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Bicycle choice: machine learning approach to understanding university students' attitudes toward cycling

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ABSTRACT

This study investigates the factors influencing university students' preferences for micro-mobility solutions, with a specific focus on conventional bicycles and electric bikes (e-bikes) in developing country context. Despite global efforts to promote cycling, micro-mobility adoption remains low in regions like Palestine due to safety concerns, economic barriers, and lack of infrastructure. To address this gap, we employ machine learning techniques, Random Forest and k-means clustering, to analyze survey data from 1,061 students at An-Najah National University. The analysis highlighted the role of factors such as gender, car ownership, daily transport mode in shaping preferences, safety perceptions, and willingness to adopt micro-mobility options. The Random Forest model provided insights into the most influential variables, while the clustering analysis segmented individuals into distinct groups, allowing for a more tailored understanding of micro-mobility behavior. The results showed that the daily transport mode is the most significant factor affecting safety perceptions and preference. Gender and car ownership also emerged as important factors, influencing willingness to adopt micro-mobility and preferences between bicycles and e-bikes. Sensitivity analysis was employed to evaluate the robustness of the models by measuring the impact of small changes in key variables on predictions. The models were evaluated using accuracy, feature importance, and sensitivity analysis. Random Forest achieved an accuracy of 78.3% in predicting preferences, highlighting daily mode choice as the most influential variable. The results offer practical insights for policymakers and urban planners, particularly in developing countries like Palestine, where economic and infrastructural challenges affect the adoption of micro-mobility solutions.

1. Introduction

Active mobility including walking, cycling, and electric-assisted travel is a cornerstone of sustainable transportation strategies worldwide [1]. Despite policy attention, adoption of these modes remains low in many developing countries, particularly among youth populations. Factors such as safety concerns, poor infrastructure, and limited economic means continue to hinder uptake. It found its place as an important set in sustainable transport strategies due to challenges of urbanization, congestion, and environmental degradation in its tri-dimensional features of environment, society, and economy [2]. Overall, the enhancement of active mobility is targeted to achieve positive effects on the transport system, health, and the environment [3,4]. Among the 17 Sustainable Development Goals (SDGs), there is some potential for implementation in transportation systems. Surely, in this respect, active transportation will play a key role. However, little is known about how these options are perceived in developing regions, particularly by university students who represent a key demographic for future mobility behavior. This study addresses this gap by using machine learning to analyze micro-mobility preferences among students in Palestine, a context shaped by economic difficulty, weak infrastructure, and shifting attitudes toward sustainability. In developing regions, e-bike adoption is increasing but remains significantly lower than in high-income countries. For instance, recent studies in Philippines, Nepal, and India show limited number of cyclists use e-bikes, primarily due to affordability and infrastructure gaps [2,5,6].

Furthermore, urban transportation is undergoing a transformation with the rise of micro-mobility solutions such as electric bikes and

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shared bicycles. As cities encourage sustainable transport options [7], understanding the factors that drive individuals' preferences and willingness to adopt micro-mobility is essential. Safety concerns, along with the mode of transportation to daily destinations such as universities, play a critical role in these decisions. Globally, the micro-mobility market, encompassing e-bikes, scooters, and shared bikes, is projected to exceed $300 billion by 2030, driven by urbanization and sustainability goals [8].

The use of bicycles, either as regular or electric (e-bikes), as a means of mobility against motorized transport continues to register an upward trend globally. This is occasioned by a unique intersection of environmental, economic, and health factors [9]. With increased traffic congestion, air pollution, and adverse climate change being felt in metropolitan cities, an ever-increasing number have opted for cycling as a sustainable alternative to motorized vehicles. Specifically, The global rise in e-bike use reflects their ability to provide the benefits of traditional cycling while minimizing physical effort during longer commutes and on hilly routes [10].

Research highlights that economic limitations, urban design, and safety infrastructure are pivotal in shaping cycling behaviors in both high- and low-income contexts [11,12]. the choice between regular bikes and e-bikes is determined by various factors. for example, what attracts riders to e-bikes in developed countries is the desire to do more cycling without the hassle of pedaling through large stretches. their appeal lies in the perfect compromise between cycling, with health benefits as the primary consideration, and convenience, with a powered assist [13,14,15]. both traditional bicycles and e-bikes are witnessing growing popularity as alternatives to motorized transport. traditional bikes remain a dominant mode in lower-income regions due to their affordability, while e-bikes are rapidly expanding in urban centers where users seek assisted mobility for longer or hillier routes. studies have shown that e-bikes offer a balance between convenience and sustainability, especially in developed settings with aging populations and comprehensive cycling networks. added to this, urban environments with bike lanes and cycling infrastructure make both kinds of bikes usable for active transportation [16].that economic limitations, urban design, and safety infrastructure are pivotal in shaping cycling behaviors in both high- and low-income contexts [11,12]. The choice between regular bikes and e-bikes is determined by various factors. For example, what attracts riders to e-bikes in developed countries is the desire to do more cycling without the hassle of pedaling through large stretches. Their appeal lies in the perfect compromise between cycling, with health benefits as the primary consideration, and convenience, with a powered assist [13,14,15]. Both traditional bicycles and e-bikes are witnessing growing popularity as alternatives to motorized transport. Traditional bikes remain a dominant mode in lower-income regions due to their affordability, while e-bikes are rapidly expanding in urban centers where users seek assisted mobility for longer or hillier routes. Studies have shown that e-bikes offer a balance between convenience and sustainability, especially in developed settings with aging populations and comprehensive cycling networks. Added to this, urban environments with bike lanes and cycling infrastructure make both kinds of bikes usable for active transportation [16].

Infrastructure; however, comes into play as a defining factor in these preferences. Cities that have comprehensive cycling infrastructures see e-bikes and regular bikes coexist very well. Bike lanes, bike-sharing programs, and safe parking would further increase the use of both. In comparison, areas with little or no such infrastructure would not allow full potential for e-bikes to be realized, making traditional bikes the most viable choice [16].

1.1. Bicycle Use in Palestine

In Palestine, cycling remains underdeveloped despite increasing awareness of its environmental and health benefits. A combination of rugged topography, security barriers, and weak infrastructure limits bicycle usage in most urban areas. While traditional bicycles are still seen in smaller towns, e-bike usage is extremely limited due to affordability and a lack of support infrastructure. Traditional bicycles are relatively common in Palestine for various purposes: transportation, business, and leisure. They are often seen in towns and small cities where they become an economical and effective mode of movement. Given the affordability and simplicity of classical bicycles, they can easily reach a wide section of the population, especially in a region with limited economic resources. The adoption of e-bike in Palestine is still at an early stage. Factors such as hilly terrain (e.g., in Nablus), extreme summer temperatures, and cultural resistance to cycling, especially among women, further discourage regular bicycle use and contribute to the growing interest in assisted mobility options like e-bikes.

Economic conditions in Palestine significantly affect transportation choices. Traditional bicycles are cheap and, therefore, in wider use. The relatively expensive e-bikes and narrow financial base in this area impede their wide adoption. There is a lack of dedicated and safe biking infrastructures that can accommodate both traditional and e-bike modes of transportation in many Palestinian cities and towns. The political and logistical complexities of the region further complicate the development of such infrastructure. The continuous conflict and political instability affect the transport infrastructures and the developing of new technologies. This situation affects the availability of e-bikes and the developing of necessary infrastructures that back up the use of e-bikes. Despite this, there is an increasing recognition of the environmental and health gain for cycling. Hence, local initiatives and NGOs work on the promotion of cycling as a healthy and sustainable transport mode, aligning with broader active mobility goals [17].

