

# Predicting Bike-Sharing Adoption for Green Mobility Planning Using Hard Voting Ensemble Classifier in Machine Learning: Evidence from Kigali City, Rwanda

Jean Marie Vianney Ntamwiza<sup>1\*</sup>, Hannibal Bwire<sup>1</sup> and Alphonse Nkurunziza<sup>2</sup>

<sup>1</sup>University of Dar Es Salaam, Department of TGE, Dar es Salaam, Tanzania; Email: [ntamwizajeanmarie@gmail.com](mailto:ntamwizajeanmarie@gmail.com), [hbwire@udsm.ac.tz](mailto:hbwire@udsm.ac.tz)

<sup>2</sup>University of Rwanda, Department of CE, Kigali, Rwanda; Email: [nzizaalphonse@gmail.com](mailto:nzizaalphonse@gmail.com)

**\*Corresponding Author:** Jean Marie Vianney Ntamwiza

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**Abstract:** Bike-sharing systems have proven to support sustainable urban mobility across the globe; however, limited research has integrated demographic, socioeconomic, and environmental factors to predict user adoption effectively. This study addresses this gap by applying a hard voting classifier that combines XGBoost, AdaBoost, and Random Forest models to analyze data collected from 5,000 residents in Kigali, Rwanda, enriched with corresponding air quality and weather variables. The model was evaluated using 10-fold cross-validation, and the voting classifier outperformed individual models with an accuracy of 97% ( $\pm 0.5\%$ ), compared to 96% ( $\pm 4\%$ ) for Random Forest, 96% for AdaBoost, and 93% for XGBoost. Feature importance analysis revealed that monthly income (13.3%), age (13.1%), location (11.9%), and household size (8.4%) were the most significant predictors of bike-sharing adoption. Among marital status groups, divorced individuals (4%) were more likely to adopt bike-sharing due to its flexibility in meeting independent travel needs. Environmental variables such as temperature (2.6%), humidity (1.5%), nitrogen dioxide (3.5%), and carbon monoxide (3.1%) also influenced usage patterns. These findings provide actionable insights for urban planners and policymakers to develop data-driven strategies that promote active mobility and reduce environmental pollution.

**Keywords:** Bike-sharing demand, key determinants, travel characteristics, machine learning algorithms, air pollution

## 1. Introduction and Literature Review

Rapid urbanization and the growing use of private vehicles in urban areas have heightened congestion across urban roads, elevated noise pollution, deteriorated air quality, which in turn increased the risk

of serious cardiovascular diseases such as stroke and hypertension[1]. In response to these challenges, bike-sharing schemes have gained traction globally as a solution for sustainable urban mobility [2]. These initiatives have been credited with reducing NOX (nitrogen oxide) and CO2 (carbon dioxide) emissions [3], credited with preventing premature deaths [4], conserving energy [6], and offering cost effective, convenient option for first and last mile solution [7],[8]. The successful implementation of those initiatives have not only limited to those high-income countries in Europe and Asia, also African cities such as Kigali city in Rwanda[9], Quelimane city in Mozambique [10], Lagos city in Nigeria [11], Accra and Kumasi cities in Ghana [12] have demonstrated promising results worldwide.

Numerous studies have globally explored bike-sharing initiatives, bike sharing cost efficiency [13], social and ecological benefits [14], impact of technology on bike sharing services[15], modal shift dynamics, viability of shared bikes in smaller and medium cities[16]. Despite the rapid global growth of shared and non-shared bike systems—operating in over 1,000 cities worldwide and enabling hundreds of millions of rides annually—empirical evidence on the determinants of their adoption in African cities remains scarce[17]. This gap is particularly pronounced in rapidly urbanizing contexts like Kigali, where challenges such as traffic congestion, limited cycling infrastructure, and rising pollution hinder sustainable mobility. Moreover, although ensemble machine learning methods, such as hard voting classifiers, have demonstrated superior predictive performance across diverse domains, their application in transportation research remains limited, restricting the accuracy of demand forecasting and the development of evidence-based policy interventions[18].

To bridge these gaps, this research proposed a hard voting ensemble classifier combining XGBoost Classifier, AdaBoost Classifier, and Random Forest to predict bike sharing adoption in the city of Kigali, Rwanda. The model was trained at 80% and tested on 20% of dataset, then validated on 10-fold cross-validation. The dataset comprises 5,000 residents across the city, air quality and weather variables. The structure of this research includes an introduction, materials and methods, results and discussion of findings, and finally, a conclusion and recommendations on policy implications.

