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A COMPARATIVE ANALYSIS OF THE FACTORS INFLUENCING UNIVERSITY STUDENTS' MICROMOBILITY PREFERENCES USING K-NEAREST NEIGHBORS AND LOGISTIC REGRESSION MODELS

K- EN YAKIN KOMŞULAR VE LOJİSTİK REGRESYON MODELLERİ KULLANILARAK ÜNİVERSİTE ÖĞRENCİLERİNİN MİKRO-MOBİLİTE TERCİHLERİNİ ETKİLEYEN FAKTÖRLERİN KARŞILAŞTIRMALI ANALİZİ

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Abstract

Shared micro-mobility services have swiftly become widely adopted in major urban centers globally. In particular, individuals are encouraged to transition to environmentally friendly modes of transportation to support a sustainable transportation system. For this reason, the tendencies and potential of individuals to use micro-mobility vehicles are being investigated. This paper focused on university students, analyzing their preferences for using micromobility vehicles, particularly for first-mile or last-mile trips in terms of gender and travel time variables. In the study, k-Nearest Neighbors (kNN) and Logistic Regression (LR) algorithms are used in machine learning approach and they were compared. A face-to-face survey was conducted with 150 students randomly to measure the potential use of micromobility vehicles among university students. As a result, LR model is better than kNN model according to the accuracy of the models, 0,63 and 0,43 respectively. On the other hand, 51,82% of male students and 62,50% of female students participating in our study reported that they are not inclined to prefer micromobility vehicles at any stage of their trips, and the main challenge for the potential users is safety.

Keywords: Gender, k-nearest neighbors, logistic regression, machine learning, micro-mobility.

Öz

Paylaşımlı mikro-mobilite hizmetleri, dünya genelinde özellikle büyük şehirlerde hızla benimsenmiştir. Son zamanlarda, bireylerin sürdürülebilir bir ulaşım sistemini desteklemek amacıyla çevre dostu ulaşım modlarına geçiş yapmaları teşvik edilmektedir. Bu nedenle, literatürde, yol kullanıcılarının mikro-mobilite araçlarını kullanma eğilimleri ve potansiyelleri araştırılmaktadır. Bu çalışma, üniversite öğrencilerini hedef alarak, cinsiyet ve yolculuk süresi değişkenleri açısından ilk ve son kilometre (ilk ve son adım) yolculukları için mikro-mobilite araçlarını kullanma eğilimlerini analiz etmektedir. Çalışmada, makine öğrenmesi yaklaşımıyla k-En Yakın Komşu (kNN) ve Lojistik Regresyon (LR) algoritmaları kullanılmış ve karşılaştırılmıştır. Üniversite öğrencileri arasında mikro-mobilite araçlarının potansiyel kullanımını ölçmek amacıyla 150 öğrenciyle yüz yüze anket yapılmıştır. Sonuç olarak, LR modelinin doğruluk açısından kNN modelinden (sırasıyla 0,63 ve 0,43) daha iyi olduğu görülmüştür. Öte yandan, çalışmamıza katılan erkek öğrencilerin %51,82'si ve kadın öğrencilerin %62,50'si, yolculuklarının herhangi bir aşamasında mikro-mobilite araçlarını tercih etme eğiliminde olmadıklarını belirtmiş, potansiyel kullanıcılar için ana zorluğun "güvenlik" kriteri olduğu sonucuna ulaşılmıştır.

Anahtar Kelimeler: Cinsiyet, k-en yakın komşu, lojistik regresyon, makine öğrenmesi, mikro-mobilite.

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1. INTRODUCTION

As cities grow rapidly, transportation demand continues to increase. As increasing travel demand brings more mobility, the issue of traffic congestion begins to emerge in cities. Traffic congestion is seen as one of the most significant problems, especially in cities with large populations and urban areas. In recent times, micro-mobility solutions have started to be preferred as a solution to traffic congestion, which brings substantial costs that can be defined as negative externalities such as time loss, fuel consumption, and air and noise pollution.