At the local level, organizations and projects working to strengthen cycling in Palestine focus towards enabling bicycle accessibility, safety, and awareness. For example, initiative for the provision of bicycles to students and low-income families to help them improve their mobility to satisfy daily needs. Although the current adoption of e-bikes is limited, with improving economic conditions and infrastructure, it could grow. As awareness of the benefits of e-bikes grows, the gradual development of infrastructure may lead to greater adoption in the future.[1] As Palestine continues to address transportation and environmental challenges [18,19], the promotion of both traditional and e-bike will be helpful to achieving sustainability goals.

Although formal studies or government reports are not available with specific statistics on the number of bicycles in Palestine, information herein has been sourced from various reports, articles, and observations by local organizations and news outlets. It is estimated that across the West Bank and Gaza Strip, there are 100,000 bicycles in use, while approximately 30–40% of the residents in cities such as Ramallah and Bethlehem have access to a bicycle.[2] This could reflect the search for options on sustainable transport and a healthier way of life, which goes on to help nurture the cycling culture in the region. A comprehensive cycling survey or database from official agencies such as the PCBS or Ministry of Transport is still lacking, despite growing public and academic interest in the subject.

Different cycling groups and clubs have emerged to promote cycling and organize activities related to biking.[3] Another step taken was Women on Wheels, under which women were to be empowered through cycling. Events like the annual Palestinian Bike Festival, with over 1,000 participating cyclists in 2023, compared to previous years' turnouts, showcased increasing activity in cycling.[4]

Positive trends are emerging despite the challenges related to infrastructure and safety in Palestinian cities, including Nablus, where

[1] Taawon: https://www.taawon.org/en/node/1099.
[2] Cycling Palestine: https://www.facebook.com/cyclingpalestine/.
[3] Palestine Riders: https://www.facebook.com/palestineriders/.
[4] Big Ride for Palestine. (2020 – 2024). https://www.thebigride4palestine.com/.

this study is conducted. Most cities lack specialized bike lanes and adequate facilities, making cycling hazardous. Advocacy organizations are actively working to promote better urban planning and raise awareness about road safety for cyclists. Overall, the growing popularity of cycling in Palestine signals a shift toward more sustainable transportation, as well as increased community engagement and cultural exchange. In Nablus, characterized by its hilly terrain, traditional bike usage has been limited to flatter areas. However, the rise of e-bikes is contributing to increased cycling, even in the absence of proper infrastructure.

Economic and infrastructure-related constraints play a crucial role in shaping transportation behavior and limiting the adoption of active mobility options in Palestine. According to Tabash et al. (2022) [20], Palestine's economy is highly sensitive to external aid and internal fiscal imbalances, with unemployment rates exceeding 25 %, particularly among youth and recent graduates, significantly constraining household mobility investments such as e-bikes or commuting infrastructure. In parallel, infrastructure deficits persist across multiple sectors. For example, although 39 MW of photovoltaic energy systems have been installed to support energy resilience, nearly half of these systems underperform due to structural barriers, including limited technical expertise and lack of supportive regulations [21]. Together, these economic and infrastructural limitations underscore the importance of context-specific, low-cost, and resilient transport interventions such as cycling, while also explaining the lag in bicycle infrastructure development and adoption of micro-mobility in Palestinian cities.

These global and regional patterns raise important questions about how young people in resource-constrained settings perceive micro-mobility options, and what factors influence their preferences and adoption behaviors. Traditional bicycles still dominate most of the developing world and are appreciated for their low cost and obvious health advantages. Fast-track adoption of e-bikes is happening, especially in developed countries, from imperatives that have a mix of convenience and sustainability. Traditional bicycles have long been at the center of transportation and mobility in the developing world but are now given the opportunity that is emerging from e-bikes to enhance mobility with reduced congestion. Knowing these preferences and factors that influence them provides a valuable insight into what the future holds for cycling and active mobility worldwide.

Despite the rise in micro-mobility solutions globally, there is a significant gap in understanding how young populations in developing countries perceive and choose between options such as bicycles and e-bikes. This study addresses that gap by applying Random Forest and clustering methods to analyze preferences and behavioral drivers among university students in Palestine. By combining these techniques, the research offers a complete picture of the drivers behind safety perception, willingness to adopt, and preferences for micro-mobility solutions. The segmentation analysis adds a practical dimension to the data-driven insights, making the findings more actionable for policymakers and urban planners. The novelty of this study lies in the application of machine learning methods—such as Random Forest and clustering—to analyze the influence of individual factors like gender, car ownership, and daily transport choices among university students in a developing country, Palestine, on micro-mobility adoption. The use of sensitivity analysis further enhances the robustness of the results by measuring the impact of small changes in these factors on model predictions.

2. Literature review

Across the globe, regular use of the bikes, including e-bikes, is drawing some key trends into mobility and active transportation. Traditional bicycles have been in use as personal means of movement for quite a long time due to their simplicity and affordability. In addition, they advance healthy lifestyles and reduce environmental impacts. They are dominating the regions where the cycling culture is imbedded and where the infrastructural arrangements support their use. On the other hand, with their higher initial cost, e-bikes are rapidly growing in developed countries and, to some extent, in less developed countries. The growth is driven by technological innovations making them more convenient all the time for longer commutes and rough terrains [22]. Besides, e-bikes offer a great deal of convenience and reduce environmental footprints. For instance, European cities are incorporating e-bikes into their transportation systems as part of broader active mobility strategies, whereby reducing car use and increasing sustainable options will have positive impacts on the economy [23,24].

One of the anticipated factors affecting the share of bicycle use in any region is the local culture. This has been established by Aldred and Jungnickel [25] as they indicated that despite policies promoting cycling as a sustainable travel option, UK cycling levels remain low, and the effectiveness of interventions is inconsistent. The research examines how cultural meanings influence cycling practices across four English urban areas, highlighting the importance of established versus emerging cycling cultures and emphasizing the need for policymakers to consider cultural factors when aiming to change transport behaviors.

In their review on the impact of road infrastructure on cycling, Heinen and Buehler [26] found that most studies indicate a positive correlation between bikeway networks and cycling rates. There may be a hierarchy of preferences among cyclists and non-cyclists that favors separate paths or lanes over riding on roads with heavy and fast-moving traffic. The review highlighted that intersections tend to detract from the cycling experience, although some design features can mitigate these effects. Furthermore, the authors identified several research gaps, including the need for empirical studies utilizing comprehensive network measures and investigations into specific facility designs and emerging types of infrastructure.

Both, et al. [27] investigated the feasibility of achieving a 30-minute to work commuting using active transportation. The study found that active transport usage in Australia is relatively low, with public transport, walking, and cycling accounting for 16.8 %, 2.8 %, and 1.1 % of workers' commutes, respectively. However, cycling showed the greatest potential for contributing to the concept of the 30-minute city, with 29.5 % of workers able to commute by bike. This percentage could potentially rise to 69.1 % if workers could find similar jobs closer to home.

Jaber and Csonka [28] examined how weather influences bike-sharing services, utilizing Negative Binomial, Poisson Regression, and Time Series models to differentiate among members, occasional users, and visitors. The study revealed that weather affects these user groups differently. As expected, favorable weather conditions lead to increased bike-sharing usage. Weekends see higher engagement from occasional users and visitors than weekdays, with visitors being particularly sensitive to temperature, wind, and the type of day, while occasional users are more influenced by precipitation. For members, temperature and the type of day emerged as the most significant factors, while the least impactful factors varied among the different user groups.