## **2. Data and Methods**

This section comprised the description of the study area, sampling techniques, data type and data sources, and machine learning models used.

### **2.1 Study Area**

Kigali is the capital city of Rwanda and serves as the country's major economic, administrative, and urban center. The city has experienced rapid urbanization and population growth over the past

decades, with an estimated population of approximately 1,745,555 inhabitants, projected to increase to about 3.8 million by 2035. This rapid growth has significantly increased travel demand, traffic congestion, energy consumption, and greenhouse gas emissions, creating a need for sustainable and efficient urban transportation systems.

Kigali has advanced sustainable urban mobility through electric buses, electric bicycles for city staff, dedicated bus lanes, and the promotion of walking and cycling, alongside internationally recognized car-free days and car-free zones that encourage active mobility and reduce pollution. Its transport system includes buses, private vehicles, motorcycles, bicycles, walking, and emerging electric mobility, but rapid urban growth and motorization continue to strain infrastructure. The city's tropical highland climate with seasonal rainfall also affects non-motorized transport. In response, Kigali has integrated sustainable mobility policies focused on low-carbon transport, public transport improvement, electric mobility, and expanded walking and cycling infrastructure, positioning it as a leading African city in sustainable urban transport.

## 2.2 Frame and Sample Strategies

This research employed a survey to collect data in Kigali city from March 20 to April 8, 2023, utilizing online and offline questionnaires. Table 1 summaries how data were collected from each district of the city of Kigali (Nyarugenge, Kicukiro, and Gasabo). Data was collected on bus stands, higher learning institutions, and bike-sharing stations. A sample size of 5,000 was determined, then distributed to those three districts based on their population percentages.

**Table 1** Stratified sample. Source: authors

| Districts of the City of Kigali | Population | Percentage | Sample size in each district |
|---------------------------------|------------|------------|------------------------------|
| Gasabo district                 | 879,505    | 50.39%     | 2,520                        |
| Kicukiro district               | 491,731    | 28.17%     | 1,409                        |
| Nyarugenge district             | 374,319    | 21.44%     | 1,072                        |

## 2.3 Weather Data

The daily weather data collected from Meteo Rwanda in Kigali city stations comprised solar radiation intensity, humidity, rainfall, temperature variations, and wind speed. These variables were selected to be incorporated in the model as they affect the comfort and safety of the riders.

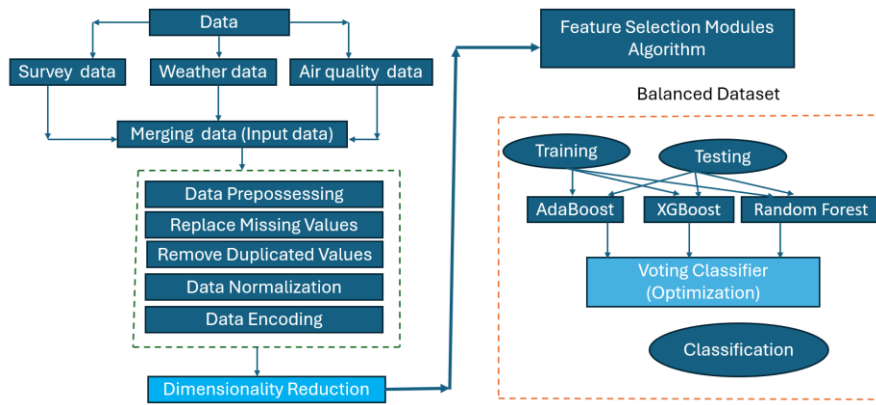
## 2.4 Air Quality Data

The daily air quality data from Rwanda Environment Management Authority in Kigali stations include carbon monoxide (CO), particulate matter (PM<sub>2.5</sub>), nitrogen dioxide (NO<sub>2</sub>), and carbon dioxide (CO<sub>2</sub>). These data were also incorporated into the model to understand how they impact bike-sharing adoption, as their levels discourage people from biking due to health risks and reduced comfort.