Recent transportation approaches have emerged to reduce the negative externalities of traffic and promote public transportation, particularly in self-driving vehicles and the mobility-as-a-service (MaaS) model. MaaS provides on-demand mobility via crowdsourced or privately owned vehicles, and this concept has expanded to include on-demand mobility via smaller vehicles (Sun et al., 2021). Small vehicles which can be classified as bicycles, scooters, e-bikes, e-scooters, etc. are defined as micro-mobility vehicles. Personal vehicles that are significantly lighter and smaller than cars are referred to as "micro-mobility" (Forum, 2024).

The use of micro-mobility vehicles is increasing in many countries and becoming a trend especially for increasing the use of public transportation. As it is stated that the absence of convenient first leg and last leg of travel options to access transit stops constitutes a significant obstacle for many individuals to utilize public transit (Yin et al., 2024). According to the report generated by National Association City Transportation Officials (NACTO), ridership in station-based bike-sharing systems has shown robust growth, reaching 67 million rides in 2022, a 17% increase compared to the previous year across the United States and in Canada (NACTO, 2023), and in line with a North American Bikeshare & Scootershare Association (NABSA) report, 37% of shared micro-mobility trips take the place of a car trip (NABSA, 2022). Moreover, in comparison to 2021, the growth rate of shared micro-mobility services in Europe was 39% in 2022 (Portal, n.d.). These results show that micro-mobility vehicles are considered a potential solution for traffic impact and it is considered that it can minimize the usage of private vehicles, particularly for short trips, and represent a transition toward more environmentally friendly modes of transportation (Jaber et al., 2024). In addition to becoming a trend, shared micro-mobility offers a practical substitute for conventional urban transportation (Wolnowska & Kasyk, 2024).

In literature, the 18-44 age range is generally more represented, while individuals aged 45 and above are not sufficiently represented in micro-mobility usage studies (Delbosc & Thigpen, 2024; NABSA, 2022; Roig-Costa et al., 2024). In other words, when considering age group variables, the studies predominantly include the younger population. This may be due to the younger population's ability to more easily follow developing technology and their physical advantages.

Typically, studies in literature analyze the micro-mobility usage behaviors of all users. However, as seen in these studies, micro-mobility users are generally within the younger age group. Furthermore, it is considered that the younger population's tendency to use micro-mobility will indicate the potential user base for both the present and future. On the other hand, this study generates invaluable data to the literature which is missing especially in Türkiye. To fill this gap in the literature, this paper focused on the young population and a survey was conducted with university students, analyzing their preferences for using micro-mobility vehicles, particularly for first-mile or last-mile trips in terms of gender and travel time variables.

2. LITERATURE REVIEW

Shared micro-mobility services have swiftly become widely adopted in major urban centers globally (Reck & Axhausen, 2021). Recently, there have been numerous studies regarding micro-mobility vehicles, which are seen as a potential solution, particularly in the context of reducing the use of private cars (Li et al., 2024). These studies often provide approaches aimed at prioritizing such initiatives within cities (Adnan et al., 2019). Micro-mobility vehicles, along with their routes and connections to public transportation systems, should be considered as an integrated system. The micro-mobility system has been examined from various perspectives in the literature. Spatio-temporal travel patterns of micro-mobility (Li et al., 2024), safety of micro-mobility system (Comi et al., 2024; Ignaccolo et al., 2022; Tzouras et al., 2024), user interest and segments (Degele et al., 2018; Hensher et al., 2024), transport equity (Guan et al., 2024), defining a procedure for data collection and analysis (Dozza et al., 2022), user satisfaction (Cheng et al., 2024).

