T.C.
ISTANBUL OKAN UNIVERSITY
INSTITUTE OF GRADUATE SCIENCES

THESIS
FOR THE DEGREE OF MASTER OF
ARTIFICIAL INTELLIGENCE ENGINEERING

Selim DÜNDAR

MODELING E-SCOOTER USER PREFERENCES USING MACHINE LEARNING METHODS

ADVISOR
Asst.Prof. Sina ALP

ISTANBUL, January 2025

T.C.
ISTANBUL OKAN UNIVERSITY
INSTITUTE OF GRADUATE SCIENCES

THESIS
FOR THE DEGREE OF
ARTIFICIAL INTELLIGENCE ENGINEERING

Selim DÜNDAR
(233307002)

MODELING E-SCOOTER USER PREFERENCES USING MACHINE LEARNING METHODS

ADVISOR
Asst. Prof. Dr. Sina ALP

ISTANBUL, January 2025

T.C.
ISTANBUL OKAN UNIVERSITY
INSTITUTE OF GRADUATE SCIENCES

THESIS
FOR THE DEGREE OF MASTER OF
ARTIFICIAL INTELLIGENCE ENGINEERING

Selim DÜNDAR (233307002)

MODELING E-SCOOTER USER PREFERENCES USING MACHINE LEARNING METHODS

Presentation Date of Thesis : 22.01.2025
Submission Date of Thesis : 24.01.2025

Advisor : Asst. Prof. Dr. Sina ALP ________________
(Istanbul Okan University)

Jury Members : Assoc. Prof. Dr. Ömer CİHAN KIVANÇ _______
(Istanbul Okan University)
Assoc. Prof. Dr. Gürkan GÜNAY ______________
(Istanbul Bilgi University)

ISTANBUL, January 2025

ACKNOWLEDGEMENTS

This thesis, titled Modeling E-Scooter User Preferences Using Machine Learning Methods, has been prepared with the support of the TÜBİTAK 1001 Project numbered 123M063, titled “Elektrikli Skuterların İstanbul Trafiğine ve Çevreye Olan Etkilerinin Belirlenmesi, En Uygun Işletme Ortamı, Koşulları ve Kurallarının Saptanması”. First and foremost, I extend my gratitude to TÜBİTAK for their support.

I completed this thesis as part of the Artificial Intelligence Engineering Master's Program at Istanbul Okan University’s Graduate Education Institute, where I was accepted as a scholarship student for the past two years of my 14 years of service at the university. Therefore, I would like to thank our university's Chairman of the Board of Trustees, Mr. Bekir OKAN; rector, Prof. Dr. Güliz MUĞAN; director of the Graduate School, Assoc. Prof. Dr. Edin Güçlü SÖZER; and the Coordinator of the Artificial Intelligence Engineering Master's Program, Prof. Dr. Pınar YILDIRIM.

I extend my deepest gratitude to my professors who expanded my knowledge through the courses I took during my master's education and provided me with unwavering support: Prof. Dr. Semih BİLGEN, Asst. Prof. Didem KIVANÇ TÜRELİ, and my thesis advisor, Asst. Prof. Sina ALP.

During my master's education, I also continued to serve as the Chair of the Department of Civil Engineering. I want to thank my colleagues from the department, whose dedicated efforts and valuable support I greatly appreciate: Prof. Dr. Atıl BULU, Asst. Prof. Onur GEDİK, Asst. Prof. Ahsanollah BEGLARIGALE, Asst. Prof. Saeid ZARDARI, Asst. Prof. Agne KARLIKANOIVAITE BALIKÇI, Asst. Prof. Mohammed Yousaf ANWAR, Asst. Prof. Hossein Zoriyeh ALIGHOLI, Lecturer Özlem VARDAR, Research Assistant İrem Merve ULU, Research Assistant Saadet DİLEKCİ, and Civil Engineer Berkay TEMİZER.

Since we first met in 2017, I have collaborated on numerous projects with Assoc. Prof. Dr. Gürkan GÜNAY, who played a significant role in the TÜBİTAK 1001 Project

I led and who was also responsible for Work Package 1. He is also one of the jury members for this thesis, and I sincerely thank him and my advisor, Asst. Prof. Sina ALP, and the other primary and substitute jury members, Assoc. Prof. Dr. Ömer Cihan KIVANÇ, Prof. Dr. Semih BİLGEN, and Asst. Prof. Mustafa Sinan YARDIM.

Onur Dursun, a third-year student in the Software Engineering department, significantly supported me in coding the machine learning methods used in this study in Python. I owe him my gratitude.

Finally, I have reserved the greatest gratitude for my beloved family, especially my mother, Gülen DÜNDAR, and my father, Sadık Ender DÜNDAR. Without their efforts, sacrifices, and guidance during my upbringing, no single letter of this thesis would have been written.

TABLE OF CONTENTS

PAGE NO

ACKNOWLEDGEMENTS i
TABLE OF CONTENTS iii
ÖZET v
ABBREVIATIONS viii
LIST OF FIGURES ix
LIST OF TABLES x
CHAPTER 1 INTRODUCTION 11
CHAPTER 2 LITERATURE RESEARCH 14
CHAPTER 3 DATA COLLECTION 17
3.1. Survey Design 17
3.2. Survey Analysis 22
CHAPTER 4 MACHINE LEARNING MODELS 25
4.1. ARTIFICIAL NEURAL NETWORKS 25
4.2. DECISION TREES 28
4.2.1. Information Gain 31
4.2.2. Gini Index 32
4.2.3. Chi-Square Test 34
4.2.4. Mean Squared Error 35
4.3. RANDOM FOREST 35
4.3.1. Algorithm 37
4.4. GRADIENT BOOSTING 38
4.4.1. The Fundamental Components of Gradient Boosting 38
4.4.2. Algorithm 38
4.4.3. Gradient Boosting Trees 39
4.4.4. Mathematical Formulation 40

4.4.5. Types of Gradient Boosting Algorithms 40
CHAPTER 5 MODEL DEVELOPMENT AND COMPARISON OF MODEL PERFORMANCES 44
CHAPTER 6 CONCLUSIONS 48
REFERENCES 50
APPENDICES 57
APPENDIX A QUESTIONNAIRES 57

ÖZET

ELEKTRİKLİ SKUTER KULLANICI TERCİHLERİNİN MAKİNE ÖĞRENMESİ YÖNTEMLERİYLE MODELLEMESİ

Karayolu motorlu taşıt trafiği kaynaklı gecikmeler, trafik kazaları, çevre kirlilikleri gibi sorunlar günümüz toplumlarının başlıca sorunları arasındadır. Bu sorunların üstesinden gelmek için ulaştırma sistemi kullanıcıları, toplu taşımanın yanı sıra, aktif ulaşım sistemleri ve mikromobilite türlerini kullanmaya özendirilmektedir. Elektrikli skuterler, özellikle araç paylaşım hizmeti veren firmaların 2018 yılında piyasaya girmesinden bu yana gözde olmaya başlayan ve COVID-19 salgınıyla birlikte bu özelliğini arttıran bir mikromobilite sistemidir.

Bu çalışma kapsamında, İstanbul'da yaşayan e-skuter kullanıcılarının demografik bilgilerinin yanı sıra, e-skuter kullanımına ilişkin tutum ve davranışları 1 Eylül 2023 – 1 Mayıs 2024 tarihleri arasında uygulanan bir çevrimiçi anket ile incelenmiştir. 462 adet e-skuter kullanıcısının geliştirilen 24 adet farklı senaryoda hangi ulaşım türünü kullanmayı seçecekleri bu anket ile kendilerine sorulmuştur. Katılımcıların anketlere verdikleri yanıtlar, Yapay Sinir Ağları, Karar Ağaçları, Rastgele Orman ve Eğim Arttırma Yöntemleri kullanılarak modellenmiştir. Geliştirilen modeler arasında Rastgele Orman, %96,51 gibi bir oranla en yüksek başarımı sağlayanı olmuştur. Bu oran literatürdeki kesikli seçim modellerinin başarımını oldukça aşmaktadır.

Çalışma kapsamında geliştirilen modeller, bilimsel araştırmacılar tarafından farklı amaçlarla kullanılabileceği gibi, merkezi ve yerel yöneticiler ile paylaşımlı e-skuter hizmeti veren firmalar da stratejik ve işletmesel kararlarını oluşturmakta bu modellerden yarar sağlayabilirler.

Gelecekteki çalışmalarda, farklı makine öğrenmesi yöntemlerinin kullanılması ve farklı şehirlerde yaşayanların tercihlerini de yansıtacak bir modelin geliştirilmesi hedeflenmektedir.

Anahtar Kelimeler: E-skuter, Mikromobilite, Makine Öğrenmesi, Yapay Sinir Ağları, Karar Ağaçları, Rastgele Orman, Eğim Arttırma

Tarih : 24.01.2025

SUMMARY

MODELING E-SCOOTER USER PREFERENCES USING MACHINE LEARNING METHODS

Delays resulting from motor vehicle traffic, traffic accidents, and environmental pollution pose significant challenges in contemporary society. To tackle these issues, users of transportation systems are encouraged to engage in active transportation methods and micromobility options alongside public transit. Electric scooters have emerged as a popular micromobility solution, particularly following the introduction of vehicle-sharing companies in 2018, a trend that was further accelerated by the COVID-19 pandemic.

This study explored the demographic characteristics, attitudes, and behaviors of e-scooter users in Istanbul through an online survey conducted between September 1, 2023, and May 1, 2024. A total of 462 e-scooter users were surveyed on their preferred transportation mode across 24 various scenarios devised for the study. The responses from participants were analyzed using Artificial Neural Networks, Decision Trees, Random Forest, and Gradient Boosting methods. Among the models developed, Random Forest demonstrated the highest performance, achieving an accuracy rate of 96,51%, significantly exceeding the performance of discrete choice models reported in the literature.

The models created in this study can serve multiple purposes for scientific researchers, central and local authorities, as well as shared e-scooter service providers, aiding in their strategic and operational decision-making processes. Future research will seek to employ different machine learning methodologies and develop a model that better reflects individual preferences across various cities.