Jaber et al. [29] explored the preferences of shared micro-mobility users in urban Budapest, Hungary, focusing on conventional bikes, e-bikes, and e-scooters using a discrete choice modeling approach. Results revealed that travelers generally favor conventional bikes over e-bikes and e-scooters. Furthermore, car drivers, individuals who frequently use micro-mobility options, graduate students, full-time workers, males, and younger individuals are more likely to opt for shared electric micro-mobility services. This research underscores the significance of socio-demographic factors in shaping preferences for different micro-mobility modes in urban environments.

Siiba [30] examined the active travel to/from school using 1236 cross-sectional surveys from 97 schools in Tamale, Ghana, focus on household and environmental characteristics. The study used a univariate logistic regression model followed by a combined logistic model to identify correlated factors and how they affect walking and cycling. The study found that the age, home ownership, and mothers' employment status are negatively correlated, while the active travel frequency of parents and distance to school are positively correlated. The study also concluded that the gender factor exists in secondary schools trips only.

Furthermore, based on 481 online surveys conducted during the COVID-19 pandemic, Xu et al. [31] investigated future preferences for shared mobility and active travel through machine learning techniques in Alabama, USA. The study found that interest in shared mobility decreases among individuals with a one-way driving commute of 30 to 45 min, whereas it increases for households with an annual income of at least $100,000.

Danielis and Scorrano [32] suggested that as cities begin to return to normal following the COVID-19 pandemic, transport planners must determine the role of active transport in future urban plans. Specifically, they need to decide whether to maintain the temporary policies that encouraged active travel in response to decreased public transport usage or revert to previous road space allocations that prioritized motorized vehicular traffic.

In a study involving 46,000 participants, Schmidt et al. [33] examined the factors influencing cycling for work and education trips in Denmark, focusing on differences between frequent and infrequent users. Using descriptive statistics and logistic regression analysis, the study found that individuals with access to cars and those living in urban or suburban areas are less likely to cycle. Conversely, factors such as having children, residing within the municipal area, being aged 15–29, being female, having a higher education, being a student, and having daily access to a bike increase the likelihood of cycling. The study also found that concerns related to time, physical appearance, safety, personal capabilities, and a preference for driving reduce the likelihood of biking or engaging in active transportation. Despite Denmark's reputation as a cycling nation, the authors were surprised to discover geographical variations that influence cycling rates. They recommended further exploration of infrastructural, cultural, and interpersonal factors that could promote greater commuter cycling in rural areas.

In another study in Seoul, South Korea, Chung et al. [34] examined factors affecting the use of bikes by analyzing GPS trajectory data from 12,106 private bikes and 29,776 dock-based public bikes across 19,153 census zones over one week using zero-inflated negative binomial models. The findings revealed that behavioral detours reduced public bikes usage on weekdays, while cyclists preferred longer separated bikeways areas. while cyclists preferred areas with longer separated bikeways. In contrast, bike usage was lower in zones with a high floating population and numerous vehicle lanes.

In summary, while several studies have explored bike use factors globally, few have used machine learning approaches to investigate micro-mobility in low-income urban settings. Moreover, even fewer studies focus on university students, a key population for active transport adoption. Recent works [35,36] highlight the importance of localized, data-driven mobility solutions. Our study addresses this gap by using Random Forest and clustering methods to uncover the behavioral drivers of micro-mobility choice among students in Palestine.

The review of literature highlighted some of the factors affecting the preference for using bikes among the different users. Several articles showed that college students have a high potential for such a use, among other user groups. Table 1 provides a summary of the reviewed studies, highlighting their geographic context, focus area, methods, and main findings. However, limited studies focused on what specific factors affect those college students in their preference to using bikes. Therefore, this study focuses particularly on these groups and in a developing country to understand the unique culture and influencing factors.

3. Methodology and data Processing

A combination of advanced analytical methods was employed, such as Random Forest and clustering analysis, to gain a deeper understanding of the key factors driving urban micro-mobility preferences. These machine learning techniques allowed us to identify the primary variables influencing individuals' safety perceptions, willingness to adopt micro-mobility solutions, and their preferences between different modes of transport, such as conventional bicycles, e-bikes, and public transportation. The segmentation analysis adds an additional layer of practicality to the results, helping to group individuals based on shared behaviors and characteristics, making the findings more accessible for policymakers and urban planners. Given that survey-based data can be subject to non-random missingness or user selection bias, approaches from other domains, such as the generative methods proposed under missing-at-random assumptions in recommender systems [37], provide conceptual alignment with our methodology, especially in modeling preferences from partially observed data.

3.1. Data Collection

Data for this study was gathered through an on-line survey posted on the students' portal system of An-Najah National University (NNU) in Palestine. An-Najah National University students were chosen as the sample group due to their diverse backgrounds and significant reliance on public transportation, making them ideal candidates for understanding micro-mobility preferences. An-Najah National University was selected due to its size (25,000 students) and demographic diversity across urban and rural backgrounds. Safety perception was assessed

Table 1
Literature Review Summary.

Authors / Year	Region	Focus Area	Methodology	Key Findings
Aldred & Jungnickel (2014) [25]	UK	Cultural influences on cycling behavior	Qualitative cultural analysis	Established cycling cultures have stronger impact than policy alone
Heinen & Buehler (2019) [26]	International	Impact of infrastructure on cycling	Literature review	Bike paths improve cycling; intersections and poor design deter users
Both et al. (2019) [27]	Australia	Feasibility of 30-min active commutes	GIS + Commute modeling	Cycling holds strong potential for short-distance urban commuting
Jaber & Csonka (2022) [28]	Hungary	Weather impact on bike-sharing	Statistical modeling (Poisson, Time Series)	Weather affects usage differently among user types
Jaber et al. (2023) [29]	Hungary	Shared mobility preferences	Discrete choice modeling	Conventional bikes preferred; gender, age, car ownership significant
Siiba (2020) [30]	Ghana	Active school travel factors	Logistic regression	Parent behavior, distance to school, gender influence cycling rates
Xu et al. (2023) [31]	USA	Post-COVID mobility preferences	Machine learning (RF, SVM)	High-income households more open to shared/active modes
Danielis & Scorrano (2022) [32]	EU	Post-pandemic active transport	Policy review	Cities must reassess temporary measures to support active travel
Schmidt et al. (2024) [33]	Denmark	Work/education cycling determinants	Logistic regression	Age, gender, car access, safety perception shape commuting behavior
Chung et al. (2024) [34]	South Korea	Bike use patterns (public vs. private)	GPS trajectory + ZINB models	Longer bike lanes encourage usage; floating population reduces it

using a 5-point Likert scale (1 = Very Low to 5 = Very High), treated as an ordinal variable. We ensured internal consistency by pretesting the survey with 30 students. As with most online surveys, there is potential for self-selection bias. To mitigate this, the survey was made available to all students via the official university portal and promoted equally across faculties. The survey captured demographic information and transportation preferences, including:

- Independent Variables:
  - o Gender: Male/Female
  - o Residence: Urban/Rural
  - o Car Ownership: Yes/No
  - o Micro-mobility Vehicle Ownership: Yes/No
  - o Daily Choice Mode to University: Public Transport, Passenger Car, Walking, etc.
- Dependent Variables (Targets):
  - o Safety Perception: Low, Average, High
  - o Willingness to use the micro-mobility system: Yes, No, Not Sure
  - o Preference: E-Bike, Bike, Public Transport
  - o Willingness to Rent/Own: Rent, Own

Using the sample size formula, the minimum sample size required for a population of 25,000 students at NNU is calculated as follows:

$$n = \frac{25000 \times (1.96)^2 \times (0.5) \times (1-0.5)}{(0.5)^2 \times (25000-1) + (1.96)^2 \times (0.5) \times (1-0.5)}$$

$$n \approx 390$$

Thus, with a sample size of over 1061, the confidence level significantly exceeds 95 %, providing a more robust representation of the student population. Table 1 provides the descriptive frequency statistics. To ensure data accuracy and reliability, we performed data cleaning procedures to address missing responses in the survey data at first. Out of the original dataset, 29 cells were identified as empty. These gaps were handled to provide a consistent sample size of 1061 respondents, ensuring that the final dataset was complete and ready for analysis. Missing values (29 entries) were imputed using mode imputation for categorical variables. Label encoding was applied to categorical variables (e.g., Gender: 0 = Male, 1 = Female), and multi-level features were also encoded numerically. A 70/30 train-test split was selected to maximize the training sample while preserving enough data for robust testing. Cross-validation was considered, but due to the small dataset, a single hold-out test set provided better interpretability for feature importance.