In studies found in the literature that focus on modeling the behaviors or preferences of micro-mobility users, the most significant challenge is data acquisition. To address this, many studies have collected field data using the stated preference survey method (Adnan et al., 2019; Cho & Shin, 2022; Espino, 2023; Hong et al., 2023; Sarker et al., 2024). The prevalence of stated preference survey studies suggests that there may still be a significant number of potential users for this mode of transportation that have not yet been fully identified.

The successful integration of the micro-mobility system into public transportation is seen as a potential solution to address the traffic problems experienced in major cities. In such an integration process, the primary focus should be on establishing safe routes for micro-mobility users. Safety problems are greatly decreased in small to medium-sized cities due to lower traffic congestion (Adnan et al., 2019). Once a safe route is established, the potential for private vehicle users to switch to micro-mobility options may emerge. Studies have shown that individuals are more inclined to use micro-mobility vehicles when a dedicated lane is available (Tait et al., 2022) and it is necessary to ensure the safety and comfort of road users to provide efficiency of transportation infrastructure (Zhang et al., 2023).

Studies have shown that young individuals exhibit a higher tendency to use micro-mobility vehicles compared to other age groups. Research indicates that students and individuals aged 18–30 demonstrate a greater affinity for cycling than full-time employees and those aged 31–60 (Adnan et al., 2019), a trend also observed in the findings of (Ji et al., 2017).

On the other hand, micro-mobility has been analyzed by using various modeling approach. In order to compare the user characteristics, univariate and multivariate probit model (Reck & Axhausen, 2021), to model user satisfaction shared mobility the structural equation model (Cheng et al., 2024), logistic binary regression model to investigate the distinguishing characteristics between e-scooter and shared bike users (Roig-Costa et al., 2024), agent-based approach to model Micro-mobility trips conducted in diverse and perceived unsafe road conditions (Tzouras et al., 2024), and some machine learning algorithms which are kNN model (Campisi et al., 2024), Extreme Gradient Boosting model (Sarker et al., 2024), XGBoost-SHAP and random parameters binary logit model (Sadeghi et al., 2024).

3. EXPERIMENTAL DESIGN AND DATA

In Türkiye, the concept of micro-mobility is not yet fully understood, nor is it widely adopted as a mode of transportation. Even in large cities, the lack of adequate infrastructure makes it difficult to obtain data of sufficient size to study user behavior. As data generated or provided by private companies offering shared micro-mobility services, municipalities, and relevant ministries are not shared, new data must be collected from the field and this situation makes the data invaluable. Since the scope of this study is to examine the micro-mobility usage preferences of young individuals, university students were selected, as in previous literature studies (Espino, 2023; Özdemir, 2023). In this context, Istanbul Aydın University was chosen as the study area due to its campus, which houses approximately 40,000 domestic and international students and is located near public transportation system connection points.

As part of the study, a survey was conducted to measure the potential use of micro-mobility vehicles among university students and a face-to-face survey was conducted with 150 students randomly. To determine the sample size for this study, Cochran's formula was utilized, as it is commonly applied in cases where the population is large or considered infinite. Cochran’s formula is shown in Eq.1 (Cochran, 1963).

$$n_0 = \frac{Z^2 p(1-p)}{e^2} \tag{1}$$

where n_0 minimum sample size, Z is z-value of the confidence interval, p is estimated population proportion (0,5 is used if there is no information), and e is margin of error.

The formula indicates that beyond a certain threshold, population size has minimal impact on the required minimum sample size. In this study, the sample size is deemed adequate at a 90% confidence level. Specifically, with a population of 40,000 (which is approximate), a Z-value of 1,645, and a p-value of 0,5, the minimum required sample size is calculated to be 68. Consequently, the number of surveys conducted is sufficient to meet the 90% confidence level criteria.

