PREDICTING WILLINGNESS TO SHIFT TOWARDS BICYCLE USING MACHINE LEARNING MODELS AND QUANTIFYING ITS ECONOMIC BENEFITS: EVIDENCES FROM KOLLAM COASTAL AREA

A PROJECT REPORT

Submitted by

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T.K.M. College of Engineering, Kollam

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DECLARATION

I undersigned hereby declare that the project report “Predicting willingness to shift towards bicycle using machine learning models and quantifying its economic benefits: Evidences from Kollam Coastal Area”, submitted for partial fulfilment of the requirements for the award of degree of Master of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of Prof, Meenu Tomson, Assistant Professor. This submission represents my ideas in my own words and where ideas or words of others have been included. I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/ or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

KOLLAM
07.07.2022 **REVATHY SURESH**

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CERTIFICATE

Certified that this report entitled **'PREDICTING WILLINGNESS TO SHIFT TOWARDS BICYCLE USING MACHINE LEARNING MODELS AND QUANTIFYING ITS ECONOMIC BENEFITS: EVIDENCES FROM KOLLAM COASTAL AREA'** is the report of seminar presented by **REVATHY SURESH, Reg. No. : TKM20CETE12** during **2020-2022** in partial fulfilment of the requirements for the award of the Degree of Master of Technology in Transportation Engineering of the A P J Abdul Kalam Technological University.

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ABSTRACT

The increase in vehicle ownership among the cities is mainly due to the predicted economic growth. These growth leads to the global warming, emission of greenhouse gas, hike in price of different fuels and traffic congestion. Due to this problems in the environmental and transportation, the health and the life style of the society is badly affected. So to reduce these effects, one of the solutions is switching to non – motorized traffic such as bicycling and walking. In this thesis, a study was conducted to know the people's willingness to shift towards non-motorized transports. The study also determined the different factors such as socio economic, environmental and transportation system characteristics that affect the commuters' choice on using bicycle as mode of travel. For the purpose of the model development, about 868 household surveys were collected in Thangassery-Thanni coastal road stretch through household interview survey. The user perception survey was conducted for identifying the perception of society about the use of bicycle as main or feeder mode. The Adaboost Classifier, a machine learning technique was used to analyze the important attributes that influences the shifting towards bicycle the study incorporated three supervised machine learning algorithms (K-Nearest Neighbor, Support vector machine, Random Forest) to predict willingness to shift towards bicycle as a mode of transport. The results indicated that Random Forest model outperformed with an accuracy of 0.94. A health benefits analysis in terms of mortality when bicycle is used as mode of travel was carried out using Health Economic Assessment Tool (HEAT) for 1% mode shift. The total economic value of carbon emission on all pathways is monetized as 3870 USD (302556 INR) and considered as the health benefit that can be saved per day while cycling in the study stretch.

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Key Words*: Global Warming, Non-Motorized Transportation , Adaboost Classifier, Attributes, Random Forest Method, Support Vector Machine, K- Nearest Neighbor, Health Benefits, Health Economic Assessment Tool (HEAT)*

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ABBREVATIONS

AICMA	-	All India Cycle Manufacturers´ Association
CART	-	Classification and Regression Tree
HEAT	-	Health Economic Assessment Tool
IG	-	Information Gain
K-NN	-	K-Nearest Neighbors
ML	-	Machine Learning
MoHUA	-	Ministry of housing and Urban Affairs
NMT	-	Non-Motorized Transportation
NMVs	-	Non-Motorized Vehicles
RR	-	Relative Risk
SVM	-	Support Vector Machine
VSL	-	Value of Statistical Life
WEC	-	World Energy Council
WHO	-	World Health Organizations

CHAPTER - 1

INTRODUCTION

1.1 General

The transportation sectors in most of the countries are lacking sustainability due to increase in motor vehicles and deficiency in natural oil reserves. It leads to the rise in motor accidents, traffic congestions and environmental pollutions which affects the life mobility. The transportation sector becomes sustainable when it is safe, economically efficient, environmental friendly and efficiency in energy consumption (Yazid et al., 2011). There was rise in population of urban regions globally from 30% to 54% between 1930 and 2014. According to the population prediction, there is an escalation of 66% in 2050 (Mansoor et al., 2022, United Nations, 2014) as shown in Figure 1.1.

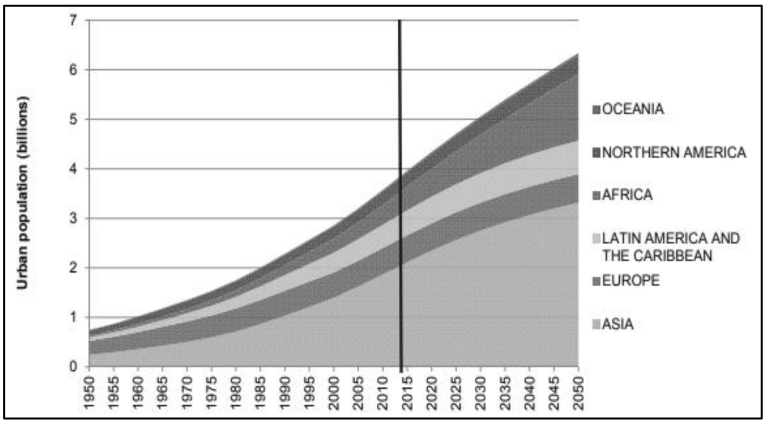

Figure 1.1 : Increase in urban population from 1950 to 2050

(Source: United Nations, 2014)

Due to increase in population, the demand of motorized mode was also surges from 2.2 to 2.6 times globally from 2014 onwards (Mansoor et al., 2022 and WEC, 2011). Most of the people are using motorized modes even for short walk-able or bicycle-able distances which resulting in increase in transportation problems. Due to the vehicle demand increase, there are popping up of new issues like accident causality, health issues and limited parking space (Bamney & Tiwari, 2020). This leads to congestion and emissions that cause notable declination in traffic speed results in time and fuel consumption (Mansoor et al., 2022 and Rith et al., 2019). The energy consumption is also observed to be increased by 69% (2002 - 2010) in most of the developing countries including India which results in hike in vehicular emissions (Mansoor et al., 2022 and Hickman et al., 2011).The emission from mobile source is one of the main root for the change in climate, global warming and environmental pollution (Mansoor et al., 2022 and Patten & Toynbee, 1972).

1.2 Problem Statement

In India, bicycles are most flexible an affordable means of transportation especially for the less income people or poor people for reaching the workplaces (Majumdar & Mitra, 2018). The choice riders in the urban regions prefer bicycle as short distance mode, recreational use, exercise or for shopping trips. This is mainly for the small and medium-sized Indian cities, where the average trip-length for bicycles varies from 1.9 to 3.1 km for small-sized cities and 3.1 – 5.4 km for medium sized and other cities (Tiwari & Jain, 2013). Even though a part of the urban regions are using bicycle as an important mode, a sharp declination in its use was observed. Even a short distance bicycle trips are being replaced by motorized vehicles can be seen in the cities. According to AICMA, 2014, the potential bicyclist are not using bicycle mainly due to inadequate bicycle facilities and unsafe conditions. Even though some of the cities have these facilities, they are not serving the exact purpose due to improper planning and implementations. The encroachment, on – street parking, poor pavement condition and intrusion by motorized vehicles are utilizing these lanes in cities such as Ahmedabad and Delhi which have provided dedicated bicycle tracks along the Bus Rapid Transit System (BRTS) corridor (AICMA, 2014). So a thorough understanding of different attributes that influences the NMT implementation is necessary for the better infrastructure provision.

Therefore, proper design and planning of bicycle facilities by considering the needs of various user groups has to be done. For the formulation of such policies for bicycle infrastructure related improvements, it is necessary to obtain user preference on various bicycle route-related improvement scenarios and evaluate them in terms of associated user benefit. The main factor which hinders the policy makers is the lack of understanding about the economic benefits they offer (Rahul & Verma, 2013a). According to them, these modes are not providing revenue to the government. So a complete understanding of economic benefits of these types of modes is necessary (Rahul & Verma, 2013a).

1.3 Research Statement

One of the solutions for the transportation problem is promoting the usage of Non-Motorized Transportation (NMT) including cycling and walking (Mansoor et al., 2022). The NMT penetration into the transportation system and vehicle technology enhancement is necessary for the improvement of use of sustainable transport (Mansoor et al., 2022 and Jacobsen et al., 2009). Most of the developed countries have already adopted the Non-Motorized Transportation for air quality improvement and to alleviate causes of global warming. Since it becomes a key element for encouraging sustainable transportation, the promotion of these types of vehicles and provision of better facilities like bike sharing programs, bike lanes etc. makes it more attractive. It can also be revived by providing policy packages consist of smart urban plans, awareness campaigns etc. The various benefits such as travel cost benefits, health, congestion and accident cost benefit that can be enjoyed by the user due to the mode shift has to be analyzed. This awareness about the benefits may convince the society for choosing the bicycle as a mode of travel (Mansoor et al., 2022).

1.4 Objectives

The objectives for the proposed study are as follows:

- To find the most significant attributes that influences the implementation of bicycle mode of transportation in Kollam coastal areas using Adaboost classifiers.
- To find the best predictive model among Random Forest, Support Vector Machine and K-Nearest Neighbors for assessing the mode shift from Motorized to Non-Motorized Transportation
- To quantifying the economic benefits in terms of health cost using HEAT tool.

1.5 Scope of Work

- The assessment of willingness to shift towards Non-Motorized Transport in the coastal areas between Thangassery and Thanni was taken for the study.

- The study was concentrated only on the bicycle mode of transport among the other Non-Motorized Transport modes.
- The assessment of willingness to shift was analyzed using only machine learning techniques.
- For the economic benefit analysis, only the health cost was considered.

1.6 Organization of Report

The thesis is structured into seven main chapters. Chapter one describes the background of the study, problem statement, research significance, objectives and scope of the study.

Chapter two reports the literature review on the benefits of NMTs, various factors influences the mode shift to Non-Motorized Transportations and the different modeling methods adopted for the study.

Chapter three discusses the research methodology. Data collection and analysis methods adopted for the study are described in this chapter. It discusses the questionnaire survey adopted to study the various factors.

Chapter four presents the study area, pilot survey, questionnaire survey and economic analysis. The sample population calculation and reliability test using SPSS software are also discussed in this session.

Chapter five reports the descriptive analysis of respondents, prediction modeling for the willingness to shift and the health impact assessment using HEAT tool.

Chapter six describes the policy and recommendations for the adoption of bicycle in the area by providing better facilities and chapter seven discusses the major findings and scope for future studies.

CHAPTER - 2

LITERATURE REVIEW

2.1 General

The Non-Motorized Transportation (NMT) is the active or human powered transportation which includes walking and Non-Motorized Vehicles (NMVs) (Yazid et al., 2011). These vehicles are more effective for short trips upto 7 km in urban areas (Zuidgeest et al., 2009). They are highly perforated and can be essential link to multimodal transport systems (Mansoor et al., 2022 and Qureshi & Lu, 2007). Some of the advantages of this mode of transportation for the society are less congestion, reduction in health and social cost etc. They are healthy mode or it is good for the community health (Singh, 2018). The Figure 2.1 shows the Non-Motorized Transportation in Indian cities.

Figure 2.1 : Non-Motorized Vehicles (NMVs) in India

(Source: MoHUA, 2016)

2.2 Benefits of Non-Motorized Transportation

The Non-Motorized Transportation (NMT) has so many benefits in terms of social, economic and environmental aspects which are being elaborately discussed in the below section (MoHUA, 2016). It does not emit greenhouse gas emissions or local air pollutants. NMT, particularly cycling, is easy, flexible and cheap. It reduces the travel times due to improved traffic flow. Congestion reduction, health benefits due to exercise are some of the social benefits. The Table 2.1 shows the benefits that can enjoy using non-motorized transport.

Table 2.1 : Benefits of Non-Motorized Transport.
(Source: MoHUA, 2016)

Social Benefits	Economic and Fiscal Benefits	Environmental Benefits
• Equitable and improved accessibility. • Improved physical health • Improved public transit access • Improved road safety • Place making	• Reduced dependency on fuel • Affordability • Tourist economy	• Reduce congestion • Better air quality • Noise reduction

2.2.1 Social Benefits

The social benefits of NMT include equitable and improved accessibility, improved physical health, improved public transit access, improved road safety and place making (MoHUA, 2016). The cycling mode improves user accessibility of their choice. It can be used by different social classes thereby provides an equitable accessibility. It also boosts individual health by improving sedentary lifestyle. An average cycling trip is same to the necessary exercise level (average of 20 – 30 mins). The NMT mode can be encouraged by integrating with multi – modal transportation, though the trip length and patterns are longer in cities. The proper road safety measures and promotion of NMT modes can self-emphasize the relation between them. It promotes the increasing use of bicycles, thereby greater impulse in creation of safe human communities.

2.2.2 Economic and Fiscal Benefits

The economic and fiscal benefits contain the reduced dependency on fuel, affordability and tourist economy (MoHUA, 2016). The daily consumption of petroleum products can be bringing down by reduces use of motorized modes for daily trips. This will reflect on country’s economy. The NMT modes are of minimum operating cost as they are not using fossil fuels. The bicycle tourism attracts people for local and short vacations towards rural areas.

2.2.3 Environmental Benefits

The Environmental Benefits includes congestion and noise reductions and better air quality (MoHUA, 2016). It improves the air quality by reducing pollutions by shifting towards NMT modes.

2.3 Factors Affecting Non - Motorized Transportation

The various attributes that affects the Non-Motorized Traffic is being discussed in this section. These factors includes Socio – Economical Characteristics, Environmental Characteristics, Transportation System Characteristics, Micro Scale Urban Design Factors on walk and cycle modes when they used as main mode (Bamney & Tiwari, 2020, Rahul & Verma, 2013a). The socio – economic characteristics includes age, gender, occupation level, income level etc. The environmental characteristics are mixed land-use, population density, topography, weather. The micro scale urban design factors contain the presence and continuity of sidewalks, bike lanes and trails, and proper street lighting, encourage the use of non-motorized modes etc. The transportation system characteristics includes travel time, travel speed, distance etc. (Bamney & Tiwari, 2020, Rahul & Verma, 2013a). The Table 2.2 shows various factors that are to be considered for Non-Motorized Transportation design.

Table 2.2 : Factors affect the Non-Motorized Transportation

(Source: Bamney & Tiwari, 2020, Rahul & Verma, 2013a)

Socio-Economical Characteristics	Environmental Characteristics	Transportation System Characteristics	Micro Scale Urban Design Factors
• Age • Gender • Occupation level • Income level • Vehicular ownership	• Mixed land-use • Population density • Slope of paths • Safety condition	• Travel time • Travel speed • Travel distance • Safety	• Sidewalks • Bike lanes and trails • Proper street lighting • Encourage the use of NMT

2.3.1 Socio Economical Characteristics

The socio – economical characteristics includes gender, level of education, age, household income, private motor vehicle ownership, the purpose of trip etc. According to Bamney & Tiwari, 2020, the age, occupation level, income level and vehicular ownership increases the willingness to use NMVs decreases. It was interesting to see that female mandatory trip makers were more willing to shift to NMT mode as compared to males. The people use the motorized modes such as car reduces the use of bicycling. Rahul & Verma, 2013a found a negative relationship between vehicle ownership and bicycle mode choice. The households with low income are mainly using bicycle as mode of travel. According to Bamney & Tiwari, 2020, the income level below 15,000 INR was showing more interest in using NMT because of high affordability and less travel distance (average of 2.5 km). But none of the people with income higher than 50,000 INR was using NMT modes for the work purpose (Joshi & Shah, 2018). As age increase, preference towards bicycle and walking decreases (Rahul & Verma, 2013b). According to Bamney & Tiwari, 2020, the respondents below 18 years are preferring NMVs. Rahul & Verma, 2013a found a positive likelihood of school purpose on choosing bicycle mode. There is a huge scope for policy makers to target this section for the promoting bicycle mode of travel.

2.3.2 Environmental characteristics

The environmental characteristics include mixed land-use, population density, slope of paths, safety condition, walking or cycling index, land-use variable. The mixed land use and population density had positive relationship with bicycle mode. But due to lack of infrastructure the safety of bicycles decreased results in usage of bicycle is reduced (Bamney & Tiwari, 2020). According to (Heinen et al., 2010; Parkin et al., 2007; Twaddle, 2016) the topographical features such as hilliness negatively influencing to choose bicycle as a mode. The level of experience preferred the grade of road, with high experiences in riding choose mountainous region while others choose the flat terrain (Stinson & Bhat, 2003; Twaddle, 2016). Also the daily weather conditions and climatic conditions has found to be influencing the bicycle mode of travel (Twaddle, 2016).

2.3.3 Transportation system characteristics

The transportation system characteristics include travel time, travel speed, distance and safety for walk and cycle. According to Bamney & Tiwari, 2020, if the bicycle speed is 15 km/hr then a person covers 3.75 km in 15 minutes. This shows that people choose bicycle for short distance travel due to low speed and physical effort.

2.3.4 Micro-scale design

Some of the micro-scale urban design factors are the presence and continuity of sidewalks, bike lanes and trails, proper street lighting, attractiveness or aesthetic quality such as scenery, landscaping, shopping opportunities etc. (Bamney & Tiwari, 2020, Rahul & Verma, 2013a).

2.4 Analytical Models Used

In a previous study conducted in the Bangalore city, the influence of different factors influence the mode shift to walk and cycle as main mode was determined. The analysis was done using logistic regression model from household survey in the city. They concluded that there is reduction in choosing the mode due to increase in age as well as travel time. The other vehicle ownership is not willing to shift towards this mode. The females were showing postiveness towards walking. Increased density and mixed land use also influences the mode shift (Rahul & Verma, 2013b). In the study of Vijesh et al., 2014 for the Calicut city, the percentage people shift towards bicycle from car if segregated track provides using logit model. It is found from the survey that 45% of people whose age below 25 years were willing to shift towards bicycle for mandatory trips.

A study was conducted in Kharagpur, India related to the influence of factors such as Physical, Psychological, Economic, Congestion, Weather etc. to choose bicycle mode. A survey related to travel behavior of users was conducted and compare with perception of experts using Analytical Hierarchical Process. It results in finding the important parameters such as safety, route related, physical factors are concerning to use bicycle for both the users and experts (Majumdar & Mitra, 2015). A study regarding behavior of mode choice modeling in Delhi by Sekhar et al., 2016, using Decision Tree and Random Forest methods. The household sample of 5000 were taken for the study and compare with the Multinomial logit model. It is found that Random forest is the best fit for the analysis with accuracy of 98.96% than logit model with 77.31%.

The quantification of bicyclist's perception for certain related attributes for willingness to pay is done in the study conducted by Majumdar et al., 2017. A comparative study for socio demographic studies in Kharagpur and Arsanol city, India was done by conducting a Stated Preference survey to evolve Multinomial logit (MNL) and Random Parameter Logit (RPL) models. The factors considered where income, road width, risks of level, journey time etc. RPL models are more superior to the other for the data for the behavior analysis. Level of risk found to be the most influential factors among others. In Kharagpur journey time was found to be less influent but in Arsanol, it is 4 to 5 times lesser and they prefer safer than shorter routes.

Bamney & Tiwari, 2020, was conducted a study regarding the potential usage of NMTs in Rewa city, India. Revealed and Stated preference data was taken for mandatory and non-mandatory trips of NMVs. 27% and 11% mandatory and non-mandatory trips were done using NMVs. The main attributes such as age, occupation, vehicle occupancy, shorter trips below 3 kms influence more for the shifting towards NMTs. A logistic Regression analysis was modeled to analyze the percentage of shift and found an accuracy of 80% in predicting. According to the study conducted in Bidar city by conducting a survey, 90.8% people are aware of health beneficial of cycle and 87% are using NMT for short trips such as shopping, other needs etc.82.4% people are willing to use NMT as an integrated public transport (Birkur et al., 2021).

CHAPTER - 3

RESEARCH METHODOLOGY

3.1 General

The conceptual frame work of methodology is mainly includes the identification of different attributes that influences the implementation of Non-Motorized transportation (NMT) and the estimation of the willingness to shift from motorized transport to Non-Motorized Transportation. It also contains quantification of the economic benefits in terms of health cost using HEAT tool for Non-Motorized Transport modes. The methodology is fabricated as below in Figure 3.1.

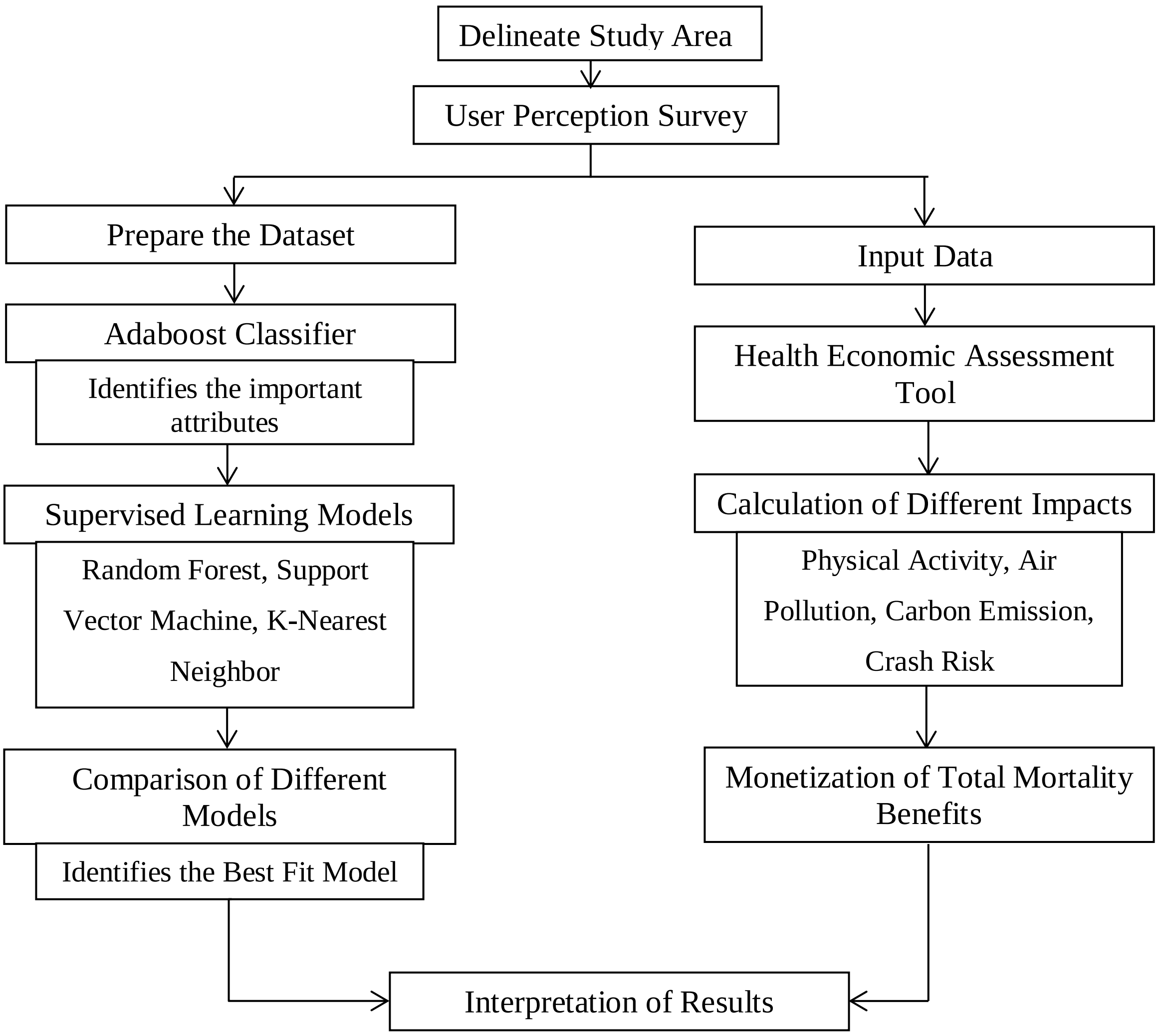

Figure 3.1: Flow chart of the methodology

3.2 Machine Learning

The Machine Learning (ML) is the research in algorithms and the models for statistics. It teaches computer about the efficient handling of data, when there is rich datasets. The implementation of algorithm type depends on variables, the problem type, model that suits best etc. (Batta, 2020). It makes system brilliant for making decisions on particular problem without any external operations (Pandey, 2019). The ML techniques are used in Face and voice recognition, Social media, Image processing etc. (Kavitha, 2020).