## 2.5 Modelling Process

Figure 1 merged survey response, weather data, and air quality data into a unified dataset, followed by preprocessing to handle missing and duplicate values, normalize data, and encode categorical variables. Dimensionality reduction was applied to reduce the number of features, improving computational efficiency and preventing overfitting. Key features were then selected to create a balanced dataset.

Machine learning models—including AdaBoost, XGBoost, and Random Forest—were trained and tested, and their predictions combined using a Voting Classifier to optimize performance, producing the final classification results. The dataset was first divided into 80% training data and 20% testing data. The training dataset was used for model development, while the testing dataset remained completely unseen during training. Within the training set, 10-fold cross-validation was applied to optimize and evaluate the models. The final model was then evaluated on the independent test set. Model performance was evaluated using accuracy, precision, recall, and F1-score.



**Fig. 1** Modelling process. Source: authors

## 2.6 XGBoost

XGBoost, a powerful algorithm for capturing complex non-linear relationships and reducing overfitting [21], was used alongside K-Nearest Neighbors (KNN) and Logistic Regression to model biking behavior. Prediction and reporting, generating classification metrics (precision, recall, F1-score) and visualizing feature contributions for interpretation.

## 2.7 AdaBoost Method

AdaBoost method is today famous as adaptive boosting which is widely used as a machine learning technique for classification tasks. Its core principle involves iteratively training a sequence of weak learners, often deciding trees or shallow classifiers, to collectively construct a strong learner[22]. In modelling, this research prepared the dataset with  $x\_main$  as features and  $y\_main$  as target labels; then, we set a 10-fold cross-validation procedure with shuffling to ensure robust evaluation. With a

maximum depth of 19, a Decision tree algorithm was used as the base learner for an Ada Boost Classifier, configured with 117 estimators, a learning rate of 0.47, and a random state of 42.

## 2.8 The Voting Classifier Method

A Voting Classifier is a method chosen due to its capacity of offering a comprehensive and robust framework where it combines predictions from multiple base classifiers, each capable of capturing different facets of bike-sharing behaviour, trip characteristics, and environmental elements. In modelling, this research prepared the dataset with `x_main` as features and `y_main` as target labels; then, we set up a 10-fold cross-validation procedure with shuffling to ensure robust evaluation. Then, a Voting Classifier was created using three base classifiers; among those bases, we have the XGB Classifier, Random Forest Classifier and Ada Boost Classifier with 50 estimators, each configured with a random state of 42.

## 2.9 Correlation Test

Figure 2 indicates a correlation matrix illustrating the correlation between all variables used in bike sharing prediction. In this visualization, each cell represents a correlation coefficient, with the intensity of color indicating both the correlation strength and direction. This correlation strength ranges from 1 to -1 where 1 indicates a positive correlation, 0 indicates that there is no correlation while -1 indicates a negative correlation.