Given its connections to the Metrobus and bus systems, as well as its large and diverse student population, data obtained from the students are expected to better reflect the tendencies of university students in general. As shown in Figure 1, the campus area of Istanbul Aydın University and nearby public transportation connection points are provided. The focus is particularly on the tendency of university students to choose micro-mobility vehicles for first-mile and last-mile connections. When considering the distance from the nearest public transportation connection point to the university campus (or vice versa), two different routes were observed. The walking distance from the Besyol Bus Rapid Transit (BRT) station and bus stop to the campus is 520 meters, while the walking distance from the Sefakoy BRT station to the campus is 945 meters.

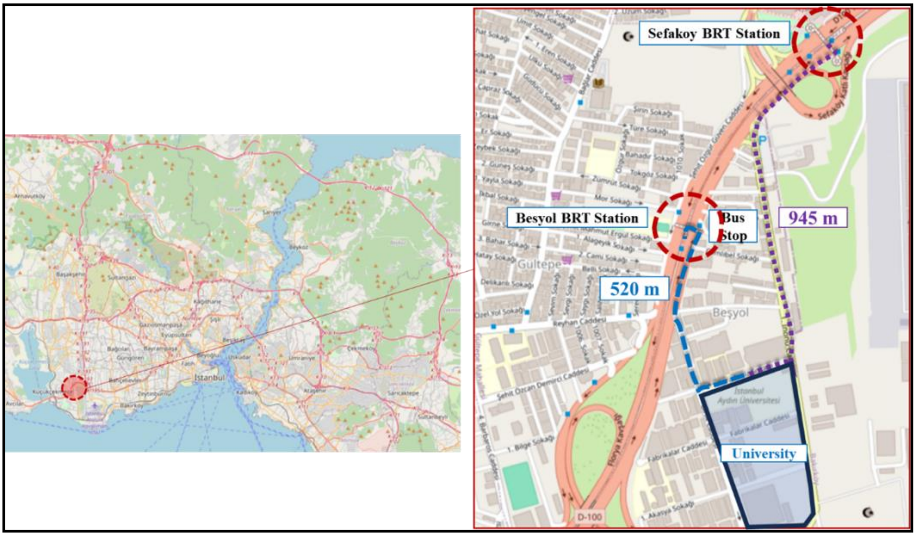

Figure 1. Study Area and Closest BRT Stations and Bus Stops

The face-to-face survey is generally composed of three main sections. The first section focuses on socio-demographic characteristics, asking individuals about their gender, age, scholarship status, income, travel time, travel cost, the number of days per week they attend university, living arrangements, and the distance from their home to the university. The second section inquiries about the individuals' daily routines, or typical trips, including questions about their preferred mode of transportation, the availability of micro-mobility options for the first and last steps of their trip, and which transportation mode they choose for these steps. The third part explores the factors that are most influential in determining their micro-mobility preferences, the factors that deter them from using micro-mobility, and their likelihood of using services like Binbin, Martı, and the Bisim Smart Bicycle System under different scenarios. The survey was conducted in April 2024. During this period, the average fees of service providers operating in Istanbul, such as Binbin, Martı, and Bisim, were calculated. Accordingly, the unlock fee was determined to be 5,49 Turkish Liras (TL), and the fee per minute was 5,99 TL/min for shared e-scooter. Additionally, for Martı motorcycles, the unlock fee was 7,69 TL, and the fee per minute was also 7,69 TL. Participants were asked which of these alternatives they tended to prefer.

The descriptive statistics for the survey study are presented in Table 1. Of the students who participated in the survey, 76,67% are between the ages of 20 and 25, and 26,67% are female. The majority, 76%, are in their second, third, or fourth year of study. Nearly half (46%), live with family members, while 22,67% live alone. A significant proportion, 73,33%, are continuing their education with a merit-based scholarship. Only 8,67% of the students have an income at or below the minimum wage in Türkiye, and the average monthly income of the students is 20,475 TL.

In the survey, students were asked whether it is possible to use micro-mobility for their first-mile trip that starts from home and ends at the nearest public transport station or car park area. 69,33% of participants responded that micro-mobility could be used for the initial phase of their trip if desired, regardless of the availability of sufficient and safe infrastructure. Similarly, 82% of participants answered "yes" to the question of whether it is possible to use micro-mobility for the last-mile trip that starts from the nearest public transit station or car park and ends at the campus.