3.2.1 Machine Learning Models

For the machine learning, the system uses given data or dataset or raw data. The process contains two steps mainly model training and model testing or decision making (Pandey, 2019). Training data trains the model by preprocess the data and extract the features. The trained model thus obtained decides the decisions for unknown or the test data. The Figure 3.2 shows the training and testing of models.

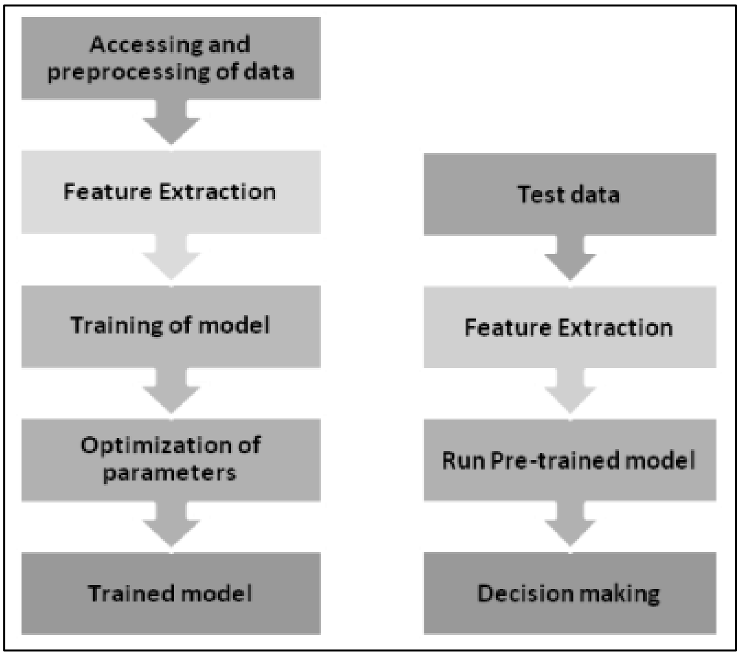

Figure 3.2 : The training and testing of ML models

(Source: Pandey, 2019)

3.2.2 *Real world data*

The machine learning models are constructed using the available data. The data are of different types such as structured, unstructured and semi structured (Sarker, 2021). The structured data are precise data in standard manner which are easily accessible. They are stored in tabular format of data such as names, addresses, dates etc. In unstructured data, they are not organized one which are difficult to process and analyze. These include PDF files, email, audio files etc. In case of semi- structured data, they are not précised one but can easily analyzed such as HTML, XML documents etc. (Sarker, 2021).

3.2.3 *Classification and Regression*

Classification

Classification refers to the predictive models for class labels. It draws a function from independent variables (x) to dependent variables (y) in the form of labelled or categorical value (Sarker, 2021). The common classification problems are binary, multi-class or multi label classifications. The binary classification is the classification tasks with two class labels such as yes/no, true/false. In multi-class class, the classification tasks have more than two class labels which are classified to one. In multi-label classification, the classification tasks belong to several classes or labels which are ranked one (Sarker, 2021).It is the one of the problems that the unknown values of previous categories-classes with discrete values. The similarities between values of two different classes are determined by their characteristics. The main task is that making a model that performs classification for new inputs (Fawcett, 2003; Marzban, 2004; Vardhan et al., 2012). The number of cases is known and finite beforehand in classification problems (Novakovi, 2017).

Regression

Regression predicts continuous variables (y) according to one or more independent variables (x). The classification predicts particular class label and regression predicts the continuous quantity. Some of the types are polynomial, linear regression etc. (Sarker, 2021). The Figure 3.3 shows the classification and regression. In classification, the linear separation of two classes represented by dotted line. In regression dotted line indicates the linear relationship between the variables.

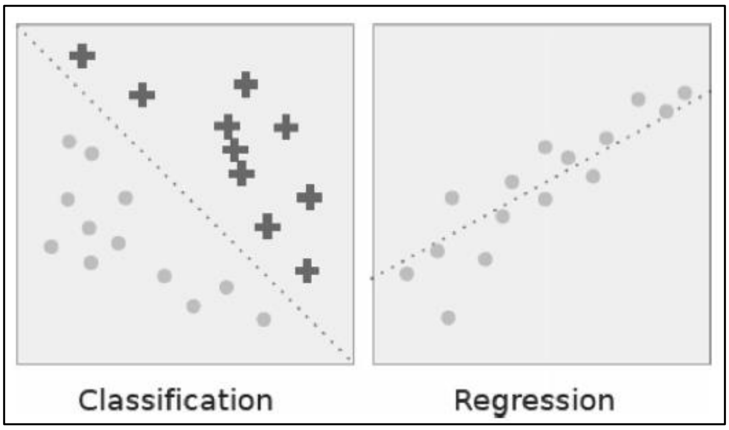

Figure 3.3 : Classification vs. regression.

(Source: Sarker, 2021)

3.2.4 Parametric and Non-parametric ML Algorithms

Parametric Algorithms

The parametric algorithms make the function simple to a known format. It condensed the data with fixed number of independent training data into permanent size in spite of the data amount. Initially select the structure for the particular task then identifies the coefficients in the training dataset. Some of the algorithms are Logistic Regression, Naïve Bayes, and Perceptron. They can be easily understandable and can be interpret easily but confirmed to particular form (Brownlee, 2022).

Non-Parametric Algorithms

This type of algorithm is used when there is abundant data with no detailed description. It fits the best training data for construct the particular function to generalize it. Some of the examples are K-Nearest Neighbors, Decision Trees like CART and C4.5, Support Vector Machines (Brownlee, 2022).

3.2.5 Tasks of ML Techniques

The major ML tasks are categorized based on character of learning available to the system (Sharma, 2017). They are supervised, unsupervised and reinforcement learning as shown in Table 3.1.

Table 3.1 : Types of Machine Learning Techniques

(Source: Batta, 2020)

Supervised Learning	Unsupervised Learning	Reinforcement Learning
• Decision Tree • K Nearest Neighbor • Support Vector Machine • Random Forest	• K-Means Clustering • Apriori Algorithm	• Markov Decision Process • Q learning

Supervised Learning Algorithm

In the supervised learning algorithm, the input dataset split into training and testing data. The training dataset contains the output variables to be predicted or classified. The algorithm follows some algorithm pattern from training set and applies to the testing set for the prediction as shown in Figure 3.4 (Dey, 2016). It is mainly used to find classification and regression problems. The classification methods solves the discrete value problems while regression predicts the problem of continuous variables (Pandey, 2019). The examples are Decision Tree, Random Forest, Support Vector Machine, k Nearest Neighbors etc. (Kavitha, 2020).

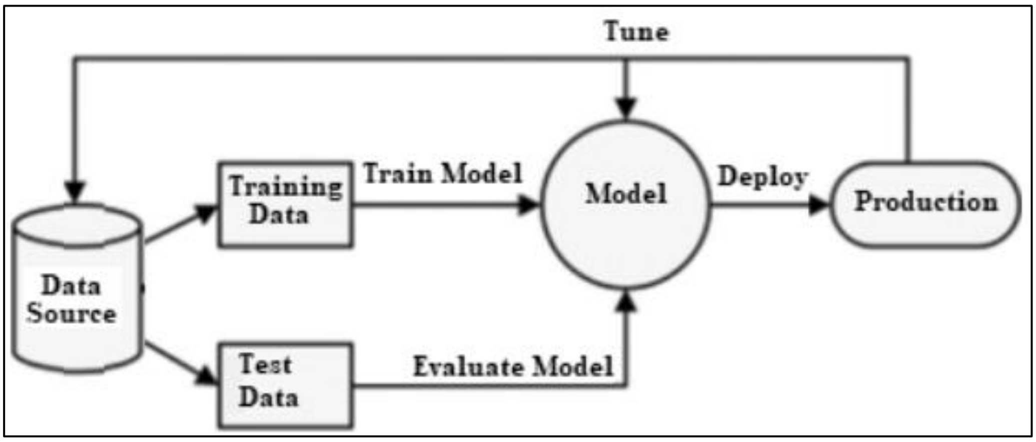

Figure 3.4 : Working of supervised machine learning algorithms

(Source: Batta, 2020)

Decision Tree

It is a structure classifier which controls the non-linearity between attributes and class (Jafarzadeh et al., 2021; Friedl and Brodley, 1997). In this method, the data which is input into the algorithm is being splits into smaller sub nodes based on thresholds (Jafarzadeh et al., 2021; Friedl and Brodley, 1997; Song & Lu, 2015). The first node which is the root node is split into different layers of sub nodes and end nodes are the leaf nodes which indicates the predicting class or result (Jafarzadeh et al., 2021; Maxwell et al., 2018; Pal & Mather, 2003). The splitting of data is based on any of the criteria such as Gini Impurity, Entropy etc. Each of the attributes are calculated using the above and arrange the tree with the highest value at the top. The Gini impurity predicts whether the randomly selected feature is incorrectly classified to a node. It is called as an impurity criterion since it shows how the mode differs by pure one. The degree ranges from 0 to 1 with 0 implies all the features belong to one class and 1 indicates random distribution of attributes over different classes (Methods for Decision Tree Split, 2022).The Gini impurity is used by Classification and Regression Tree (CART) algorithms which constructs exactly binary internal nodes (children) (Saud & Shakya, 2022). The Formula is given in Equation 1 (Medicherla et al., 2020).

$$GINI = 1 - (P_1^2 + P_2^2 + \cdots \ldots \ldots \ldots + P_N^2) = 1 - \sum_{i=1}^{m} p_i^2 \qquad (1)$$

where,

N is the number of different classes in the training dataset

P is the probability or fraction of particular class to the data set.

The entropy E(D) is the uncertainty measurement of random variables or the sample homogeneity. It is given by Equation 2 (Saud & Shakya, 2022).

$$E\,(D) = -\sum_{i=1}^{m} p_i \, log_2 p_i \qquad (2)$$

where,

p: probability of attribute in a particular class.

The information gain evaluates entropy reduction after transform the data by compare before and after transform or the parental and children nodes. The Iteration Dichotomiser 3 (ID3) calculates information gain for every attributes and selects the highest one. The Equation 3 shows the Information Gain (IG(A)) (Saud & Shakya, 2022).

$$IG (A) = E (D) - E_A(D) \tag{3}$$

Random Forest

It is used for classification and regression analysis. It makes various decision trees using the dataset, predicts the result from each of them and finally chooses the best option using voting (Kavitha, 2020). The decision trees produce trees having appropriate solutions for the problem of certain conditions. The trees are produce by induction and pruning. In induction, the decision trees are built and in pruning, the trees are simplified by remove its complexities. It starts with the single root or decision which splits into different branches until gets a correct prediction (Kavitha, 2020). Random forest is an ensemble technique that declines the over fitting by taking the average of result. Figure 3.5 shows the working algorithm of Random Forest.

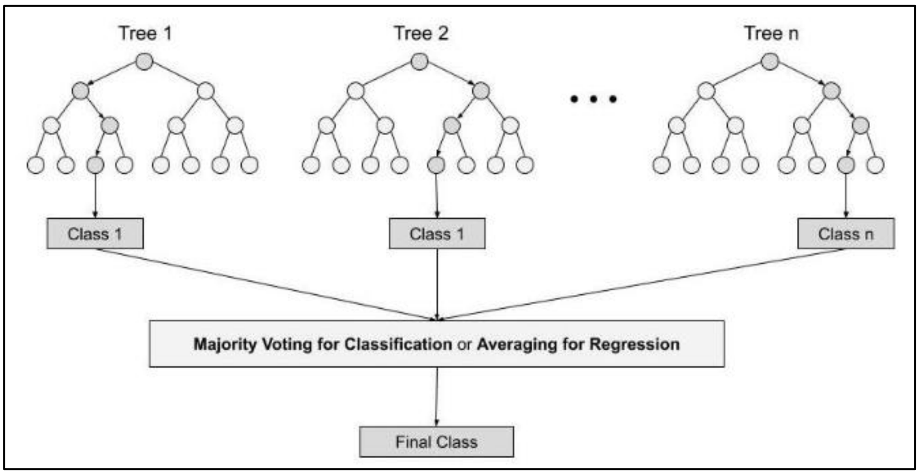

Figure 3.5 : Working Algorithm of Random Forest Method

(Source: Introduction to Random Forest Algorithm, 2022)

Ensemble method is a combination of different learning techniques. It provides better result for the problems. The two most well-known methods are boosting and bagging. The boosting reduces the variance and bias. It combines the weak learning approaches that produce seldom makes logical result (Pandey, 2019). The bagging is the systematic ensemble method to combine different predictors individually by averaging such as major voting etc. The difference between bagging and boosting are shown in

Table 3.2 (Jafarzadeh et al., 2021). The bagging or bootstrapping makes stable results by reducing invariance problems and controls the over fitting (Pandey, 2019).

Table 3.2 : Difference between Boosting and bagging

(Source: Jafarzadeh et al., 2021)

Bagging	Boosting
Independent models or predictors.	Models or the predictors are dependent on each other.
The predictors are not learning from each other.	Succeeding by reducing the predictive error of the preceding individual predictors or models.
Decreasing the variance is the main aim.	Reducing the bias is the main aim.

K-NN (K- Nearest Neighbors)

K-NN is the K-Nearest Neighbors is an instance-based or non-generalized or lazing learning. In lazy learning, for generating the models there is no need of training data. It is used for data mining and machine learning. Based on same data as that of present data and identifies the pattern they follow (e.g., Euclidean distance). Using majority of voting of each data points, the classification is decided. Larger training data implies the accurate model (Kavitha, 2020, Sarker, 2021 and Pandey, 2019).

Support Vector Machine

The basic working principle of support vector machine is the margin calculation (Dey, 2016). The dataset are separate using the margin such that maximizes the minimum distance between margin and data points that minimize classification error (Batta, 2020). The apt boundary is the hyper plane and the data point which are closest to this the support vectors shows in Figure 3.6.

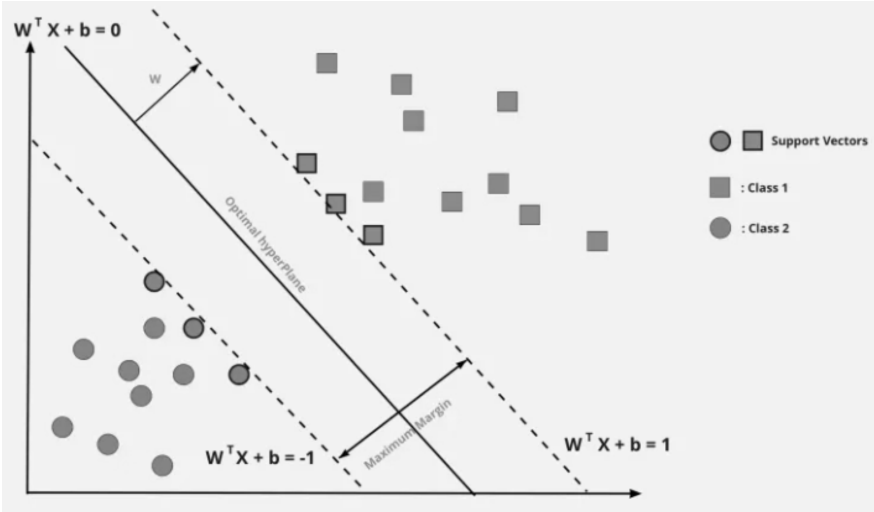

Figure 3.6 : Support Vector Machine Algorithm

(Source: Seven Most Popular SVM Kernels, 2022)

The support vector machine performs both linear and non-linear classifications. One of the problems in the analysis is the diversification of data dispersion which is the nonlinear classification problem. The nonlinear classification is the kernel trick which maps input into high dimensional spaces (Nanda et al., 2018). The kernel functions are given by equation 4:

$$K(\overline{x}) = \begin{cases} 1, & if\ \|\overline{x}\| \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The different SVM kernel functions are linear, polynomial, radial basis functions (Seven Most Popular SVM Kernels, 2022). Linear kernel is the basic kernel function in one dimensional nature. It is the best for text classification problems with lots of attributes. They are linearly separated one. Polynomial kernel is the generalized forms which are less efficient and not preferred as others. The Gaussian radial basis function used in nonlinear data. It separates data properly even though no basic knowledge about data. The Table 3.3 shows the different kernel functions.

Table 3.3 : The different kernel functions

(Source: Nanda et al., 2018)

Kernel Types	Kernel Formula	
Linear Kernel Function	$F(x_i, x_j) = \Sigma(x_i \times x_j)$	x_i, x_j are the data to be classified
Polynomial Kernel Functions	$F(x_i, x_j) = (x_i^T \times x_j + 1)^d$	d is the degree
Gaussian Radial Basis Function	F(x_i, x_j) = exp(-gamma × ||x_i - xj||^2)	Gamma range between 0 to 1 preferably 0.1

Adaboost Algorithm

Adaboost technique maintains a collection of weights over training data and adaptively modifies them after each weak learning cycle to produce a set of poor learners. While the weights of the training samples that the current poor learner incorrectly classified will grow, the weights of the samples that were successfully classified will decrease. Maintaining a distribution or set of weights across the training set is one of the core concepts of the Adaboost algorithm. This distribution's weight for training example i on round t is indicated as D_t (i). All weights are initially initialised evenly, but after each round, the weights of the examples that were mistakenly identified are increased, forcing the poor learner to concentrate on the challenging examples in the trading set. One of the most promising, quickly convergent, and easily implementable machine learning algorithms is Adaboost. It can be easily integrated with other methods to find weak hypotheses, such as support vector machines, and it doesn't require any prior knowledge of the weak learner (Wang, 2012). The Figure 3.7 shows the features selection steps.

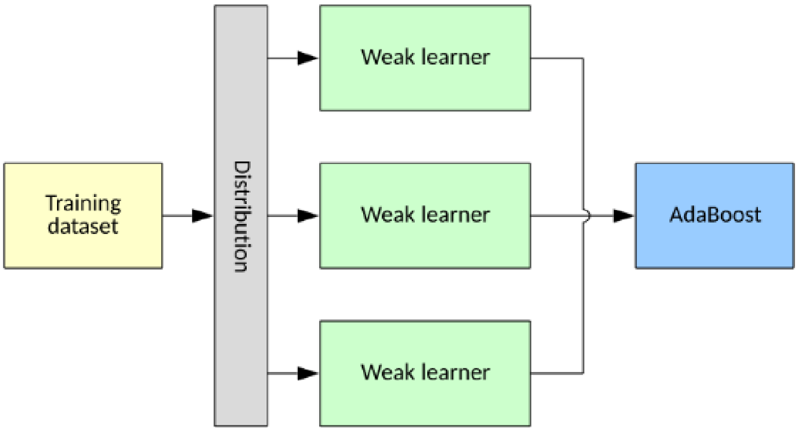

Figure 3.7 : Steps of feature selection

(Source: "IBM Developer", 2022)

Unsupervised Learning Algorithm

In unsupervised learning, the output variables to be predicted are unknown. It is mainly used for clustering problems (Kavitha, 2020) and reducing features (Dey, 2016). When new dataset is provided, it learns from the previous to identify the data class (Dey, 2016).The Figure 3.8 shows the algorithm implementation.

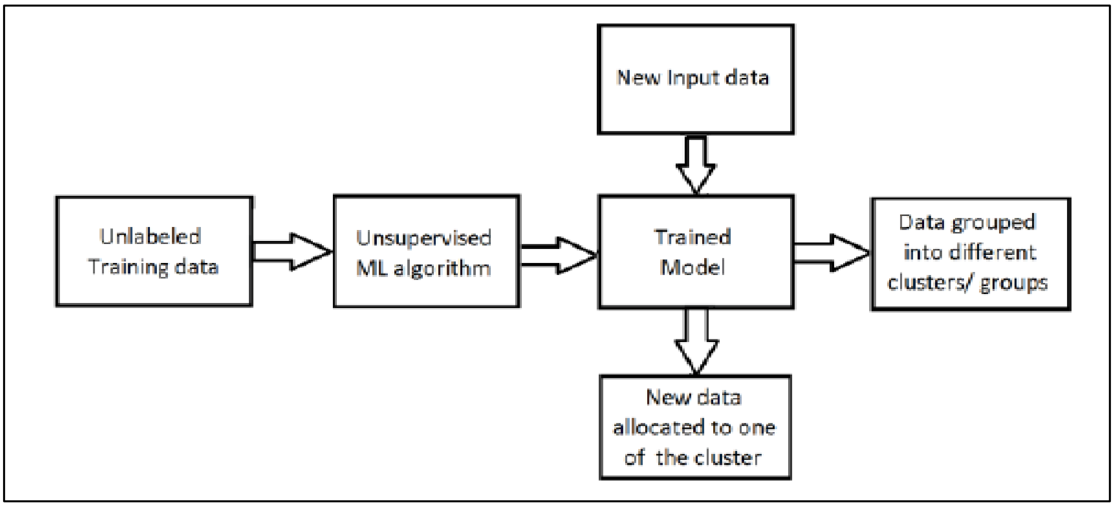

Figure 38: The flow chart of unsupervised learning algorithm

(Source: Pandey, 2019)

Some of the unsupervised algorithms are K- means clustering, Apriori Algorithm etc. Apriori Algorithm sorts abundant data with the principle of association rules. It shows the familiarization of data in the different sets. With this type of categorization, the prediction of new dataset is done. It is the basis of Artificial Neural Networks (Kavitha, 2020). K mean clustering is the simplest algorithm for solving clustering problems (Batta, 2020).

Reinforcement Learning Algorithm

In this algorithm, it makes particular decisions using trial and error when it exposed to specific environment. Some of the Reinforcement Learning Algorithms are Markov Decision Process, Evolutionary Algorithm etc. (Dey, 2016).

3.2.6 Measures of Classification Model Evaluation

The classification models are evaluating how much degree is the suggested classification to the actual one. Depend on type of problem and implementation, the proper measures were chosen. If the prediction of classification is differ from the actual then results in classification error. Accuracy is one of the measurements for the classification model quality. It is the ratio of correctly classified to the total number of classification. But accuracy disdained the type of error and its difference. It is depending on the class distribution in the particular dataset (Novakovi, 2017).