Keywords: E-scooter, Micromobility, Machine Learning, Artificial Neural Networks, Decision Trees, Random Forest, Gradient Boosting

Date: 24.01.2025

SYMBOLS

A	**:** Starting fee of taxi (TL)
B	**:** Starting fee of e-scooter (TL)
BF	**:** Price of 1 liter of gasoline (TL)
BS	**:** The average fuel consumption per kilometer (L/km)
C	**:** Per-minute usage fee of e-scooter (TL)
D	**:** Dataset
d	**:** Usage duration of e-scooter (min)
$\mathbf{E_i}$	: Expected frequencies
$\mathbf{F_{escooter}}$	**:** E-scooter fare (TL)
$\mathbf{F_{privatecar}}$	**:** Travel cost for a private car (TL)
$\mathbf{F_{taxi}}$	**:** Taxi fare (TL)
$\mathbf{h_t(x)}$	**:** Prediction of the t^{th} tree
$\boldsymbol{\eta}$	: Learning rate
k	**:** Number of sub-levels
$\boldsymbol{\lambda}$	: Smoothing factor
M	**:** Per kilometer charge of taxi (TL)
m	**:** Number of iterations
$\mathbf{O_i}$	: Observed frequencies
$\mathbf{\Omega(T_k)}$	: Penalty function
P	**:** Average parking fee for a round trip per hour (TL)
$\mathbf{p_i}$	**:** The probability of a specific instance belonging to a particular class
T	**:** Number of trees
$\mathbf{T_m(x)}$	**:** Tree predictor at step m.
t	**:** Travel time (h)
$\mathbf{x_i}$	**:** Input features
x	**:** Distance traveled (km)
$\mathbf{X^2}$	**:** Chi-Square
$\mathbf{y_i}$	**:** Actual value of the target variable for the i^{th} data point
$\hat{y}_i$	**:** The predicted value for the ith data point i
Z	**:** Hourly rate of taxi (TL)

ABBREVIATIONS

ANN **:** Artificial Neural Networks
BL : Binary Logit
CART : Classification and Regression Trees
CatBoost : Categorical Boosting
COS **:** Change of Score
DT **:** Decision Trees
EFB **:** Exclusive Feature Bundling
EU **:** European Union
FFBP **:** Feed Forward Back Propagation
GB **:** Gradient Boosting
GBT **:** Gradient Boosting Trees
GNN **:** Graph Neural Networks
GOSS **:** Gradient-based One-Side Sampling
IBB **:** İstanbul Büyükşehir Belediyesi (Istanbul Metropolitan Municipality)
LightGBM **:** Light Gradient Boosting Machine
ML : Mixed Logit
MNL : Multinomial Logit
MSE : Mean Squared Error
NL : Nested Logit
RAM : Random Access Memory
RF : Random Forest
SSD : Solid State Drive
TÜBİTAK **:** Türkiye Bilimsel ve Teknolojik Araştırma Kurumu (The Scientific and Technological Research Council of Türkiye)
TÜİK **:** Türkiye İstatistik Kurumu (Turkish Statistics Institute)
UK **:** United Kingdom
US **:** United States
USA **:** United States of America
UYM **:** Ulaşım Yönteim Merkezi (Transport Management Center)
XGBoost **:** eXtreme Gradient Boosting

LIST OF FIGURES

PAGE NO

Figure 3.1. Screenshot of Travel Time Measurements for the 4 km Route Between Bostancı and Selamiçeşme (Google Maps, 2025) 19

Figure 4.1. FFBP network structure (Varol Malkoçoğlu et al., 2022).........................26

Figure 4.2. Underfitting and overfitting examples (Ledziński and Grześk, 2023) 28

Figure 4.3. Illustration of DT regression (Yazdani et al., 2023)..................................29

Figure 4.4. A two-tree random forest model (Donges, 2024).....................................36

Figure 4.5. The Architecture of Gradient Boosting Decision Tree (Deng et al., 2024) 39

Figure 5.1. The architecture of the developed ANN...46

Figure 5.2. Flow chart of the three-way data split validation method (Murat, 2006) 47

LIST OF TABLES

PAGE NO

Table 3.1. Travel Times of Modes (minutes).. 19
Table 3.2. Travel costs of the modes….. 20
Table 3.3. The prepared scenarios….. 22
Table 3.4. Demographic Data 23
Table 4.1. Classes and variables 33
Table 5.1. Data set combinations used in determining the network architecture 45
Table 5.2. Performance values of the developed machine learning models 47

CHAPTER 1 INTRODUCTION

One of the most significant challenges facing modern society is highway traffic and its associated issues, such as delays, traffic accidents, and environmental pollution. Every additional minute spent in traffic represents an irreversible loss of time in a person's life, significantly reducing overall quality of life. Traffic congestion-related delays are particularly severe in large cities. In Türkiye, Istanbul is the most populous city, with an official population of 15.655.924 (TÜİK, 2024). This figure does not account for irregular migrants or individuals traveling for daily trips or tourism, which makes it unsurprising that traffic-related problems in Istanbul are pronounced. Despite various investments in rail systems, city traffic issues continue to escalate. Data released by INRIX indicates that the average delay experienced by a driver in Istanbul increased by 15,38% in 2024 compared to 2023, reaching a staggering 105 hours (Pishue, 2025). This statistic positions Istanbul as the global leader in traffic delays.

In response to these challenges, individuals experiencing delays in road traffic are striving to develop innovative solutions. Various micromobility systems, such as bicycles, e-bikes, and e-scooters, have gained popularity in this context. E-scooters, in particular, have recently emerged as a transportation option in Türkiye. With several rental companies entering the market, the number of users has surged, making e-scooters a viable alternative for various transportation modes, especially for short distances. However, the regulations surrounding e-scooter use in urban traffic are still underdeveloped. Recently, the "Electric Scooter Regulation" was published in the Official Gazette (T.C. Resmi Gazete, April 14, 2021, Issue: 31454), and the Istanbul Metropolitan Municipality (İstanbul Büyükşehir Belediyesi - IBB) has created an e-scooter directive for Istanbul (IBB Ulaşım Yönetim Merkezi - UYM, 2021). Similar initiatives are also in progress in other cities across Türkiye.

In recent years, e-scooters have become a popular last-mile transportation option in Türkiye, particularly among young people. However, regulations regarding the operating conditions and rules for e-scooters on highways have only recently begun to be developed. As a result, many e-scooter users and other highway traffic stakeholders are operating vehicles without being fully informed about these regulations. The published regulations are often based on examining similar rules in other countries and are sometimes adapted to suit the conditions in Türkiye. However, since traffic conditions in each country are primarily influenced by driver behavior, they can differ significantly. Therefore, it may be appropriate to establish different operating conditions for e-scooters tailored to each country or city.

It is crucial for central and local governments to comprehensively assess public attitudes, behaviors, and preferences regarding e-scooter usage. This evaluation can provide valuable guidance for planning effective regulations. Additionally, understanding user attitudes, behaviors, and preferences is equally important for companies that offer e-scooter sharing services. This understanding can help them develop strategic and operational policies, enhance service quality, and increase market share. As a result, well-regulated e-scooter services and improved service quality can lead to increased demand for e-scooters, helping to alleviate problems caused by motorized highway traffic.

Within the scope of this study, various preferences of e-scooter users regarding their usage have been analyzed, and their mode choices under different conditions have been predicted using machine learning methods. An online survey was conducted with 462 current or potential e-scooter users living in Istanbul. The decisions obtained from the survey results were modeled using *Artificial Neural Networks (ANN), Decision Trees (DT), Random Forest (RF),* and *Categorical Boosting (CatBoost)* methods. The high success rates of the developed models in comparison to discrete choice models demonstrate their potential as decision support systems for central and local authorities. Furthermore, the results serve as a valuable data source for shared e-scooter service providers, enabling them to refine their strategies and operations. Researchers can also utilize these model outcomes in traffic simulation studies to assess mode preferences in the population.

The second chapter of the study provides a literature review of models used in mode choice and their applications in micromobility. The third chapter discusses the surveys and data collection process. The fourth chapter focuses on the machine learning methods employed in the study. The fifth chapter presents model development and a comparison of model performances. Finally, the sixth and concluding chapter summarizes and discusses the findings of the study.

CHAPTER 2 LITERATURE RESEARCH

In modern transportation planning, mode choice models are typically developed using discrete choice models. These models are applied to various aspects of transportation, including urban and intercity transportation (Ben-Akiva and Lerman, 1985), freight transportation (Günay, Ergün, and Gökaşar, 2016), airport access mode preferences (Gökaşar and Günay, 2017; Günay and Gökaşar, 2021), driving safety (Mo et al., 2021), route choice (Yang et al., 1993; Prato, 2009), and the growing interest in new transportation modes (Ilahi et al., 2021). The most commonly used discrete choice models are the *Binary Logit (BL), Multinomial Logit (MNL)*, and *Nested Logit (NL)* models (Ben-Akiva and Lerman, 1985). However, since the early 2000s, *Mixed Logit (ML)* has also become widely adopted (McFadden and Train, 2000; Hensher and Greene, 2003).

According to Ben-Akiva and Lerman (1985), discrete choice models are based on the theory of utility maximization by individuals. In the MNL model, coefficients for each variable are fixed across all individuals, whereas in the ML model, these coefficients vary among individuals. This variability reflects the differences in perception among individuals (Hensher and Greene, 2003).

Reck et al. (2021) applied mode choice models to e-scooters, utilizing MNL and ML to analyze user preferences for e-scooter and e-bike types in Zurich. Their results indicated that micromobility solutions with parking facilities were more likely to be preferred during peak hours, suggesting that such modes could help reduce motor vehicle trips. Beyond this study, there is limited research specifically applying mode choice models to the e-scooter field. However, Zuniga-Garcia et al. (2021) recommended developing a model for selecting infrastructure types conducive to e-scooter usage. Zuniga-Garcia et al. (2022) examined how individuals integrate e-scooters into their transit trips, while Cao et al. (2021) utilized ML models in Singapore to compare e-scooters with rail transit services for short-distance trips. Their findings revealed demographic differences—such as those based on gender and age—in preferences for rail transit versus e-scooters, and indicated that e-scooter usage increased when access to rail transit became more difficult. Similarly, Psarrou Kalakoni et al. (2024) created a choice model to evaluate preferences between e-scooters and public transit in France, finding that e-scooters were more popular than public transit for trips under 15 minutes, although public transit remained the more cost-effective option. Another mode choice analysis conducted by Esztergár-Kiss et al. (2022) employed MNL, ML, and NL models to explore preferences among automobiles, e-scooters, public transport, and bicycles across five cities. Their research highlighted differences in e-scooter usage efficiency, with Barcelona showing the highest efficiency. They also identified variations in sensitivity to e-scooter fees and travel times due to differences in model coefficients across cities. However, traditional discrete choice models have struggled to adequately capture the mode choice preferences of e-scooter users (Dündar et al., 2024).

Studies have explored the types of users who prefer e-scooters over other modes of transportation. Findings indicate that young men, particularly those with higher education levels, primarily favor e-scooters (Laa and Leth, 2020; Abouelela, 2021; Christoforou et al., 2021; Nikiforiadis et al., 2021; Esztergár-Kiss and Lizarraga, 2021). However, regional differences in the transportation modes that e-scooters replace have been identified (Şengül and Mostofi, 2021). According to their study, e-scooters and e-bikes can substitute for other transportation modes on trips shorter than 8 kilometers, which account for approximately 50-60% of total trips in the EU, USA, and China.