All categorical variables were label-encoded to transform the data into a format suitable for machine learning models. After encoding, the data was split into training (70 %) and testing (30 %) sets. Following this, we analyzed the data based on the random forest and clustering. Starting with random forest, it allows for the identification of the most critical factors driving micro-mobility preferences. Once these key factors are identified, clustering is performed to segment individuals based on their behavior, ensuring that the segmentation reflects the primary drivers of their choices. This approach not only helps in understanding which factors are most influential, but also enables a more meaningful grouping of individuals, based on shared characteristics and preferences. Random Forest was chosen for its high accuracy, ability to handle categorical data, and interpretability via feature importance ranking. Clustering (k-means) was used to segment the data into behavioral groups due to its simplicity and effectiveness in uncovering hidden patterns in unsupervised data. These methods complement each other, Random Forest identifies key predictors, while clustering interprets behavior across population segments.

3.2. Random Forest modeling

The Random Forest algorithm is a popular ensemble learning method known for its effectiveness in both classification and regression tasks. Developed by Breiman [38], it operates by constructing multiple decision trees during the training process and aggregating their results for predictions. Each decision tree is created using a random subset of the data and features, which helps make the ensemble robust against overfitting and noise in the dataset [39]. This method enhances the predictive accuracy and generalizability of the model, making it well-suited for complex datasets with many interacting variables. One of the key advantages of Random Forest is its ability to measure feature importance. By averaging the decrease in model accuracy when a particular feature is excluded, Random Forest ranks the influence of each feature on the target variable. This characteristic makes Random Forest highly interpretable, especially in applications where understanding the drivers behind predictions is crucial. Additionally, Random Forest is known for its ability to handle both categorical and continuous variables, and it performs well with missing data [40]. These qualities make it an ideal choice for studying complex behaviors in transportation and micro-mobility, where many interacting factors influence outcomes like safety perception and mode preferences.

We used the Random Forest Classifier to model each of the four dependent variables individually. Random Forest was chosen due to its ability to handle categorical data, provide feature importance, and be resistant to overfitting [41,42]. Each model was trained on the independent variables, and its performance was evaluated on the test set.

To optimize model performance, we conducted a grid search for hyperparameter tuning. The key parameters adjusted included the number of trees (number of estimators: 100, 200, 300), maximum tree depth (max_depth: 5, 10, None). The best performance was achieved using 200 trees and a maximum depth of 10, yielding an accuracy of 78.3 % on the test set. Further experimentation with neural models like SMOTEDNN or CDLSTM presents an opportunity for future work.

3.3. Clustering

Clustering is an unsupervised machine learning technique used to group data points based on their similarities. Unlike classification, which relies on labeled data, clustering algorithms automatically identify patterns and form groups (or clusters) of similar observations [43,44]. The objective of clustering is to segment the data into distinct groups, ensuring that data points within the same cluster are more similar to one another than to those in other clusters. Among the various clustering methods, k-means clustering is particularly popular due to its simplicity and efficiency. The k-means algorithm partitions the dataset into a pre-defined number of clusters (k) [45,46]. It iteratively assigns each data point to the nearest cluster center and then updates the centers based on the mean of the assigned points. This process continues until the cluster assignments stabilize. A key challenge with k-means is determining the optimal number of clusters, typically addressed using techniques like the Elbow Method and Silhouette Score, which help strike a balance between capturing sufficient variability in the data and maintaining a manageable number of clusters for interpretation. Clustering is especially valuable in transportation research, as it can uncover hidden patterns in travel behavior, preferences, and demographic characteristics, facilitating more tailored interventions and policies. Although applied in a different context, clustering approaches based on spatiotemporal app usage to generate behavioral profiles [47] offer useful parallels to our segmentation analysis of mobility behavior using demographic and travel features. Moreover, previous work on spatio-temporal behavior modeling in mobile app usage [48] reinforces our rationale for including contextual features such as daily transport mode as key predictors of micro-mobility preferences.

4. Results

4.1. Random Forest model results

4.1.1. Model performance

The accuracy of the Random Forest models varied depending on the outcome being predicted. Preference had the highest accuracy (78.3 %), while Safety Perception showed the lowest (45.1 %). Table 2 shows the accuracy of the Random Forest models for each target variable. In addition to accuracy, we computed F1-score for each Random Forest model. For the Preference prediction model, F1-score was 0.78. Confidence intervals for accuracy were computed using bootstrapping, yielding a 95 % CI of [75.5 %, 80.8 %] for the Preference model.

The average training time for the final model was approximately 3.2 s. Given the relatively small dataset size, computational cost was low and did not require advanced computing resources. To mitigate overfitting, the maximum tree depth was limited, and the model was evaluated on a separate test set comprising 30 % of the total data. Additionally, training accuracy was compared with test accuracy to ensure generalization. No significant performance gap was observed, suggesting overfitting was effectively controlled.

4.1.2. Feature importance

The Random Forest models provide insight into which features are most influential in predicting the outcomes. Table 3, and Fig. 1 show the feature importance values for each target variable, presented both in table and figure form. Feature importance was computed using the Gini importance (mean decrease in impurity), the default method in Random Forest models. To validate the consistency of these importance rankings, a bootstrapping method was applied across 1,000 resamples of the training data, confirming the stability of top-ranked features. To check for potential collinearity, we computed the Variance Inflation Factor (VIF) for each predictor. All VIF values were below 2.5, indicating no serious multicollinearity concerns and confirming the interpretability of the model.Table 4.

Table 2
Descriptive Frequency Statistics.

Variable	Frequency	Percentage
Gender		
Female	558	53 %
Male	503	47 %
Residence		
From the City	548	52 %
Outside the City	513	48 %
Car Ownership		
Yes	171	16 %
No	890	84 %
Do you have a micro-mobility vehicle?		
Yes	113	11 %
No	948	89 %
Daily Mode Choice to University		
Passenger Car	218	21 %
Public Transportation	687	65 %
Walking	142	13 %
Motorcycle	3	0 %
Bike	3	0 %
Others	8	1 %
Safety Perception		
Very Low	125	12 %
Low	194	18 %
Average	471	44 %
High	160	15 %
Very High	111	10 %
Willingness to use bikes		
Yes	618	58 %
No	157	15 %
Not Sure	286	27 %
Preference		
E-Bike	814	77 %
Conventional Bike	247	23 %
Willing to Owning or Renting?		
Rent	539	51 %
Own	522	49 %

Table 3
Accuracy of the Random Forest models for each target variable.