For the home-to-campus trip, the most commonly preferred mode of transportation is public transportation, at 78%. Only 5,33% of participants commute to the university by private car, while 16,67% walk to campus. The factor most influencing students' decision to use micro-mobility was identified as safety, cited by 32,67% of respondents. Other important factors included time savings and cost-effectiveness, at 18% and 15,33%, respectively.

On average, students spend 13,29 TL per trip and travel for 40,3 minutes on their trip from home to campus. The average distance from their residence to the campus is 12,136 meters. When considering all participants, the average monthly expenditure on transportation is 578 TL.

Table 1. Descriptive Statistics of the Data

Attributes	Levels	Number (n)	Percentage
Gender	Male	110	73.33%
	Female	40	26.67%
Age Groups	17-19	30	20.00%
	20-22	66	44.00%
	23-25	49	32.67%
	26+	5	3.33%
What year in university?	1	29	19.33%
	2	34	22.67%
	3	41	27.33%
	4	39	26.00%
	5	7	4.67%
Who do you live with?	Family members	69	46.00%
	Friends	43	28.67%
	Dormitory	4	2.67%
	Alone	34	22.67%
Scholarship	100%	110	73.33%
	75%	4	2.67%
	50%	5	3.33%
	25%	16	10.67%
	No	15	10.00%

Attributes	Levels	Number (n)	Percentage
Income Groups (TL)	< 11,700	13	8.67%
	20,001-30,000	29	19.33%
	30,001-40,000	54	36.00%
	40,001-50,000	39	26.00%
	50,000 >	15	10.00%
Is it available to use micro-mobility in your first mile? (Home to campus)	No	46	30.67%
	Yes	104	69.33%
Is it available to use micro-mobility in your last mile? (Home to campus)	No	27	18.00%
	Yes	123	82.00%
Typical Mode (Main mode)	Walking	25	16.67%
	Public Transit	117	78.00%
	Private Vehicle	8	5.33%
What is the most important factor that would influence your decision to use micro-mobility vehicles?	Cost-effectiveness	23	15.33%
	Convenience	16	10.67%
	Environmental impact	13	8.67%
	Safety	49	32.67%
	Availability of micro-mobility options	17	11.33%
	Infrastructure (e.g., bike lanes, scooter parking)	5	3.33%
	Saving time	27	18.00%

Attributes	Mean	St.dv.	Attributes	Mean	St.dv.
Travel Cost (TL)	13.29	29.12	**Distance (Between Home - Campus) (m)**	12,136	7,572
Travel Time (min)	40.30	22.78	**Monthly Payment for Transportation (TL)**	578	1,500

4. METHODOLOGY

To identify the factors influencing university students' preferences for micro-mobility vehicles, k-Nearest Neighbors (kNN) and Logistic Regression (LR) models with machine learning were employed. Each approach in the literature has different advantages and disadvantages. In this study, kNN and LR machine learning methods were chosen because they are faster and more efficient for studies with smaller datasets. With LR, the model is easier to interpret, and with kNN, a more flexible model can be obtained by not making prior assumptions. On the other hand, approaches like Support Vector Machines, Decision Trees, or Artificial Neural Networks are also potential alternatives. However, such approaches require a large dataset. Therefore, it is considered that the most suitable approaches are kNN and LR. Following the preprocessing and organization of the survey data to fit the kNN and LR models, the dataset was randomly split into training (60%), validation (20%), and testing (20%) subsets for machine learning. The dependent variable in the machine learning process was "preference" (i.e., whether students preferred to use micro-mobility vehicles for any part of their trip: Yes or No). Graphical analyses revealed that "gender" and "travel time" had a stronger influence on the "preference" variable, leading to their inclusion as independent variables in the machine learning models. On the other hand, the correlation between gender and travel time also tested and the value R is 0,0019.