Research by Laa and Leth (2020), Christoforou et al. (2021), Kopplin et al. (2021), Luo et al. (2021), and Nikiforiadis et al. (2021) has shown that e-scooters are often preferred over walking and public transportation for specific trips. When considering the factors influencing individuals' views on e-scooter usage, a notable focus is on the elements that users prioritize when selecting this mode of transportation. In this regard, Reck et al. (2021) developed specific mode choice models for e-scooters, examining preferences for e-scooters and e-bikes in Zurich. Their study found that micromobility solutions with dedicated parking facilities were more frequently chosen during peak hours, helping to reduce motor vehicle trips. Similar findings were reported by Leger et al. (2018) in the UK and the Netherlands and by James et al. (2019) and Lee et al. (2021) for ride-sharing and taxi trips in the US. While there is still limited literature specifically focused on mode choice models for e-scooters, recommendations for developing infrastructure choice models for e-scooter usage have been made by Zuniga-Garcia et al. (2021) and Polat et al. (2023). Further research on user profiles is needed.

CHAPTER 3 DATA COLLECTION

An online survey was conducted using Google Forms as part of the study, which received approval from the Ethics Committee of Istanbul Okan University during meeting number 158 on September 21, 2022. The survey was carried out between September 1, 2023, and May 1, 2024, and involved 512 participants. However, due to the requirements of the TÜBİTAK 1001 project (project number 123M063), responses from individuals outside of Istanbul were excluded, resulting in a final sample size of 462 participants.

This number exceeds the required sample size of 384 for a population of over 500,000 in a heterogeneous universe, as established by Fox et al. (2007) and Meyer (1979). Although there is no definitive data on the total number of e-scooter users in Istanbul, one of the leading e-scooter sharing companies, Martı, reported through its founder, Oğuz Alper Öktem, that its user base had surpassed 5 million as of 2021 (Muradoğlu, 2021). Considering the potential users who have yet to try e-scooters, it is estimated that the total population exceeds 500.000. Therefore, the sample size of 462 is regarded as sufficient for this study.

3.1. Survey Design

The first section of the survey collected demographic information about e-scooter users, including details such as gender, age, income level, education level, and car ownership.

The second section focused on questions related to e-scooter usage, which addressed the following aspects:

- Whether there is a bike lane within 250 meters of their residence.
- Their primary mode of transportation for daily travel.
- The main purpose of their trips (e.g., work, school, health, shopping).
- Their preferred type of infrastructure for riding e-scooters (e.g., roads, sidewalks, bike lanes).

- Whether they currently use or would consider using e-scooters on sidewalks.
- The transportation modes they replace or would consider replacing with e-scooters.
- The traffic conditions under which they prefer to use e-scooters (e.g., light, moderate, congested).
- The maximum duration, in minutes, they prefer for a one-way e-scooter trip.
- Their perception of the safety of using e-scooters.
- Their opinions on the use of e-scooters on sidewalks.
- Whether they currently use or would use e-scooters on roads with one-way or two-way traffic.
- Their views on parking locations for e-scooters.
- Whether they currently park or would park e-scooters in designated parking spots.
- Their level of compliance with traffic rules.
- Whether cost or safety is the primary factor influencing their preference for e-scooters.
- The maximum hourly cost (in Turkish Lira) they find acceptable for using e-scooters.

In the third and final section of the survey, respondents were presented with scenarios that included varying travel times and costs for private cars, public transportation, taxis, and e-scooters. For each scenario, participants were asked to indicate their preferred mode of transportation. These scenarios were based on a 4-kilometer distance along Bağdat Avenue, between the neighborhoods of Bostancı and Selamiçeşme in Istanbul. The online survey, which was prepared in Turkish, was completed by the participants and is provided in Appendix A.

Since the participants were unfamiliar with traffic engineering terminology, traffic conditions were categorized into three verbal levels: light, moderate, and congested. The travel times for these conditions along the specified 4 km route were measured using Google Maps. Figure 3.1 shows a screenshot of these measurements, and Table 3.1 displays the travel times defined for the four transportation modes.

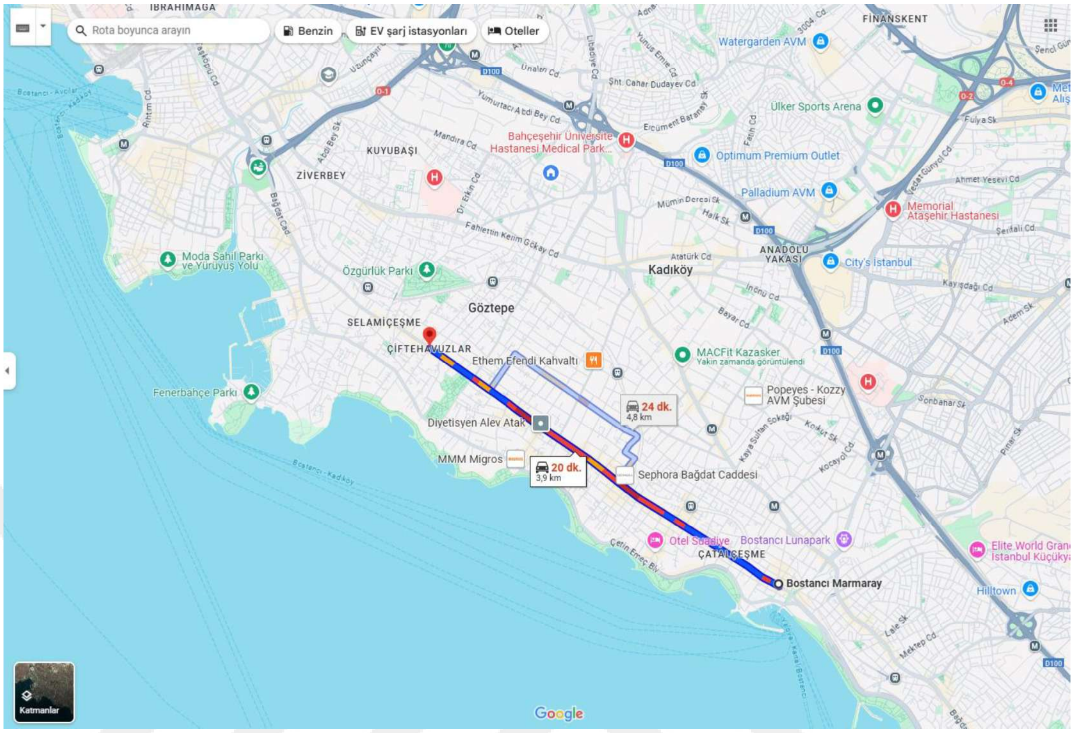


Figure 3.1. Screenshot of Travel Time Measurements for the 4 km Route Between Bostancı and Selamiçeşme (Google Maps, 2025)

Table 3.1. Travel Times of Modes (minutes)

	Light Traffic	Moderate Traffic	Congested Traffic
Private Car	9	20	30
Public Transport	15	29	45
Taxi	9	20	30
E-scooter	16	16	16

Two levels have been established for travel costs across four modes of transportation: the current costs and the increased costs. The increase has been set at 65%, reflecting the inflation rate for 2023. The calculation of fees for a 4 km journey has been conducted as follows:

For Private Car:

$$F_{privatecar} = BF\left(\frac{TL}{km}\right) * BS\,(\frac{L}{km}) * \frac{100}{4} + P \tag{3.1}$$

In Equation 3.1, $F_{privatecar}$ represents the travel cost for using a private car. The variables involved are as follows: BF is the price of one liter of gasoline in Turkish Lira (TL), BS is the average fuel consumption in liters per kilometer, and P is the average parking fee for a round trip per hour. In 2023, BF was set at 34.48 TL (source: OPET, 2023), BS was 8 liters, and P was 52 TL (source: NTV, 2023).

For Public Transport:

In Istanbul, the price of a full ticket fare is 15 TL (İBB, 2023a).

For Taxi:

$$F_{taxi} = A + M * x(km) + Z * t\ (h) \tag{3.2}$$

In Equation 3.2, F_{taxi} denotes the taxi fare, where A represents the starting fee, M is the charge per kilometer, Z is the hourly rate, x is the distance traveled in kilometers, and t is the travel time in hours. In 2023, the rates in Istanbul were set as follows: A was 19.17 TL, M was 13.75 TL, and Z was 152.73 TL (İBB, 2023b).

For E-scooter:

$$F_{escooter} = B + C * d\ (min) \tag{3.3}$$

In Equation 3.3, $F_{escooter}$ represents the fare for e-scooter rides, where B is the starting fee, C is the per-minute usage charge, and d is the duration of usage in minutes.

The average fare for a 4 km journey was determined by calculating the prices from three different companies. Based on this, a journey at the legal speed limit of 15 km/h would take approximately 16 minutes. In 2023, both Binbin and Hop companies charged 75 TL for this distance, while Martı charged 82 TL. The average fare, which was calculated to be 77 TL, was rounded down to 75 TL for simplicity in responding to the survey. The fares presented in Table 3.2 were derived from Equations 3.1 to 3.3.

Table 3.2. Travel costs of the modes

	Base Fare (TL)	Increased Fare (TL)
Private Car	65	105
Public Transport	15	25
Taxi	75	125
E-scooter	75	125

When calculating the number of scenarios, it is impossible to take into account the combinations of travel time levels for the various modes of transportation. This is because the car, taxi, and public transit modes will be similarly affected at each level of traffic speed. In other words, while one mode may be traveling quickly, the others cannot be moving very slowly at the same time. The speed of the e-scooter is considered constant across all congestion levels, set at 15 km/h, which is the legal speed limit for these vehicles in the country. As shown in Table 3.1, the travel time remains the same for all traffic conditions and is calculated to be 16 minutes.

However, combinations between modes are possible when considering travel cost levels. Using a full factorial experimental design for each travel time (Hensher et al., 2005), the total number of scenarios would be calculated as 2^4 x 1 = 16. Therefore, the total number of scenarios would then be 16 x 3 = 48. However, this high number would overwhelm respondents, so an alternative experimental design was utilized to reduce this total.

In this case, a fractional factorial design was applied, which resulted in a calculated total of 24 scenarios for respondents to answer. The fractional factorial design is commonly used when a full factorial design yields too many scenarios to manage. It preserves the orthogonality feature of the full factorial design while reducing the number of total combinations. In this instance, a fraction of ½ was applied, meaning that half of the variable combinations from the full factorial design were utilized. The scenarios that were prepared for participants to answer in the survey are presented in Table 3.3.