Target Variable	Accuracy
Safety Perception	45.1 %
Willingness	58.9 %
Preference	78.3 %
Rent/Own	53.3 %

The Daily Choice Mode to University had the highest impact on safety perception, contributing 37.36 % to the model. This result suggests that how individuals commute to university significantly shapes their perception of safety, potentially due to varying exposure to risks in different modes of transport. The model predicting willingness to use micro-mobility solutions also found Daily Choice Mode to University as the strongest predictor, followed by Gender, indicating that males and females have differing attitudes towards micro-mobility, possibly driven by safety or convenience factors, in addition to culture. For preferences between e-bikes, bikes, and public transport, Daily Choice Mode to University again dominated, with Micro-Mobility Vehicle Ownership also contributing significantly. This may reflect the tendency of those who already own micro-mobility devices to prefer them for commuting. The decision to rent or own micro-mobility vehicles was most influenced by Daily Choice Mode to University followed by the Residence (22.20 %), indicating that people from different residential areas (urban vs. rural) may have varying levels of access to these transportation options.

4.1.3. Sensitivity analysis

The sensitivity analysis measures how much a small change in a particular feature result across all four target variables. Sensitivity analysis was performed using a one-at-a-time approach: each feature was perturbed by $\pm$ 1 unit, and the model's prediction probability changes were recorded. This process was repeated across all observations, and average marginal effects were computed. The results show that Daily Choice Mode to University has the highest sensitivity across all targets, especially for Preference and Rent/Own, with impacts of 0.00173 and 0.00115, respectively. These values mean that small changes in the daily choice mode (whether the respondent walks, drives, bikes, or uses public transport) have a measurable but relatively small effect on how the model predicts their Preference or Rent/Own for micro-mobility. On the other hand, other features, such as Gender, Residence, Car Ownership, and Micro-Mobility Vehicle Ownership, have negligible sensitivity impacts across the targets and this suggests that they don't have a strong impact on changing predictions in these models.

4.2. Clustering analysis results

4.2.1. Number of clusters

The clustering analysis results show three distinct clusters based on key features like Gender, Residence, Car Ownership, Micro-mobility Vehicle Ownership, and Daily Choice Mode to University. The choice of using 3 clusters in the segmentation analysis was an initial hypothesis to explore the data, but it's important to justify or refine this choice based on specific criteria. To ensure that 3 clusters is the right choice (or to find a better number), there are several methods to evaluate the optimal number of clusters:

1. Elbow Method: This technique helps determine the optimal number of clusters by plotting the Within-Cluster Sum of Squares (WCSS) against the number of clusters. The "elbow" point occurs where the

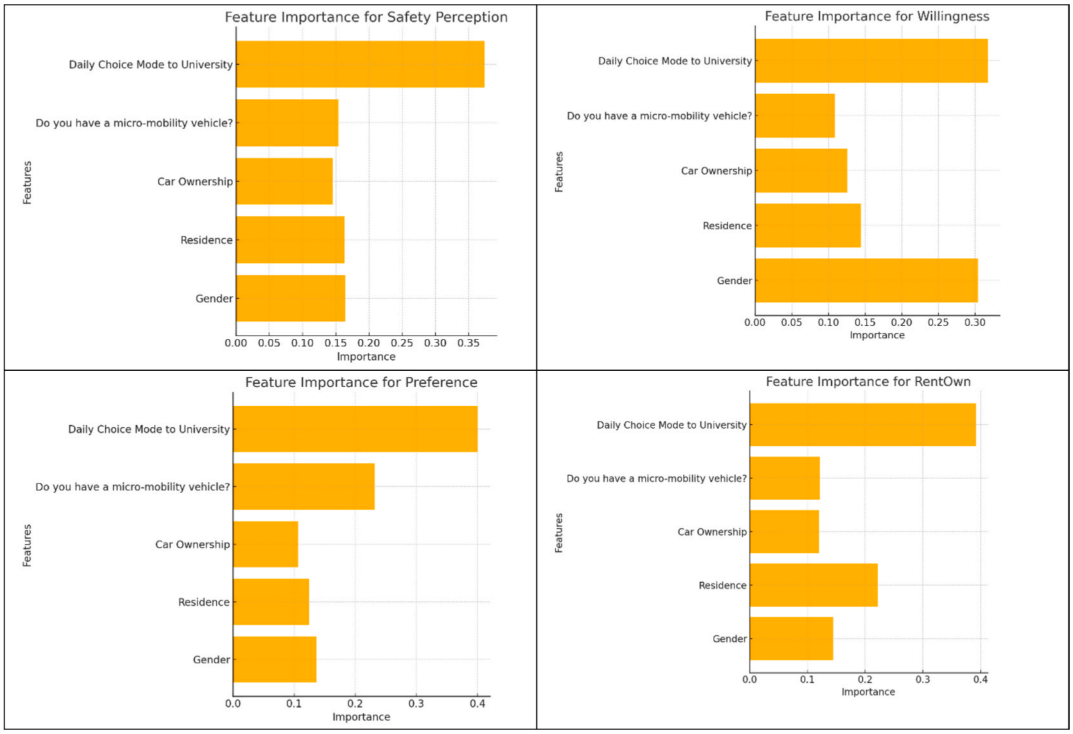

Fig. 1. Feature importance plots for each of the outcomes.

Table 4
Feature importance values for each target variable.

Feature	Safety Perception	Willingness	Preference	Rent/ Own
Gender	16.41 %	30.38 %	13.62 %	14.49 %
Place of Residence	16.31 %	14.44 %	12.44 %	22.20 %
Car Ownership	14.53 %	12.55 %	10.68 %	11.97 %
Micro-mobility Vehicle Ownership	15.39 %	10.87 %	23.21 %	12.11 %
Daily Choice Mode to University	37.36 %	31.76 %	40.04 %	39.23 %

WCSS begins to decrease at a slower rate, indicating the most suitable number of clusters.

2. Silhouette Score: It measures how similar points within a cluster are, compared to points in other clusters. A higher silhouette score suggests better-defined clusters. We calculated this score for different numbers of clusters to see which number maximizes the score.

Fig. 2 shows that the Elbow method indicates the point where the WCSS begins to decrease more slowly, suggesting that beyond this point, adding more clusters does not significantly improve the model. Based on the plot, the Elbow appears to be around 3 or 4 clusters, which supports the initial choice of using 3 clusters. While the Silhouette Score plot shows the cohesion and separation of the clusters. A higher score indicates better-defined clusters. The score is relatively higher for 3 clusters, but slightly increases for 4 clusters as well. Both methods suggest that 3 clusters are a reasonable choice. ANOVA tests were used to confirm significant differences ($p < 0.05$) in safety perception, willingness, and preference across clusters. These findings validate the behavioral distinctions between the segments.