3.2.7 Confusion Matrix

When there is need of identifying the error types in result, a two dimensional matrix with actual and predicted class was formed. This is the confusion matrix which is shown in Table 3.4 with four possible results are foreseeing (Novakovi, 2017). It is a table that visualize model performance (Fiaidhi et al., 2020). Really or True Positive (TP) and Negative (TN) results are classified correctly and False Positive (FP) and Negatives (FN) are the Type I and II error respectively (Novakovi, 2017).

Table 3.4 : Confusion Matrix with two classes

(Source : (Novakovi, 2017)

		Predicted Class	
		Positives	**Negatives**
Actual Values	**Positives**	True Positive (TP)	False Negative (FN)
	Negatives	False Positive (FP)	True Negative (TN)

In True positive, total correctly predicted positive one are indicated as positive and for True negative total negatively predicted are indicated as negative. While False Positive and negatives are wrongly classified as positive and negative respectively (Novakovi, 2017).

3.2.8 Classification Report

The classification report is the justification of evaluating the model performance by certain indicators such as Recall, Accuracy, Precision, F1 score. Each of these parameters are calculated using the Confusion matrix results that are correctly predicted and misclassified classes (Chen et. al, 2020).

Accuracy

It is the ratio of sum of the true positive and negative to the overall predictions from dataset. It measures how much predictions are correctly classified from the total predictions of dataset (Chen et. al, 2020).

$$\mathbf{Accuracy} = \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}} \qquad (5)$$

Precision

It is the percentage of positive observation which is being predicted (Novakovi, 2017).

$$\mathbf{Precision} = \frac{\mathbf{TP}}{\mathbf{TP + FP}} \qquad (6)$$

Recall/ True positive rate

It shows how many correct predictions on the positive observations (Chen et. al, 2020).

$$\mathbf{Recall} = \frac{\mathbf{TP}}{\mathbf{TP + FN}} \qquad (7)$$

F1 Score

It is the combination of both precision and recall using harmonic mean (Sarker et al., 2019).

$$\textbf{F1 Score} = 2 \text{ x } \frac{\textbf{Precision x Recall}}{\textbf{Precision+ Recall}} \tag{8}$$

In the Yes/ No labeling, accuracy indicates that how many class labels are correctly predicted as "Yes" and "No" as in actual class label. It is good indicator for overall performance of classifiers (Santos et al., 2022).Since it shows that false positive and false negative as the same amount, the other parameters have to be considered (Santos et al., 2022). Precision implies how many predicted class labels correctly predicted as "Yes" from the total "Yes" labeled class. Higher the precision implies that the incorrect labeling of "Yes" is less (Santos et al., 2022). Higher the recall indicates less chance of labeling "Yes" as "No" (Santos et al., 2022). The F1 score is the powerful indicator which shows information with single score (Santos et al., 2022)

3.2.9 Python implementation steps

The basic steps involved in the implementation are install python and SciPy, dataset input, summary and visualizing the data, evaluate algorithms for predictions (Brownlee, 2022)

Installation of libraries

The libraries required are SciPy, numpy, matplotlib, pandas, sklearn etc. using Anaconda. Check the versions of each for working as expected.

Data loading

The dataset has to be upload and summarize the dataset by consider the x and y variables separately. Using label encoder the range of value from 0 to (n-1) where n is the number of variables is assigned for the easy execution of data. The descriptive analysis is done by calculating maximum, minimum, mean, standard deviation etc.

Evaluation of algorithms

The splitting the data into training and testing data (here 70:30) is done. For getting the validation to estimate accuracy of the model to find the best fit. The validation can be done using cross validation, k fold validation, and random states. Here the random state is used to help learn algorithm efficiently for the better predictions. The different algorithm is introduced and analyses each data. The classification report shows the performance of each model. From that the best performed model can be taken as the best fit model

3.3 Economic Impact Assessment

The quantification of economic benefits related to Non-motorized transport modes has become a subject in policy makers and researchers worldwide. A study conducted by Litman, 2009, suggested that the cost related to motorized vehicles for entire travel distance in dollar per mile can be used as potential benefits or savings due to shift towards non-motorized modes. The different types of benefits considered in his studies were reduction in congestion, noise and air pollution, savings in roadway and vehicle cost, benefits due to traffic safety, health and fitness, user enjoyment etc. Another study conducted by Litman, 2012, user and social cost savings, revealed preference and extravagant pricing etc. to quantifying the benefits of non-motorized traffic. Rahul & Verma, 2013, calculate the economic benefits for congestion reduction, health cost, accidents and emission reductions when a unit shifts to NMT modes in Bangalore city. The total savings of 2.5 lakhs INR in a day due to 1% shift to NMT. These benefits can be used to assure the policy makers to form a structure in decision makings for NMT modes.

Even though quantifying the return benefits on investments from hiking health is a difficult point (Deenihan & Caul, 2014 and Börjesson & Eliasson, 2012), the Health Economic Assessment Tool (HEAT) evaluates these benefits. It is a user friendly approach for health benefit assessments in transport field (Deenihan & Caul, 2014 and Rutter et al., 2013). According to WHO, 2011 and Deenihan & Caul, 2014, if there is healthier population with less sick annually can lead to more productive population. In Deenihan & Caul, 2014 concluded in their studies that if the cycling infrastructure improves then by switching towards bicycle leads to reduced mortality rate of 18%. Depend on modal switching the 5 year benefits with European Statistical Value of Life of 15.47 lakh Euro, benefits of 141.22 million Euros was accumulated.

The Health Economic Assessment Tool (HEAT) was developed by WHO for cycling and walking. It estimates how much reduction in mortality due to use of cycling and walking. It implies that the impact on health on mortality in premature stage and the economic value, if ‘x’ people walk or cycle regularly in ‘y’ amount. It also take into account of effect in mortality rate due to exposure to air pollution, traffic crashes, carbon emissions etc. when shift to NMTs. It is composed of explaining the evaluation of cycling, travel data and its adjustments, parameter evaluation and the results. This tool is used for different types of evaluation such as analyzing the present or the past, before and after implementation, new or existing cycling level in a city or country level. The relative risk is used for quantifying the assessments. It is the comparison of risk of dying etc. when exposed (regular cycling) and note exposed (not or less cycling). In the single case evaluation, the reference case of cycling which is compared with no cycling is done (World Health Organization, 2017).

3.3.1 Assumptions in HEAT tool

The background values used in the assessment refereed as background values based on several epidemiological studies are the values that cannot change according to the user. But the basic default values considered can overwrite according to the particular local area. The estimation for health effects cannot applied for the individual assessment since depend on genes, lifestyle etc. No thresholds for each parameter reached for health benefit is assumed. Men and women attained same relative risk (RR) is assumed. For the single assessment, a steady state situation is applied i.e., each activities happened in the previous year. The key assumptions are discussed below (World Health Organization, 2017).

Physical Activity

Assuming a linear relationship between cycling time and mortality rate, risk reduction of maximum 60 min of cycling per day for each dose is attained. The RR of all-cause mortality from cycling is same for adult age group of 20 – 74 years is considered.

Air Pollution

Assuming a linear relationship between air pollution and mortality rate, risk reduction with maximum level of 50 $\mu g/m^3$ for each dose is attained as that of European countries when cycles per day.

Road Crashes

The background crash rates are determined by dividing the combined national database with traffic fatalities and volume of travel mode within the specified region. It can be used for city level assessment if the values are unknown.

Carbon Emissions

The change in travel in passenger km by motorized vehicle, emission changes in mass of CO_2 per passenger km for each mode, carbon emission factor in mass of CO_2 per passenger km are assumed to be linearly related. Emission factors derived from the linearity between emission per km and average occupancy rate. The occupancy rates for car, local bus, motorbikes are 1.6, 12.2, and 1.05 respectively.

3.3.2 Data Adjustments

The input data for the assessment are sometimes not adequate so some adjustments are provided for adjusting or additional information depends on the specialty of calculation. It includes the adjustments for unrelated features such as effect of weather, temporal effect, spatial effects, trip proportion when shift from other modes to bicycle, proportion of travel for traffic expect for leisure, exercise etc. and traffic conditions whether free flow (mean speed of 45km/hr), peak time etc.,

3.3.3 Assessing the Physical Activity

The health benefit for physical activity due to regular use of cycling is derived from relative risk (RR) of mortality. This is being applied by consider the linear relationship between cycling and mortality. The updated version of HEAT tool use 0.90 as the relative risk for cycling for 100 min per week annually. The equation used is as below (World Health Organization, 2017):

$$\text{Physical Activity} = (1-\text{RR}) \times \frac{\text{Local Volume of cycling}}{\text{Reference volume of cycling}} \qquad (9)$$

The reference volume of cycling is calculated based on 100 min per week with speed of 14 km/hr for the age of 20-64 years for the confidence interval between 0.87 - 0.94.

3.3.4 Assessing the Air Pollution Risk

In this method, the $PM_{2.5}$ is used as a measurement of air pollution for background values with conversion factor of 2.0 for cycling. They were considered for particular location for cycling mainly on road with motorized vehicle or away from it. The RR for 10 μg/m3 of concentration is 1.07 with confidence interval between 1.04 and 1.09. It implies that 7 % increase in death per each extra exposure for long time to 10 μg/m3 concentration without the age difference. The equation used is as below (World Health Organization, 2017):

$$\text{Air pollution risk} = (1 - \text{RR}) \times \left(\frac{\text{Air Pollution exposure of active mode users}}{\text{Reference Air Pollution exposure}} \right) \qquad (10)$$

3.3.5 Assessing the Crash Risk

HEAT interpolates by assuming a linear relationship of crash risk in road over time. Since there is shortage of available data for particular city, the national level rates are used for the estimation but can overwrite. It is not take into account the variation of exposure to motorized modes and injuries. Generally evaluation is done using fatality and exposure data from different source. The equation used is as below (World Health Organization, 2017):

$$\text{Crash risk} = \text{Local volume of active mode} \times \left(\frac{\text{Country wide fatal crashes}}{\text{Country wide volume of active mode}} \right. \qquad (11)$$

3.3.6 Assessing the Carbon Emission

The three main views considered in the estimation are evaluating the mode shift bicycle and vice versa, carbon emissions from switching and economic value of its societal impact. The assumption made is that cycling for recreation is not considered here. The equation used is as below (World Health Organization, 2017):

Reduction in emissions from substituting motorized modes = Local volume of active modes shifted from motorized modes × carbon emission factors (12)

3.3.7 Economic valuation of Value of statistical life (VSL)

The method that derives the VSL is the willingness to pay based on statistical life expectancy. It accumulates individual perception for reduce the risk of premature mortality related to the expected year the individual expected to live. It is the economic value of society for work impotence, utilization, health cost, individual pain etc. So it represents the value for premature death reduction thus can be used in transport estimation. The country specified local currency value for particular year after applies the adjustments with respect to purchase power parity is given by (World Health Organization, 2017):

$$\mathrm{VSL}_{\mathrm{INDIA},2022(\mathrm{INR})} = \mathrm{VSL}_{\mathrm{OECD},2005(\mathrm{USD})} \times \frac{(\mathrm{Y}_{\mathrm{INDIA},2005})^{0.8}}{(\mathrm{Y}_{\mathrm{OECD},2005})^{0.8}} \times \mathrm{PPP}_{2022} \times (1\ \%\Delta\mathrm{P}_{2005-2022}) \times (1\ \%\Delta\mathrm{Y}_{2005-2022})^{0.8} \tag{13}$$

where,

$\mathrm{VSL}_{\mathrm{OECD},2005(\mathrm{USD})}$ = base value for OECD of US$ 3.013M from OECD study (Health and Transport Policies, 2012)

$\mathrm{Y}_{\mathrm{INDIA},2005}$ = real gross domestic product (GDP) per capita at purchasing power parity in 2005 of India (World Bank Open Data, 2022)

$\mathrm{Y}_{\mathrm{OECD},2005}$ = average real GDP per capita at purchasing power parity in 2005 of OECD countries, which equals US$ 30 801(in 2005) (World Bank Open Data, 2022)

0.8 = income elasticity of VSL according to the OECD study (Health and Transport Policies, 2012)

PPP_{2005} = exchange rate adjusted for purchasing power parity in 2005 (local currency per US$) (World Bank Open, 2022)

$(1 + \%\Delta\mathrm{P}_{2005–2022})$ = inflation adjustment with consumer price index of the respective country between 2005 and 2022

$(1 + \%\Delta\mathrm{Y}_{2005–2022})$ = income adjustment with growth in real GDP per capita in the respective country between 2005 and 2022

3.3.8 Social costs of carbon

It is the monetization of total damage due to additional impact of carbon dioxide equivalency emission in a particular area. Carbon value depends on this monetized value which provides a value for carbon.

3.3.9 Estimation of each parameters

Each parameter is calculated based on VSL of the country and different risks such as air pollution, carbon emission, physical activity and crash risk.

3.3.10 Steps involved in HEAT

The basic steps involved in the evaluation are as follows:

Define the evaluation

With knowledge of scope of the tool provide the information such as active travel mode (cycling), Geographical position (country, city), single or two case evaluations, the year to be assessed, effects to be considered (physical activity, carbon emission, crash risk, air pollution), refined categories of vehicle (car, local bus, motor bike). Based on the input data, tool selects the appropriate default and background values for different parameters (World Health Organization, 2017).

Input parameters

The amount of walking (km/ min/trips etc.), Type of population, the distance travelled etc. are the input data need to be collected for the analysis (World Health Organization, 2017).

Adjustment data

The adjustment related to unrelated factors, proportion of shift from different refined categories, active travel mode in traffic and transport purpose, the type of traffic (free flow, congested etc.), proportion for each trip purpose etc. are the adjusting data for the assessment (World Health Organization, 2017).

Calculation parameters

The different default and background values are provided which is being set with currently available information. The main local values used are VSL (form base for the calculation and strongly affect the economic value), annual mortality rate of population, and the discount rate (World Health Organization, 2017).

Results and economic value

The detailed results include the prevented total premature death per year, reduction in CO_2 equivalent emissions in tonnes, the economic value of carbon emission, mortality etc. (World Health Organization, 2017).

CHAPTER - 4

DATA COLLECTION

4.1 Study Area

The study area includes the stretch between Thangassery to Thanni with total distance of 10.9 km. The stretch includes Kollam Beach, Eravipuram, and Pallithottam where the user perception survey had done. The map of the study area is shown in the Figure 4.1.

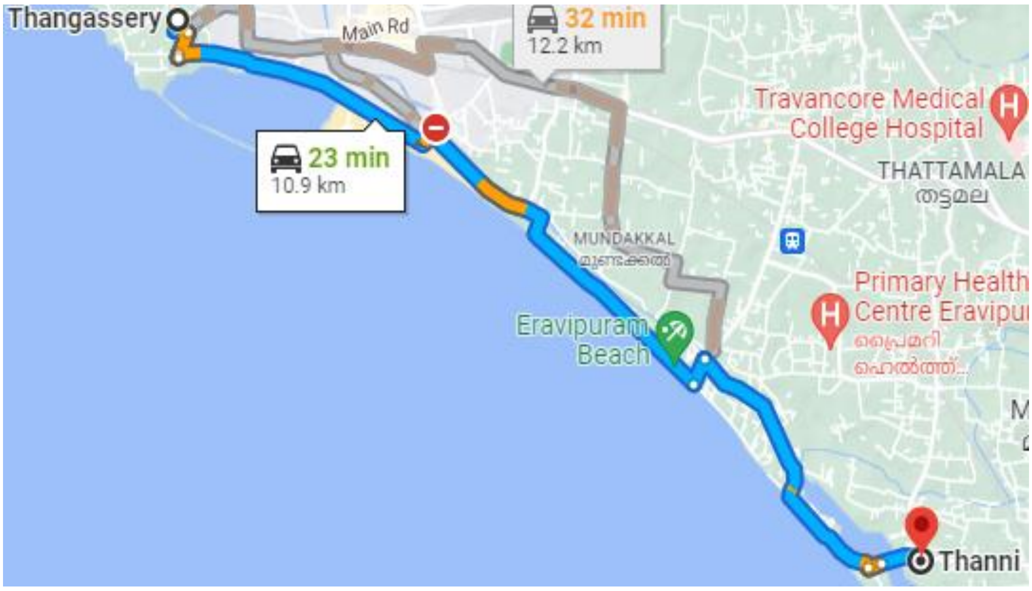

Figure 4.1 : Map of the study area

(Source: Google image)

From 8th to 12th of April, 139 responses were taken from the Kollam Beach Road. Followed by 17th to21st April 191 responses, 22nd to 27th April 184 responses, 16th to 21st May 171 responses and 24th to 28th May 183 responses were collected from Pallithottam, Vaady, Eravipuram and Thangassery respectively. In total 838 responses were collected from the study stretch of 10.9 km.

4.2 Study of Literature

An extensive literature review was carried out to identify the attributes that influences for choosing bicycle as travel mode. The provisional list of factors such as socio economic characteristics, trip characteristics, link and route related factors, safety factors etc. were identified from the previous studies carried out by the researchers worldwide which is shown in Table 4.1.

Table 4.1: Provisional list of attributes identified

Sl. No.	ATTRIBUTES	REFERENCES
1	**Socio Economic Characteristics**	
	Gender	[1], [2]
	Age	
	Household Size	
	Monthly Income	
	Occupation Status	[3]
2	**Trip Characteristics**	
	Usual Travel Mode	[3]
	Travel Distance	
	Travel Time	
	Bicycle Ownership	
	Trip Purpose	
3	**Link Related Factor**	
	Dedicated Bicycle Facility	[4], [5]
4	**Route Related Factor**	
	Route Visibility	[6]
5	**Safety Factor**	
	Level of Risk with Motorized Vehicle	[5]
6	**Perception Towards**	
	Environmental Awareness	[5]
	Physical Fitness	
	Psychological Comfort	

[1] Hernández et al., 2021; [2] Mansoor et al., 2021; [3] Rahul & Verma, 2013; [4] Hardinghaus & Papantoniou, 2020; [5] Majumdar & Mitra, 2015; [6] Majumdar & Mitra, 2017.

The user perception survey which is used for the project especially the perception survey is used to know the insight of community towards the Non-Motorized

Transportation is also recognized through the different previous studies. The literature review is also conducted for the Machine Learning Techniques which is an advanced technology, its importance and its different methods.

4.3 Pilot Survey

The stated preference survey has been prepared with reference to the identified attributes from literature review. The stated preference survey is attached in Appendix A. A pilot survey was conducted with people in Pallithottam which is one of the coastal areas via questionnaire survey from 10-02-2022 to 14-02-2022. The aim of the pilot survey was to confirm whether the preliminary list of attributes are all possible factors in context of the Indian condition and any factors need to be added or could be deleted. The final list of attributes identified will form the basis of the questionnaire survey. It is useful for knowing the perception of communities towards the willingness of shift towards Non-Motorized Transport when the facilities are improved. The 62 responses were taken for the initial analysis to identify the important factors and the accuracy of the survey and the excel sheet of the response is attached in Appendix B.

Based on the pilot survey, the questionnaire was modified based on the respondents and the road conditions. The final list of factors includes socio economic characteristics, trip characteristics, link and route related factors, safety factors etc. as shown in Table 4.2.

Table 4.2 : Final list of attributes

Sl. No.	ATTRIBUTES	REFERENCES
1	**Socio Economic Characteristics**	
	Gender	[1], [2]
	Age	
	Household Size	
	Monthly Income	
	Occupation Status	[3]
2	**Trip Characteristics**	
	Usual Travel Mode	[3]
	Travel distance	
	Bicycle Ownership	
	Trip Purpose	
3	**Attitudinal Characteristics**	
	Dedicated bicycle facility	[4], [5]
	Level of risk with motorized vehicle	[5], [6]
	Perception towards environmental awareness	[5]
	Weather conditions	[5]
	Travel Cost	[5]
	Road Terrain	[5], [1]
	Parking Fee	[5], [1]
	Difficult in intersection crossings	[7]

[1] Hernández et al., 2021; [2] Mansoor et al., 2021; [3] Rahul & Verma, 2013; [4] Hardinghaus & Papantoniou, 2020; [5] Majumdar & Mitra, 2015; [6] Majumdar & Mitra, 2017; [7] Barberan & Monzon, 2017

4.4 Questionnaire Survey

A user perception survey was conducted to collect opinion of people about the willingness of shift towards bicycle, if the facilities improve. The detailed questionnaire is provided in Appendix C. It includes socio-economic, trip and attitudinal characteristics as listed in Table 6. The household survey was conducted in the stretch between Thangassery and Thanni in the month of April and May. The responses were taken mainly from Thangassery, Vaady, Pallithottam, Kollam beach, Thanni, Eravipuram. The combined responses of these places were attached in Appendix D.

4.5 Sample Population Calculation

The minimum size for the population is given by the equation (Adhikari, 2021).

$$n = \frac{z^2 \times \hat{p} \times (1- \widehat{p)}}{\in^2} \tag{14}$$

where,

z: critical value for the confident level

n : Size of sample population for the study

N: Total population

$\hat{p}$: Probability of maximum variation or the probability of the mode shift from N

ε: marginal error or desired precision

4.6 Reliability Test

The two important survey qualities measuring instruments are the consistency and accuracy. The consistency and accuracy are evaluated by reliability and validity. Based on design and purpose of survey used, there are different types of evaluations. Reliability is the precision (Barbera et al., 2021) or robustness of consistency in the questionnaire surveys. Internal consistency is mainly checking the dependability of respondent's feedback on particular survey. It is the level of inter connection between each variables (Nawi et al., 2020). Validity gives the fitness of collected information for the actual problem. So it evaluates the accuracy or what to be measured (Taherdoost, 2016). The internal and external validity are the two parts of validity. Good validate questionnaire indicates higher reliability.

4.6.1 Cronbach's Alpha

It is the widely used measurement for internal consistency which is the mean of split half coefficients and stability of the measurement used for particular variable check. It shows percentage flexibility between each variable. (Nawi et al., 2020). The formula for the Cronbach's alpha as shown.

$$\boldsymbol{\alpha} = \frac{\mathbf{K\,x\,r}}{(\mathbf{1}+(\mathbf{K}-\mathbf{1})\mathbf{r})} \tag{15}$$

where,

K: Total factors

r: Average mean of all factors $\frac{K(K-1)}{2}$

It is easy to interpret the result and when degree is 1.0 indicates high internal consistency. If the value is low, reflects on data validity may be due to insufficient variables or partial correlation among them. But if the value is high indicates unnecessary variables or the evaluation of alike idea in different things (Nawi et al., 2020).The figure 14 shows the range of acceptable value of Cronbach's alpha for the questionnaire. So, alpha values were in the range as 0.93–0.94 is said to be excellent. If the range is 0.91–0.93, 0.81 then said to be strong, robust respectively. The value is said to be high, good, relatively high if it is 0.73–0.95, 0.71–0.91 and 0.70– 0.77 respectively. The values are adequate for 0.64–0.85, satisfactory for 0.58–0.97, acceptable for 0.45–0.98, and low (0.11) (Taber, 2018).

4.6.2 Reliability Test and SPSS

Dataset which is taken for the analysis can be evaluate in Statistical Package for Social Sciences, by IBM incorporated (SPSS) The two types of information given as output are "correlation matrix" and " view alpha if item deleted". For the Cronbach's alpha test in SPSS, at least 10 items should be there otherwise low value will get. The alpha value of 0.70 and higher is considered higher (Bolarinwa, 2015). But according to Murugan & Marisamynathan, 2022 and Zhang et. al, 2011 Cronbach's alpha greater than 0.50 is acceptable.