Table 3.3. The prepared scenarios

		Private Car		Taxi		E-Scooter		Public Transport	
		Fare (TL)	Time (min)	Fare (TL)	Time (min)	Fare (TL)	Time (min)	Fare (TL)	Time (min)
1	1-Light	105	9	125	9	125	16	25	15
2	1-Moderate	105	20	125	20	125	16	25	29
3	1-Congested	105	30	125	30	125	16	25	45
4	2-Light	105	9	125	9	75	16	15	15
5	2-Moderate	105	20	125	20	75	16	15	29
6	2-Congested	105	30	125	30	75	16	15	45
7	3-Light	105	9	75	9	125	16	15	15
8	3-Moderate	105	20	75	20	125	16	15	29
9	3-Congested	105	30	75	30	125	16	15	45
10	4-Light	105	9	75	9	75	16	25	15
11	4-Moderate	105	20	75	20	75	16	25	29
12	4-Congested	105	30	75	30	75	16	25	45
13	5-Light	65	9	125	9	125	16	15	15
14	5-Moderate	65	20	125	20	125	16	15	29
15	5-Congested	65	30	125	30	125	16	15	45
16	6-Light	65	9	125	9	75	16	25	15
17	6-Moderate	65	20	125	20	75	16	25	29
18	6-Congested	65	30	125	30	75	16	25	45
19	7-Light	65	9	75	9	125	16	25	15
20	7-Moderate	65	20	75	20	125	16	25	29
21	7-Congested	65	30	75	30	125	16	25	45
22	8-Light	65	9	75	9	75	16	15	15
23	8-Moderate	65	20	75	20	75	16	15	29
24	8-Congested	65	30	75	30	75	16	15	45

3.2. Survey Analysis

Table 3.4 displays the percentage distribution of survey participants based on gender, driving license ownership, income, preferred infrastructure for e-scooter use, and their perceptions of e-scooter safety. The gender distribution among participants is nearly equal. A significant majority hold a driving license, while only about 30% of respondents own a car. Regarding income, most participants report having no income or earning at a minimum wage level, largely due to the fact that 60% of the survey participants are students. When asked about their preferred infrastructure for e-scooter use, the majority (68,3%) prefer bike lanes.

Table 3.4. Demographic Data

Age	Min		16
	Max		66
	Mean		25,74
	Standard Deviation		7,84
		Number	**Percentage**
Gender	Female	228	49,35
	Male	233	50,43
	Does not wish to specify	1	0,21
Automobile License Ownership	Yes	352	76,19
	No	110	23,81
Automobile Ownership	Yes	137	29,65
	No	325	70,35
Income Level	0 TL	138	29,87
	1- Minimum wage	101	21,42
	Minimum wage -20000 TL	40	8,65
	20001-30000 TL	54	11,69
	30001-40000 TL	51	11,04
	40001-50000 TL	31	6,71
	More than 50000	49	10,61
Which infrastructure would you use the e-scooter on?	Bicycle Path	317	68,61
	Sidewalk	51	11,04
	Road	94	20,35
How safe do you find the e-scooter?	Very Safe	3	0,65
	Safe	33	7,14
	Moderate	186	40,26
	Slightly Safe	138	29,87
	Not Safe at All	102	22,08

However, survey responses indicate that e-scooters are not perceived as very safe, with only about 8% of participants considering them safe or very safe. This perception is likely influenced by the lack of bike lanes in Istanbul, as e-scooters have no designated lanes apart from main roads and sidewalks, which may lead to concerns about safety. Additionally, Polat et al. (2023) have noted the deficiency of bike lanes in Istanbul.

In the context of the TÜBİTAK 1001 Project numbered 123M063, the transportation modes chosen by survey participants under various conditions were modeled using traditional discrete choice models. The variables presented in Table 3.4, along with their counts and percentages, were entered as categorical variables into these models. Each sublevel of each variable was treated as a dummy variable, assigned a value of 1 if applicable to the participant and 0 otherwise. For each variable with k sublevels, k-1 dummy variables were created.

In the developed discrete choice models, the total number of observations was calculated as 462 participants multiplied by 24 scenarios each, resulting in 11.088 observations. In all models, e-scooter was used as the reference mode of transportation, with the utility function including only travel time and cost. Demographic variables were included for other transportation types. Travel time, travel cost, the number of cars in the household, and household size are treated as continuous variables, while other variables serve as dummy variables representing the sublevels of categorical variables.

Initially, a pooled model that disregarded car ownership was developed. Subsequently, two separate preference models were created for car owners and non-owners. The pooled model had a performance rate of 54% in correctly predicting the type of transportation chosen. For non-car owners, the performance rate was also 54%, whereas for car owners, it dropped to 40%. These performance levels may be attributed to the higher prevalence of public transportation users with varying demographic characteristics. The models suggested some preferences for private vehicles and classified e-scooters as a form of public transportation (Dündar et al., 2024).

Since the models developed did not achieve the targeted 70% accuracy rate outlined in the project proposal, we implemented the backup plan that involved using machine learning methods with at least 70% accuracy. In this context, we employed machine learning models, the theoretical framework of which is detailed in Chapter 4 of this study, to achieve better prediction performance. The details of the models and their performance results are presented in Chapter 5.

CHAPTER 4 MACHINE LEARNING MODELS

In this study, four different machine learning models have been utilized to analyze e-scooter user preferences: *Artificial Neural Networks (ANN), Decision Trees (DT), Random Forest (RF)*, and *Categorical Boosting (CatBoost)*. This section presents the theoretical foundations of these models.

4.1. ARTIFICIAL NEURAL NETWORKS

ANN are a modeling technique inspired by the fundamental working principles of the human brain. Similar to how the human brain can learn, recall, generalize, improve with new information, and memorize, ANN simulate these capabilities within a software environment. ANN consist of interconnected units called neurons, which are organized into layers. Typically, ANN include an input layer, one or more hidden layers, and an output layer. The number of neurons in the input and output layers is determined by the specific data of the problem being modeled, while the number of hidden layers and the neurons within them are usually decided through trial and error in order to optimize the model's performance. However, increasing these numbers raises the computational demands of the network, creating a trade-off between training speed, operational efficiency, and overall performance (Dündar et al., 2021).

In ANN, a black-box modeling technique, learning occurs by adjusting the numerical values, or *weights*, of the connections between neurons. Consequently, the primary goal of an ANN is to ensure that the given input data can generate the desired output values. The specific mathematical operations performed to achieve these outputs are not as critical; rather, the focus is on how accurately the ANN can produce the targeted output values. This accuracy is what defines the network's performance.

Various network structures have been developed in the literature to address different problems. In this study, we utilized a *Feed Forward Back Propagation (FFBP)* network structure to predict which mode of transportation participants would prefer under varying price and traffic conditions. In this *supervised learning* method, input information is transmitted forward through the network, allowing it to generate one or more output values. The structure of the FFBP network is illustrated in Figure 4.1.

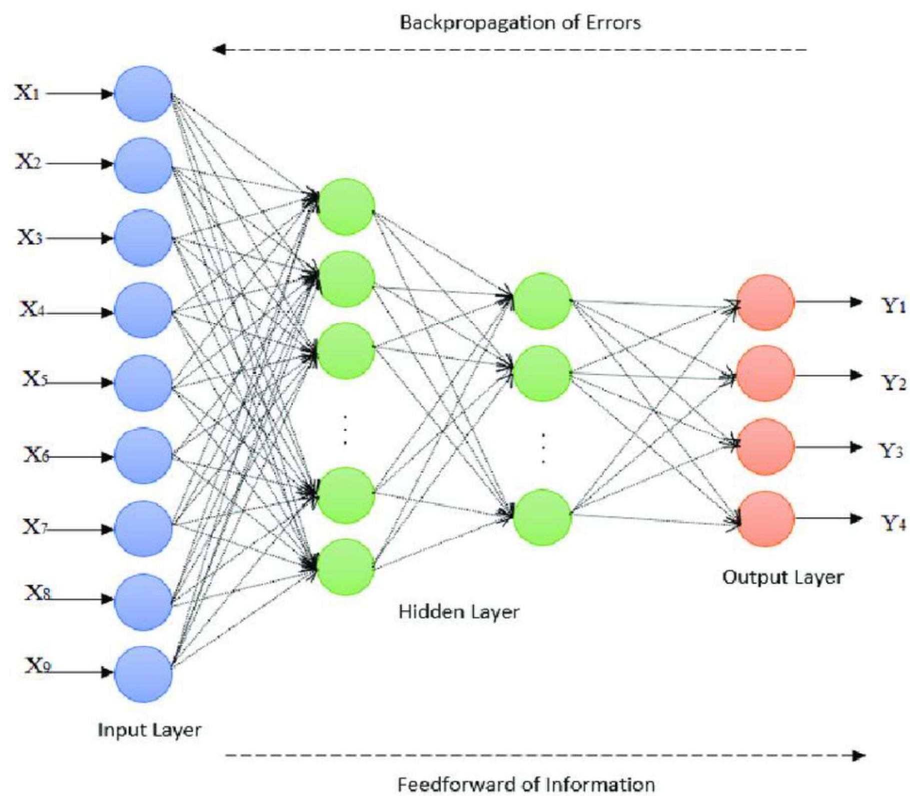


Figure 4.1. FFBP network structure (Varol Malkoçoğlu et al., 2022).

The difference between the output value produced by the network and the actual *(target)* output value is referred to as the error. This error propagates backward through the network, leading to updates in the weight values that connect the neurons. When this process is completed for all input-output data pairs provided to the network, a training step is considered concluded. By repeating these training steps, the network is effectively trained. A trained ANN can successfully generate *(predict)* output values for data it has not encountered during training. This capability allows trained networks to predict which mode of transportation different users will prefer based on various price levels and traffic conditions.

In ANN, determining when to stop training is crucial for the network's performance. While various rules or algorithms exist for training, many are based on *gradient descent*, which ensures that the error decreases with each step compared to the previous one. As a result, the error metric being evaluated becomes smaller with each training iteration.

However, a significant challenge in ANN is *overtraining*, which can lead to *memorization* or *overfitting*. When the network begins to memorize, the error may decrease for the training data, but when it encounters new data not used during training, the error often increases. This reduces the network's ability to generalize. Therefore, deciding when to stop training is critical for the network's success.

To address overfitting, the available data is usually divided randomly into three subsets: *training*, *testing*, and *validation* sets. During the training phase, the training set is used to learn, while the error for the test set is monitored. Training is stopped when the error in the test set starts to increase. The validation set is then utilized to assess the success of the training process. Various studies explore the appropriate distribution ratios for these subsets, and in this study, 70% of the data was allocated to the training set, while the testing and validation sets each received 15%. An example illustrating underfitting and overfitting in ANN is shown in Figure 4.2.