4.1. k - Nearest Neighborhood Model (kNN)

The kNN classification algorithm, originally introduced by Cover and Hart in 1967 (Cover & Hart, 1967), is recognized for its simplicity among machine learning algorithms and is extensively applied in classification tasks due to its highly adaptable and straightforward design (Mahesh, 2019). In this method, observations are classified using the kNN algorithm based on the majority class of the 'k' closest neighbors within the feature space (Alrefaei & Ilyas, 2024). Generally Eucledian algorithm is used to find the nearest point in this method (Cunningham & Delany, 2021). The kNN classifier categorizes a query by assigning it to the class that is most commonly represented among its k-nearest neighbors in the training set, based on the majority voting principle (Uddin et al., 2022; Wang et al., 2022). The kNN classifier requires calculating the distance between the input sample and each individual sample in the training dataset. (Gallego et al., 2018).

The kNN classifier first calculates the Euclidean distances $d_{(x,\ yi)}$ between the test sample x and each training sample y_i which is element of training set. Next, the kNNs of x are identified and sorted in ascending order based on their Euclidean distances (Wang et al., 2020). The Euclaedian distances is calculated as in Eq. 2.

$$d(x, y_i) = \sqrt{(x - y_i)^T (x - y_i)}\,, \quad i > 0 \tag{2}$$

Lastly, the test sample x is classified into class ω_C based on a majority voting process, as expressed in Eq.3 (Trevor, Hastie; Tibshirani, Robert; Friedman, 2019; Wang et al., 2020) .

$$\omega_C = argmax_{\omega_j} \sum_{(y_i^{NN}, c_i^{NN}) \in NN_k^{Tr}(x)} \delta(\omega_j = c_i^{NN})\,, \qquad j > 0 \tag{3}$$

$\delta(\omega_j = c_i^{NN})$ is the Kronecker delta function. It takes "1" if $\omega_j = c_i^{NN}$ or "0" otherwise. "j" is the number of classes, *Tr* presents the training samples, c_i corresponds class label of y_i and $c_i \in \{\omega_1, \omega_2, \dots, \omega_M\}$, *NN* specifies nearest neighbor.

4.2. Logistic Regression Model (LR)

LR is a widely used statistical model designed for analyzing categorical data with a binary dependent variable (Regulski et al., 2024). This classification method estimates the likelihood of an outcome falling into one of two categories based on independent variables, such as a rolling median and time (Regulski et al., 2024; Rymarczyk et al., 2019). LR is also recognized as a statistical approach within the domain of machine learning (Maalouf, 2011; Rymarczyk et al., 2019). The LR model employs a sigmoid function to map real-valued independent variables to a range between 0 and 1, thereby converting the continuous output from a linear regression into a categorical output (Geeksforgeeks, 2024). LR works as follow:

Xs are independent input features, and they are stored in a matrix. *Y* represents the dependent variable which is binary coded. The independent and dependent variables are shown in Eq. 4.

$$X = \begin{bmatrix} x_{11} \cdots x_{1m} \\ x_{21} \cdots x_{2m} \\ \cdots \cdots \cdots \\ x_{n1} \ldots x_{nm} \end{bmatrix} \; and \; Y = \begin{cases} 0 \; if \; Class \; 1 \\ 1 \; if \; Class \; 2 \end{cases} \tag{4}$$

After that, in LR model the multi-linear function to input variables X is applied by using Eq.5.

$$Y = a \cdot X + b \tag{5}$$

Here Y is dependent variable and it can be defined as the preference of choosing micro-mobility vehicle or not. Since the dependent variable "preference" binary coded, there will be two functions and each of "$Y_{preference}$" functions can be named as "*utility function*" of the "*prefer*" and "*not prefer*" options. "a" is the coefficient of independent variable and "b" is bias term which is also known as intercept. As it is stated that LR employs the Sigmoid function to estimate the probability that the dependent variable belongs to a specific class, which converts any continuous variable into a value between 0 and 1. In the binary logit model, the likelihood that preference 1 will be picked is given by the preference set, which includes "prefer (which is coded "1")" and "not prefer (which is coded "0") (Ergin & Tezcan, 2022).