4.7 Economic Analysis

The HEAT tool 5.0.6 version is used for the health assessment. The flexible user interface is selected which is good for the refined categories of vehicle. For the single case assessment, the reference case provided with comparison of no walking and cycling is done. In this assessment 1% mode shift from motorized to non-motorized mode was being assumed for a stretch of 10.9 km between Thangassery and Thanni (Rahul & Verma, 2013a).

4.7.1 Input Data

The Active Travel Mode as Cycling, Geographical Scale provided are Country as India and city as Kollam, Year of reference as 2022 and the number of years to be assessed as 1 year, the impact to be assessed as Physical Activity, Air pollution, Crash Risk, Carbon Emissions are input as data. The refined category of motorized modes includes car, motorcycle, and local bus with traffic condition of free flow (45 km/hr mean speed) is considered. The data of active mode includes data source (Population survey), Cycling data in km per person per day as 10.9 km (the distance of study stretch), General population of adult (20-64 years) is considered. The total population of Kollam in the year 2022 is 2025984 ("Kollam Population 2022 (Demographics, Maps, Graphs)", 2022). While in the Kollam Municipal Corporation, the number of household's population was 84088 (Census data, 2011). Assume a 25% population of total in Kollam coastal area as 21022. From the survey data 90% people are willing to shift from bicycle of 788 responses. Since all the people are not using bicycle as daily mode of travel, assume 25% shift from motorized mode. The adjustments of weather and climate factors are assumed to be -30%.

The proportion of transport considered as 62.83% and percentage of walking, car, motorcycle, local bus shift to bicycle as 0%, 7.59%, 48.22, 13.58% respectively (from the household survey). The proportion in traffic considered as 16.23% (from the household survey). The mortality rate for the country is taken as 1.2 (Lancet Health, 2019). The $PM_{2.5}$ concentration of Kollam district is 26.8 $\mu g/m^3$ ("Kollam Air Quality Index (AQI) and India Air Pollution | IQAir", 2022).The fatality rate for cycling in the assessment is taken as 1.8 fatalities per 100million km (Lancet Health, 2019). Economic discounting such as discount rate is considered as 3% (Haacker et al., 2020).

4.7.2 Default Data

The default value of Carbon for India in 2023 is change to 86 tonnes of CO_2 ("US, China and India: Top carbon emitters to face the biggest economic losses", 2022). Average occupancy rate of car is taken as 2 persons. Average mean speed in free flow condition is considered as 45 km/hr. Default proportion shifted from bus, car, motorbike to bicycle is changed to 13.6%, 7.59%, 48.2% respectively (from the household survey). The average default cycling, bus, car and bike speed is changed to 15, 36, 50, 42 km/hr from the spot speed study.

CHAPTER - 5

ANALYSIS AND RESULTS

5.1 Sample Population

The sample population for the household survey was given by considering the population of Kollam.

$$n' = \frac{2.58^2}{0.01^2}(0.01(1-0.01)) = 658.5 = 659 \text{ samples}$$

z : 2.58 for 99% confidence level

N: Total population of Kollam area is 2,635,375 in 2021

$\hat{p}$: Probability of maximum variation or the probability of the mode shift 1%

ε : marginal error or desired precision 1%

n’: Size of sample population for the study

Since the sample population is 659 numbers, the total responses collected from the area is appropriate for the analysis. Reliability test was conducted for the questionnaire in SPSS software 26.0 for checking the internal consistency. The Cronbach’s alpha obtained is 0.67 which indicates fair in reliability of questionnaire.

5.2 Descriptive Analysis of Responds

5.2.1 Gender

In the total respondents, 49.77% were the female respondents and 50.23% were male respondents in the study area.

5.2.2 Age

The below Figure 5.1 shows the percentage of different age groups participate in the survey. The most of the participants were the age group between 31-40 years of about 23.04% and least were the age group between16-20 years with 3.80%.

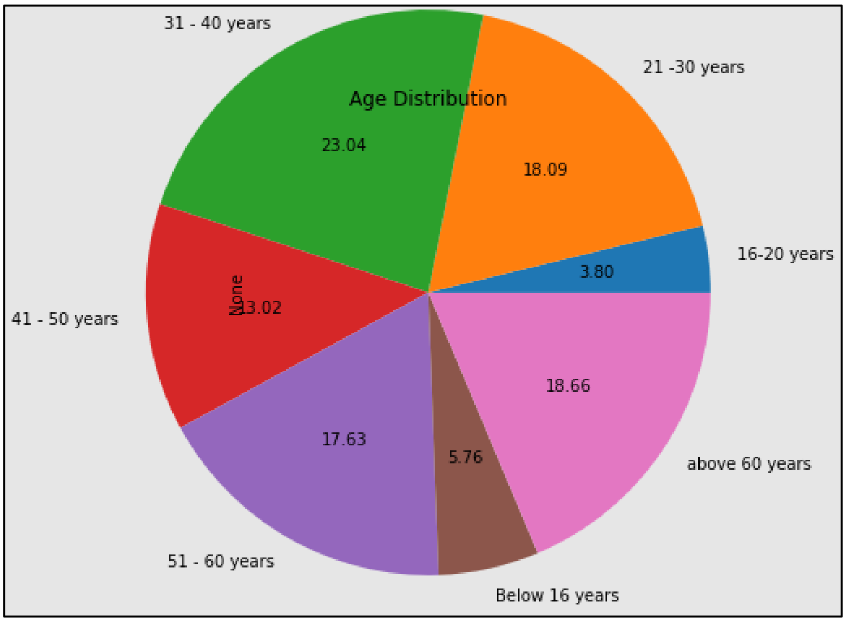

Figure 4 Percentage of different age groups distribution

5.2.3 Occupation Status

The Figure 5.2 shows the percentage of occupation status of people in the study stretch. The higher portions of the people are unemployed with 31.22%. The less people were retired person with 1.50%. The Self-employees, Merchandisers, Students, Private Employees and Government Employees who participate in the survey were of 26.73%, 16.94%, 10.02%, 9.56% and 4.03% respectively.

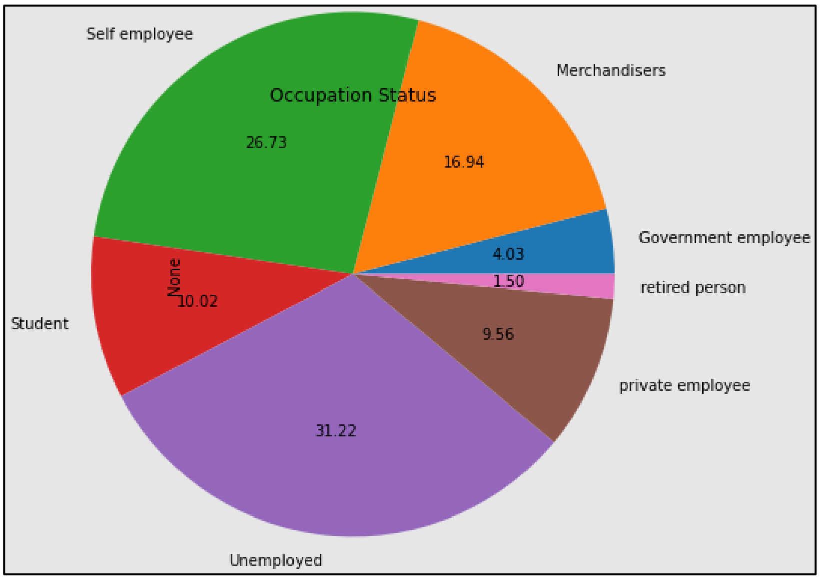

Figure 5 Percentage of different occupation status distribution

5.2.4 *Monthly Income*

The most of the people in the study area having monthly income upto 15000 INR and less people with income more than 50000 INR as shown if Figure 5.3.

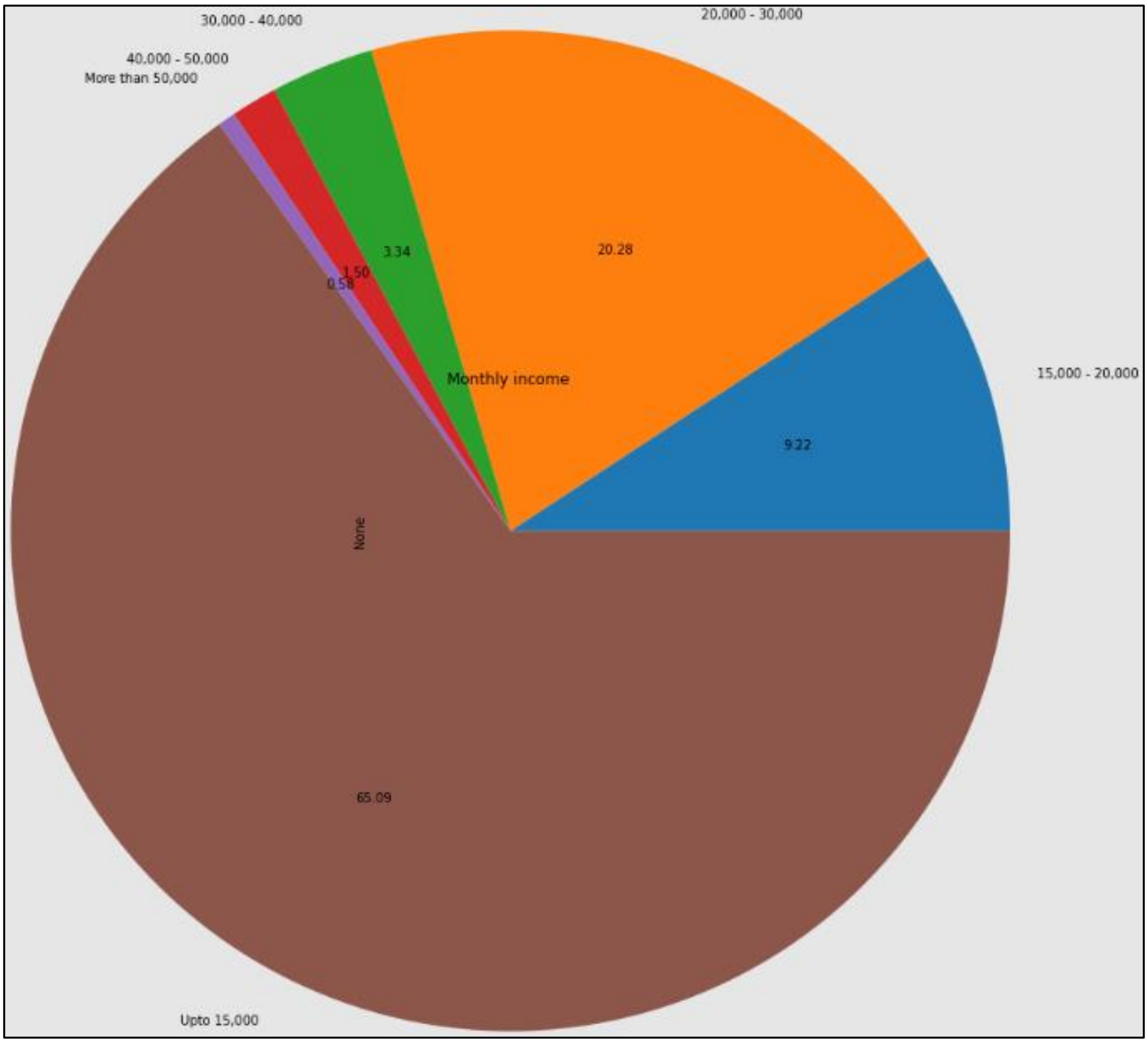

Figure 5.3 : Percentage of monthly income distribution

5.2.5 *Vehicle ownership*

Most of the people own 2-wheeler in the study area (47.47%). According to the status, 16.01 were using bicycle as daily mode compare to other means. The Figure 5.4 shows the vehicle ownership.

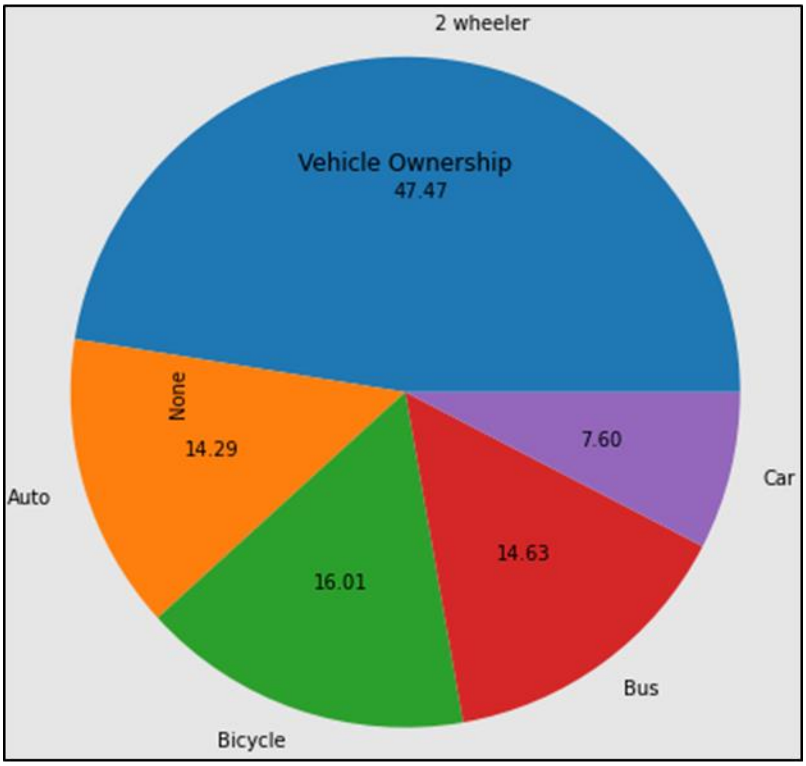

Figure 6 : Vehicle ownership

5.2.6 Bicycle Ownership

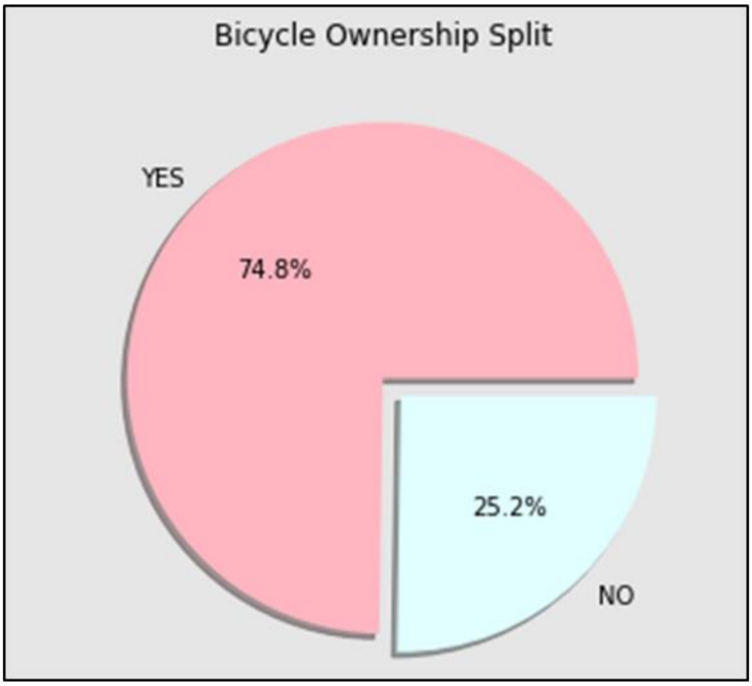

Figure 5.5 : Bicycle ownership Distribution

From the bicycle ownership, 74.8% own bicycle but 16.01 % people are using it as daily mode of travel as shown in Figure 5.5.

5.3 Choice Modeling

The collected responses were analyzed using supervised machine learning algorithm using python script. The supervised machine learning technique used was Random Forest, Support Vector Machine and K- Nearest Neighbor (Santos and Vasallo, 2022). These are applied to the proposed methodology using libraries in the python script such as sklearn or Scikit-learn (Fiaidhi et al., 2020).The analysis for the important features that influences the mode shift was analyzed in Jupiter notebook using Adaboost Classifier (Rani et al., 2021). The various indicators were used to describe the performance of different models using Confusion Matrix and Classification Report. Using the various indicators, the best fit model for the analysis of mode shift towards bicycle as mode of travel was identified. The python script is attached in Appendix E The code as shown below was used for analysis of peoples' perception towards bicycle and important features influence the mode shift. The code describes the different models used to find the best fit among them.

5.4 Willingness to Shift

As mentioned before, the supervised machine learning was used for developing a best model for the analysis for the shift towards bicycle as a mode of travel. The identified classifier can be used to assign the unknown class label of the test data for the known predictor attributes. The test data were split into training and testing data in the ratio 70:30. The Adaboost is used to find the important attributes that influence the people's decision to choose bicycle as a mode. Using the Information Gain, the factors are arranged in descending order as most influential attribute at the top which is shown in the Table 5.1

Table 5.1 : The important features using Adaboost classifiers

Sl. No.	Important Attributes	Information Gain Values
1	Vehicle ownership	0.24
2	Occupation Status	0.18
3	Travel distance (km)	0.16
4	Trip purpose	0.10
5	Road Terrain	0.08
6	Age	0.06
7	Household size	0.04
8	Gender	0.02
9	Monthly income	0.02
10	Bicycle ownership	0.02
11	Environmental factor	0.02
12	Interaction with motor vehicle	0.02
13	preference if parking fee available	0.02
14	Difficulty in intersection crossing	0.02

According to the analysis using the Adaboost Classifier, these are the information gain values as shown in Table 5.1. If considering the confidence interval of 95%, the important features found were vehicle ownership, occupation status, travel distance, trip purpose, road terrain, age ("sklearn.ensemble.AdaBoostClassifier", 2022).The vehicle ownership with Information Gain of 0.24 is the most influential factors. The least influential factor is the difficulty in intersection crossings. Higher Information gain implies higher preference.

Using the above mentioned classifiers, the accuracy, confusion matrices and classification reports are generated for getting a better understand of each model and selection of best fit model for the analysis. The confusion matrix differentiates the correctly and incorrectly predicted class labels and breakdown with countable values. If the actual value i.e, response for the willingness to shift towards bicycle is “Yes” and the predicted value by the classifier is “Yes” then is the True Positive. If the actual and predicted is “No” then is the True Negative. If the predicted value is “Yes”, but they are not choosing the bicycle then it is the False Positive. If the predicted value is “No” but the actual value is “Yes” then is the False Negative. The Table 0 shows the confusion 5.2 matrix of different models.

Table 5.2: Confusion matrix for different classifiers

Confusion Matrix For Different Classifiers					
Possible Results	**Random Forest**	**Support Vector Machine**			**KNN**
		RBF	**Linear**	**Polynomial**	
True Positive	258	0	17	7	0
True Negative	12	265	264	265	22
False Positive	13	0	1	0	3
False Negative	4	22	5	15	262

From the above table, the Random forest classifier predicted that 271 people are willing to shift towards the bicycle but in actually 262 people was said “Yes”. But in case of SVM rbf, the prediction is 22 and actual were 0. Likewise the actual predictions of SVM linear and polynomial are 18 and 7 but the predicted values are 22 and 22 respectively. In KNN, the actual values are 3 and predicted were 262. From the above inference shows that Random Forest is comparatively giving good results.

But to understand more about each classifier, the classification report has to be generated. The different models show variables values in classification reports. It shows some parameters which provide more information about each classifier. It includes the accuracy, precision, and F1 score of each classifier. Based on size of class the final score of each parameter is taken as the weighted average of scores of two class labels. The Table 5.3 shows the summary of classification report for all classifiers.

Table 5.3 : Different indicators for various classifiers

Classifiers	Accuracy	Weighted Average		
		Precision	Recall	F1 Score
Random Forest	0.94	0.93	0.94	0.93
SVM rbf	0.91	0.83	0.91	0.87
SVM linear	0.92	0.89	0.92	0.89
SVM polynomial	0.91	0.83	0.91	0.87
KNN	0.88	0.83	0.88	0.86

From the above results show that Random forest method is the best fit model for the analysis of willingness to shift towards bicycle as a mode in the study area. It is higher than other models with F1 score of 0.93 which is a main indicator for comparing models. The SVM linear is the second ranked one, followed by SVM rbf and polynomial and KNN.

5.5 Economic Analysis

The VSL for the Indian currency was calculated using following parameters:

Y_{India} = 6503.90 int. Dollar (World Bank, 2022)

$Y_{OECD\ countries}$ = 38168.10 int. Dollar (OECD Data, 2022)

Purchase Power Parity = 22.8 (OECD Data, 2022)

1 + %ΔP = 5.6 (Indian budget, 2022)

1 + %ΔY = 9.10 (National Income, 2020-21)

VSL is given by $3.013 \text{ x } (\frac{6503.90}{38168.10})^{0.8} \text{ x } 22.80 \text{ x } \frac{5.6}{100} \text{ x } (\frac{9.1}{100})^{0.8}$ as 137256.80 USD i.e. 0.14 million USD

These VSL is used to calculate the total economic impact, mortality and carbon emission etc. for air pollution, crash risk, and physical activity.

5.6 Summary Of Heat Tool Results

The total economic impact for the year 2022 is calculated for the physical activity, carbon emission, air pollution and crash risk. The volume data entered corresponds to an increase of 30 min. per person and day for the assessed population of 4204.

5.6.1 Results for cycling and physical activity

Summary of impacts for mortality

As a result, 0.011 premature deaths are prevented per year. Over the full assessment period of 1 year, 0.011 premature deaths are prevented.

Economic value of impacts for mortality

Mortality is monetized using value of statistical life (VSL) of 137000 USD (PPP). This corresponds to an economic value of 1420 USD (PPP) per year. Over the full assessment period of 1 year, the total economic impact is 1420 USD (PPP). Adjusted to 2022 value (i.e. discounted/inflated), the total economic impact is 1380 USD (PPP) can be saved in terms of physical activity.

5.6.2 Results for cycling and air pollution

Summary of impacts for mortality

As a result, 0.00081 premature deaths are caused per year. Over the full assessment period of 1 year, 0.00081 premature deaths are caused.

Economic value of impacts for mortality

Mortality is monetized using value of statistical life (VSL) of 137 000 USD (PPP). This corresponds to an economic value of 108 USD (PPP) per year. Over the full assessment period of 1 year, the total economic impact is 108 USD (PPP). Adjusted to 2022 value (i.e. discounted/inflated), the total economic impact is 105 USD (PPP)

5.6.3 Results for cycling and crash risk

Summary of impacts for mortality

As a result, 0.21 premature deaths are caused per year. Over the full assessment period of 1 year, 0.21 premature deaths are caused.

Economic value of impacts for mortality

Mortality is monetized using value of statistical life (VSL) of 137000 USD (PPP). This corresponds to an economic value of 27500 USD (PPP) per year. Over the full assessment period of 1 year, the total economic impact is 0275 USD (PPP). Adjusted to 2022 value (i.e. discounted/inflated), the total economic impact is 26700 USD (PPP) can be saved per day in terms of crash risk.

5.6.4 Results for cycling and carbon emissions

Summary of impacts for carbon emissions

As a result, carbon emissions are reduced by 351 tons of CO_2 equivalent per year. Over the full assessment period of 1 year, carbon emissions are reduced by 351 tons of CO_2 equivalent.