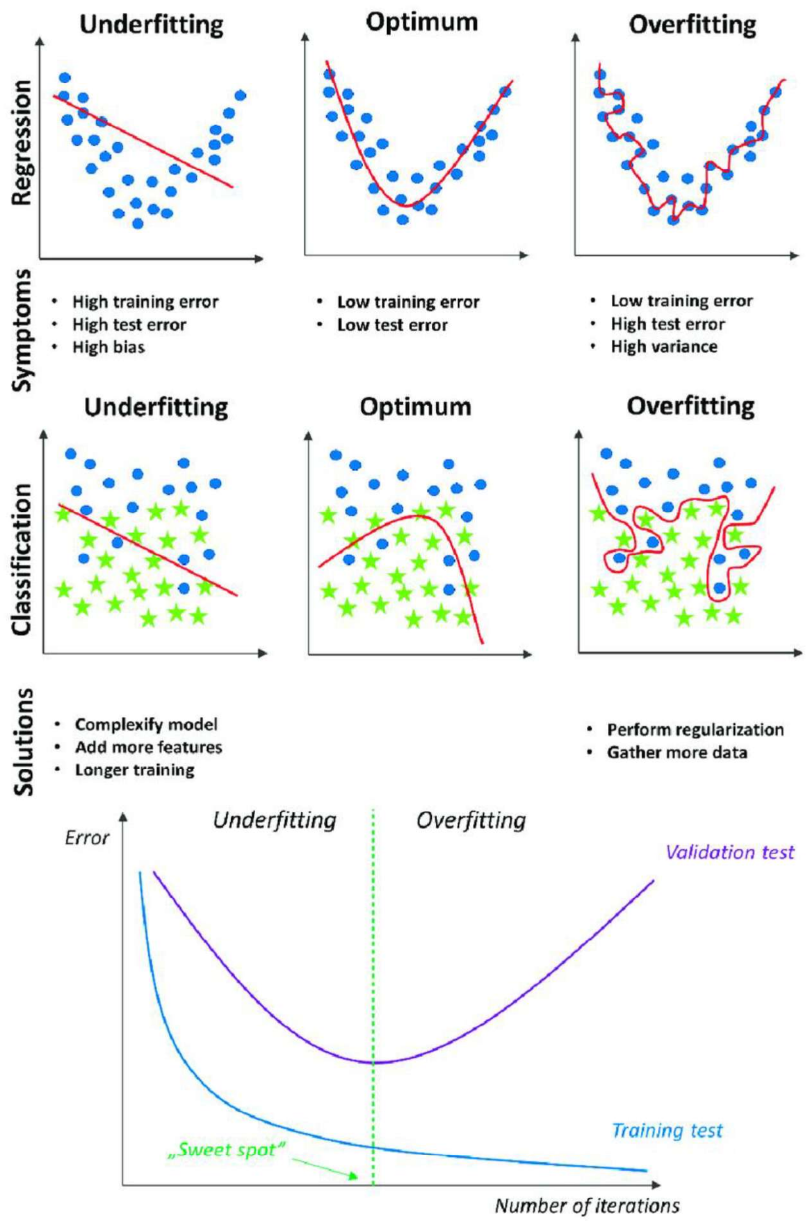


Figure 4.2. Underfitting and overfitting examples (Ledziński and Grześk, 2023).

4.2. DECISION TREES

DT form the foundation of classical machine learning algorithms such as Random Forests, *Bagging*, and *Boosting*. Leo Breiman, a statistician at the University of California, Berkeley, was the first to propose them. Breiman's key idea was to represent data in a tree structure. In this structure, each internal node represents a test or condition on an attribute, each *branch* represents the outcome of that test, and each *leaf node* (terminal node) represents a class label. DTs are widely used in predictive models for both classification and regression tasks and are often referred to as *CART (Classification and Regression Trees)*.

DT operate as sequential models that logically combine a series of simple tests. Each test either compares a numerical attribute against a threshold value or compares a nominal attribute against a set of possible values. These symbolic classifiers provide an advantage in interpretability over *"black-box"* models like neural networks. The logical rules followed by a DT are much easier to interpret than the numerical weights of connections between nodes in a neural network. Consequently, decision-makers often feel more comfortable using models they can understand (Kotsiantis, 2013).

When performing classification with DT, a dataset is progressively divided into smaller subsets, gradually developing the tree. The resulting tree consists of decision nodes and leaf nodes. In the constructed DT, a decision node can have two or more *branches*, while leaf nodes represent a class or a decision. The primary goal when building a DT from a dataset is to create a tree with as few nodes as possible (Torun, 2022). An example of a DT is illustrated in Figure 4.3.

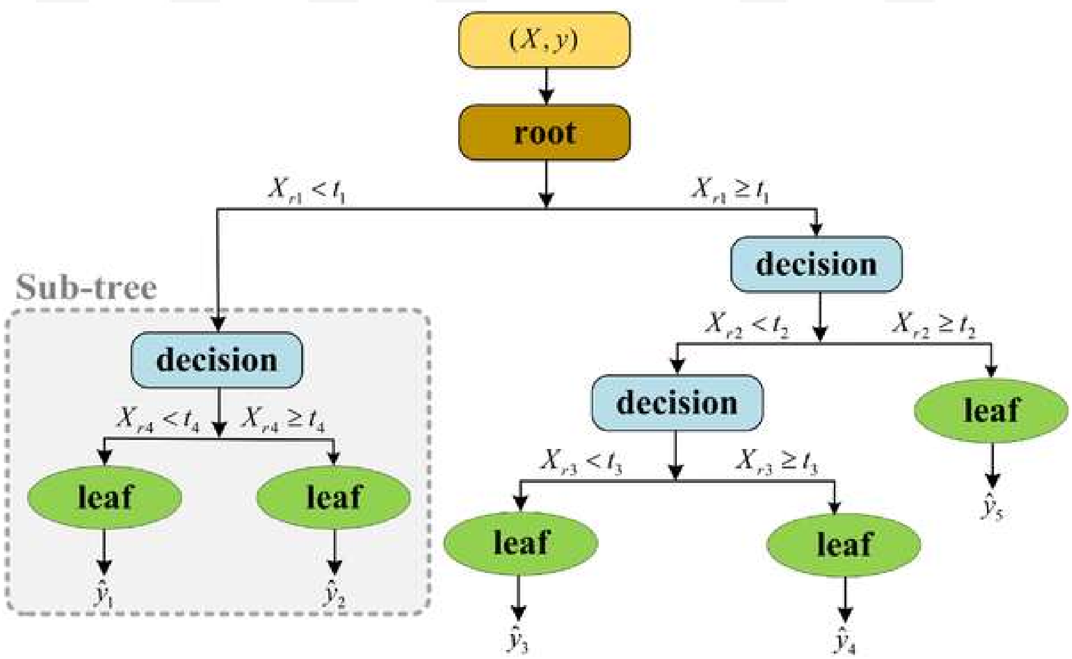


Figure 4.3. Illustration of DT regression (Yazdani et al., 2023).

Tree-based algorithms are a popular family of non-parametric, supervised methods used for classification and regression tasks. *Supervised learning* involves training models with data that includes both input and output labels. A DT resembles an inverted tree, beginning with a *"root"* node that contains a decision rule and branching down with additional rules. For example, a decision rule might determine whether a person exercises. Some nodes may not contain decision rules; these are referred to as *"leaf nodes."*

Decision Trees can be categorized based on the type of target variable:

1. **Categorical Variable Decision Trees:** In these trees, the target variable is categorical. For instance, when predicting the price of a computer as "low," "medium," or "high," features such as monitor type, speaker quality, RAM, and SSD may be utilized. The Decision Tree learns from these features by passing each data point through the nodes and ultimately reaching a leaf node that corresponds to one of the categories: "low," "medium," or "high."
2. **Continuous Variable Decision Trees:** In this scenario, features (e.g., attributes of a house) are used to predict a continuous output (e.g., the price of the house).

Every tree has a root node where the inputs are processed. This root node is then divided into decision nodes, where outcomes and observations are determined conditionally. The process of dividing a node into multiple nodes is called *"splitting."* If a node cannot be split further, it is referred to as a "leaf node" or *"terminal node."* Sections of a DT are known as branches or sub-trees. For example, the section enclosed in a box in a Figure 4.3 representing a DT illustrates a sub-tree.

There is also a concept that is the opposite of splitting. If certain decision rules in a DT can be eliminated, they are removed from the tree. This process is called *"pruning"* and is useful for reducing the algorithm's complexity.

Several techniques are used to determine how the data should be split. The primary goal of a DT is to divide the data into the correct classes as efficiently as possible by making optimal splits between nodes. Achieving this depends on the application of appropriate decision rules, which significantly influence the algorithm's performance. Some key assumptions to consider include:

- All data is initially considered the root node, which is subsequently divided into sub-trees using algorithms.
- Feature values are assumed to be categorical. If the values are continuous,

they are transformed into categories before the model is built.

- Records are distributed recursively based on feature values.
- Features are ranked as root or internal nodes using a statistical approach.

Commonly used splitting techniques include *Information Gain*, *Gini Index*, *Chi-Square Test*, and *Mean Squared Error*.

4.2.1. Information Gain

This technique assesses how each split increases the *Information Gain* within the dataset. The Information Gain at a node is measured by the reduction in the *entropy* of the dataset. Splits that yield high Information Gain are preferred because this indicates that the feature is significant in terms of the information it provides. When constructing a DT, identifying the optimal splitting node is crucial for achieving high accuracy. Therefore, Information Gain focuses on locating the best nodes that offer the highest values of Information Gain.

This calculation relies on a concept called entropy. Entropy defines the level of disorder in a system—the greater the disorder, the higher the entropy. When a sample is completely homogeneous, its entropy is zero; conversely, if the sample is partially organized (for example, 50% organized), its entropy will be one. This measure is fundamental in calculating Information Gain. Together, entropy and Information Gain are utilized in constructing the Decision Tree, a process that employs the ID3 algorithm.

To calculate Information Gain and subsequently build the Decision Tree, the entropy of the output feature (before the split) is determined using Equation 4.1.

$$Entropy(T) = -(plog_2p + qlog_2q) \tag{4.1}$$

In this context, *p* represents the probability of success (e.g., "Correct" outcomes), while *q* signifies the probability of failure (e.g., "Incorrect" outcomes). For instance, if 5 out of 10 data points are classified as "Correct" and the other 5 as "Incorrect," then p = 0.5 and q = 0.5. In this scenario, entropy can be calculated as follows:

$$Entropy(T) = -(0{,}5log_2 0{,}5 + 0{,}5log_2 0{,}5) = 1$$

The next step involves calculating the entropy for each input feature. For instance, let's consider a feature called "Priority," which has two values: low and high. Associated with these values are the possible outcomes: "Correct" and "Incorrect."

For the low value, we have a sample of 5 data points, out of which 2 are “Correct” and 3 are “Incorrect.” Therefore, the probabilities are calculated as follows: p = 2/5 = 0,4 and q =3/5 = 0,6.