$$P_1 = \frac{e^{a_1 \cdot X_1 + b_1}}{e^{a_1 \cdot X_1 + b_1} + e^{a_2 \cdot X_2 + b_2}}, \quad and \quad P_2 = 1 - P_1 \tag{6}$$

In the Eq. 6, P_1 represents the probability of selecting choice 1, $(a_1 \cdot X_1 + b_1)$ represents the utility functions of alternatives 1 and 2.

5. MODEL ESTIMATION RESULTS

In the machine learning-based kNN and LR models, the dependent variable "preference," indicating whether individuals would choose micro-mobility vehicles at any stage of their trip under suitable conditions, was used alongside the independent variables "gender" and "travel time." The same variables were applied to both models (kNN and LR). For the kNN model, it is necessary to determine the number of classes, which was done using the Elbow method (Figure 2). In this figure, Within-Cluster Sum of Squares (WCSS) acts as an indicator of the error or variability within clusters. It shows how closely data points are positioned within a cluster, highlighting the compactness and uniformity of the clusters. Accordingly, the optimal number of neighbors was determined to be 3, and the analyses were conducted based on this selection.

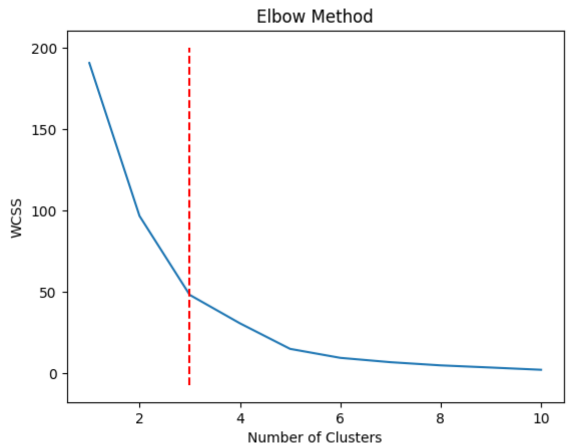

Figure 2. Elbow Method Result

As part of the machine learning process, the KNeighborsClassifier and LogisticRegression algorithms, which are included in the open-source machine learning library scikit-learn, were utilized (Scikit-learn, n.d.-a, n.d.-b). Model results are given in Table 2.

Table 2. kNN and LR Model Results

Sentiments	kNN Model Result				LR Model Result			
	Precision	Recall	F1-score	Support	Precision	Recall	F1-score	Support
0	**0.5**	**0.29**	0.37	17	**0.75**	**0.53**	0.62	17
1	**0.4**	**0.62**	0.48	13	**0.56**	**0.77**	0.65	13
Evaluation Measures								
accuracy			0.43	30			0.63	30
macro avg	0.45	0.45	0.43	30	0.65	0.65	0.63	30
weighted avg	0.46	0.43	0.42	30	0.67	0.63	0.63	30

The model results are compared based on precision, recall, and F1-score metrics. Precision evaluates the accuracy of positive predictions by determining how many of the predicted positives are truly positive, with higher precision indicating fewer false positives. When examining the precision values, the LR model's results (0,75; 0,56) are significantly better than those of the kNN model (0,5; 0,4). On the other hand, recall measures the model's ability to identify all true positive events, with higher recall indicating fewer false negatives. In this assessment, the LR model also outperforms the kNN model, with recall values of (0,53; 0,77) compared to (0,29; 0,62) for kNN. The F1-Score offers a comprehensive metric by balancing both precision and recall, making it especially valuable in situations with imbalanced class distributions. The superiority of the LR model over the kNN model is further evident in the F1-score. Additionally, the accuracy rate of the LR model (0,63) is better than that of the kNN model (0,43).