Economic value of impacts for carbon emissions

Carbon emissions have been monetized using an average carbon value of 86 USD/t CO_2e. This corresponds to an economic value of USD 30200 per year. Over the full assessment period of 1 year, the total economic impact is USD 30200. Adjusted to 2022 value (i.e. discounted/inflated), the total economic impact is USD 29300. An amount of 39367.30 INR can be saved per day in terms of carbon emissions.

5.6.5 Results for cycling (all pathways)

Summary of impacts for mortality and carbon emissions

As a result, 0.20 premature deaths are caused per year. Over the full assessment period of 1 year, 0.20 premature deaths are caused. As a result, carbon emissions are reduced by 351 tons of CO_2 equivalent per year. Over the full assessment period of 1 year, carbon emissions are reduced by 351 tons of CO_2 equivalent.

Economic value of impacts

Mortality is monetized using value of statistical life (VSL) of 137000 USD (PPP) per premature death. Carbon emissions have been monetized using an average carbon value of USD 86 per ton of CO_2 equivalent. This corresponds to an economic value of USD 3980 per year. Over the full assessment period of 1 year, the total economic impact is USD 3980. Adjusted to 2022 value (i.e. discounted/inflated), the total economic impact is USD 3870.

The total economic impact of air pollution (105 USD), physical activity (1380 USD), crash risk (26700 USD) and carbon emission (29300 USD) is 57480 USD i.e. 4494177.3 INR for 2022. The total economic value of carbon emission on all pathways is monetized as 3870 USD (302556 INR).

CHAPTER - 6

POLICIES AND RECOMMENDATIONS

The analysis implies that implementation of policies for bicycling for sustainable transportation as well as urban planning is important for the cities. Some of the policies and recommendations are discussed below:

- The transport policy makers should provide separate lanes for the NMTs and motorized transport. The provision of dedicated, high quality, user friendly cycle tracks and associated facilities will increase the bicycle ridership.
- The dedicated bicycle tracks are exploited for meeting the parking demand in congested areas. The policy makers should ensure that this can be avoided by providing raised bicycle lanes or providing bicycle lane separators.
- As per the findings of the study, the road terrain influences the willingness to shift towards bicycle mode of transport. This can be achieved by providing leveled surface so that users can conveniently and comfortably use the tracks.
- Provide bicycle rental system as a feeder service and integrate it with the public transportation mode of the city
- Introduce tax incentives for NMT usage in work places to attract more number of people towards non-motorized transport. This can only be implemented if the bicycle infrastructure facilities are at place.
- The policy makers should ensure the bicycle track connectivity with the nearby residential areas, commercial and institutional establishments to promote the ridership.
- Organize awareness campaign in institutions, schools regarding the physical and health benefits that they can enjoy while using NMTs.

CHAPTER - 7

CONCLUSION

The Non-Motorized mode can be used as an effective solution for the various transport problems and health problems faced by the society. The study tries to understand the willingness of people for shifting to bicycle as a mode of travel, if the facilities were improved. According to the survey done in Thangassery- Thanni road stretch of 10.9 km and its analysis, 74.8% of people own the bicycle. But the users restricted their usage as they are concerned about socio demographic, trip and attitudinal characteristics. From the pilot survey, the factors identified were Socio Economic Characteristics such as gender, age, household size, occupation status, monthly income, Trip characteristics such as usual travel mode, daily travel distance, bicycle ownership, trip purpose and Attitudinal characteristics such as environmental friendly, cost effective, weather condition, interaction with motorized traffic, dedicated bicycle facility, sloping terrain, parking fee, difficulty in intersection crossing. The perception of society towards bicycle mode of transport needs to be analyzed to attract more ridership

The major findings of the study are:

- The important attributes that influence the people's choice of using bicycle as a mode of travel was found using Adaboost Classifier. the important features found were vehicle ownership, occupation status, travel distance, trip purpose, road terrain, age. This feature selection will be of immense help to the planners, engineers, policy makers to select the attributes that are likely affects the bicycle use.
- To identify the best fit model to predict the willingness to shift towards bicycle mode of transport, three different machine learning models i.e., K-Nearest Neighbor, Support Vector Machine, and Random Forest were applied in the dataset. According to the analysis using various models, it was found that Random Forest with an accuracy of 0.94 was the best model. Using machine techniques the accurate data analysis can be done to help policy makers in decision making. This type of analysis is critical in providing important insights into effective transport policies.
- The total economic impact of air pollution (105 USD), physical activity (1380 USD), crash risk (26700 USD) and carbon emission (29300 USD) is 57480 USD i.e. 4494177.3 INR for 2022. The total economic value of carbon emission on all pathways

is monetized as 3870 USD (302556 INR).

7.1 Scope for Future Studies

Identifying the new barriers related to the implementation of cycling in the study area. Usage of deep learning models to predict the willingness to shift towards the bicycle mode of travel. Applying the methods illustrated in the study to other citywide areas and compare the outcome of this study. The quantification of health benefit was considered here, other economic benefits such as fuel cost, congestion cost, travel costs can be used to find the overall benefits of cycling.

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APPENDIX A

STATED PREFERENCE SURVEY

1. General - Socio - Demographic distribution

a. What is your gender?

- Male ◯
- Female ◯

b. What is your age?

- Children (under 10yrs) ◯
- Adolescence (11 - 18yrs) ◯
- Adult (19 - 59yrs) ◯
- Senior adult (60yrs & above) ◯

c. What is your Household size?

- 1 ◯
- 2 ◯
- 3 ◯
- 4 ◯
- > 5 ◯

d. What is your education status?

- Student ◯
- Full time employed ◯
- Part time employed ◯
- Un employed ◯

e. How much is your household annual income (Bamney, 2020)?

- < 15000 ◯
- 15000 – 20000 ◯
- 20000 – 30000 ◯
- 30000 – 40000 ◯
- 40000 – 50000 ◯
- > 50000 ◯

f. Usual mode of travel

- Bicycle ◯
- 2 wheeler ◯
- 3 wheeler ◯
- 4 wheeler ◯
- Bus ◯

2. How much distance do you normally ride ?

………………. km

3. How long you usually ride in a trip?

………………. min

4. Do you own a bicycle that is in working condition?

- Yes ◯
- No ◯

5. Would you consider cycling if the facilities were improved?

- Yes ◯
- No ◯

(If yes, follow next questions & if no, then move to 11th questions)

6. What is the main reason you ride your bicycle on working days?

- School ◯
- Work purposes ◯
- Recreational ◯
- Social Activities ◯

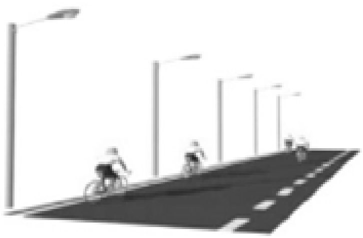
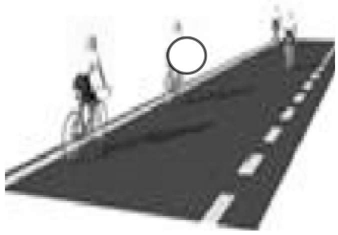
7. How often do you use bicycle as a mode of travel?

- Once a week ◯
- more than twice a week ◯
- Everyday ◯
- Never ◯

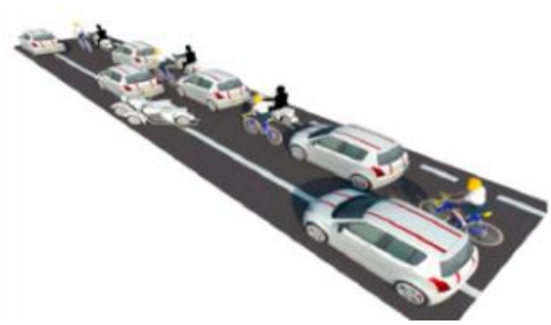
8. Among the following facilities which would you prefer for riding? (Nebiyou,2007) :

 Off-road bicycle facility share with pedestrians.	 Bicycle-lane with no side parking facilities for vehicles on road	 Bicycle-lane with on-street parking facilities for vehicles on road.
 Road with no separate lane for bicycles and parking facilities	 Road with parking facilities for vehicles but no separate lane for bicycles	

9. Which would you prefer most for route visibility, if provided the following facilities as shown in figure? (Majumdar,2018)

 The street lightings and edge line illuminations are provided	 If the street lightings are provided with no illuminated corridor	 No provision of street lightings and edge line illumination

10. Among the following below which road facilities would you choose while Level of risk / Safety is concerned (Majumdar,2018)

 Less no. of motorized traffic with low density on street parking ◯	 Less no. of motorized traffic with high density on street parking ◯
 High level of motorized traffic with low density on street parking ◯	 High level of motorized traffic with high density on street parking ◯

11. Indicate the preferred reasons of not using bicycle as an access mode

- Automobile is available for trip ◯
- Health does not permit to bicycle ◯
- Heavy sweating gives bad feeling ◯
- Does not suits the status ◯
- Dust and Exhaust deters me ◯
- Carrying baggage is difficult ◯
- Do not like bicycle at all ◯

12. Bicycle is a non-polluting, energy and material conserving, healthy and environment friendly mode. Does this stimulate you to bicycle to your destinations?

- Yes ◯
- No ◯

13. Bicycling requires balancing, makes one sweat, is unsafe if using same carriageway as used by automobiles and has less baggage carrying capacity. But it is cheaper and efficient in congested conditions and is competitive upto a distance of 5 to 6 km. With this information will you continue bicycling?

- Yes ○
- No ○

APPENDIX B

RESPONSE SHEET (a)

Responses	Socio Demographic characteristics - Gender	Socio Demographic characteristics - Age	Socio Demographic characteristics - House hold size	Socio Demographic characteristics - Education Status	Socio Demographic characteristics - House hold Income	Usual Travel Mode	Distance travel (km)	Own bicycle in working condition	Facility improved - consider bicycle as mode	If yes, Purpose of trip in bicycle	If yes, How often use as a mode	If yes, for riding which facility use (Fig)	If yes, for route facility which woud you prefer (Fig)	If yes, level of risk which woud you choose (Fig)	If yes, comfort level which will you prefer (Fig)	If No , Preferred reason for not using (choice)	If No, non-polluting , healthy and environment friendly mode - use bicycle or not	If No ,with disadvantages in using, it is cheaper and efficient in congested conditions and can use upto 6 km. will you choose bicycle
1	M	Adult	4	Part time employed	< 15000	2W	12	No	No	0	0	0	0	0	0	1	Yes	Yes
2	F	Adult	3	Part time employed	15000-20000	Bicycle	4	Yes	Yes	Work purpose	3	4	3	1	1	0	NA	NA
3	F	Adolescence	5	Student	20000-30000	Bus	12	No	Yes	School	3	2	3	2	5	0	NA	NA
4	F	Adult	2	Full time employed	30000-40000	4W	15	No	Yes	Recreational	1	2	3	1	2	0	NA	NA
5	M	Children	7	Student	20000-30000	2W	6	No	Yes	School	3	4	3	1	3	0	NA	NA
6	M	Adolescence	6	Student	< 15000	Bus	12	No	No	0	0	0	0	0	0	1	No	No
7	F	Adult	2	Student	15000-20000	Bus	14	No	No	0	0	0	0	0	0	7	Yes	Yes
8	M	Children	3	Student	20000-30000	Bus	12	No	No	0	0	0	0	0	0	1	Yes	Yes
9	F	Adult	4	Part time employed	< 15000	2W	15	Yes	Yes	Work purpose	2	2	2	2	4	0	NA	NA
10	M	Senior Adult	2	Unemployed	< 15000	Bicycle	8	Yes	Yes	Work purpose	2	4	2	2	3	0	NA	NA
11	F	Adolescence	5	Student	20000-30000	Bicycle	8	Yes	Yes	School	3	2	3	1	3	0	NA	NA
12	M	Senior Adult	7	Unemployed	< 15000	2W	18	Yes	Yes	Work purpose	2	2	3	2	2	0	NA	NA
13	M	Adult	6	Student	15000-20000	Bus	20	No	No	0	0	0	0	0	0	1	Yes	Yes
14	F	Senior Adult	4	Part time employed	< 15000	2W	12	Yes	Yes	Work purpose	2	2	3	2	1	0	NA	NA
15	F	Children	5	Student	20000-30000	Bus	10	No	No	0	0	0	0	0	0	1	Yes	Yes
16	F	Children	3	Student	< 15000	Bus	10	No	Yes	School	3	2	3	1	3	0	NA	NA

17	M	Adult	8	Full time employed	20000-30000	4W	15	No	No	0	0	0	0	0	0	1	No	No
18	M	Adult	5	Full time employed	20000-30000	4W	20	No	No	0	0	0	0	0	0	7	Yes	Yes
19	F	Senior Adult	6	Part time employed	< 15000	2W	12	No	Yes	Recreational	1	4	3	1	5	1	Yes	Yes
20	F	Senior Adult	3	Unemployed	< 15000	Bicycle	15	Yes	Yes	Work purpose	2	2	2	2	2	0	NA	NA
21	M	Adolescence	4	Student	20000-30000	Bus	15	No	Yes	School	3	2	3	1	4	0	NA	NA
22	M	Senior Adult	8	Part time employed	15000-20000	2W	10	No	No	0	0	0	0	0	0	1	Yes	Yes
23	F	Adult	6	Student	30000-40000	Bicycle	10	Yes	Yes	School	3	4	3	2	1	0	NA	NA
24	M	Children	7	Student	20000-30000	Bicycle	5	Yes	Yes	School	3	4	3	1	2	0	NA	NA
25	F	Senior Adult	5	Part time employed	< 15000	2W	10	No	No	0	0	0	0	0	0	1	Yes	Yes
26	M	Adult	3	Part time employed	15000-20000	3W	15	Yes	Yes	Work purpose	2	2	3	1	1	0	NA	NA
27	M	Adolescence	4	Student	20000-30000	Bus	15	No	No	0	0	0	0	0	0	7	No	No
28	F	Senior Adult	5	Part time employed	15000-20000	Bicycle	10	Yes	Yes	Work purpose	2	4	3	1	2	0	NA	NA
29	M	Senior Adult	7	Part time employed	15000-20000	Bicycle	5	Yes	Yes	Work purpose	2	2	3	1	3	0	NA	NA
30	M	Adolescence	3	Student	20000-30000	Bus	15	No	No	0	0	0	0	0	0	1	Yes	Yes
31	M	Adult	4	Unemployed	15000-20000	2W	15	No	Yes	Work purpose	1	2	3	1	5	0	NA	NA
32	F	Adult	6	Part time employed	15000-20000	Bus	20	No	No	0	0	0	0	0	0	1	No	No
33	M	Adult	2	Full time employed	40000-50000	4W	10	No	No	0	0	0	0	0	0	1	Yes	Yes
34	M	Adolescence	3	Student	20000-30000	3W	10	Yes	No	0	0	0	0	0	0	1	No	No
35	M	Adolescence	5	Student	< 15000	Bicycle	10	Yes	Yes	Work purpose	3	2	2	1	2	0	NA	NA
36	F	Senior Adult	2	Full time employed	20000-30000	Bicycle	5	Yes	Yes	Work purpose	3	4	3	1	4	0	NA	NA
37	F	Senior Adult	4	Part time employed	20000-30000	2W	15	No	No	0	0	0	0	0	0	5	Yes	Yes
38	M	Adult	10	Part time employed	< 15000	Bus	25	No	No	0	0	0	0	0	0	4	No	No
39	F	Children	7	Student	15000-20000	2W	10	Yes	No	0	0	0	0	0	0	6	Yes	Yes
40	M	Children	2	Student	< 15000	4W	20	No	Yes	School	3	2	2	1	3	0	NA	NA

41	M	Adolescence	5	Student	15000-20000	3W	25	Yes	Yes	Work purpose	3	5	3	1	2	0	NA	NA
42	F	Adult	8	Part time employed	15000-20000	2W	15	No	No	0	0	0	0	0	0	1	Yes	Yes
43	F	Adult	3	Part time employed	15000-20000	3W	25	Yes	No	0	0	0	0	0	0	5	No	No
44	F	Senior Adult	2	Unemployed	< 15000	Bus	30	No	No	0	0	0	0	0	0	5	Yes	Yes
45	F	Adult	4	Part time employed	20000-30000	Bicycle	8	Yes	Yes	Recreational	3	3	3	1	5	0	NA	NA
46	M	Adult	4	Part time employed	15000-20000	Bicycle	8	Yes	Yes	Work purpose	3	2	3	1	3	0	NA	NA
47	M	Senior Adult	5	Unemployed	15000-20000	4W	30	Yes	Yes	Work purpose	3	5	3	1	2	0	NA	NA
48	F	Adolescence	3	Student	< 15000	3W	25	No	Yes	Work purpose	3	3	2	1	4	0	NA	NA
49	M	Adult	4	Unemployed	15000-20000	2W	15	No	Yes	Work purpose	1	2	3	1	5	0	NA	NA
50	M	Children	7	Student	20000-30000	Bicycle	5	Yes	Yes	School	3	4	3	1	2	0	NA	NA
51	F	Senior Adult	5	Part time employed	15000-20000	Bicycle	10	Yes	Yes	Work purpose	2	4	3	1	2	0	NA	NA
52	M	Adult	10	Part time employed	< 15000	Bus	25	No	No	0	0	0	0	0	0	4	No	No
53	M	Adult	4	Part time employed	15000-20000	Bicycle	8	Yes	Yes	Work purpose	3	2	3	1	3	0	NA	NA
54	F	Adult	3	Part time employed	15000-20000	Bicycle	4	Yes	Yes	Work purpose	3	4	3	1	1	0	NA	NA
55	M	Adolescence	6	Student	< 15000	Bus	12	No	No	0	0	0	0	0	0	1	No	No
56	M	Children	3	Student	20000-30000	Bus	12	No	No	0	0	0	0	0	0	1	Yes	Yes
57	M	Senior Adult	2	Unemployed	< 15000	Bicycle	8	Yes	Yes	Work purpose	2	4	2	2	3	0	NA	NA
58	M	Senior Adult	7	Unemployed	< 15000	2W	18	Yes	Yes	Work purpose	3	2	3	2	2	0	NA	NA
59	F	Senior Adult	4	Part time employed	< 15000	2W	12	Yes	Yes	Work purpose	2	2	3	2	1	0	NA	NA
60	F	Adult	6	Student	30000-40000	Bicycle	10	Yes	Yes	School	3	4	3	2	1	0	NA	NA
61	M	Senior Adult	7	Part time employed	15000-20000	Bicycle	5	Yes	Yes	Work purpose	2	2	3	1	3	0	NA	NA
62	F	Adult	6	Part time employed	15000-20000	Bus	20	No	No	0	0	0	0	0	0	1	No	No

APPENDIX C

USER PERCEPTION SURVEY

A) **Socio - Economic Characteristics**

1. Select your Gender
    1) Female
    2) Male
2. Age
    1) Below 16 years
    2) 16 - 20 years
    3) 21 - 30 years
    4) 31 - 40 years
    5) 41 - 50 years
    6) 51 - 60 years
    7) Above 60 years
3. Number of persons in the household

    …………….
4. Select your occupation status
    1) Student
    2) Government employee
    3) Self-employee
    4) Private Employee
    5) Merchandisers
    6) Retired person
    7) Unemployed
5. Annual family income (in rupees)
    1) Upto 15,000
    2) 15,000 - 20,000
    3) 20,000 - 30,000
    4) 30,000 - 40,000
    5) 40,000 - 50,000
    6) More than 50,000

B) **Trip Characteristics**

1. Usual mode of travel
    1) Bicycle

2) 2 Wheeler
3) Auto rickshaw
4) Car
5) Bus

2. How much distance do you normally ride? (in km)

………………………………………….

3. Do you own a bicycle?

1) Yes
2) No

4. If you select bicycle as a mode of travel, then what is the purpose of trip?

1) School
2) Work purpose
3) Recreation
4) Exercise

B) **Attitudinal Characteristics**

1. The bicycle is environmental friendly mode of travel. If so, will you prefer for riding?

1) Yes
2) No

2. Will you choose bicycle, if it is a cost effective mode of transport?

1) Yes
2) No

3. Will you prefer bicycle in extreme weather conditions?

1) Yes
2) No

4. Would you concern about the motorised traffic as an obstacle for bicycle riding?

1) Yes
2) No

5. Which type of infrastructure would you prefer most for a dedicated bicycle facility?

1) Raised Bicycle Lane

2) Segregated Bicycle Lane

3) Protected Bicycle Lane

6. If the ground condition has sloping terrain, would you like to ride the bicycle?

   1) Yes
   2) No

7. If there is a parking fee facility for bicycle, will you use bicycles an intermittent travel mode?

   1) Yes
   2) No

8. Do you feel any difficulties while crossing the intersection?

   1) Yes
   2) No

9. If bicycle friendly infrastructure is improved, would you choose bicycle as a mode?

   1) Yes
   2) No

APPENDIX D

RESPONSE SHEET (b)

Sl. No.	Gender	Age	Household size	Occupation Status	Monthly income (Rs)	Vehicle ownership	Travel distance (km)	Bicycle ownership	Trip purpose	Environmental factor	Travel Cost	Interaction with motor vehicle	Dedicated bicycle facility	Road Terrain	Preference if parking fee available	Difficulty in intersection crossing	Preference if infrastructure improves
1	Male	59	3	Merchandisers	20000	Car	25	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
2	Female	73	4	Unemployed	1000	Bicycle	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
3	Male	35	5	Government employee	35000	Car	15	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
4	Male	34	6	Private Employee	12000	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
5	Female	10	3	Student	25000	Bicycle	15	YES	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
6	Female	12	2	Student	20000	Bus	10	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
7	Male	32	5	Unemployed	1000	Bus	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
8	Female	35	6	Unemployed	0	2 wheeler	10	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
9	Male	36	3	Private Employee	20000	Auto	35	NO	Recreation	NO	YES	YES	Raised bicycle lane	YES	NO	YES	YES
10	Male	58	3	Merchandisers	21000	Car	25	NO	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
11	Female	72	4	Unemployed	1500	Bicycle	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
12	Male	22	8	Unemployed	2000	Bicycle	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
13	Female	34	4	Self-Employee	5000	2 wheeler	5	NO	Work	YES	NO	YES	Segregated bicycle lane	YES	YES	NO	YES
14	Female	15	7	Student	25000	Car	10	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
15	Female	12	2	Student	15000	2 wheeler	15	YES	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
16	Male	45	5	Merchandisers	22000	2 wheeler	5	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
17	Female	26	6	Private Employee	10000	Bicycle	10	YES	Work	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
18	Female	67	4	retired person	35000	Car	10	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