Using these probabilities, we can now calculate the entropy for the low value.

$$E(T, Low) = -\left(\frac{2}{5}\log_2\frac{2}{5} + \frac{3}{5}\log_2\frac{3}{5}\right) = 0{,}971$$

For the “high” value, where 4 out of 5 data points are “Correct” and 1 is “Incorrect,” the probabilities are as follows:

$$E(T, High) = -\left(\frac{4}{5}\log_2\frac{4}{5} + \frac{1}{5}\log_2\frac{1}{5}\right) = 0{,}721$$

Then, we calculate the total entropy for the input feature “Priority.” This is done by taking the weighted average of the entropies for each subset—specifically, the “Low” and “High” categories. Since there are 5 data points in the “Low” category and 5 data points in the “High” category within the dataset, both subsets carry equal weight. Thus, the total entropy is determined accordingly:

$$E(T, X) = \frac{5}{10} \times\ E(T, Low) + \frac{5}{10} \times E(T, High) = 0{,}5 \times 0{,}971 + 0{,}5 \times 0{,}721$$
$$= 0{,}846$$

The final step involves calculating the Information Gain:

$$Information\ Gain = E(T) - E(T, X) = 1 - 0{,}846 = 0{,}154$$

This process is repeated for each input feature, and the feature that provides the highest Information Gain is selected. Ultimately, the feature with the highest Information Gain is chosen as the split node in the decision tree. This procedure continues until the entire dataset is classified. A leaf node is defined as a node with no entropy, or zero entropy, meaning that no further splitting occurs at this node. Only those branches that require splitting—specifically when entropy is greater than zero, indicating confusion—will undergo this splitting process.

4.2.2. Gini Index

The Gini Index is a measure of impurity in a node. A low Gini Index indicates that the node is homogeneous, making it suitable for accurate classification. This method is commonly used, particularly in classification problems.

In an ideal scenario, if all elements are accurately divided into distinct classes, the split is considered *"pure."* The Gini Index quantifies the likelihood of misclassifying a randomly selected instance at a given node. *Impurity* reflects how much the model's split deviates from a pure division. The Gini Index score ranges from 0 to 1:

- A score of 0 means that all elements belong to a single class (a pure split).
- A score of 1 indicates that elements are randomly distributed across different classes.
- A Gini Index of 0.5 suggests that elements are evenly distributed among several classes.

The mathematical representation of the Gini Index is provided in Equation 4.2.

$$Gini = 1 - \sum_{i=1}^{c} (p_i)^2 \tag{4.2}$$

In this context, *"p_i"* represents the probability of a specific instance being classified into a particular category. To help clarify the concept of the Gini Index, we present a simple example. In Table 4.1, each instance (or row) is defined by two variables and is associated with a class label.

Table 4.1. Classes and variables

Class	Variable1	Variable2
A	0	33
A	0	54
A	0	56
A	0	42
A	1	50
B	1	55
B	1	31
B	0	-4
B	1	77
B	0	49

The splitting criterion for Variable1 indicates that out of 10 examples, 4 are equal to 1 and 6 are equal to 0.

For Variable1 == 1, we have the following distribution among classes:

- Class A: 1 out of 4 examples belongs to Class A.
- Class B: 3 out of 4 examples belong to Class B.

The Gini Index for this group is calculated as:

$$1 - \left(\left(\frac{1}{4}\right)^2 + \left(\frac{3}{4}\right)^2\right) = 0{,}375$$

For Variable1 == 0, the distribution among classes is as follows:

- Class A: 4 out of 6 examples belong to Class A.
- Class B: 2 out of 6 examples belong to Class B.

The Gini Index for this group is:

$$1 - \left(\left(\frac{4}{6}\right)^2 + \left(\frac{2}{6}\right)^2\right) = 0{,}444$$

In this process, each split is assigned a weight and summed based on the proportion of data it includes.

$$\frac{4}{10} \times 0{,}375 + \frac{6}{10} \times 0{,}444 = 0{,}4167$$

This process evaluates the effectiveness of each split by considering the proportion of data it represents in the dataset. A weighted average is calculated to determine the overall Gini Index, which helps assess which split results in a purer distribution. This method assists the decision tree in selecting the most optimal split at each step.

4.2.3. Chi-Square Test

This test is designed to assess the relationship between features and classes at each split, particularly when dealing with categorical data. It evaluates how features relate to the target variable by conducting an independence test. The chi-square method is effective when the target variables are categorical, such as success-failure or high-low classifications. The primary objective of the algorithm is to determine the statistical significance of the differences between the child nodes and the parent node. The mathematical formula used to calculate the chi-square statistic is presented in Equation 4.3.

$$\mathrm{X}^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{4.3}$$

O_i represents the observed frequencies, while E_i represents the expected frequencies. This formula calculates the sum of the squared standardized differences between the observed and expected frequencies of the target variable. One of the main advantages of using the chi-square test is that a node can perform multiple splits, leading to increased accuracy and precision.

4.2.4. Mean Squared Error

A common technique for regression problems is to minimize the *Mean Squared Error (MSE)* at each node. This approach targets continuous variables and splits the data based on the differences between target values. The formula for calculating MSE is presented in Equation 4.4.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4.4}$$

Let n represent the number of data points. For each data point i, y_i denotes the actual value of the target variable, while $\hat{y}_i$ represents the predicted value for that same data point.

Please note that the section on decision trees is based on the source: Kurama (2019).

4.3. RANDOM FOREST

RF is an ensemble learning method that combines multiple DT to improve accuracy and reduce overfitting. It operates by constructing numerous DT during training and aggregating their predictions through majority voting (for classification) or averaging (for regression).

RF creates multiple DT that are combined to provide more accurate predictions. The concept behind the RF model is that independent and uncorrelated models (individual DT) perform significantly better when grouped together than when operating alone. In classification tasks, each tree in the random forest produces a classification or *"vote."* The overall classification is determined by the majority of these votes. In regression, the forest calculates the average of the outputs from all the trees. The key to this approach is maintaining a low (or ideally, no) correlation between the individual models, which are the DT that comprise the larger RF model. While individual DT may make errors, the collective output of the group is usually correct, guiding the overall result in the right direction (Meltzer, 2023).

The most significant advantage of RF is their versatility; they can be applied to both classification and regression problems. Figure 4.4 illustrates a simple RF model consisting of two trees.

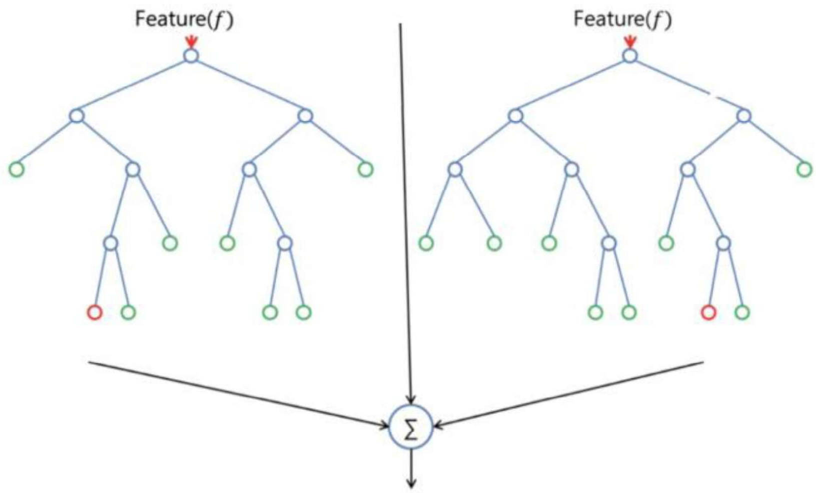


Figure 4.4. A two-tree random forest model (Donges, 2024).

RF shares many hyperparameters with DT and *boosting classifiers*. However, it is unnecessary to combine a DT with a boosting classifier since the classification feature of the RF can be utilized independently. RF introduces additional randomness into the model while constructing the trees. Instead of identifying the most important feature during a node's split, it selects the best feature from a random subset of features. This approach often leads to greater diversity among the trees, resulting in a more robust model. Thus, in an RF classifier, only a random subset of features is considered when splitting a node. Additionally, trees can be further randomized by incorporating random threshold values instead of looking for the best threshold value for each feature.

Although RF is fundamentally a collection of DT, some key differences exist between them. When a training dataset with features and labels is provided to a DT, it generates a set of rules for making predictions. For instance, to predict whether a person will click on an online advertisement, the model might analyze past ad clicks and various features that influence the person's decision. In contrast, the RF algorithm creates multiple DT by randomly selecting observations and features, followed by averaging the results of these trees.

Another notable difference is that deep DT may suffer from overfitting. RF mitigate this risk by creating shallower trees using random subsets of features and then combining these smaller trees. However, this strategy does not guarantee success and can slow down computation, depending on the number of trees constructed in the RF.

To achieve more accurate predictions with RF, a greater number of trees is typically required, which can increase memory usage and slow down the model. While the algorithm is generally fast enough for most real-world applications, excessive trees can render the model too slow for real-time predictions. Additionally, although RF algorithms usually train quickly, generating predictions can be slower, which may lead to inefficiencies in scenarios where runtime performance is critical. In such situations, alternative methods might be more appropriate.

It's important to note that RF models are primarily predictive tools rather than explanatory ones. They are designed to make predictions based on data patterns rather than elucidating the relationships among various factors. Different modeling approaches may be better suited for understanding these relationships.

(Note: This section on Random Forest is based on the source Whitfield, 2024.)

4.3.1. Algorithm

Given a dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$, where x_i represents input features and y_i representes target values:

1. Randomly sample (with replacement) from the dataset to create multiple bootstrapped trees.
2. Construct a decision tree for each dataset, using a random subset of features at each split.
3. Aggregate the outputs:
   - **Classification:** Use majority voting (Equation 4.5)

$$\hat{y} = arg \max_{k} \sum_{t=1}^{T} 1(h_t(x) - k) \tag{4.5}$$

   - **Regression:** Compute the average prediction (Equation 4.6)

$$\hat{y} = \frac{1}{T} \sum_{t=1}^{T} h_t(x) \tag{4.6}$$

Where T is the number of trees, and $h_t(x)$ is the prediction of the t^{th} tree.

RF effectively reduces variance while maintaining relatively low bias, making it robust to overfitting.

4.4. GRADIENT BOOSTING

Gradient Boosting (GB) is a powerful machine learning technique for regression and classification tasks. It is particularly effective at handling complex and nonlinear datasets. GB is an ensemble learning technique that builds models sequentially, optimizing errors iteratively. Unlike RF, which builds trees independently, GB corrects the mistakes of previous trees by fitting new trees to residual errors.

4.4.1. The Fundamental Components of Gradient Boosting

In GB, the fundamental building blocks are DT. These models make predictions by splitting the data based on specific conditions. Unlike RF, which create trees independently, GB builds these trees sequentially. Each new tree aims to correct the errors made by the previous one.

The term *"gradient boosting"* is derived from the gradient descent algorithm, which is used to minimize errors. Gradient descent is an iterative method that moves toward the lowest point of a loss function—this function measures the difference between the model's predictions and the actual values—to find the best parameters for the model. The objective is to reduce the loss function, which quantifies the discrepancy between the predicted and actual values. GB effectively minimizes this loss function by continuously refining its predictions.