6. DISCUSSION AND CONCLUSION

This study aims to identify the factors influencing the use of micro-mobility vehicles, with a particular focus on the effects of gender and travel time variables. Shared micro-mobility vehicles are especially preferred by the younger population, which is why research in the literature has often focused on the preferences of university students (Özdemir, 2023) or examined the status of being a university student (Hong et al., 2023). In parallel to this study, it is found that younger individuals, particularly students in universities, are more inclined to cycle compared to older adults and full-time employees (Adnan et al., 2019).

Some studies claim that e-scooters provide a faster, cost-effective, and environmentally friendly alternative to walking and driving, with easier accessibility than taxis, and are especially popular among young people for short-distance travel (Özdemir, 2023). However, in cities with high population density such as Istanbul, where infrastructure services are insufficient for the use of micro-mobility vehicles, their usage is quite dangerous. Consequently, 51,82% of male students and 62,50% of female students participating in our study reported that they are not inclined to prefer micro-mobility vehicles at any stage of their trips. Similarly, the literature indicates that micro-mobility is not exclusively favored by low-income individuals or students as a mode of transportation (Campisi et al., 2024). The primary factor causing the lack of preference for micro-mobility vehicles among university students is "safety." For 36% of male students and 35% of female students, "safety" was reported as the most important factor. Likewise, Wolnowska and Kasyk (2024) stated that the student group is closely linked to the perception that cycling is highly unsafe (Wolnowska & Kasyk, 2024).

In the literature, there are studies that examine the tendencies of young individuals to prefer micro-mobility vehicles through various independent variables. In these studies, latent variable model and error component model (Hong et al., 2023), logit model (Cho & Shin, 2022), hybrid choice model (Adnan et al., 2019), multilevel linear mixed effects model (Cubells et al., 2023) and so on are used. In this study, LR model and kNN model results are compared in order to show the performance of the models in terms of gender and travel time independent variables which are used to train the dataset. In accordance with the model results, it can be obviously claimed that the LR model generally outperforms the kNN model. Particularly, the high recall and F1-score values in the "would prefer" category indicate that this model better identifies this class and minimizes the number of false negatives. Given that the independent variables, gender and travel time, are included in the data used to train these models, it can be said that these variables are more influential in the LR model. This, in turn, has contributed to the model making more accurate predictions.

Current technological advancements allow for a deeper analysis of the data obtained. Therefore, in this study, the dataset was trained using the independent variables of gender and travel time, and the effects of gender and travel time were observed more strongly. Since the results of models obtained using different variables were quite low, only the independent variables of gender and travel time were considered.

The study also has some limitations. More comprehensive analyses can be conducted once these limitations are addressed. Although the study focuses on students, it could also analyze larger datasets based on students' income levels, scholarship status, and the geographic locations of their homes relative to the university. Additionally, overcoming these limitations may enable more detailed analyses in future studies using different methods, potentially shorter surveys, and larger sample sizes.

As a result, increasing the use of micro-mobility vehicles as an environmentally friendly mode of transportation is essential for a cleaner future and sustainability. Hence, it is necessary to implement geometric arrangements in urban areas to specifically address safety issues and to provide a good price-performance ratio service that encourages the use of micro-mobility vehicles. Geometric arrangement, education, legal rights, and supervision could lead to the acceptance of micro-mobility vehicles as a mode of transportation and increase their preference rate. Following the adoption of this usage as a behavior, a cultural change will also be experienced. Studies have shown that young individuals are more inclined to use micro-mobility vehicles compared to other age groups. Therefore, targeting young individuals as the primary focus of strategies aimed at promoting the widespread use of micro-mobility in society would be a more effective approach.

Research and Publication Ethics Statement

Research and publication ethics have been complied with in the study conducted.

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