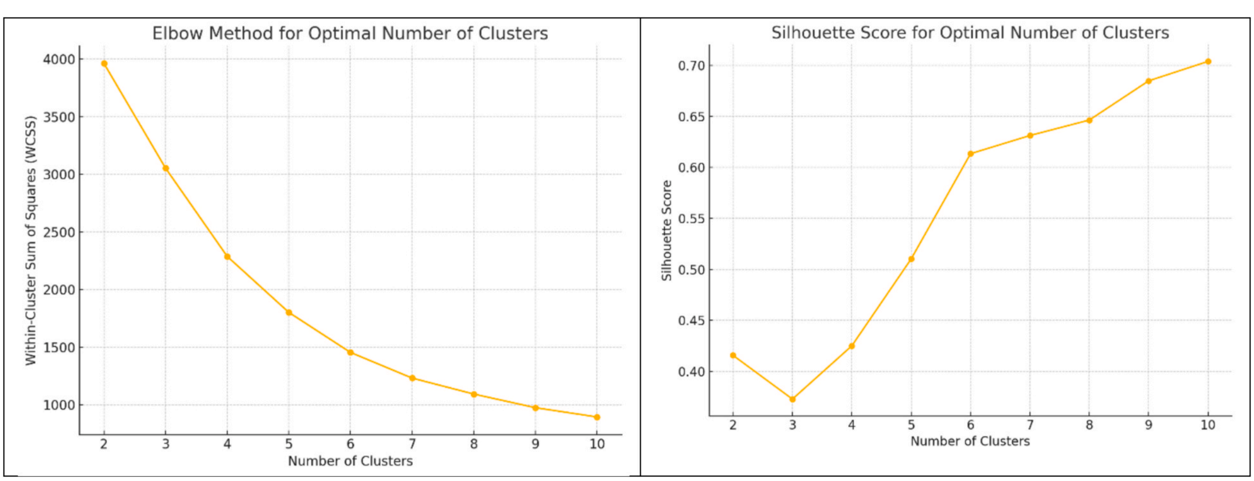

Fig. 2. Results of Elbow and Silhouette Methods.

4.2.2. Cluster profiles

This section provides an overview of the clusters formed, focusing on the average characteristics of the features used in the clustering (e.g., Gender, Car Ownership, Daily Choice Mode):

Cluster 0: The Rural, Low-Ownership, Public Transport Segment.

- Profile:
  - o Gender: Slightly more males.
  - o Residence: Entirely from rural areas.
  - o Car Ownership: Very low car ownership.
  - o Micro-mobility Ownership: Low ownership of micro-mobility vehicles.
  - o Daily Choice Mode: Primarily use public transport or walk.
- Behavior and Preferences:
  - o Safety Perception: Moderate to low. Since rural residents may have less exposure to micro-mobility options in urban settings, their lower safety perception might reduce from unfamiliarity or less access to well-maintained infrastructure.
  - o Willingness: Moderately high willingness to adopt micro-mobility, potentially driven by the lack of personal vehicle ownership.
  - o Preference: Likely to prefer shared transportation (e.g., public bikes), suggesting that rental solutions appeal more due to low ownership of personal vehicles or micro-mobility options.
  - o Rent/Own: Strong preference for renting over owning, likely reflecting their economic or practical needs in rural settings where commuting distances might be longer.

Cluster 0 represents individuals in rural areas with low access to personal vehicles. Their public transport dependency and low car ownership likely explain why they favor shared and rental micro-mobility solutions. Improving safety perception through better infrastructure in rural areas and offering more affordable rental options could increase their adoption of micro-mobility.

Cluster 1: The Urban, Low-Car Ownership, Public Transport Users.

- Profile:
  - o Gender: Balanced gender distribution.
  - o Residence: Entirely urban.
  - o Car Ownership: Very low car ownership.
  - o Micro-mobility Ownership: Low micro-mobility vehicle ownership.
  - o Daily Choice Mode: Heavy reliance on public transport.
- Behavior and Preferences:
  - o Safety Perception: This group has the lowest safety perception across the clusters, which could be related to their reliance on public transport and walking, where safety concerns are often higher.
  - o Willingness: Moderately high, but slightly lower than Cluster 0. This indicates a level of openness to micro-mobility solutions, though they might be hesitant due to safety concerns.
  - o Preference: Lean toward renting shared options (e.g., bikes, scooters), likely because of urban density and easy access to shared transportation options.
  - o Rent/Own: Strong preference for renting, which is common in urban areas where ownership of personal vehicles or micro-mobility devices may not be practical or cost-effective.

Cluster 1 consists of urban residents who rely heavily on public transport but have lower car ownership. Their lower safety perception likely stems from the risks associated with walking or public transport in crowded urban areas. Improving urban safety infrastructure (e.g., safer bike lanes, better lighting) could encourage higher micro-mobility adoption. Providing affordable, safe rental options tailored to urban commuting would likely appeal to this group.

Cluster 2: The Higher-Income, Car Owners with High Safety Perception

- Profile:
  - o Gender: Higher proportion of females.
  - o Residence: Mixed urban and rural.
  - o Car Ownership: High car ownership.
  - o Micro-mobility Ownership: High ownership of micro-mobility vehicles.
  - o Daily Choice Mode: More likely to use personal vehicles, both cars and micro-mobility options.
- Behavior and Preferences:
  - o Safety Perception: This group has the highest safety perception, likely due to their access to personal vehicles and better infrastructure in their environments.
  - o Willingness: High willingness to adopt micro-mobility solutions, likely because they are already familiar with micro-mobility options and have the financial means to own them.
  - o Preference: Strong preference for personal ownership (e.g., e-bikes, electric scooters), reflecting their higher income and tendency to prefer personal, convenient transport solutions.
  - o Rent/Own: More likely to own micro-mobility vehicles, with a balanced preference for renting in situations where personal ownership is not practical.

Cluster 2 represents individuals with more resources, likely higher income, and ownership of both cars and micro-mobility vehicles. Their high safety perception and strong willingness to adopt micro-mobility indicate that they are already comfortable with these solutions. Policy recommendations for this group could focus on promoting infrastructure improvements to further encourage micro-mobility use, even in areas where they primarily use personal vehicles. Offering tax incentives for e-bike ownership or expanding charging infrastructure for electric vehicles could also cater to this segment.

4.2.3. K-Means clustering results

K-means clustering was selected for its simplicity, scalability, and interpretability, particularly for large survey datasets with mixed variables. While other algorithms such as DBSCAN or hierarchical clustering were considered, preliminary tests showed that k-means produced more stable and coherent clusters with clear centroids, which are easier to analyze in behavioral segmentation. Furthermore, k-means aligned better with the Euclidean-based distance structure after standardization of numeric inputs. Prior to clustering, all numeric variables were normalized using Min-Max scaling to ensure equal weighting in the distance calculations. This was necessary because k-means is sensitive to feature magnitude, and variables such as income, safety perception, and frequency of use were on different scales. Categorical variables such as gender, car ownership, and transport mode were encoded using one-hot encoding prior to clustering. This allowed the inclusion of these variables without imposing artificial ordinal relationships. The resulting binary variables were included alongside normalized continuous variables in the k-means input matrix.

The K-means clustering algorithm was employed to segment individuals based on shared characteristics, including Gender, Residence, Car Ownership, Micro-mobility Vehicle Ownership, and Daily Choice Mode to University. Each cluster represents a group of individuals with similar behavioral and demographic patterns, which allows for the analysis of micro-mobility preferences and perceptions within these segments. In Fig. 3, we visualize the results of K-means clustering with PCA, where t**hree clusters** represent groups of data points that were assigned to different clusters based on similarity, and the **'X' markers** indicate the centroids of each cluster, which are the points that represent the center of each cluster. The algorithm tries to minimize the distance between the data points and their respective cluster centroids.