4.4.2. Algorithm

1. Initialize with a weak model (e.g., constant predictor) (Equation 4.7)

$$F_0(x) = arg\min_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma) \tag{4.7}$$

2. For each iteration$m = 1,2, \dots, M$:
   - Compute pseudo-residuals (Equation 4.8):

$$r_{im} = -\left[\frac{\partial L\big(y_i, F(x_i)\big)}{\partial F(x_i)}\right]_{F=F_{m-1}} \tag{4.8}$$

   - Fit a weak model $h_m(x)$ to residuals.
   - Update the model (Equation 4.9):

$$F_m(x) = F_{m-1}(x) + \eta h_m(x) \tag{4.9}$$

Where η is the learning rate.

GB works well for both classification and regression tasks but requires careful tuning of hyperparameters to avoid overfitting.

4.4.3. Gradient Boosting Trees

Gradient Boosting Trees (GBT) is a machine learning algorithm used for both regression and classification problems. GBT relies on the gradient boosting approach, which is an ensemble method consisting of a series of DT. In this method, trees are created sequentially, with each new tree designed to correct the errors made by the existing ensemble of trees. GBT apply GB specifically using DT as base learners. Instead of simple weak learners GBT uses deep DT to minimize loss function gradients.

The trees in GBT, typically DT, are generated by partitioning the input space (*features*) to minimize a specific loss function. After each tree is added to the model, the algorithm computes the loss function to assess how much the predictions of the current ensemble differ from the actual values. Subsequently, the *residuals*—representing the differences between the predicted values and the actual values—are used to build the next tree. The objective of the new tree is to predict these residuals.

The working mechanism of gradient boosted trees is illustrated in Figure 4.5.

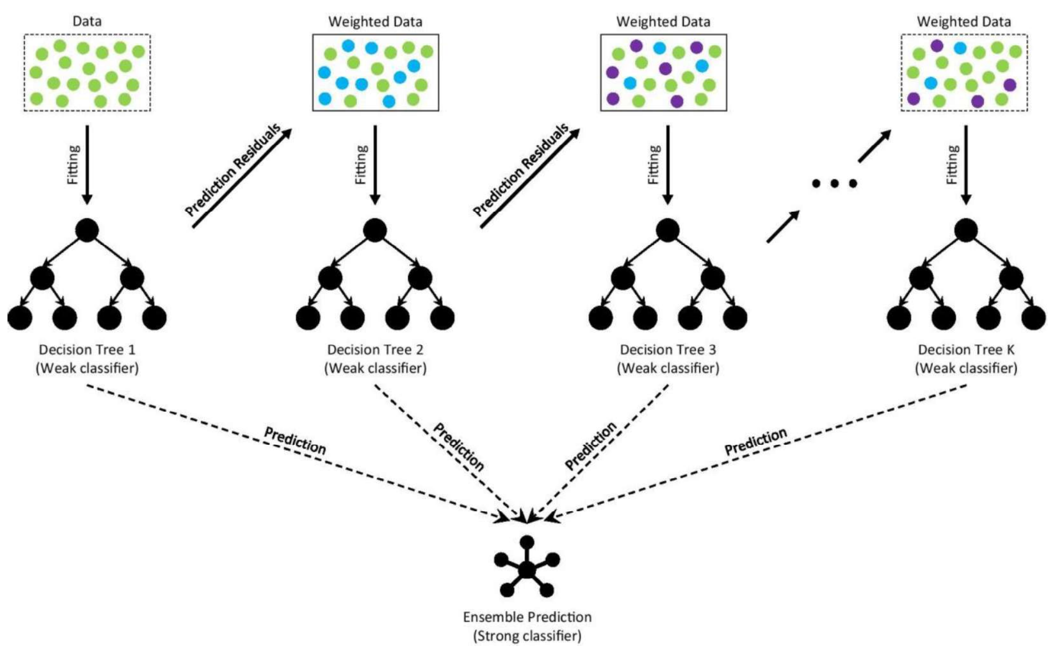


Figure 4.5. The architecture of Gradient Boosting Decision Tree (Deng et al., 2024).

Each tree in GBT is a DT that is created by dividing the data into branches based on specific thresholds for features. The choices made during these splits are aimed at minimizing the loss function for each segment of the data. In simpler terms, the algorithm chooses splits that effectively reduce the errors identified in the previous trees.

The learning rate is a crucial parameter in GBT as it determines the contribution of each new tree to the overall ensemble. A lower learning rate means that the impact of each individual tree is more cautious. Consequently, this may require adding more trees, which often leads to a more robust model.

4.4.4. Mathematical Formulation

Using the same iterative boosting framework:

1. Fit trees to residuals at each step.
2. Update the model with weighted sum of tree predictions (Equation 4.10):

$$F_m(x) = F_{m-1}(x) + \eta T_m(x) \tag{4.10}$$

Where $T_m(x)$ is the tree predictor at step *m.*

GBT models require tuning the depth of trees, learning rate, and number of boosting iterations for optimal performance.

4.4.5. Types of Gradient Boosting Algorithms

Gradient boosting algorithms are available in various types and customizations, each offering distinct advantages and applications. Among the notable gradient boosting algorithms are *eXtreme Gradient Boosting (XGBoost)*, *Light Gradient Boosting Machine (LightGBM)*, and *Categorical Boosting (CatBoost)*.

4.4.5.1. eXtreme Gradient Boosting

XGBoost is an optimized distributed gradient boosting library known for its efficiency, flexibility, and portability. It implements machine learning algorithms within the gradient boosting framework. XGBoost is an optimized implementation of GBT that improves computational efficiency and regularization. It employs second-order Taylor expansion for loss approximation and introduces L1/L2 regularization for better generalization. Some key features of XGBoost can be listed as follows:

- Speed and Performance: XGBoost is designed for speed and high performance. It utilizes a more regularized model to help prevent overfitting, which leads to improved outcomes.

- Scalability and Flexibility: XGBoost can handle billions of examples and performs effectively across various computing environments, including distributed systems.
- Customizability: The library supports custom objective functions and evaluation metrics, allowing for greater flexibility in diverse applications.

Mathematical Formulation

For a given dataset (x_i, y_i), the objective function includes both the loss function and regularization term (Equation 4.11):

$$L = \sum_{i=1}^{n} L\,(y_i, \hat{y}_i) + \sum_{k=1}^{T} \Omega\,(T_k) \tag{4.11}$$

where $\Omega(T_k)$ penalizes complexity of trees (Equation 4.12):

$$\Omega(T) = \gamma T + \frac{1}{2}\lambda \sum_{j} w_j^2 \tag{4.12}$$

XGBoost uses shrinkage, column subsampling, and spare-aware splits to improve efficiency and accuracy.

4.4.5.2. Light Gradient Boosting Machine

LightGBM is a gradient boosting framework that utilizes tree-based learning algorithms, specifically designed for efficient and distributed training on large datasets. LightGBM is a highly efficient GB framework designed to handle large datasets with lower memory usage. It introduces:

- **Histogram-based learning:** Bins feature values into histograms to speed up computation.
- **Leaf-wise tree growth:** Expands the most promising leaf first instead of level-wise expansion.

Its key advantages include:

- Efficiency with Large Datasets: LightGBM is faster than other gradient boosting implementations when working with extensive datasets.
- Lower Memory Usage: It employs innovative techniques such as *Gradient-based One-Side Sampling (GOSS)* and *Exclusive Feature Bundling (EFB)*,

which significantly reduce memory consumption.

- Handling Large-Scale Data: LightGBM performs exceptionally well with large datasets and can effectively manage numerous features.
- Distinctive Features: Its primary distinction is its ability to handle large datasets with lower memory requirements, making it an ideal choice for scenarios with limited computational resources.

Mathematical Formulation

Like XGBoost, it optimizes (Equation 4.13):

$$L = \sum_{i=1}^{n} L\,(y_i, \hat{y}_i) + \lambda \sum_{j} w_j^2 \tag{4.13}$$

But uses a more efficient GOSS and FB to reduce computational cost.

4.4.5.3. Categorical Boosting

CatBoost is an open-source gradient boosting library that is particularly effective at handling categorical data. CatBoost is a gradient boosting algorithm optimized for categorical data. Unlike other boosting methods that require explicit encoding (e.g., one-hot encoding), CatBoost efficiently handles categorical features using Ordered Target Statistics and Ordered Boosting to prevent target leakage. Some key features of XGBoost can be listed as follows:

- Handling Categorical Data: Unlike other gradient boosting algorithms, CatBoost eliminates the need for extensive preprocessing to convert categorical data into numerical format. It automatically processes categorical features by using various statistics derived from the combinations of categorical features and the target variable.
- Robustness and Accuracy: CatBoost minimizes the need for extensive hyperparameter tuning and reduces the risk of overfitting, resulting in more robust and accurate models.
- User-Friendly: The library is user-friendly and can be easily integrated with deep learning frameworks.

Mathematical Formulation

Uses ordered target encoding for categorical features (Equation 4.14):

$$E(x_i) = \frac{\sum_{j=1}^{i-1} y_j}{i - 1 + \lambda} \tag{4.14}$$

where λ is a somoothing factor to prevent overfitting.

CatBoost also impements Ordered Boosting, which prevents overfitting by using permutations of data during training.

In this study, since categorical data were utilized, gradient boosting was implemented using the CatBoost algorithm. For a comprehensive understanding of the algorithm's mathematical foundations, refer to Prokhorenkova (2016).

Note: The section on gradient boosting is based on the source by Ibrahim (2024).

CHAPTER 5 MODEL DEVELOPMENT AND COMPARISON OF MODEL PERFORMANCES

In this study, the input data for the developed models were derived from two sections of the survey: the *"Demographic Characteristics"* section (Part 1) and the *"Opinions and Preferences Regarding E-Scooters"* section (Part 2). The survey is included in Appendix A. Additionally, travel times and costs defined in the scenarios under the *"Scenarios"* section (Part 3) (see Table 3.3) were also used as inputs for the models.

Among the demographic characteristics, age was treated as a continuous variable. It was normalized to a range between 0 and 1 by dividing each participant's age by 100, represented by a single input neuron. Similarly, the number of household members and the number of cars in the household were normalized by dividing by 10, resulting in values between 0 and 1, with each represented by a single input.

Questions regarding ownership of a driving license, private car, and e-scooter were binary (yes/no) and represented as a single input value. A dummy variable was used, with 1 indicating "yes" and 0 indicating "no."

For questions that had more than two response options, such as education level, the number of inputs corresponded to the number of categories. For instance, if a participant was male, the first input for gender would take a value of 1, while the other two inputs would be 0. For female participants, the first and third inputs would be 0, and the second would be 1. If a participant chose not to disclose their gender, the first and second inputs would be 0, while the third would be 1.