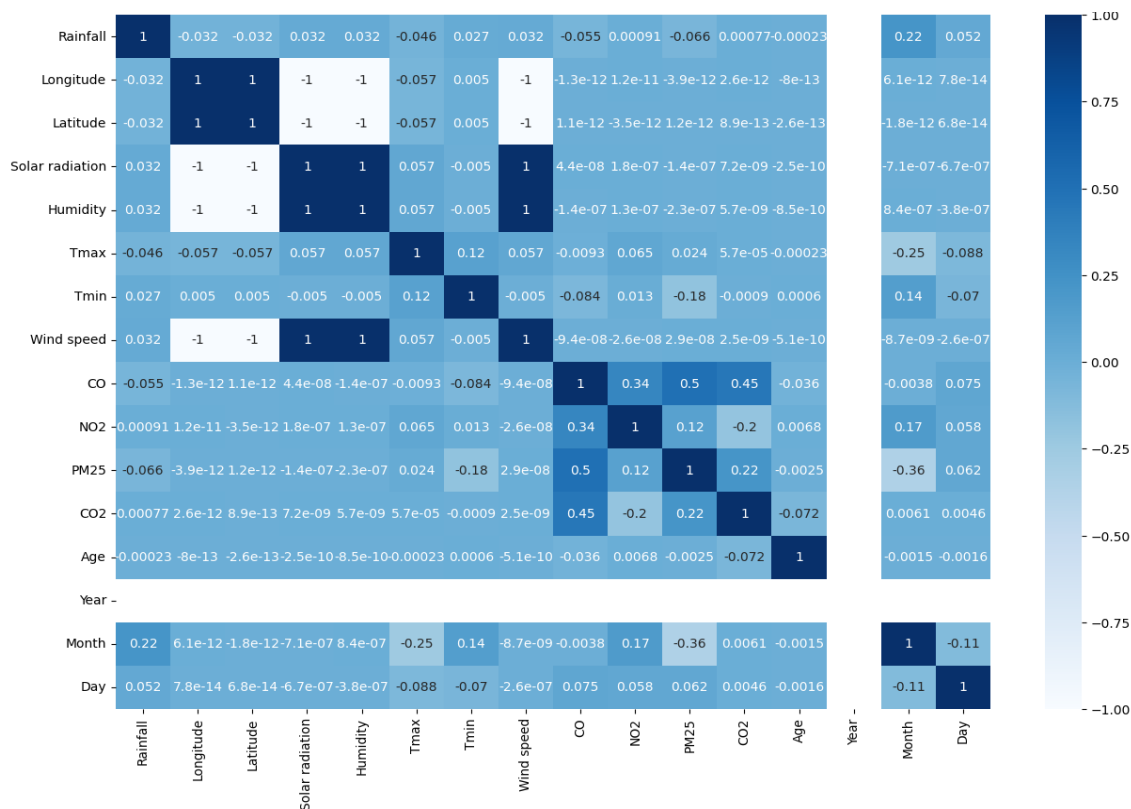


Fig. 2 A correlation heatmap. Source: authors

## **2.10 Model Metrics**

The models are evaluated through cross-validation, employing the accuracy metric to gauge their predictive performance. The outcome of each fold's accuracy scores is stored, and the mean and standard deviation are printed on the model's effectiveness.

## **2.11 Limitations Associated with Approaches Used**

This research used a hard voting classifier that combined AdaBoost, XGBoost, and Random Forest. Each model has its specific limitations in modelling. XGBoost is computationally expensive and sensitive to hyperparameters. AdaBoost, while effective in bias reduction, is highly sensitive to outliers and prone to overfitting. Although robust, it's interpretable; Random Forest is slow because it trains multiple trees and performs poorly when dealing with high-dimensional data. Additionally, the hard voting classifier is rigid, ignore a strong individual classifier prediction, and does not indicate the probability outputs. Addressing these limitations requires carefully tuning hyperparameters, selecting features (observed behaviour) to optimize demand prediction performance.

## **3. Results**

### **3.1 Social Demographic Characteristics and Biking Adoption**

The findings in Table 2 reveal that bike-sharing in Kigali city is adopted by young people with age ranging between 16–45 years, single people dominate with (66%), people with income less or equal to 100,0000 Rwandan Francs represent 66% in adoption, with males representing a majority (54%). The majority, corresponding to (71%) use shared bikes while 29% of them adopted private ones. The commuting to mandatory activities (work, school, or health services) represents (51%), followed by leisure (27%) and social activities (11%). Key factors influencing bike sharing adoption include the type of bike-sharing system (20%), price (19%), station location (19%), and availability of biking infrastructure (19%), while environmental concerns (6%) and time savings (3%) are less influencing. Notably, 10% of bike sharing users have disabilities, highlighting the importance of inclusive in infrastructure, service design and policy elaboration. Additionally, the results show that barriers related to shared space (lack of lanes, safety concerns = 54%) dominate over natural/environmental barriers (slope + weather = 46%).

