used in the output layer, indicate that the model gave better test results compared to BLR and thus showed a high ability to predict the acceptability of microvehicle use.

The results of predicting acceptability using a binary logistic regression indicate a very good predictive power of the model in terms of its significant classification accuracy, including when using all independent variables. Namely, the model can correctly classify 84.7% of all cases, that is, 90.9% of users who would accept the use of a microvehicle and 70.6% of those who would not. However, the multilayer perceptron proved to have better predictive power, with a prediction accuracy of 85.0% when tested. It predicted very well those users who would (91.9%) and those who would not (65.4%) use electric-powered microvehicles. Although both models have almost the same predictive power, the MLP model has slightly better accuracy, as many authors who have carried out research also concluded by comparing their mentioned models [27,28,55].

Also, by comparing the sensitivity parameter, identical findings are reached, indicating that both models can find a large number of instances of the “Yes” class (a sensitivity 0.88 for both) and a little less of the “No” class (0.74 for MLP and 0.78 for BLR) in the test data set. Combining the previously discussed precision and sensitivity measures indicates that the highest prediction accuracy for the entire data set for the answer “Yes” was that of the MLP (0.90), while for the answer “No” the highest accuracy was that of the BLR (0.74) model.

Both classification models indicate the great importance of certain independent variables when accepting the use of electric-powered microvehicles from an environmental point of view. Namely, the respondents’ awareness of the pollution of the environment in Belgrade by road vehicles, in terms of pollutant emissions, had a significant influence on their ultimate acceptance of microvehicles, as indicated by both considered models (BLR (p < 0.001) and MLP (NI = 100%)). This fact is confirmed by the chi-square test of independence ($\chi^2 = 21,594; p = 0.001$), which indicates the existence of a statistically significant association of this factor with the acceptability of microvehicles. The frequency of the use of bicycles when making trips for other purposes also has great significance when accepting electric-powered microvehicles, from the perspective of the BLR model (p < 0.001) and the MLP model (NI = 90.74%). The chi-square test of independence also, this time, confirms a significant statistical association with the ultimate acceptability of microvehicles ($\chi^2 = 24,565; p = 0.001$), indicating that users who have almost never used a bicycle for the stated purposes are more ready to accept them (35.4%). Such results are favorable, bearing in mind that, in this way, users can be influenced to reduce their use of the environmentally unfavorable vehicles that they use more often in exchange for the use of electric-powered microvehicles. Also, both models gave equally good results regarding the impact of the mileage traveled during commuting (BLR (p < 0.001) and MLP (NI = 84.02%)). In this regard, respondents who travel an average of 5 to 8 km one way during commuting trips
(35.4%) would most likely accept that the use of microvehicles to reduce environmental pollution. This is evidenced by a statistically significant association ($\chi^2 = 36,493; p = 0.001$).

In order to generate a reduction of environmental pollution, it is important to look at attitudes, regarding the microvehicles’ acceptability, of passenger car users. Namely, the frequency of using a passenger car when commuting also indicates a significant impact on the final outcome of acceptability ($\chi^2 = 39,446; p = 0.001$). According to the BLR model, users who never commute by passenger car ($p = 0.02$) have a higher chance of accepting the use of a microvehicle. Such a result is also confirmed by the percentage of users who would really accept using microvehicles and never commuting by passenger car (32.0%). However, a slightly smaller percentage of those who use a passenger car to commute every day (29.7%) are also willing to accept the use of a microvehicle, hence the normalized importance of 40.02% by the MLP model. In addition to the frequency of using a passenger car, the use of public transport when commuting is also statistically significant ($\chi^2 = 11,115; p = 0.025$) in influencing the acceptability of using a microvehicle. The BLR model indicates that users who use public transport to commute several times a month or a year ($p = 0.048$ and $p = 0.028$, respectively) have a higher chance of accepting these vehicles. However, in addition to a significant percentage of users who use public transport with these mentioned frequencies (12.3% and 19.7%, respectively), there are more who use public transport every day when commuting (38.3%) and are ready to use microvehicles to reduce pollution. The MLP model here indicates that the frequency of public transport use has moderate importance (NI = 46.88%). The results of the BLR model, which indicates that there is a significant influence of the (non)existence of infrastructure on acceptability ($p = 0.004$), fit with the statistical significance of the chi-square test of independence ($\chi^2 = 11,206; p = 0.024$). Namely, 42.6% of respondents would be ready to accept the use of microvehicles if the infrastructure for them was built. In addition, the MLP model here indicates that the impact of infrastructure has moderate importance (NI = 37.59%). Such results are confirmed by research, the findings of which indicate that, if there was a built infrastructure in Belgrade, the users of passenger cars, who mostly use them for other purposes, would switch to the use of environmentally sustainable modes of transport [56,57].