As shown in Fig. 3, cluster 0 shows a dense grouping of points around its centroid, meaning that data points in this cluster are closely related to each other and to the centroid. Moreover, cluster 1 also exhibits a tightly packed formation of points around its centroid. Finally, cluster 2 has a

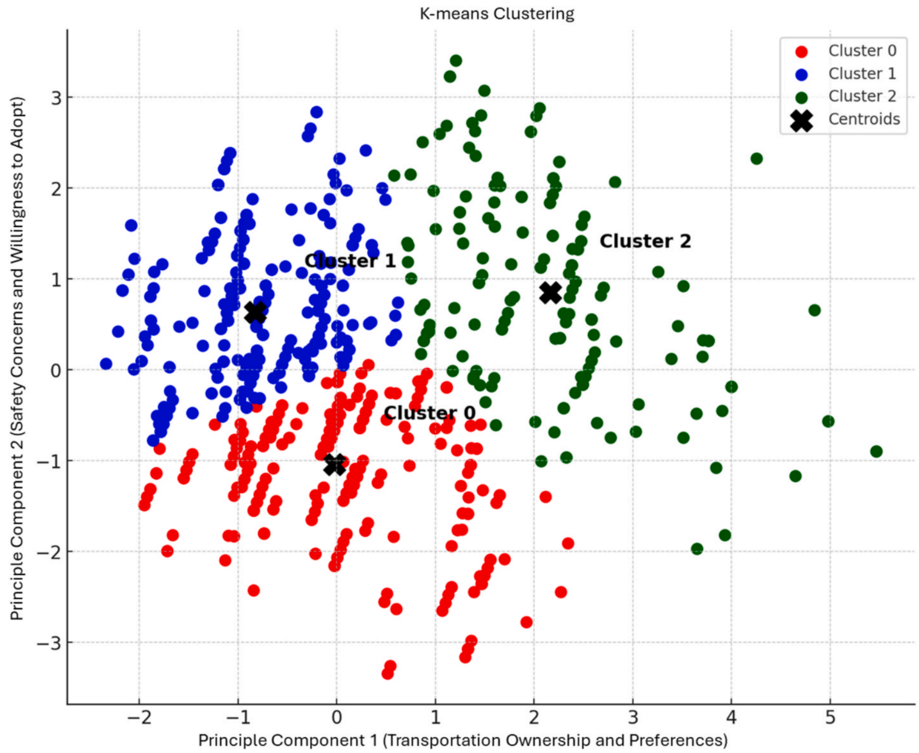

Fig. 3. K-means clustering.

similar formation, indicating good separation between clusters, and each point is closer to its respective centroid. The centroids represent the "average" location of the points in each cluster, and the distance between points and centroids is minimized by the K-means algorithm.

When we cluster the data using K-means and then plot it using PCA, we project the original data (which may have many dimensions) into this 2D space. The values along PC1 and PC2 are combinations of the original features (e.g., Gender, Residence, Car Ownership), weighted by how much each feature contributes to explaining the variance in the data. The component of PC1 likely captures the differences in car ownership, micro-mobility ownership, and daily choice modes. Individuals with high PC1 values may have more access to personal transportation (cars, e-bikes), while those with low PC1 values rely more on public transport or shared mobility. On the other hand, the component of PC2 likely captures differences in safety perception and willingness. Individuals with high PC2 values may have higher safety concerns and are more hesitant to adopt micro-mobility, while those with lower PC2 values may have stronger safety perceptions and a higher willingness to own personal transportation solutions. PC1 and PC2 capture 68.5 % and 18.9 % of the total variance in the data, respectively. This variance indicates that PC1 primarily reflects ownership and mobility preferences, while PC2 captures differences in safety perception and willingness.

In summary, Cluster 0 has lower PC1 values, moderately lower PC2 values. This group tends to rely on public transport, has low car ownership, and moderate to lower willingness to adopt new transportation solutions, possibly showing mixed safety perceptions. While Cluster 1 has higher PC1 values, slightly lower PC2 values. This group likely includes individuals with higher car ownership and stronger preferences for personal mobility. The lower PC2 values indicate lower safety concerns and higher willingness to adopt new mobility solutions. We notice that Cluster 2 has higher PC1 values, higher PC2 values. This group has higher car and micro-mobility ownership, higher safety concerns and lower willingness to adopt certain shared mobility options, favoring personal transportation solutions. To evaluate the cohesion within clusters and the clustering model's generalizability, Root Mean Square Error (RMSE) values were calculated for each cluster in both the training and test sets. In the training set, RMSE values for Clusters 0, 1, and 2 were 1.12, 0.96, and 0.88, respectively, indicating that data points in each cluster are tightly grouped around their centroids. The slightly lower RMSE values in the test set (0.97 for Cluster 0, 0.82 for Cluster 1, and 0.91 for Cluster 2) show comparable clustering quality, suggesting that the model performs well on unseen data. This similarity between training and test RMSE values highlights the model's robustness, affirming that the clustering solution is neither overfitted nor underfitted. The RMSE values for each cluster indicate a reasonable degree of compactness, suggesting internal cohesion within the clusters. Future research could compare these results with alternative clustering algorithms—such as hierarchical clustering or DBSCAN—to evaluate the robustness and external validity of the segmentation.

4.2.4. *Clusters characteristics*

This section focuses on how each cluster differs in terms of the key target variables (e.g., Safety Perception, Willingness, Preference, Rent/Own). Fig. 4 shows the visualization of Target Variables by Cluster. It shows how the clusters differ in Safety Perception, Willingness, Preference, and Rent/Own patterns.

Cluster 2 represents individuals with greater resources (higher car ownership and micro-mobility ownership) and higher safety perceptions, making them more likely to adopt and lean towards owning micro-mobility solutions. Clusters 0 and 1 consist of users with lower car ownership and moderate-to-low safety perceptions. These groups show more willingness for shared options (like bikes or public transport) and are more inclined toward renting rather than owning micro-mobility vehicles.

5. Discussion

In developing countries, the choice between regular bikes and e-bikes presents a distinct set of challenges and opportunities. Traditional bicycles are the dominant means of travel because they are inexpensive and can be used in diverse ways, from rural mobility to vital means for

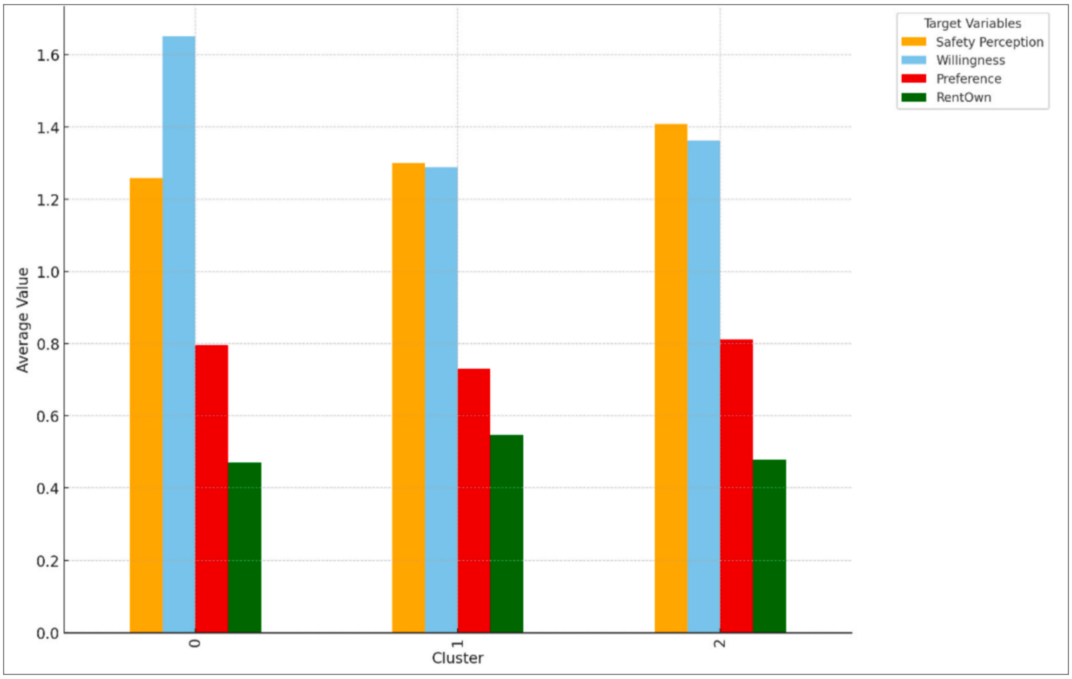

Fig. 4. Visualization of Target Variables by Cluster.

work, school, or personal trips. They are relatively inexpensive and, therefore, within reach of a broad range of users, depending on their priorities.