**Table 2** Social demographic characteristics and bike sharing adoption. Source: authors

| Description of variables                                   | N=5,000<br>Percentage |
|------------------------------------------------------------|-----------------------|
| 1. Gender                                                  |                       |
| a) Female                                                  | 41%                   |
| b) Male                                                    | 54%                   |
| c) Prefer not to say                                       | 5%                    |
| 2. Age                                                     |                       |
| a) Less than 25                                            | 28%                   |
| b) 26-45                                                   | 63%                   |
| c) Above 45                                                | 9%                    |
| 3. Marital status                                          |                       |
| a) Married                                                 | 29%                   |
| b) Single                                                  | 66%                   |
| c) Divorced                                                | 3%                    |
| d) Widower                                                 | 2%                    |
| 4. Disability                                              |                       |
| a) No                                                      | 90%                   |
| b) Yes                                                     | 10%                   |
| 5. Income                                                  |                       |
| a) A: Income $\leq$ 100,000 Rwf                            | 66%                   |
| b) B: 100,000 Rwf < Income $\leq$ 200,000 Rwf              | 13%                   |
| c) C: 200,000 Rwf < Income $\leq$ 300,000 Rwf              | 7%                    |
| d) Income > 400,000 Rwf                                    | 14%                   |
| 6. Biking adoption                                         |                       |
| a) Bike sharing                                            | 71%                   |
| b) Non shared bike                                         | 29%                   |
| 7. Trip Purpose                                            |                       |
| a) Commute for mandatory activities                        | 51%                   |
| b) Leisure                                                 | 27%                   |
| c) Social and errands                                      | 22%                   |
| 8. Factors influencing shared and non-shared bike adoption |                       |
| a) Environmentally friendly                                | 6%                    |
| b) Price                                                   | 19%                   |
| c) Flexibility and accessibility                           | 14%                   |
| d) Time saving                                             | 3%                    |
| e) Availability of cycling infrastructure                  | 19%                   |
| f) Type of bike sharing                                    | 20%                   |
| g) Bike sharing station location                           | 19%                   |
| 9. Barrier to shared and non-shared bike usage             |                       |
| a) Lack of dedicated cycling lanes                         | 34%                   |
| b) Steep slopes (>10%)                                     | 31%                   |
| c) Safety of riders                                        | 20%                   |
| d) Adverse weather conditions                              | 15%                   |

### 3.2 Descriptive Statistics

The results in Table 3 indicate descriptive statistics of all numerical variables fitted in the model. The descriptive analysis provides insights into the dataset's various environmental and socio-economic variables. The count for each variable indicates a sample size of 5,000. The mean values reveal the average levels, where rainfall is 1.6, solar radiation is 174.5, humidity is 57.9, Tmax (Maximum Temperature) is 28.0, Tmin (Minimum Temperature) is 17.9, CO (Carbon Monoxide) is 575.7, NO<sub>2</sub> (Nitrogen Dioxide) is 20.1, MP<sub>2.5</sub> (Particulate Matter) is 51.1, CO<sub>2</sub> (Carbon Dioxide) is 278.8, age is 30.1, and Monthly Income is 299,559.0.

Standard deviations indicate the degree of variability, showing, for instance, that monthly income has a significant spread with a standard deviation of 2,106,597. Additionally, CO, NO<sub>2</sub>, and MP2.5 have score with diverse ranges while the quartiles provide further insights, with 25% of monthly income falling below 40,000 Rwanda Francs. The median values (50%) indicated that solar radiation and humidity remain relatively consistent. The upper quartiles (75%) provide information on the higher end of the distribution.

**Table 3** Descriptive statistics. Source: authors

|       | Rainfall | Solar radiation | Humidity | Tmax  | Tmin  | CO      | NO <sub>2</sub> | MP2.5 | CO <sub>2</sub> | Age     | Monthly income |
|-------|----------|-----------------|----------|-------|-------|---------|-----------------|-------|-----------------|---------|----------------|
| count | 5,000    | 5,000           | 5,000    | 5,000 | 5,000 | 5,000   | 5,000           | 5,000 | 5,000           | 5,000.0 | 5,000          |
| mean  | 1.6      | 174.5           | 57.9     | 28.0  | 17.9  | 575.7   | 20.1            | 51.1  | 278.8           | 30.1    | 299,559.0      |
| std   | 4.2      | 58.1            | 28.6     | 1.5   | 1.4   | 295.0   | 4.2             | 19.6  | 169.2           | 11.2    | 2,106,597.0    |
| min   | -        | (99.0)          | (99.0)   | 23.8  | 15.5  | 112.9   | 8.4             | 5.1   | -               | 12.0    | -              |
| 25%   | -        | 176.1           | 58.5     | 27.0  | 17.0  | 368.7   | 17.4            | 39.2  | 285.0           | 23.0    | 40,000.0       |
| 50%   | -        | 176.1           | 58.5     | 28.1  | 17.6  | 506.5   | 19.9            | 48.5  | 285.0           | 26.0    | 120,000.0      |
| 75%   | -        | 186.2           | 66.2     | 29.1  | 18.3  | 714.7   | 22.8            | 61.4  | 417.9           | 34.0    | 300,000.0      |
| max   | 35.0     | 381.3           | 99.0     | 32.3  | 22.3  | 2,245.6 | 38.5            | 227.2 | 625.4           | 82.0    | 55,955,574.0   |

### 3.3 Modelling Results

The findings in Table 4 offer insights into the transport field in terms of modelling and prediction.