7. Conclusions

Road vehicles with internal combustion engines, both in the Republic of Serbia and Belgrade, have an increasing impact on air pollution through the emission of pollutants such as nitrogen oxides and PM particles. After a consideration of the various strategies for reducing environmental pollution that have been applied in many European cities, eco-mobility has proven to be very important in the fight against environmental pollution, and primarily exhaust gas emissions. In this regard, this work aimed to analyze the influence of different factors and predict the acceptability of the use of environmentally acceptable modes of eco-mobility transportation by the public in Belgrade.

Using the data obtained from our research, it was possible to determine how binary logistic regression algorithms and artificial neural networks could contribute to assessing the importance of the mentioned impacts, as well as the respondents’ attitudes regarding the use of environmentally friendly microvehicles. According to the research results, the MLP model was slightly more accurate compared to the BLR model when testing acceptability. With 85.0% of users correctly classified, the MLP model, with the hyperbolic tangent function as the activation function in its hidden layers and the identity function used in its output layer, conferred a high predictive ability to the model. This was followed by the BLR model, with an accuracy of 84.7%, indicating that both models are almost equally able to accurately classify users. In this regard, both models more accurately classified users who would accept the use of eco-mobility vehicles (91.9% MLP and 90.9% BLR), compared to those who would not (65.4% MLP and 70.6% of BLR).

The best ANN model was identified by the area under its ROC for each response class (0.895), with a predicted pseudo-probability greater than 0.5 primarily for the “Yes” response. In addition, according to the analysis of the MLP neural network, the most
powerful predictors of acceptability are the respondents’ awareness of the environmental pollution in Belgrade by road vehicles in terms of pollutant emissions (NI = 100%), the frequency of respondents using bicycles when moving for other purposes (NI = 93.53%), and the average mileage covered while commuting (NI = 84.02%). The BLR model is associated with similar predictive results \((p = 0.001; p = 0.001\) and \(p = 0.014\), respectively). In contrast to the BLR model, the MLP model also indicates that the frequencies of motorcycle and bicycle use when commuting (NI = 73.91% and 71.35%, respectively) play a significant role in the willingness of people to use these eco-mobility vehicles. Finally, in addition to the frequency of trips by different modes of transport and with purposes of travel, the income of the respondents has the most significant influence (NI = 66.66%), which indicates that respondents with the lowest income (less than EUR 250 per month (30.6%)) have a greater willingness to use electric-powered microvehicles, which justifies ensuring the affordability of the vehicle price and lower travel costs, in addition to their environmental benefits.

The results of this study can greatly help the authorities to develop strategies to reduce environmental pollution, based on the most influential indicators of the acceptance of the use of electric microvehicles obtained from this study. Also, although the research was conducted with the example city of Belgrade, this does not prevent decision-makers from potentially considering the introduction of microvehicles into cities with a similar problem of environmental pollution to Belgrade, based on the results of this study. On the other hand, based on their relatively good prediction accuracy, the applied mathematical models can significantly benefit decision-makers in predicting the acceptability of microvehicles based on publicly available data.

Future studies on the acceptability of new modes of transportation, from an ecological aspect, could deal with an analysis of the acceptability of the use of eco-mobility shared systems as an incentive to change travel behavior. Despite strong indications that our proposed neural network model could be more effectively applied to forecasting, our binary logistic regression model gives very good results without correcting the originally developed model. In this regard, future studies could be based on increasing the sample size, as well as conducting field research to obtain more precise answers. An interviewer would greatly help resolve doubts during the survey and gather more accurate answers, which, in addition to generating a better sample, would have significant advantages in the formation, and later training and testing, of the model. This would also eliminate potential bias from data collection, a limiting factor in this study.

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**References**


15. Jiao, J.; Bai, S. Understanding the Shared E-scooter Travels in Austin, TX. ISPRS Int. J. Geo-Inf. 2020, 9, 135. [CrossRef]

16. Bai, S.; Jiao, J. Dockless E-scooter usage patterns and urban built Environments: A comparison study of Austin, TX, and Minneapolis, MN. Travel Behav. Soc. 2020, 20, 264–272. [CrossRef]


18. Zhang, C.; Wang, C.; Sullivan, J.; Han, W.; Schuetzle, D. Life cycle assessment of electric bike application in Shanghai. SAE Tech. Pap. 2001, 9, 3727. [CrossRef]


27. Agirre-Basurko, E.; Ibarra-Berastegi, G.; Madariaga, I. Regression and multilayer perceptron-based models to forecast hourly O3 and NO2 levels in the Bilbao area. Environ. Model. Softw. 2006, 21, 430–446. [CrossRef]


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