19	Female	82	3	Unemployed	1000	Bus	10	NO	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
20	Male	74	2	retired person	35000	2 wheeler	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
21	Female	55	3	Merchandisers	20000	2 wheeler	5	YES	Exercise	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
22	Male	32	4	Self-Employee	7500	Auto	10	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
23	Male	58	3	Self-Employee	8000	2 wheeler	25	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
24	Male	31	5	Government employee	35000	2 wheeler	30	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
25	Female	27	4	Unemployed	0	2 wheeler	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
26	Female	21	2	Self-Employee	9000	Bus	10	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
27	Female	35	4	Unemployed	0	Bus	10	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
28	Male	35	2	Self-Employee	8000	Auto	40	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
29	Female	26	3	Private Employee	17000	Car	10	YES	Work	YES	NO	YES	Segregated bicycle lane	YES	YES	NO	YES
30	Female	72	4	Unemployed	2000	Bicycle	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
31	Male	44	3	Merchandisers	21000	2 wheeler	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
32	Male	29	4	Merchandisers	23000	2 wheeler	25	YES	Work	NO	YES	YES	Protected bicycle lane	YES	NO	YES	YES
33	Female	30	3	Merchandisers	30000	Bicycle	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
34	Male	52	5	Government employee	40000	Car	25	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
35	Female	33	2	Unemployed	0	2 wheeler	30	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
36	Male	45	3	Merchandisers	25000	Auto	10	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
37	Male	32	4	Government employee	40000	Bicycle	40	YES	Work	YES	NO	YES	Segregated bicycle lane	YES	YES	NO	YES
38	Female	54	5	Self-Employee	7500	2 wheeler	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
39	Female	56	6	Unemployed	1000	Bicycle	15	NO	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
40	Male	35	3	Self-Employee	8000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
41	Male	33	2	Self-Employee	5000	2 wheeler	5	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
42	Female	82	5	Unemployed	1500	2 wheeler	20	YES	Work	YES	YES	YES	Raised	YES	YES	YES	YES

													bicycle lane				
43	Male	32	4	Self-Employee	7500	2 wheeler	5	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
44	Female	22	3	Private Employee	12000	2 wheeler	10	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
45	Male	27	2	Private Employee	15000	2 wheeler	5	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
46	Male	35	5	Government employee	45000	Car	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
47	Female	36	6	Government employee	40000	Car	5	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
48	Female	77	2	Unemployed	1500	Bus	10	NO	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
49	Male	16	3	Student	20000	Bus	5	YES	School	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
50	Female	32	4	Self-Employee	8000	2 wheeler	5	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
51	Male	43	2	Self-Employee	9500	2 wheeler	10	YES	Work	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
52	Male	22	5	Private Employee	20000	Auto	20	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
53	Female	65	3	Unemployed	1000	Bicycle	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
54	Male	32	8	Merchandisers	25000	2 wheeler	15	YES	Work	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
55	Male	53	5	Self-Employee	9500	2 wheeler	0	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
56	Female	84	3	Unemployed	1000	Bicycle	5	NO	Recreatio n	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
57	Male	44	4	Government employee	55000	Auto	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
58	Female	35	5	Self-Employee	20000	2 wheeler	5	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
59	Female	37	3	Self-Employee	21000	Car	5	NO	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
60	Female	52	7	Government employee	45000	Car	20	YES	Exercise	NO	NO	YES	Raised bicycle lane	YES	NO	NO	YES
61	Female	42	3	Merchandisers	7500	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
62	Male	35	5	Unemployed	2000	Bicycle	10	YES	Recreatio n	YES	NO	YES	Segregated bicycle lane	YES	YES	NO	YES
63	Female	41	2	Merchandisers	20000	2 wheeler	25	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
64	Male	32	3	Self-Employee	8000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
65	Male	29	4	Self-Employee	8500	2 wheeler	5	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

66	Female	38	5	Merchandisers	22000	Car	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
67	Male	43	3	Self-Employee	9000	Car	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
68	Male	32	2	Self-Employee	5000	2 wheeler	5	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
69	Female	21	5	Government employee	45000	Car	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
70	Female	75	3	Government employee	30000	Car	30	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
71	Female	19	2	Student	8000	2 wheeler	5	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
72	Male	35	4	Merchandisers	25000	Bus	10	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
73	Male	22	6	Private Employee	15000	Auto	25	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
74	Male	13	5	Student	5000	Auto	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
75	Female	42	3	Merchandisers	25000	2 wheeler	20	YES	Work	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
76	Male	25	2	Self-Employee	5500	Bicycle	5	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
77	Male	36	2	Merchandisers	25000	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
78	Male	78	8	Self-Employee	6000	Auto	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
79	Female	32	4	Unemployed	1000	2 wheeler	20	NO	Recreation	NO	NO	YES	Raised bicycle lane	YES	NO	NO	YES
80	Female	65	5	retired person	40000	Car	35	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
81	Female	55	3	retired person	45000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
82	Female	22	2	Private Employee	20000	Auto	5	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
83	Female	82	5	Unemployed	1500	Car	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
84	Male	23	4	Private Employee	15000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
85	Female	15	3	Student	6000	2 wheeler	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
86	Male	41	2	Merchandisers	25000	2 wheeler	20	YES	Work	NO	NO	YES	Raised bicycle lane	YES	NO	NO	YES
87	Male	11	3	Student	30000	Auto	20	YES	Work	NO	NO	YES	Raised bicycle lane	YES	NO	NO	YES
88	Female	75	5	Unemployed	1000	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
89	Female	82	5	Unemployed	1500	Auto	20	YES	Work	YES	YES	YES	Raised	YES	YES	YES	YES

													bicycle lane				
90	Male	35	2	Self-Employee	8000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
91	Male	53	2	Self-Employee	7000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
92	Female	34	5	Government employee	35000	Car	25	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
93	Female	28	3	Unemployed	1000	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
94	Female	51	2	Merchandisers	20000	2 wheeler	25	YES	Work	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
95	Female	69	3	Unemployed	1500	2 wheeler	30	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
96	Male	22	2	Self-Employee	6500	Car	45	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
97	Female	15	3	Student	30000	Auto	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
98	Female	32	4	Merchandisers	25000	Auto	15	NO	Work	NO	NO	YES	Raised bicycle lane	YES	NO	NO	YES
99	Female	23	5	Self-Employee	9000	2 wheeler	10	NO	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
100	Male	45	3	Merchandisers	20000	Bicycle	5	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
101	Female	52	5	Unemployed	0	Bus	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	NO	NO	YES
102	Female	75	2	Merchandisers	25000	Bicycle	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
103	Female	15	2	Student	15000	Bicycle	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
104	Male	35	2	Merchandisers	25000	Auto	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
105	Male	20	3	Self-Employee	8000	2 wheeler	25	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
106	Male	22	2	Self-Employee	8500	Auto	10	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
107	Female	32	2	Merchandisers	25000	2 wheeler	20	YES	Work	YES	NO	YES	Segregated bicycle lane	YES	YES	YES	YES
108	Female	15	3	Student	8000	Car	40	NO	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	NO	NO	YES
109	Female	25	5	Unemployed	1500	2 wheeler	20	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	NO	NO	YES
110	Male	24	5	Self-Employee	9000	2 wheeler	15	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
111	Female	36	2	Merchandisers	25000	2 wheeler	15	YES	Exercise	NO	NO	YES	Segregated bicycle lane	YES	YES	YES	YES
112	Male	56	3	Self-Employee	7000	Auto	10	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

113	Female	32	4	Private Employee	15000	Bicycle	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
114	Male	30	7	Private Employee	12000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
115	Female	75	2	Unemployed	1000	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
116	Male	82	5	Unemployed	1500	Bus	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	NO	YES
117	Female	35	2	Unemployed	0	Auto	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
118	Male	21	4	Private Employee	25000	Bicycle	20	NO	School	NO	NO	YES	Raised bicycle lane	YES	YES	YES	YES
119	Female	57	4	Merchandisers	25000	2 wheeler	10	NO	Work	NO	NO	YES	Raised bicycle lane	YES	YES	YES	YES
120	Male	45	4	Merchandisers	20000	Bicycle	20	YES	School	YES	YES	YES	Segregated bicycle lane	YES	NO	NO	YES
121	Male	63	3	Self-Employee	5000	Bicycle	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
122	Male	31	1	Self-Employee	6500	Bicycle	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
123	Female	78	2	Unemployed	1000	Bus	20	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	NO	NO	YES
124	Female	47	2	Unemployed	1500	2 wheeler	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
125	Male	38	2	Merchandisers	22000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
126	Female	22	3	Unemployed	0	2 wheeler	10	YES	Work	YES	NO	YES	Raised bicycle lane	YES	YES	YES	YES
127	Female	71	1	Unemployed	1000	Bicycle	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
128	Male	42	2	Self-Employee	4500	Car	25	NO	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
129	Male	55	3	Self-Employee	8000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
130	Female	16	5	Student	20000	2 wheeler	10	YES	Work	NO	NO	YES	Raised bicycle lane	YES	NO	NO	YES
131	Male	17	2	Student	6500	Bicycle	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	NO	NO	YES
132	Female	53	3	Merchandisers	20000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
133	Male	77	5	Self-Employee	7500	Bicycle	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
134	Male	12	3	Student	25000	Bus	15	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
135	Female	35	3	Unemployed	0	2 wheeler	5	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
136	Male	32	8	Merchandisers	20000	Auto	15	NO	Recreatio	YES	YES	YES	Raised	YES	YES	YES	YES

									n				bicycle lane				
137	Female	25	3	Private Employee	15000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
138	Female	32	2	Private Employee	20000	Auto	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	NO	YES
139	Male	44	2	Government employee	50000	Car	35	NO	Recreatio n	YES	NO	YES	Raised bicycle lane	YES	YES	YES	YES
140	Male	34	3	Merchandisers	20000	2 wheeler	5	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
141	Male	52	3	Merchandisers	30000	Auto	5	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
142	Female	77	2	Unemployed	1500	Bicycle	15	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	NO	NO	YES
143	Female	55	2	Unemployed	1500	2 wheeler	5	NO	Recreatio n	NO	NO	YES	Raised bicycle lane	YES	YES	YES	YES
144	Male	45	3	Self-Employee	8000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
145	Female	67	3	Merchandisers	25000	2 wheeler	15	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	NO	NO	YES
146	Female	20	4	Private Employee	20000	Bus	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
147	Male	49	5	Merchandisers	22000	Auto	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
148	Female	33	3	Private Employee	20000	Bus	10	NO	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
149	Female	55	2	Unemployed	6500	Bus	5	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
150	Female	25	3	Private Employee	22000	2 wheeler	10	YES	Work	NO	NO	YES	Segregated bicycle lane	YES	YES	YES	YES
151	Female	36	4	Unemployed	0	2 wheeler	25	YES	Work	NO	NO	YES	Raised bicycle lane	YES	YES	YES	YES
152	Male	12	3	Student	35000	Bus	10	YES	School	YES	YES	YES	Protected bicycle lane	YES	NO	NO	YES
153	Male	75	4	Self-Employee	10000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	NO	NO	YES
154	Female	45	3	Merchandisers	20000	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
155	Male	35	3	Merchandisers	20000	Bus	15	YES	Recreatio n	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
156	Female	54	3	Unemployed	1500	Auto	10	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
157	Female	42	4	Unemployed	2000	Car	20	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
158	Male	41	3	Merchandisers	23000	2 wheeler	10	NO	Work	YES	NO	YES	Segregated bicycle lane	YES	YES	YES	YES
159	Female	26	2	Merchandisers	25000	2 wheeler	5	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES

160	Male	35	2	Self-Employee	6000	Bus	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	NO	YES
161	Female	45	2	Self-Employee	7000	Bus	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
162	Female	65	3	Merchandisers	20000	Auto	10	YES	Work	NO	NO	YES	Segregated bicycle lane	YES	YES	YES	YES
163	Male	47	3	Private Employee	12000	Auto	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
164	Female	19	4	Student	8000	Bus	20	YES	School	YES	YES	YES	Raised bicycle lane	YES	NO	NO	YES
165	Male	18	3	Student	25000	Bicycle	15	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
166	Male	22	3	Private Employee	15000	2 wheeler	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
167	Female	75	4	Unemployed	1000	Bicycle	10	NO	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
168	Male	82	3	retired person	45000	Bicycle	5	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
169	Male	94	5	Unemployed	1500	Bicycle	5	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
170	Female	56	2	Merchandisers	15000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
171	Male	54	3	Self-Employee	20000	Auto	15	YES	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
172	Female	12	4	Student	20000	2 wheeler	25	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
173	Female	35	5	Private Employee	20000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
174	Male	13	6	Student	8500	2 wheeler	25	NO	School	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
175	Female	17	3	Student	5000	2 wheeler	35	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
176	Female	55	2	Government employee	45000	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
177	Female	23	5	Private Employee	20000	Auto	25	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
178	Male	62	4	Self-Employee	25000	2 wheeler	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
179	Female	35	3	Government employee	55000	2 wheeler	35	NO	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
180	Female	24	2	Private Employee	15000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
181	Female	85	5	Unemployed	4500	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
182	Male	24	2	Self-Employee	25000	Bus	25	YES	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
183	Female	36	5	Private	20000	Bus	10	YES	Work	YES	YES	YES	Segregated	YES	YES	YES	YES

				Employee									bicycle lane				
184	Male	95	6	Unemployed	2500	Auto	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
185	Male	22	3	Self-Employee	9000	Car	10	NO	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
186	Female	29	6	Private Employee	15000	Auto	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
187	Female	31	3	Unemployed	0	2 wheeler	5	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
188	Female	14	5	Student	20000	Car	10	NO	School	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
189	Male	12	2	Student	10000	2 wheeler	15	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
190	Male	80	5	Unemployed	6500	Car	10	NO	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
191	Female	52	6	Merchandisers	24000	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
192	Male	43	3	Self-Employee	6000	Auto	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
193	Female	57	2	Unemployed	0	2 wheeler	10	YES	Exercise	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
194	Male	26	5	Self-Employee	5500	Auto	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
195	Female	35	2	Private Employee	20000	Car	35	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
196	Male	47	3	Self-Employee	5000	2 wheeler	10	NO	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
197	Male	58	4	Self-Employee	6000	Auto	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
198	Female	36	6	Unemployed	0	Bicycle	10	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
199	Male	21	3	Private Employee	21000	2 wheeler	10	YES	School	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
200	Female	24	2	Private Employee	25000	2 wheeler	15	NO	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
201	Male	51	5	Merchandisers	16000	2 wheeler	20	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
202	Female	37	2	Unemployed	0	Bus	5	NO	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
203	Female	29	3	Unemployed	0	Auto	25	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
204	Female	32	4	Unemployed	0	2 wheeler	30	YES	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
205	Male	51	2	Unemployed	1000	Bus	5	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
206	Male	22	3	Self-Employee	4500	2 wheeler	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

207	Male	32	2	Merchandisers	24000	2 wheeler	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
208	Male	15	5	Student	15000	2 wheeler	25	NO	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
209	Female	46	2	Unemployed	0	Car	45	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
210	Male	65	3	Unemployed	1000	Bus	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
211	Female	75	4	Unemployed	1500	Bicycle	10	NO	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
212	Male	42	3	Self-Employee	8500	Bicycle	5	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
213	Female	94	5	Unemployed	2000	Bicycle	5	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
214	Male	56	2	Merchandisers	20000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
215	Male	54	3	Merchandisers	24000	Auto	15	YES	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
216	Female	12	4	Student	15000	2 wheeler	25	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
217	Male	35	5	Private Employee	12000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
218	Male	13	6	Student	1500	2 wheeler	25	NO	School	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
219	Female	17	3	Student	25000	2 wheeler	35	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
220	Male	55	2	Self-Employee	7500	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
221	Male	23	5	Self-Employee	7000	Auto	25	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
222	Female	62	4	Self-Employee	7000	2 wheeler	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
223	Male	35	3	Government employee	40000	2 wheeler	35	NO	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
224	Female	24	2	Self-Employee	5000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
225	Male	62	5	Merchandisers	20000	Auto	10	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
226	Female	74	6	Unemployed	0	Bus	5	YES	Recreation	NO	YES	YES	Protected bicycle lane	NO	YES	YES	NO
227	Female	71	2	Unemployed	0	Bicycle	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
228	Female	54	3	Unemployed	0	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
229	Male	48	4	Merchandisers	25000	2 wheeler	25	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
230	Male	49	2	Merchandisers	20000	Auto	10	NO	Work	YES	YES	YES	Segregated	YES	YES	YES	YES

													bicycle lane				
231	Female	30	5	Government employee	25000	2 wheeler	35	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
232	Male	25	3	Self-Employee	5500	2 wheeler	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
233	Female	21	8	Self-Employee	4500	2 wheeler	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
234	Male	34	5	Merchandisers	22000	Auto	5	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
235	Female	31	3	Unemployed	15000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
236	Male	44	2	Self-Employee	6500	Car	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
237	Female	29	3	Private Employee	15000	2 wheeler	10	NO	Work	NO	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
238	Male	30	4	Merchandisers	20000	Auto	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
239	Male	52	3	Merchandisers	25000	Bus	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
240	Female	33	5	Unemployed	0	Auto	15	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
241	Male	45	2	Merchandisers	22000	2 wheeler	15	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
242	Female	32	3	Private Employee	15000	Auto	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
243	Male	54	4	Self-Employee	2000	Auto	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
244	Female	56	5	Unemployed	0	Bicycle	5	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
245	Male	35	6	Self-Employee	8500	2 wheeler	20	YES	Work	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
246	Female	33	3	Private Employee	15000	2 wheeler	25	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
247	Female	82	2	Unemployed	1500	Bicycle	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
248	Male	32	5	Merchandisers	22000	Auto	10	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
249	Male	22	4	Self-Employee	4000	2 wheeler	15	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
250	Male	21	3	Self-Employee	6500	2 wheeler	35	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
251	Female	14	3	Student	6000	2 wheeler	15	NO	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
252	Male	15	4	Student	20000	2 wheeler	25	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
253	Female	18	2	Student	25000	2 wheeler	30	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

254	Male	84	3	Unemployed	2500	Bicycle	5	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
255	Female	54	2	Private Employee	5500	2 wheeler	25	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
256	Male	75	5	retired person	40000	Car	25	YES	Recreation	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
257	Female	55	2	Private Employee	2200	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
258	Male	21	3	Merchandisers	15000	2 wheeler	15	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
259	Male	23	4	Self-Employee	2400	Auto	10	YES	Work	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
260	Male	28	2	Self-Employee	3500	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
261	Male	72	4	Unemployed	1500	Bus	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
262	Male	44	2	Government employee	30000	Car	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
263	Female	91	3	Unemployed	1000	Bicycle	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
264	Female	77	5	Self-Employee	25000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
265	Female	25	6	Unemployed	0	2 wheeler	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
266	Female	52	8	Unemployed	0	2 wheeler	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
267	Male	43	7	Merchandisers	24000	Auto	15	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
268	Male	36	4	Self-Employee	4500	2 wheeler	10	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
269	Female	33	5	Private Employee	2500	2 wheeler	5	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
270	Female	45	2	Private Employee	3200	2 wheeler	5	YES	Work	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
271	Female	32	6	Private Employee	2000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
272	Male	54	2	Merchandisers	25000	2 wheeler	5	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
273	Male	56	4	Unemployed	1500	Bicycle	5	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
274	Male	35	3	Merchandisers	11000	2 wheeler	10	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
275	Male	21	5	Self-Employee	4500	2 wheeler	20	NO	Work	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
276	Male	52	3	Self-Employee	3000	2 wheeler	25	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
277	Male	41	3	Government	35000	Car	20	YES	Recreatio	YES	YES	YES	Raised	YES	YES	YES	YES

				employee					n				bicycle lane				
278	Female	48	4	Unemployed	0	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
279	Female	39	2	Unemployed	0	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
280	Female	41	3	Unemployed	0	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
281	Female	75	2	Private Employee	16500	Bus	15	YES	Recreatio n	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
282	Male	57	5	Self-Employee	2500	2 wheeler	25	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
283	Male	56	2	Self-Employee	2200	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
284	Male	14	3	Student	30000	2 wheeler	15	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
285	Female	15	4	Student	25000	2 wheeler	25	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
286	Female	22	2	Student	20000	2 wheeler	35	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
287	Female	88	4	Unemployed	1000	Bicycle	15	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
288	Male	74	2	Unemployed	1500	FALSE	20	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
289	Male	51	5	Private Employee	15000	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
290	Female	62	6	Unemployed	2000	2 wheeler	30	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
291	Male	53	4	Merchandisers	25000	2 wheeler	25	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
292	Female	43	3	Merchandisers	10000	2 wheeler	15	YES	Recreatio n	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
293	Male	25	2	Self-Employee	20000	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
294	Female	36	5	Government employee	25000	Car	25	YES	Exercise	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
295	Male	75	3	Self-Employee	2000	2 wheeler	5	YES	Recreatio n	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
296	Male	88	4	Unemployed	1500	Bicycle	20	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
297	Male	44	2	Merchandisers	25000	2 wheeler	5	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
298	Female	29	3	Unemployed	20000	2 wheeler	20	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
299	Female	30	4	Unemployed	0	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
300	Female	52	2	Merchandisers	25000	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

301	Male	33	3	Self-Employee	2000	2 wheeler	5	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
302	Male	45	2	Self-Employee	3000	2 wheeler	10	YES	Recreatio n	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
303	Female	32	5	Private Employee	10000	2 wheeler	20	YES	Recreatio n	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
304	Female	54	2	Government employee	30000	Car	10	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
305	Male	56	3	Self-Employee	3500	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
306	Female	35	4	Government employee	25000	2 wheeler	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
307	Male	33	2	Merchandisers	20000	2 wheeler	15	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
308	Male	82	4	Unemployed	1000	Bicycle	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
309	Male	32	3	Merchandisers	30000	2 wheeler	25	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
310	Female	22	5	Private Employee	25000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
311	Female	52	6	Unemployed	2000	2 wheeler	25	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
312	Male	51	3	Merchandisers	25000	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
313	Female	33	2	Merchandisers	20000	2 wheeler	15	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
314	Male	45	4	Self-Employee	1500	2 wheeler	10	YES	Recreatio n	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
315	Male	32	2	Self-Employee	2500	2 wheeler	20	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
316	Male	54	2	Self-Employee	2000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
317	Female	56	3	Merchandisers	15000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
318	Female	35	3	Private Employee	20000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
319	Female	27	2	Private Employee	18000	2 wheeler	25	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
320	Male	39	5	Private Employee	24000	2 wheeler	15	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
321	Male	87	3	retired person	55000	Bicycle	5	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
322	Female	81	4	retired person	25000	Bicycle	5	NO	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
323	Female	52	6	Private Employee	20000	2 wheeler	15	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
324	Male	77	5	Unemployed	1000	Bicycle	15	NO	Recreatio	YES	YES	YES	Segregated	YES	YES	YES	YES

									n				bicycle lane				
325	Female	48	7	Merchandisers	15000	2 wheeler	10	NO	Work	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
326	Male	29	2	Unemployed	3000	2 wheeler	25	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
327	Male	51	3	Government employee	35000	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
328	Female	33	4	Unemployed	0	2 wheeler	20	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
329	Female	41	2	Government employee	20000	2 wheeler	10	NO	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
330	Male	65	3	Merchandisers	25000	2 wheeler	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
331	Male	98	2	Unemployed	1500	Bus	5	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
332	Female	21	5	Unemployed	0	Auto	10	NO	Recreatio n	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
333	Female	59	2	Merchandisers	25000	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
334	Female	44	3	Merchandisers	20000	2 wheeler	25	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
335	Female	58	4	Merchandisers	25000	2 wheeler	20	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
336	Male	22	2	Self-Employee	4500	2 wheeler	15	YES	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
337	Male	57	4	Self-Employee	3000	Auto	10	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
338	Male	33	3	Merchandisers	20000	2 wheeler	25	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
339	Female	45	2	Government employee	40000	2 wheeler	10	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
340	Male	32	5	Government employee	30000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
341	Female	54	4	Merchandisers	25000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
342	Male	56	7	retired person	35000	Auto	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
343	Female	35	6	Unemployed	0	2 wheeler	5	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
344	Male	33	2	Merchandisers	20000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
345	Male	29	5	Self-Employee	2100	Auto	10	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
346	Male	35	4	Self-Employee	3200	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
347	Male	37	3	Self-Employee	2500	2 wheeler	10	NO	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES

348	Female	45	5	Unemployed	1000	2 wheeler	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
349	Female	32	4	Merchandisers	20000	2 wheeler	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
350	Female	54	7	Unemployed	0	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
351	Male	56	3	retired person	30000	2 wheeler	25	YES	Work	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
352	Female	35	2	Unemployed	0	Auto	10	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
353	Male	47	5	Merchandisers	12000	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
354	Female	25	4	Unemployed	0	Auto	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
355	Male	39	6	Self-Employee	5000	2 wheeler	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
356	Female	71	7	Unemployed	2000	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
357	Female	91	3	Unemployed	2500	Bus	5	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
358	Female	56	2	Unemployed	0	2 wheeler	20	NO	Recreation	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
359	Male	35	5	Self-Employee	5500	2 wheeler	25	YES	Recreation	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
360	Male	41	6	Self-Employee	7500	2 wheeler	10	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
361	Male	37	4	Self-Employee	7500	Auto	15	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
362	Female	29	2	Private Employee	20000	2 wheeler	15	NO	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
363	Female	81	3	Unemployed	1500	Bus	5	YES	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
364	Female	22	4	Unemployed	0	2 wheeler	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
365	Male	33	2	Self-Employee	5000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
366	Female	45	3	Merchandisers	20000	Auto	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
367	Male	32	2	Merchandisers	25000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
368	Female	84	5	retired person	55000	Bus	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
369	Male	56	2	Self-Employee	7500	Auto	25	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
370	Male	35	3	Self-Employee	6000	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
371	Female	33	4	Unemployed	0	2 wheeler	10	YES	Work	YES	YES	YES	Segregated	YES	YES	YES	YES

													bicycle lane				
372	Female	33	2	Unemployed	0	2 wheeler	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
373	Male	45	4	Merchandisers	20000	Auto	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
374	Female	32	6	Private Employee	15000	2 wheeler	10	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
375	Male	54	4	Merchandisers	20000	2 wheeler	10	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
376	Male	35	6	Merchandisers	20000	2 wheeler	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
377	Female	61	6	Unemployed	1500	Bicycle	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
378	Female	28	6	Private Employee	15000	2 wheeler	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
379	Male	75	5	Unemployed	1000	Car	25	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
380	Female	18	4	Student	20000	Bicycle	10	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
381	Male	20	3	Student	15000	2 wheeler	35	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
382	Female	25	6	Private Employee	10000	Bus	20	NO	Work	NO	NO	YES	Raised bicycle lane	YES	NO	YES	YES
383	Male	53	3	Self-Employee	6500	2 wheeler	5	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
384	Female	42	5	Unemployed	0	Auto	5	YES	Work	YES	NO	YES	Raised bicycle lane	YES	NO	YES	YES
385	Female	38	4	Government employee	25000	2 wheeler	20	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	NO
386	Male	19	2	Student	9500	Bus	25	NO	Work	YES	NO	YES	Protected bicycle lane	YES	NO	YES	YES
387	Male	23	5	Merchandisers	20000	Auto	20	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
388	Male	27	6	Self-Employee	5500	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
389	Female	56	3	Merchandisers	15000	2 wheeler	10	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
390	Female	75	2	Unemployed	1000	Bicycle	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
391	Female	82	5	Unemployed	1500	2 wheeler	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
392	Male	35	2	Merchandisers	20000	Auto	40	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	NO
393	Male	58	3	Merchandisers	25000	Car	25	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
394	Female	72	4	Unemployed	1000	Bicycle	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES

395	Female	33	2	Private Employee	1500	Car	30	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
396	Male	29	4	Self-Employee	6500	2 wheeler	25	YES	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
397	Male	59	2	Self-Employee	7000	Auto	20	YES	Work	YES	NO	YES	Protected bicycle lane	YES	NO	YES	NO
398	Female	51	5	Unemployed	0	Bicycle	10	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
399	Male	38	4	Self-Employee	3500	Car	30	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
400	Female	26	3	Unemployed	0	Car	10	YES	Work	YES	NO	YES	Segregated bicycle lane	YES	NO	YES	NO
401	Male	13	3	Student	6500	Bus	15	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
402	Male	36	4	Merchandisers	20000	Car	25	YES	Work	YES	YES	NO	Protected bicycle lane	YES	YES	YES	YES
403	Female	18	5	Student	15000	Bus	15	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
404	Male	31	6	Merchandisers	20000	Auto	25	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	NO
405	Male	49	4	Self-Employee	8500	Auto	10	YES	Work	NO	NO	YES	Raised bicycle lane	YES	NO	YES	YES
406	Male	53	3	Self-Employee	5000	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
407	Female	50	3	Unemployed	0	Bicycle	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
408	Male	22	6	Self-Employee	5000	Auto	15	YES	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	NO
409	Male	36	5	Self-Employee	7500	Auto	30	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
410	Male	42	4	Self-Employee	7000	Car	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
411	Female	19	3	Student	15000	Car	25	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
412	Female	29	6	Unemployed	0	Bus	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
413	Male	82	3	Unemployed	1500	Car	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
414	Female	75	5	Unemployed	2000	Bus	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
415	Male	45	4	Merchandisers	25000	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
416	Male	22	2	Student	15000	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	NO
417	Female	15	3	Student	10000	Auto	35	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
418	Female	32	4	Unemployed	0	Bicycle	15	YES	Work	NO	NO	YES	Raised	YES	NO	YES	YES

													bicycle lane				
419	Female	25	5	Unemployed	0	Bicycle	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
420	Female	69	3	Unemployed	2000	Auto	30	YES	Work	YES	NO	YES	Raised bicycle lane	YES	NO	YES	YES
421	Male	29	4	Self-Employee	6500	2 wheeler	20	NO	Recreatio n	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
422	Male	45	5	Self-Employee	8500	Car	15	YES	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
423	Female	12	6	Student	15000	2 wheeler	30	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
424	Male	78	4	Self-Employee	5000	Auto	20	YES	Work	NO	YES	NO	Protected bicycle lane	YES	YES	YES	YES
425	Male	92	3	Unemployed	2000	2 wheeler	5	NO	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
426	Female	48	3	Government employee	35000	2 wheeler	5	YES	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
427	Male	33	6	Self-Employee	5500	Auto	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
428	Male	24	5	Self-Employee	9000	2 wheeler	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
429	Female	15	4	Student	15000	Bicycle	30	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
430	Male	11	3	Student	10000	Bus	15	YES	School	YES	NO	YES	Protected bicycle lane	YES	NO	YES	YES
431	Male	28	6	Merchandisers	20000	2 wheeler	10	NO	Recreatio n	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
432	Male	36	3	Merchandisers	30000	Auto	35	NO	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
433	Male	55	5	Self-Employee	6500	Bicycle	10	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
434	Female	24	2	Private Employee	15000	Bus	25	YES	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
435	Female	36	5	Unemployed	0	Bus	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
436	Male	95	6	Unemployed	1500	Auto	20	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
437	Female	88	3	Unemployed	1000	Car	15	NO	Recreatio n	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
438	Male	25	2	Self-Employee	25000	Car	35	YES	Work	YES	NO	YES	Raised bicycle lane	YES	NO	YES	YES
439	Female	47	5	Unemployed	0	2 wheeler	25	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
440	Male	58	2	Self-Employee	6500	Car	10	YES	Recreatio n	YES	YES	NO	Raised bicycle lane	YES	YES	YES	NO
441	Male	65	3	Self-Employee	7000	Bus	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

442	Male	35	4	Self-Employee	8500	Auto	30	NO	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
443	Female	24	2	Unemployed	0	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
444	Female	15	4	Student	15000	Bicycle	25	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
445	Male	26	2	Private Employee	15000	2 wheeler	35	NO	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
446	Female	44	4	Unemployed	0	Car	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
447	Male	25	3	Merchandisers	25000	2 wheeler	30	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
448	Male	75	6	Unemployed	1500	Auto	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
449	Female	24	3	Unemployed	0	2 wheeler	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
450	Female	16	5	Student	20000	Bicycle	20	YES	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
451	Female	19	2	Student	15000	Bus	15	YES	School	YES	YES	NO	Raised bicycle lane	YES	YES	YES	YES
452	Female	32	5	Unemployed	0	Bicycle	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
453	Male	37	6	Self-Employee	7500	2 wheeler	35	YES	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
454	Male	54	3	Self-Employee	8500	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
455	Female	49	2	Unemployed	0	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
456	Female	77	5	Unemployed	2000	2 wheeler	10	NO	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
457	Male	52	2	Self-Employee	9000	Auto	25	YES	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
458	Male	36	3	Merchandisers	15000	2 wheeler	35	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
459	Female	47	4	Merchandisers	20000	Auto	10	NO	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	NO
460	Female	12	6	Student	10000	2 wheeler	20	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
461	Female	54	3	Unemployed	0	Auto	25	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
462	Male	36	2	Self-Employee	8500	Auto	35	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
463	Male	25	5	Merchandisers	15000	2 wheeler	15	NO	Work	YES	YES	NO	Raised bicycle lane	YES	YES	YES	YES
464	Female	15	2	Student	10000	Car	20	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
465	Female	77	3	Unemployed	1500	Bus	10	NO	Work	YES	YES	YES	Raised	YES	YES	YES	YES

													bicycle lane				
466	Male	84	4	Unemployed	2000	Bus	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
467	Female	91	2	Unemployed	1500	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
468	Male	25	3	Self-Employee	20000	2 wheeler	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
469	Male	38	2	Private Employee	15000	2 wheeler	10	YES	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
470	Female	11	5	Student	2000	Auto	15	NO	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
471	Female	25	2	Private Employee	15000	2 wheeler	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
472	Female	36	3	Private Employee	20000	Auto	10	YES	Recreation	NO	NO	YES	Protected bicycle lane	YES	NO	YES	YES
473	Female	54	4	Unemployed	0	2 wheeler	20	NO	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
474	Male	28	2	Private Employee	15000	FALSE	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
475	Male	42	4	Private Employee	20000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
476	Female	36	2	Merchandisers	20000	Bus	15	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
477	Female	25	6	Unemployed	0	2 wheeler	5	YES	Recreation	NO	NO	YES	Segregated bicycle lane	YES	YES	YES	NO
478	Female	14	3	Student	10000	Bicycle	15	YES	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
479	Female	36	5	Unemployed	0	Auto	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
480	Male	25	2	Merchandisers	10000	2 wheeler	5	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
481	Male	47	5	Self-Employee	8500	Auto	10	YES	Work	YES	NO	YES	Segregated bicycle lane	YES	NO	YES	YES
482	Female	55	6	Merchandisers	25000	2 wheeler	5	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
483	Female	88	3	Unemployed	1000	Bus	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
484	Male	36	2	Self-Employee	5000	Bicycle	10	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
485	Male	39	5	Self-Employee	7500	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	NO
486	Female	25	2	Unemployed	0	2 wheeler	10	YES	Recreation	YES	YES	NO	Segregated bicycle lane	NO	YES	YES	YES
487	Female	16	3	Student	10000	Bus	15	YES	School	YES	YES	YES	Raised bicycle lane	YES	NO	YES	YES
488	Male	64	3	Self-Employee	7500	2 wheeler	15	NO	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES

489	Female	75	2	Unemployed	1000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	NO	YES
490	Male	78	5	Unemployed	2000	Bicycle	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	NO
491	Male	59	2	Self-Employee	7000	Car	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	NO	YES
492	Female	32	3	Unemployed	0	2 wheeler	5	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
493	Female	56	4	retired person	30000	Bus	15	NO	Recreation	YES	YES	YES	Raised bicycle lane	NO	YES	YES	YES
494	Male	54	2	Self-Employee	4500	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
495	Female	12	4	Student	8000	Bus	15	YES	School	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
496	Male	35	2	Private Employee	15000	2 wheeler	10	YES	Work	YES	NO	YES	Segregated bicycle lane	YES	YES	YES	YES
497	Female	13	4	Student	10000	Bicycle	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
498	Female	17	2	Student	8000	Bus	10	YES	School	YES	YES	NO	Segregated bicycle lane	YES	YES	YES	YES
499	Male	52	3	Merchandisers	20000	Car	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
500	Male	43	4	Government employee	30000	2 wheeler	10	YES	Recreation	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
501	Female	57	6	Unemployed	0	Bus	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
502	Female	26	3	Unemployed	0	2 wheeler	5	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	NO	YES
503	Male	35	2	Private Employee	15000	Auto	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	NO
504	Male	47	3	Merchandisers	20000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	NO	YES	YES	YES
505	Female	58	4	Unemployed	0	Bicycle	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
506	Female	36	2	Private Employee	20000	2 wheeler	5	YES	Work	NO	NO	NO	Protected bicycle lane	YES	YES	YES	YES
507	Male	21	3	Self-Employee	5000	Bus	10	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
508	Female	24	2	Unemployed	0	2 wheeler	10	YES	Exercise	YES	YES	YES	Raised bicycle lane	NO	YES	YES	YES
509	Male	51	5	Merchandisers	20000	2 wheeler	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
510	Female	37	2	Merchandisers	25000	Bus	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
511	Male	29	3	Self-Employee	7500	2 wheeler	5	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
512	Male	32	4	Self-Employee	6000	2 wheeler	10	YES	Work	YES	YES	YES	Raised	YES	YES	YES	NO

													bicycle lane					
513	Female	51	2	Unemployed	0	Bus	5	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
514	Female	22	4	Unemployed	0	Bicycle	10	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	NO	YES
515	Female	24	3	Private Employee	15000	Auto	25	YES	Recreation	YES	NO	YES	Protected bicycle lane	YES	NO	YES	YES
516	Male	35	2	Self-Employee	7000	Auto	10	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
517	Female	42	5	Unemployed	0	Bicycle	10	YES	Recreation	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
518	Male	82	2	Unemployed	1500	Auto	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
519	Female	77	3	Unemployed	1000	Bus	5	YES	FALSE	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
520	Male	54	4	Merchandisers	20000	Bus	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
521	Male	65	3	Self-Employee	8500	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
522	Female	32	5	Unemployed	0	Bicycle	5	YES	Exercise	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
523	Male	14	2	Student	15000	2 wheeler	15	NO	School	YES	NO	YES	Raised bicycle lane	YES	NO	YES	YES
524	Female	32	3	Private Employee	20000	2 wheeler	20	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
525	Male	52	4	Self-Employee	8000	Auto	20	NO	Recreation	YES	YES	NO	Raised bicycle lane	YES	YES	YES	NO
526	Female	62	5	Self-Employee	8000	2 wheeler	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
527	Female	24	6	Unemployed	0	2 wheeler	15	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
528	Female	25	3	Private Employee	20000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
529	Female	23	2	Unemployed	0	2 wheeler	5	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
530	Male	87	5	Unemployed	2000	Bus	5	NO	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
531	Male	43	4	Self-Employee	7500	Car	20	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
532	Male	17	3	Student	15000	Car	25	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
533	Female	29	2	Private Employee	20000	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
534	Male	93	5	Unemployed	2000	Bicycle	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
535	Female	88	6	Unemployed	2000	Car	15	NO	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES

536	Male	36	4.3952381	Self-Employee	9000	2 wheeler	20	YES	Work	YES	YES	NO	Raised bicycle lane	YES	YES	YES	YES
537	Female	53	4.4614719	Unemployed	0	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
538	Male	44	4.5277056	Self-Employee	7500	Bus	15	YES	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
539	Male	26	3	Self-Employee	6000	2 wheeler	25	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
540	Female	33	4	Unemployed	0	Bus	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
541	Male	29	2	Merchandisers	20000	2 wheeler	20	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
542	Female	51	4	Unemployed	0	Bus	5	YES	Recreation	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
543	Male	66	2	Self-Employee	7500	Auto	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
544	Female	47	4	Unemployed	0	Bus	10	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	NO
545	Female	51	3	Unemployed	0	Bicycle	5	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
546	Female	37	6	Unemployed	0	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
547	Female	42	3	Government employee	35000	Bus	15	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
548	Male	63	5	Self-Employee	6500	Bus	15	YES	Work	YES	YES	NO	Raised bicycle lane	YES	YES	YES	YES
549	Male	79	2	Unemployed	2000	Auto	20	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
550	Female	51	5	Unemployed	0	Bicycle	10	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
551	Male	62	6	Merchandisers	6000	2 wheeler	15	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
552	Female	88	3	Unemployed	0	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
553	Male	19	2	Student	15000	2 wheeler	25	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
554	Female	71	5	Unemployed	3000	Bus	15	NO	Recreation	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
555	Male	55	2	Self-Employee	6000	2 wheeler	25	NO	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
556	Male	67	3	Self-Employee	8000	Auto	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
557	Female	18	4	Student	10000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
558	Male	47	6	Merchandisers	20000	2 wheeler	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
559	Female	69	3	Unemployed	4000	Bicycle	10	YES	Recreatio	YES	YES	YES	Segregated	YES	YES	YES	NO

									n				bicycle lane				
560	Male	52	2	Merchandisers	25000	Car	25	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
561	Female	18	5	Student	15000	2 wheeler	10	NO	School	NO	NO	YES	Raised bicycle lane	YES	NO	YES	YES
562	Male	32	2	Self-Employee	10000	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
563	Female	57	3	Unemployed	0	Bicycle	10	YES	Recreatio n	YES	NO	YES	Raised bicycle lane	YES	NO	YES	YES
564	Female	26	5	Unemployed	0	Bus	25	YES	Recreatio n	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
565	Male	35	6	Merchandisers	20000	2 wheeler	15	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
566	Male	47	8	Merchandisers	15000	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
567	Male	58	4	Self-Employee	15000	2 wheeler	10	YES	Exercise	NO	YES	NO	Protected bicycle lane	YES	YES	YES	YES
568	Female	36	6	Unemployed	0	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	NO
569	Female	21	5	Unemployed	0	2 wheeler	25	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
570	Female	24	2	Unemployed	0	2 wheeler	10	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
571	Male	51	4	Self-Employee	8000	Bus	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
572	Female	37	3	Merchandisers	20000	Bicycle	20	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
573	Female	29	1	Unemployed	0	Bus	15	NO	Recreatio n	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
574	Male	32	2	Self-Employee	7500	Bus	25	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
575	Female	51	5	Unemployed	0	Bicycle	15	NO	Recreatio n	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
576	Male	22	2	Self-Employee	6000	2 wheeler	10	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
577	Male	33	3	Self-Employee	8000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
578	Male	45	2	Merchandisers	20000	2 wheeler	15	YES	Work	YES	NO	YES	Raised bicycle lane	YES	YES	NO	YES
579	Female	33	5	Unemployed	0	Bus	20	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
580	Male	54	4	Self-Employee	8000	2 wheeler	25	NO	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
581	Female	56	3	Unemployed	0	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
582	Male	37	3	Merchandisers	15000	2 wheeler	30	NO	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES

583	Female	21	6	Student	20000	Auto	25	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
584	Female	52	2	Unemployed	0	Bicycle	10	YES	Recreation	NO	NO	YES	Raised bicycle lane	YES	NO	NO	YES
585	Female	41	3	Unemployed	0	Bicycle	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
586	Male	48	2	Self-Employee	8500	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
587	Male	39	2	Self-Employee	9000	Auto	25	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
588	Female	41	5	Unemployed	0	Bus	10	YES	Recreation	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
589	Male	75	2	Self-Employee	7500	2 wheeler	15	YES	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
590	Male	57	3	Self-Employee	7000	Auto	15	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
591	Female	54	5	Unemployed	0	Bus	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
592	Male	55	6	Merchandisers	25000	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
593	Male	57	8	Self-Employee	8500	2 wheeler	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
594	Female	33	4	Unemployed	0	Bicycle	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
595	Male	54	6	Self-Employee	7500	2 wheeler	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
596	Male	56	2	Self-Employee	6500	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
597	Male	37	4	Self-Employee	8500	2 wheeler	10	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
598	Male	21	2	Self-Employee	5500	Auto	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
599	Female	52	4	Government employee	30000	Bicycle	10	NO	Recreation	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
600	Female	41	3	Unemployed	0	Bus	5	YES	Exercise	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
601	Male	66	6	Self-Employee	8500	2 wheeler	10	NO	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
602	Female	67	3	Unemployed	0	Bicycle	15	NO	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
603	Male	33	5	Merchandisers	20000	2 wheeler	10	NO	Work	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
604	Female	29	2	Unemployed	0	Bicycle	15	YES	Recreation	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
605	Male	35	5	Self-Employee	7000	2 wheeler	25	YES	Recreation	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
606	Male	37	6	Self-Employee	6000	2 wheeler	25	NO	Work	NO	YES	YES	Raised	YES	YES	YES	YES

													bicycle lane				
607	Male	45	3	Self-Employee	8000	2 wheeler	30	NO	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
608	Female	27	2	Unemployed	0	Bus	5	NO	Exercise	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
609	Female	23	5	Private Employee	10000	2 wheeler	10	NO	Recreatio n	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
610	Male	19	2	Student	7500	2 wheeler	15	YES	School	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
611	Female	14	3	Student	20000	2 wheeler	20	YES	School	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
612	Male	47	4	Self-Employee	5000	2 wheeler	25	YES	Work	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
613	Male	25	6	Self-Employee	6000	2 wheeler	10	NO	Work	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
614	Female	39	3	Unemployed	0	Auto	15	YES	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
615	Female	71	2	Unemployed	0	2 wheeler	20	YES	Recreatio n	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
616	Female	91	5	Unemployed	3000	Bicycle	20	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
617	Female	56	2	retired person	30000	Bus	5	YES	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
618	Male	82	3	Self-Employee	8000	2 wheeler	20	YES	Work	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
619	Male	90	2	Self-Employee	7000	Auto	15	YES	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
620	Female	41	5	Unemployed	0	2 wheeler	25	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
621	Female	75	4	Unemployed	3000	2 wheeler	10	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
622	Male	57	3	Self-Employee	8000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
623	Male	54	3	Self-Employee	7000	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
624	Female	33	6	Private Employee	15000	Bicycle	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
625	Female	45	2	Private Employee	15000	Bus	5	NO	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
626	Female	32	3	Merchandisers	20000	Bus	5	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
627	Male	25	2	Self-Employee	7000	2 wheeler	20	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
628	Male	32	5	Self-Employee	8000	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
629	Female	54	5	Unemployed	0	Bus	5	NO	Recreatio n	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO

630	Female	56	4	Unemployed	0	Bicycle	15	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
631	Male	35	6	Merchandisers	15000	2 wheeler	10	YES	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
632	Female	47	8	Unemployed	0	Bus	5	NO	Recreation	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
633	Male	90	7	Unemployed	3000	2 wheeler	15	NO	Work	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
634	Male	49	3	Self-Employee	8500	2 wheeler	20	NO	Work	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
635	Female	37	5	Unemployed	0	Bicycle	25	NO	Recreation	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
636	Female	51	6	Unemployed	0	Bicycle	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
637	Female	35	4	Private Employee	20000	Bus	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
638	Female	24	2	Unemployed	0	2 wheeler	10	YES	Work	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
639	Male	62	3	Self-Employee	7500	2 wheeler	15	NO	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
640	Male	74	4	Merchandisers	15000	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
641	Female	71	7	Unemployed	3000	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
642	Female	54	8	Unemployed	0	Bicycle	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
643	Female	48	5	Government employee	20000	Bus	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
644	Female	65	2	Unemployed	0	Bicycle	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
645	Male	35	3	Self-Employee	7500	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
646	Male	41	4	Self-Employee	7000	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
647	Female	37	6	Private Employee	10000	Bicycle	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
648	Female	29	3	Unemployed	0	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
649	Male	81	2	Unemployed	3000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
650	Male	52	8	Merchandisers	20000	2 wheeler	20	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
651	Female	66	5	Unemployed	0	Bicycle	15	NO	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
652	Female	54	3	Unemployed	0	Bus	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
653	Male	88	6	Unemployed	3000	2 wheeler	10	NO	Recreatio	YES	YES	YES	Raised	YES	YES	YES	YES

									n				bicycle lane				
654	Female	25	4	Unemployed	0	Auto	15	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
655	Male	47	8	Self-Employee	4000	2 wheeler	20	NO	Work	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
656	Male	58	7	Self-Employee	6000	2 wheeler	25	YES	Work	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
657	Female	65	5	Unemployed	0	Bicycle	35	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
658	Female	35	6	Unemployed	0	Bicycle	30	NO	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
659	Male	24	3	Self-Employee	7000	2 wheeler	15	NO	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
660	Female	15	5	Student	10000	Car	25	NO	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
661	Male	26	6	Self-Employee	7000	2 wheeler	20	NO	Exercise	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
662	Female	44	3	Unemployed	0	Bicycle	15	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
663	Female	25	4	Unemployed	0	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
664	Male	75	2	Merchandisers	20000	2 wheeler	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
665	Male	24	7	Self-Employee	7000	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
666	Female	16	4	Student	10000	2 wheeler	15	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
667	Female	19	3	Student	15000	Car	30	YES	School	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
668	Male	32	3	Self-Employee	7000	Bicycle	20	YES	Work	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
669	Male	37	4	Self-Employee	6000	2 wheeler	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
670	Male	54	2	Merchandisers	25000	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
671	Female	49	3	Unemployed	0	2 wheeler	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
672	Male	77	2	Self-Employee	7000	2 wheeler	25	YES	Work	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
673	Female	52	5	Unemployed	0	2 wheeler	10	YES	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
674	Female	36	3.6666667	Merchandisers	6000	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
675	Female	35	5	Government employee	20000	Bus	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
676	Female	47	3	Unemployed	0	Bus	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES

677	Male	90	6	Unemployed	4000	2 wheeler	10	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
678	Female	49	4	Unemployed	0	Bus	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
679	Male	37	8	Self-Employee	7000	2 wheeler	15	NO	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
680	Male	51	7	Merchandisers	15000	2 wheeler	20	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
681	Female	35	5	Unemployed	0	Bus	5	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
682	Male	24	5	Self-Employee	7000	2 wheeler	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
683	Male	32	3	Merchandisers	15000	2 wheeler	20	YES	Work	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
684	Female	29	6	Private Employee	20000	Bicycle	25	NO	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
685	Female	26	4	Private Employee	15000	Bicycle	20	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
686	Female	22	8	Student	10000	2 wheeler	35	NO	Recreation	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
687	Male	90	7	Unemployed	3000	2 wheeler	30	NO	Work	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
688	Male	49	5	Merchandisers	15000	2 wheeler	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
689	Male	37	3	Self-Employee	7000	Auto	15	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
690	Female	88	4	Unemployed	0	Auto	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
691	Male	25	5	Self-Employee	7000	2 wheeler	15	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
692	Male	47	6	Merchandisers	15000	Bus	15	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
693	Male	58	3	Self-Employee	7000	Bus	20	YES	Work	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
694	Female	65	2	Unemployed	0	Bicycle	15	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
695	Female	35	5	Government employee	20000	Bus	20	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
696	Female	24	4	Private Employee	15000	Bus	5	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
697	Female	15	3	Student	10000	2 wheeler	15	YES	Work	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
698	Male	23	4	Private Employee	20000	2 wheeler	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
699	Male	25	5	Private Employee	25000	2 wheeler	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
700	Female	63	2	Unemployed	2000	Bicycle	5	YES	Exercise	YES	YES	YES	Protected	YES	YES	YES	YES

													bicycle lane				
701	Female	14	5	Student	15000	Auto	10	NO	School	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
702	Male	71	4	Self-Employee	7500	2 wheeler	5	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
703	Male	45	2	Merchandisers	20000	2 wheeler	10	YES	Recreatio n	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
704	Female	62	3	Unemployed	3000	Bicycle	5	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
705	Male	35	4	Merchandisers	25000	2 wheeler	10	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
706	Female	64	5	Unemployed	2000	Bus	5	YES	Exercise	NO	YES	YES	Protected bicycle lane	YES	YES	YES	YES
707	Male	42	2	Self-Employee	7500	Auto	15	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
708	Male	15	3	Student	10000	2 wheeler	20	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
709	Female	47	5	Unemployed	0	Bus	5	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
710	Female	82	5	Unemployed	2000	Bus	15	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
711	Male	58	3	Merchandisers	10000	2 wheeler	20	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
712	Female	48	2	Merchandisers	15000	Auto	25	YES	Exercise	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
713	Male	39	2	Self-Employee	7000	2 wheeler	15	YES	Recreatio n	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
714	Male	41	4	Self-Employee	8000	2 wheeler	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
715	Male	75	2	Self-Employee	6500	Bicycle	15	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
716	Female	57	3	Unemployed	0	Bus	25	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
717	Female	45	5	Government employee	35000	Car	40	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
718	Male	68	3	Self-Employee	7000	2 wheeler	25	NO	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
719	Male	56	6	Self-Employee	6000	2 wheeler	10	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
720	Female	59	2	Unemployed	0	Bus	15	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
721	Male	60	4	Self-Employee	7000	2 wheeler	25	YES	Recreatio n	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
722	Male	61	3	Self-Employee	8000	2 wheeler	30	NO	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
723	Male	56	6	Merchandisers	15000	Auto	15	YES	Recreatio n	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

724	Female	37	5	Private Employee	20000	Bus	20	YES	Recreation	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
725	Female	21	2	Unemployed	0	Bus	10	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
726	Male	52	4	Self-Employee	8000	Bicycle	30	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
727	Female	41	3	Unemployed	0	Bus	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
728	Male	54	3	Self-Employee	7000	2 wheeler	25	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
729	Male	75	2	Self-Employee	8000	2 wheeler	35	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
730	Female	55	5	Unemployed	0	Bus	40	YES	Recreation	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
731	Female	21	5	Student	6500	Auto	10	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
732	Male	23	3	Merchandisers	12000	2 wheeler	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
733	Male	28	2	Merchandisers	15000	2 wheeler	30	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
734	Female	72	6	Unemployed	0	Bus	25	YES	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
735	Male	44	4	Self-Employee	8000	Car	25	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
736	Female	33	2	Unemployed	0	Bus	15	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
737	Male	54	3	Self-Employee	7000	Bus	10	YES	Exercise	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
738	Male	56	6	Self-Employee	8000	Bicycle	5	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
739	Female	37	5	Private Employee	20000	2 wheeler	5	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
740	Female	21	4	Student	10000	2 wheeler	5	YES	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
741	Male	32	2	Self-Employee	7000	Auto	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
742	Female	36	3	Unemployed	0	2 wheeler	15	NO	Exercise	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
743	Male	25	7	Self-Employee	8000	Auto	10	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
744	Male	20	5	Self-Employee	6000	2 wheeler	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
745	Female	45	3	Private Employee	20000	Bus	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
746	Female	68	4	Unemployed	0	2 wheeler	5	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
747	Female	72	6	Unemployed	2000	Bus	10	YES	Recreatio	YES	YES	YES	Raised	YES	YES	YES	YES

									n				bicycle lane				
748	Male	29	7	Self-Employee	7000	2 wheeler	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
749	Female	25	5	Private Employee	20000	Bicycle	20	NO	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
750	Female	36	2	Private Employee	15000	Auto	10	YES	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
751	Male	22	3	Self-Employee	6500	2 wheeler	30	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
752	Male	54	6	Self-Employee	6000	Auto	25	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
753	Female	64	5	Unemployed	0	2 wheeler	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
754	Male	12	4	Student	10000	Bus	5	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
755	Female	33	7	Merchandisers	20000	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
756	Male	41	3	Merchandisers	15000	Bicycle	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
757	Female	55	2	Unemployed	0	2 wheeler	5	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
758	Male	28	4	Self-Employee	10000	2 wheeler	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
759	Male	17	5	Student	15000	2 wheeler	10	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
760	Female	42	7	Merchandisers	22000	Car	30	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
761	Male	38	6	Self-Employee	4500	2 wheeler	25	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
762	Female	65	5	Unemployed	0	2 wheeler	10	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
763	Female	79	7	Unemployed	0	2 wheeler	25	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
764	Female	50	4	Unemployed	0	Bus	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
765	Male	22	2	Student	10000	Car	25	YES	Work	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
766	Female	31	3	Private Employee	10000	Bus	15	NO	Recreation	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
767	Female	92	5	Unemployed	3000	Bus	5	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
768	Male	88	7	Self-Employee	8500	Bicycle	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
769	Male	74	6	Self-Employee	7000	2 wheeler	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
770	Female	51	6	Unemployed	2000	2 wheeler	10	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

771	Male	62	8	Self-Employee	8500	Auto	5	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
772	Female	53	2	Unemployed	3000	2 wheeler	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
773	Female	43	3	Government employee	35000	Auto	10	NO	Exercise	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
774	Female	25	4	Unemployed	0	2 wheeler	20	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
775	Female	36	7	Unemployed	0	Bus	5	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
776	Male	75	5	Merchandisers	15000	2 wheeler	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
777	Female	88	6	Unemployed	2000	2 wheeler	10	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
778	Male	44	3	Merchandisers	15000	Bus	10	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
779	Male	25	2	Merchandisers	25000	Bicycle	25	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
780	Female	24	5	Unemployed	0	Bus	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
781	Male	36	4	Self-Employee	6000	Auto	10	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
782	Male	56	3	Self-Employee	7000	Bicycle	15	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
783	Female	32	6	Unemployed	0	2 wheeler	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
784	Female	30	6	Unemployed	0	Bicycle	10	YES	Recreation	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
785	Female	75	3	Unemployed	0	Bicycle	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
786	Male	82	2	Self-Employee	4500	Bicycle	10	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
787	Male	35	8	Self-Employee	6000	Bus	20	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
788	Male	21	5	Self-Employee	7000	2 wheeler	30	YES	Work	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
789	Female	57	3	Unemployed	0	2 wheeler	25	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
790	Male	45	4	Self-Employee	5500	2 wheeler	15	NO	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
791	Male	63	2	Self-Employee	6500	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
792	Female	31	6	Unemployed	0	Car	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
793	Female	78	3	Unemployed	0	2 wheeler	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
794	Male	47	2	Merchandisers	20000	2 wheeler	25	NO	Recreatio	YES	YES	YES	Raised	YES	YES	YES	YES

									n				bicycle lane				
795	Male	38	2	Self-Employee	7000	2 wheeler	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
796	Female	35	5	Unemployed	0	2 wheeler	10	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
797	Male	13	5	Student	10000	2 wheeler	15	NO	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
798	Male	17	3	Student	10000	Bus	25	YES	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
799	Male	39	4	Self-Employee	7000	Car	15	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
800	Female	87	6	Unemployed	2000	Bus	25	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
801	Male	81	7	Merchandisers	20000	Bus	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
802	Female	52	2	Unemployed	0	Bicycle	25	YES	Recreation	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
803	Female	77	8	Unemployed	0	2 wheeler	10	YES	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
804	Female	48	3	Unemployed	0	2 wheeler	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
805	Female	29	2	Unemployed	0	Bicycle	15	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
806	Male	51	5	Self-Employee	6500	Bus	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
807	Female	33	4	Unemployed	0	Auto	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
808	Male	36	3	Self-Employee	7000	Bicycle	5	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
809	Male	25	6	Self-Employee	8000	2 wheeler	5	YES	Work	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
810	Female	15	6	Student	20000	Bicycle	10	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
811	Male	77	3	Merchandisers	20000	Bicycle	5	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
812	Male	84	2	Self-Employee	6000	Bicycle	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
813	Female	15	7	Student	15000	Bus	5	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
814	Female	23	5	Unemployed	0	2 wheeler	10	NO	Recreation	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
815	Female	28	3	Unemployed	0	2 wheeler	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
816	Male	36	4	Self-Employee	7000	2 wheeler	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
817	Male	55	3	Self-Employee	8500	Bicycle	5	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

818	Male	24	3	Merchandisers	10000	Car	5	NO	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
819	Female	36	6	Unemployed	0	2 wheeler	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
820	Male	30	2	Self-Employee	6500	2 wheeler	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
821	Male	17	3	Student	15000	Bicycle	15	NO	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
822	Female	78	2	Unemployed	0	Bicycle	25	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
823	Female	26	5	Private Employee	15000	Bus	10	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
824	Male	25	5	Merchandisers	22000	2 wheeler	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
825	Male	75	4	Self-Employee	6500	2 wheeler	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
826	Female	78	6	Unemployed	0	2 wheeler	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
827	Male	59	8	Self-Employee	2500	Bicycle	25	YES	Recreation	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
828	Female	32	7	Unemployed	0	Car	10	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
829	Male	56	3	Merchandisers	15000	Bicycle	20	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
830	Female	54	5	Unemployed	0	Bus	5	YES	Exercise	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
831	Female	12	6	Student	10000	Auto	10	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
832	Female	35	4	Merchandisers	15000	Bicycle	15	YES	Recreation	NO	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
833	Male	13	2	Student	10000	2 wheeler	25	YES	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
834	Male	17	3	Student	15000	Bicycle	10	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
835	Female	78	4	Unemployed	3000	Bicycle	20	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
836	Male	59	7	Self-Employee	7000	Bicycle	5	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
837	Female	32	8	Unemployed	0	Bus	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
838	Male	56	5	Self-Employee	5500	2 wheeler	25	NO	Recreation	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
839	Female	54	3	Unemployed	5500	2 wheeler	15	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
840	Male	14	2	Student	10000	2 wheeler	25	YES	School	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
841	Female	15	5	Student	10000	Bicycle	10	YES	School	YES	YES	YES	Raised	YES	YES	YES	YES

													bicycle lane				
842	Male	57	6	Merchandisers	6500	Car	20	NO	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
843	Male	54	4	Merchandisers	7500	2 wheeler	15	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
844	Female	33	7	Unemployed	0	2 wheeler	25	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
845	Male	45	5	Self-Employee	5500	Bus	20	NO	Recreation	YES	YES	YES	Raised bicycle lane	NO	YES	YES	NO
846	Female	32	3	Unemployed	0	Bicycle	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
847	Male	84	8	Self-Employee	8500	2 wheeler	25	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
848	Female	56	3	Unemployed	0	2 wheeler	10	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
849	Male	35	2	Merchandisers	10000	Auto	15	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
850	Male	33	4	Merchandisers	15000	2 wheeler	10	YES	Recreation	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES
851	Male	83	3	Merchandisers	20000	Auto	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
852	Female	45	2	Unemployed	0	2 wheeler	10	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
853	Female	57	5	Unemployed	0	Bus	5	YES	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
854	Male	54	4	Self-Employee	8500	Auto	5	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
855	Female	33	3	Unemployed	0	Bus	10	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
856	Male	45	6	Self-Employee	7000	2 wheeler	20	YES	Recreation	YES	YES	YES	Segregated bicycle lane	NO	YES	YES	NO
857	Male	32	6	Self-Employee	8500	Auto	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
858	Female	25	3	Unemployed	0	Bus	15	YES	Recreation	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
859	Female	32	2	Private Employee	10000	2 wheeler	25	YES	Recreation	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
860	Female	19	7	Student	10000	2 wheeler	15	YES	School	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
861	Female	32	5	Unemployed	0	Bus	10	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
862	Male	65	3	Self-Employee	7000	2 wheeler	20	NO	Exercise	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
863	Male	45	4	Self-Employee	7000	2 wheeler	5	YES	Recreation	YES	YES	YES	Protected bicycle lane	NO	YES	YES	NO
864	Female	25	3	Unemployed	0	Bus	5	YES	Recreation	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES

865	Male	44	3	Self-Employee	8000	2 wheeler	5	YES	Exercise	YES	YES	YES	Raised bicycle lane	YES	YES	YES	YES
866	Male	78	6	Self-Employee	8500	2 wheeler	5	NO	Recreatio n	YES	YES	YES	Protected bicycle lane	YES	YES	YES	YES
867	Male	13	2	Student	10000	Bicycle	10	YES	School	YES	YES	YES	Segregated bicycle lane	YES	YES	YES	YES
868	Female	35	3	Private Employee	10000	Auto	25	YES	Exercise	NO	YES	YES	Raised bicycle lane	YES	YES	YES	YES

APPENDIX - E

Python Script

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
df = pd.read_excel("D:\mtech subjects\semesters\semster 4\Questionnaire response with options for ML.xlsx")
df
df.groupby('Gender').size().plot(kind='pie', autopct='%.2f',radius=2,title='Gender');
df.groupby('Age').size().plot(kind='pie', autopct='%.2f',radius=2,title='Age Distribution');
df.groupby('Household Size').size().plot(kind='pie', autopct='%.2f',radius=2,title='Household Size');
df.groupby('Occupation Status').size().plot(kind='pie', autopct='%.2f',radius=2,title='Occupation Status');
df.groupby('Monthly Income ').size().plot(kind='pie', autopct='%.2f',radius=4.5,title='Monthly Income ');
df.groupby('Travel Distance (km)').size().plot(kind='pie', autopct='%.2f',radius=2,title='Travel Distance (km)');
df.groupby('Dedicated Bicycle Facility').size().plot(kind='pie', autopct='%.2f',radius=2,title='Dedicated Bicycle Facility');
df.groupby('Vehicle Ownership').size().plot(kind='pie', autopct='%.2f',radius=2,title='Vehicle Ownership');
df.groupby('Bicycle Ownership').size().plot(kind='pie', autopct='%.2f',radius=2,title='Bicycle Ownership');
df.groupby('Trip Purpose').size().plot(kind='pie', autopct='%.2f',radius=2,title='Trip Purpose');
df.columns
print("Rows:",df.shape[0])
print("\nColumns:",df.shape[1])
print("\nColumn names:",df.columns)
print("\nNull Values are:\n",df.isnull().sum())
print("\nUnique Values are:\n",df.nunique())
df.groupby('Preference if infrastructure improves').size()
df.dtypes
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for feat in objList:
    df[feat] = le.fit_transform(df[feat].astype(str))
print (df.info())
```

```
data1 = df.drop(columns = ['Responses'])
des = data1.describe()
des
data_rep = data1.replace(0,np.NaN)
print("\nNull Values are:\n",data_rep.isnull().sum())
data_rep.fillna(data_rep.mean(), inplace=True)
x = data1.drop(columns=['Preference if infrastructure improves'])
y = data1['Preference if infrastructure improves']
y
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
stdsclr =  StandardScaler()
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.33)
x_train_std = stdsclr.fit_transform(x_train)
x_test_std = stdsclr.fit_transform(x_test)
x_train
from sklearn.ensemble import ExtraTreesClassifier
model = ExtraTreesClassifier()
model.fit(x,y)
ft_importances = pd.Series(model.feature_importances_,x.columns)
print(ft_importances.nlargest(15))
ft_importances.nlargest(10).plot(kind='barh',color='lightblue');
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.ensemble import RandomForestClassifier
modelrand = RandomForestClassifier(n_estimators=8)
modelrand.fit(x_train_std,y_train)
print(classification_report(y_test, y_pred_random))
accuracy_score(y_test, y_pred_random)
```

```
pd.DataFrame(confusion_matrix(y_test, y_pred_random),
             columns=['Predicted Negative', 'Predicted Positive'],
             index=['Actual Negative', 'Actual Positive'])
from sklearn.svm import SVC
svm_model = SVC()
svm_model.fit(x_train, y_train)
y_pred_svc = svm_model.predict(x_test)
pd.DataFrame(confusion_matrix(y_test, y_pred_svc),
             columns=['Predicted Negative', 'Predicted Positive'],
             index=['Actual Negative', 'Actual Positive'])
print(classification_report(y_test, y_pred_svc))
accuracy_score(y_test, y_pred_svc)
model_linear_kernal = SVC(kernel='linear')
model_linear_kernal.fit(x_train, y_train)
y_pred_svcl = model_linear_kernal.predict(x_test)
pd.DataFrame(confusion_matrix(y_test, y_pred_svcl),
             columns=['Predicted Negative', 'Predicted Positive'],
             index=['Actual Negative', 'Actual Positive'])
print(classification_report(y_test, y_pred_svcl))
accuracy_score(y_test, y_pred_svcl)
model_polynomial_kernal = SVC(kernel='poly')
model_polynomial_kernal.fit(x_train, y_train)
y_pred_svcp = model_polynomial_kernal.predict(x_test)
pd.DataFrame(confusion_matrix(y_test, y_pred_svcp),
             columns=['Predicted Negative', 'Predicted Positive'],
             index=['Actual Negative', 'Actual Positive'])
print(classification_report(y_test, y_pred_svcp))
accuracy_score(y_test, y_pred_svcp)
model_sigmoid_kernal = SVC(kernel='sigmoid')
model_sigmoid_kernal.fit(x_train, y_train)
y_pred_svcs = model_sigmoid_kernal.predict(x_test)
pd.DataFrame(confusion_matrix(y_test, y_pred_svcs),
             columns=['Predicted Negative', 'Predicted Positive'],
             index=['Actual Negative', 'Actual Positive'])
```

```
accuracy_score(y_test, y_pred_svcs)
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors=3)
classifier.fit(x_train, y_train)
y_pred_knn = classifier.predict(x_test)
pd.DataFrame(confusion_matrix(y_test, y_pred_knn),
             columns=['Predicted Negative', 'Predicted Positive'],
             index=['Actual Negative', 'Actual Positive'])
print(classification_report(y_test, y_pred_knn))
accuracy_score(y_test, y_pred_knn)
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.linear_model import LogisticRegression
models =[]
models.append(("Random Forest Classifier",RandomForestClassifier(n_estimators=50, random_state=5)))
models.append(("SupportVectorMachine(rbf)",SVC()))
models.append(("SupportVectorMachine(Linear)",SVC(kernel='linear')))
models.append(("SupportVectorMachine(Poly)",SVC(kernel='poly')))
models.append(("SupportVectorMachine(sigmoid)",SVC(kernel='sigmoid')))
models.append(("KNearestNeighbors Classifier",KNeighborsClassifier(n_neighbors=3)))
results =[]
names = []
recall = []
f1score = []
for name,model in models:
    kfold = KFold(n_splits=6)
    cv_results = cross_val_score(model,x_train_std,y_train,cv=kfold,scoring="accuracy")
    recl = cross_val_score(model, x_train_std, y_train, cv=5, scoring='recall')
    f1s = cross_val_score(model, x_train_std, y_train, cv=5, scoring='f1_macro')
    results.append(cv_results)
    recall.append(recl)
    f1score.append(f1s)
    names.append(name)
    print(name, "\tAccuracy:",cv_results.mean(),"\tRecall:" ,recl.mean(),"\tf1score:" ,f1s.mean())
```