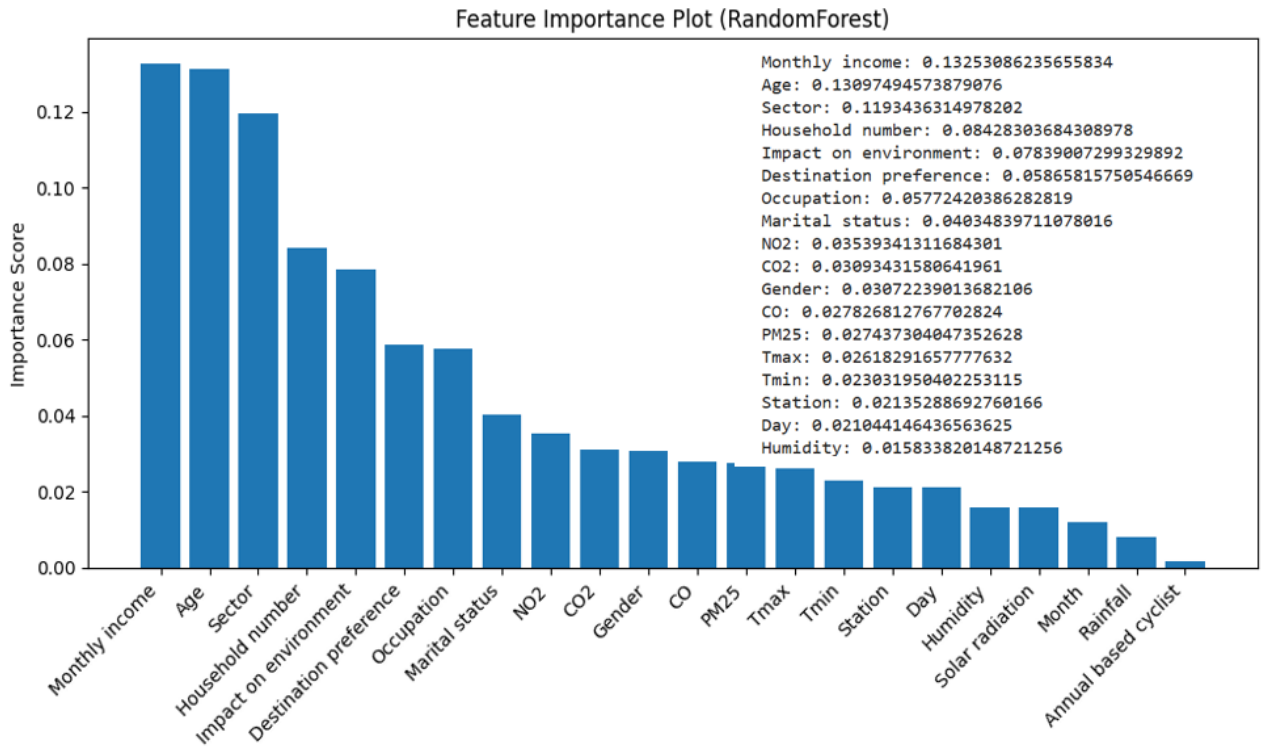
- The Voting classifier has an outstanding performance of 97% with a low standard deviation of 0.50%. This performance indicates the potential and robustness of the voting classifier for demand prediction, which is crucial for decision-makers in transport planning and modelling.
- The AdaBoost model has achieved an accuracy of 96% with a great standard deviation of 2.7%. These results indicate that even if ensemble models can perform better in modelling, their stability may vary from one dataset to another.
- The XGBoost classifier achieved an accuracy of 93% with a low standard deviation of 0.5%. These results confirmed the effectiveness of XGBoost classifier in predicting biking transport demand.
- Logistic Regression (LR) model was implemented as a baseline, achieving an accuracy of 85.2% under 10-fold cross-validation. In comparison, the ensemble models performed substantially better, with Random Forest achieving 96% accuracy, the Voting Ensemble 97%, and AdaBoost 96%.