While e-bikes have been penetrating in some developing countries, their full potential has not yet been exploited due to several barriers. The high cost of the bikes, coupled with a lack of infrastructure for charging, raises concerns over battery life and maintenance. In addition, a lack of dedicated cycling infrastructure or safety measures is a big turn-off to using an e-bike. Even so, opportunities are emerging [49].

Policies have traditionally focused on supporting regular bicycles due to their lower cost and widespread use. There is growing interest in developing policies that could facilitate e-bike adoption, including financial incentives and infrastructure investments. These policies aim to enhance active mobility while addressing the specific challenges faced in these regions [50]. User groups for regular and e-bikes vary in a way that e-bikes are a favored among commuters, city residents, and older adults seeking for a more accessible form of active mobility in developed countries. Traditional bikes are favored by enthusiasts and people who want to have a more economical way of cycling [14,29].

Our study aligns with other findings from developing contexts, such as in Kathmandu, Nepal, where the adoption of e-bikes is slowed by high costs and insufficient marketing or infrastructure development [6]. This reflects similar barriers noted in research, where safety concerns and financial limitations prevent more widespread adoption of e-bikes, despite a growing interest. Additionally, our findings regarding students' safety perceptions align with Wu et al. [14], who observed that safety concerns significantly influence commuter cycling behavior in Sydney. Similarly, Adsule and Kadali [2] found that in Nagpur, India the lack of infrastructure deterred cycling among commuters.

The economic factors are also important. Traditional bicycles are more affordable and, hence, of wide application, especially among low-income segments. While e-bikes are more expensive, they do present a valid alternative for people who can afford the investment and who want to reduce the efforts associated with longer distances or steep gradients. In developed countries, financial incentives come through subsidies and tax breaks to spur on this adoption, which aligns with goals for increased active mobility and reduced carbon emissions [31]. For instance, a study on bike-sharing in European cities noted that subsidies and financial incentives helped accelerate e-bike adoption [51]. However, in Palestine, such financial incentives are either minimal or non-existent, resulting in the slow uptake of e-bikes, especially in rural areas. In our study, the segmentation analysis showed that urban residents, particularly students, demonstrated a preference for e-bikes when financial constraints were alleviated, indicating that introducing similar incentives in Palestine could accelerate e-bike adoption, especially in urban areas where economic conditions are somewhat more favorable.

This economic disparity echoes the findings from multiple global studies, such as the Barcelona bike-sharing system, where the introduction of e-bikes significantly improved urban mobility due to the city's investment in infrastructure and subsidies [52]. Without similar policies in place, the potential for e-bike growth in Palestine remains limited. Our study supports this by revealing that economic factors, including high initial costs, significantly deter e-bike adoption in both urban and rural areas of Palestine. This mirrors global findings that highlight the importance of financial incentives in driving e-bike usage, especially in regions with limited financial resources.

Cycling in developed countries goes along with wide infrastructural development, supplemented by policies that promote active mobility and a fast-growing regard toward environmental sustainability. Cities like Amsterdam and Copenhagen have put in huge investments in building up their cycling infrastructure, which yields high rates of usage and has contributed to a cultural shift wherein cycling becomes not just a viable but very efficient mode of transportation [53,54]. Our study reflects a similar need for dedicated cycling infrastructure in Palestine. The clustering analysis showed that urban residents, despite having a higher willingness to adopt micro-mobility solutions, are deterred by the lack of safe cycling paths, reinforcing the notion that infrastructural investment is crucial for driving adoption, as seen in developed countries.

To enhance cycling and e-bike adoption in Palestine, several policy measures are necessary. First, significant improvements to cycling infrastructure should be prioritized. This aligns with global research, which shows that safe and dedicated bike lanes increase adoption rates. In Palestine, urban centers like Nablus need protected cycling paths, while rural areas would benefit from the integration of cycling with public transport, helping to facilitate longer commutes. Expanding multi-modal transport hubs would make cycling more accessible and reduce reliance on motorized vehicles.

Financial incentives are another critical factor. In cities like Seoul and Barcelona [34,52], subsidies and tax breaks for e-bikes have successfully reduced costs for users and encouraged widespread adoption. Implementing similar programs in Palestine, such as subsidies for e-bike purchases and affordable bike-sharing schemes, would help alleviate the economic burden, particularly for students and low-income individuals who have shown interest in micro-mobility, but face financial constraints.

Lastly, fostering a cultural shift toward cycling is essential. Awareness campaigns can play a pivotal role in changing perceptions of cycling from a low-cost necessity to a viable, environmentally friendly transportation mode. Collaboration with local NGOs, educational institutions, and community groups could amplify the message, encouraging more people to consider cycling as a daily transportation option. By promoting the health, environmental, and economic benefits of cycling, these campaigns can increase micro-mobility adoption and contribute to more sustainable urban transport systems in Palestine. Our findings on gendered perceptions of safety also resonate with broader discussions on inclusive design, such as the multisensory experiences of wheelchair users in urban mobility contexts [55], emphasizing the need for transport systems that integrate sensory and embodied perspectives.

This highlights significant sustainable engineering issues and principles in the context of developing countries, particularly regarding the adoption of e-bikes versus traditional bicycles. The analysis underscores the importance of a multi-faceted approach that includes economic support, infrastructural investment, and cultural shifts toward cycling. By addressing these sustainable engineering principles, such as promoting efficient, environmentally friendly transport solutions, developing countries can enhance mobility, reduce reliance on motorized vehicles, and foster a more sustainable urban environment.

6. Conclusions

This study provides a comprehensive analysis of the factors influencing university students' preferences for micro-mobility solutions, with a particular focus on conventional bicycles and electric bikes in a developing country context. The application of machine learning techniques, such as Random Forest and clustering, has allowed for a detailed understanding of the key variables driving micro-mobility adoption, including gender, car ownership, and daily transport mode.

The results reveal that the daily transport mode is the most significant factor affecting safety perceptions, willingness to adopt micro-mobility, and preferences for different modes of transport. Furthermore, clustering analysis has shown that different segments of the population, particularly urban and rural residents, exhibit distinct preferences and barriers to adopting micro-mobility. While urban residents demonstrate a higher willingness to adopt e-bikes, financial constraints and the lack of dedicated infrastructure remain key challenges in Palestine. The study underscores the importance of targeted policy interventions, such as improving cycling infrastructure and providing financial incentives, to encourage greater adoption of micro-mobility solutions. These findings have direct implications for urban planners and policymakers aiming to promote sustainable transport in developing regions. Future research should focus on longitudinal studies to track the evolving preferences and behavior patterns related to micro-mobility and explore the potential impact of large-scale infrastructure improvements on adoption rates.

CRediT authorship contribution statement

Ahmed Jaber: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Khaled Al-Sahili:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Fady M.A. Hassouna:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization. **Batool Al-Tanbour:** Data curation, Conceptualization. **Diala Juma:** Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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