**Table 4** Model performance. Source: authors

| Metric       | XGBoost (%) | AdaBoost (%) | Random Forest (%) | Voting Classifier (%) |
|--------------|-------------|--------------|-------------------|-----------------------|
| Accuracy     | 93          | 96           | 96                | 97                    |
| Precision    | 94          | 96           | 95                | 95                    |
| Recall       | 99          | 95           | 96                | 96                    |
| F1-score     | 96          | 96           | 96                | 96                    |
| Weighted avg | 94          | 96           | 96                | 96                    |
| Std. Dev     | 0.5         | 2.7          | 0.4               | 0.5                   |

### 3.4 Features Associated with Demand

- Demographic features in Figure 3 stood out as key influential factors in biking demand modelling. Among those demographic features, monthly income (13.3%) was the top feature, followed by age (13.1%), household number (8.4%), and occupation (5.8%), collectively contributing to 40.6 % of the overall importance.
- While air quality factors, NO2 (3.5 %), CO2 (3.1%), CO (2.8) and MP2.5 (2.7%) hold moderate importance, indicating their relevance in the modelling process.
- Weather factors like Tmax (2.6%), Tmin (2.3%) and humidity (1.5%) have been assigned negligible importance, indicating minimal impact on the modelling process.



**Fig. 3** Feature importance. Source: authors

## 4. Discussion

- The superior predictive performance of ensemble models observed in this study corroborates a growing body of transportation research demonstrating that machine learning techniques, particularly Random Forest and Gradient Boosting, consistently outperform traditional statistical approaches in modeling travel behavior and bike-sharing demand[23][24]. Unlike conventional models such as logistic regression, which rely on restrictive linearity assumptions and limited interaction effects, ensemble methods effectively capture complex nonlinear relationships, high-order interactions, and heterogeneity across socio-demographic, environmental, and spatiotemporal variables. This methodological advantage enhances both predictive accuracy and

model generalizability, making such approaches particularly suitable for analyzing dynamic and multifaceted mobility behaviors.

- With respect to feature importance, the prominence of income as the strongest predictor of cycling adoption is strongly aligned with existing literature, which consistently identifies economic constraints as a key driver of non-motorized transport use. Specifically, lower-income populations tend to favor bicycles due to their affordability, accessibility, and minimal operating costs, especially in contexts where access to private or public motorized transport is limited[23].
- Importantly, this study advances literature by identifying marital status—specifically, the higher likelihood of cycling among divorced individuals—as a significant yet underexplored determinant of bike-sharing adoption. While prior research has largely overlooked this variable, the observed relationship may reflect greater temporal flexibility, reduced household travel coordination, and lower dependency on shared vehicle ownership. This novel insight not only extends existing behavioral frameworks but also suggests new avenues for segmenting and targeting users in cycling promotion strategies[25]-[26].
- Overall, these findings reinforce global evidence on cycling behavior while highlighting context-specific dynamics in African cities, where infrastructure limitations and socio-economic disparities strongly influence mobility choices. This research therefore contributes to addressing the empirical and methodological gap in sustainable urban mobility research in underrepresented regions.

## 5. Conclusion

Ensemble learning models particularly the voting classifier, demonstrated superior predictive performance, achieving 97% accuracy and outperforming XGBoost, AdaBoost, and Random Forest models. These findings indicate that the Voting Classifier is not limited to the medical domain; it also demonstrates strong performance in transportation engineering applications.

Feature importance analysis revealed that socio-demographic factors, including monthly income, age, household size, and occupation—were the key drivers of cycling behavior, collectively accounting for over 40% of model importance. Environmental and air-quality variables (NO<sub>2</sub>, CO<sub>2</sub>, CO, PM<sub>2.5</sub>) had moderate influence, while weather variables contributed minimally, indicating that economic and demographic factors are the dominant determinants of biking demand.

From a policy perspective, these findings underscore the need to integrate socio-economic considerations into cycling promotion strategies, such as expanding infrastructure, improving accessibility, and addressing equity to enhance adoption, particularly among lower-income groups. The study also demonstrates the effectiveness of ensemble-based machine learning approaches for transport demand modeling, providing a robust tool for evidence-based planning and sustainable

mobility initiatives. Future research should explore additional behavioral, spatial, and infrastructure factors, as well as comparisons across diverse urban settings.

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