Due to numerous alternatives, variables such as the participant's district of residence and occupation were not included in the models.

In the "Opinions and Preferences Regarding E-Scooters" section, six questions with binary responses (yes/no) were represented by a single input. For the remaining 17 questions, the number of inputs corresponded to the number of selectable answers for each question.

The study defined each of the eight scenarios with different traffic conditions (light, moderate, or congested) as a separate data point. Thus, for each participant, 3 traffic conditions multiplied by 8 scenarios resulted in 24 different scenarios, asking for their preferred mode of transportation (private car, taxi, e-scooter, or public transportation) under each condition. The costs and travel times for each transportation mode under the different conditions were also defined as the last eight input values and were normalized to a range between 0 and 1 by dividing the cost values by 200 and time values by 60.

As a result, each of the developed models utilized 126 inputs. The model's output represents the mode of transportation that a user would prefer under the current conditions. Since there are four options for output, a separate output was defined for each option. The output corresponding to the chosen category is assigned a value of 1, while the others are assigned a value of 0.

Therefore, the models were designed to predict four outputs based on 126 inputs. With 462 participants evaluating 24 scenarios each, a total of 11.088 data points were used. For all models, 70% of the total data was allocated for model training (training data), 15% for testing (test data), and the remaining 15% for validation (validation data).

The study employed ANN, DT, RF, and GB algorithms to predict which mode of transportation (private car, taxi, e-scooter, or public transportation) survey participants would prefer under various scenarios and conditions. During the model creation process for all methods, the same division of data was maintained: 70% for training, 15% for testing, and 15% for validation.

As shown in Table 5.1, models were developed for five different datasets, and the model with the highest performance was selected as the base model. The predictive performance of the models was evaluated solely based on the test set, while their overall accuracy in reflecting participants' preferences was assessed using all 11.088 data points.

Table 5.1. Data set combinations used in determining the network architecture

<table>
<tr><td>Partition I</td><td colspan="8">Training</td><td>Validation</td><td>Test</td></tr>
<tr><td>Partition II</td><td colspan="6">Training</td><td>Validation</td><td>Test</td><td colspan="2">Training</td></tr>
<tr><td>Partition III</td><td colspan="4">Training</td><td>Validation</td><td>Test</td><td colspan="4">Training</td></tr>
<tr><td>Partition IV</td><td colspan="2">Training</td><td>Validation</td><td>Test</td><td colspan="6">Training</td></tr>
<tr><td>Partition V</td><td>Validation</td><td>Test</td><td colspan="8">Training</td></tr>
</table>

The ANN model model consists of 126 input neurons and four output neurons. The number of hidden layers and the number of neurons in each layer were determined using a grid search method. One or two hidden layers, with each layer containing between 1 and 50 neurons were tested. The architecture of the developed ANN is illustrated in Figure 5.1.

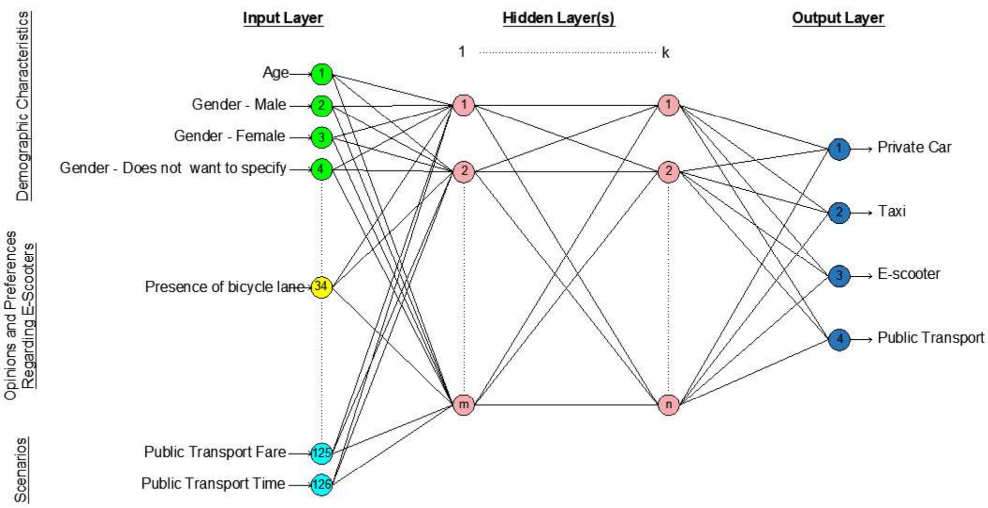


Figure 5.1. The architecture of the developed ANN.

A three-way data split method was employed to prevent overfitting and to identify the optimal network architecture. The flowchart illustrating this three-way data split method can be found in Figure 5.2. Initially, the data was randomly shuffled and divided into three sets: training (70%), testing (15%), and validation (15%). The investigation of the best network architecture was conducted based on the dataset combinations outlined in Table 5.1. The optimal architecture for each ANN model was selected based on the MSE performance metric.

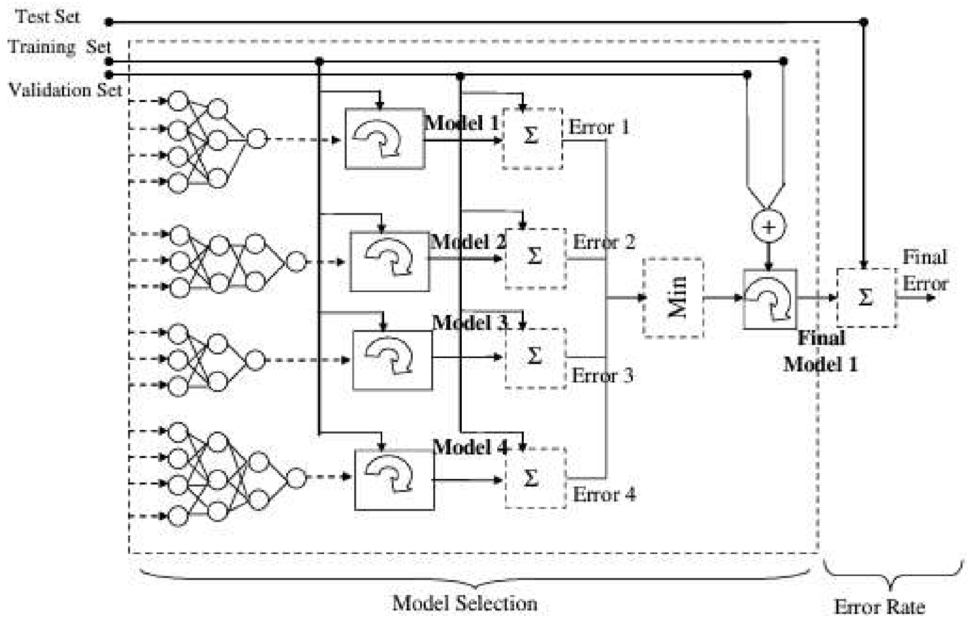


Figure 5.2. Flow chart of the three-way data split validation method (Murat, 2006).

The highest-performing architecture for the ANN model included 126 neurons in the input layer, two hidden layers with 50 neurons each, and four output neurons. Table 5.2 presents a comparison of the performance metrics for the developed models. The accuracy of these models was calculated using Equation 5.1.

$$Accuracy = \frac{Correct\ Predictions}{Total\ Number\ of\ Predictions} \tag{5.1}$$

Table 5.2. Performance values of the developed machine learning models

Model	Accuracy (%)
Artificial Neural Networks	70,42
Decision Trees	86,08
Random Forest	**96,51**
Gradient Boosting	94,92

As shown in Table 5.2, the Random Forest method achieved the highest correct prediction rate at 96.51%. While all four methods demonstrated significantly better performance than the 54% success rate reported for the discrete choice models by Dündar et al. (2024), the Random Forest model outperformed the other models utilized in this study.

CHAPTER 6 CONCLUSIONS

The study was developed under the TÜBİTAK 1001 Project titled "Elektrikli Skuterların İstanbul Trafiğine ve Çevreye Olan Etkilerinin Belirlenmesi, En Uygun Işletme Ortamı, Koşulları ve Kurallarının Saptanması." The first work package of the project focuses on creating a choice model that reveals the attitudes and preferences of e-scooter users. In this context, traditional discrete choice methods were not employed to model user preferences, with the goal of achieving at least 70% accuracy. If this target was not met, the backup plan involved using various machine learning techniques to reach the desired accuracy. This approach laid the groundwork for the developed study.

An online survey was conducted as part of the study, with responses from 512 participants, of which 462 users living in Istanbul were included in the evaluation. The survey consists of three sections, outlined in Appendix A. The first section gathers demographic information about the participants, the second section focuses on e-scooter usage, and the third section contains questions about different scenarios and the transportation mode participants would choose in those scenarios.

To develop predictive models for transportation mode choices based on demographic characteristics, e-scooter usage, and various scenario conditions, methods such as Artificial Neural Networks, Decision Trees, Random Forest, and Gradient Boosting were utilized. All developed models outperformed the 54% accuracy achieved by the discrete choice models from Dündar et al. (2024). Furthermore, all models exceeded the project's target accuracy of 70%, with the Random Forest method achieving the highest performance at 96.51%.

The Random Forest model is intended for use in traffic simulations that will be conducted in the project's second work package. It will help create synthetic populations and determine their distribution within those simulations. The model's output will predict which transportation mode different user types prefer under various conditions and be integrated into traffic simulation software. This integration will also facilitate the evaluation of the effects of different future scenarios.

With a user-friendly interface, the developed model can be made available to central and local governments, allowing decision-makers to anticipate public responses to strategic decisions regarding transportation or pricing policies. For instance, the model can predict how transportation choice distribution will shift with a price increase in public transportation. Additionally, the models can forecast the potential effects of measures aimed at increasing micromobility usage, especially e-scooters, to mitigate the negative environmental impacts of transportation. This capability positions the model as a valuable tool for decision-makers.

Moreover, the user-friendly interface will assist companies that offer shared e-scooter services in better predicting potential returns on investment. The model can also be utilized to develop policies that enhance customer satisfaction.

In future studies, collecting survey data from users in cities outside of Istanbul could help generalize the developed models. By incorporating factors such as population density, demographic structure, land conditions, and climate into the models, it may be possible to create a universal model that provides accurate predictions for any city where user preferences are to be assessed.

REFERENCES

Abouelela, M., Al Haddad, C., Antoniou, C.: (2021), *"Are young users willing to shift from carsharing to scooter–sharing?"*, Transportation Research Part D: Transport and Environment, 95(April), 102821. https://doi.org/10.1016/j.trd.2021.102821

Aguilera-García, Á., Gomez, J., Rangel, T., Baeza, M. de los Á., Vassallo, J.M.: (2024), *"Which factors influence the use of shared and privately-owned e-scooters in the city of Madrid? Implications for urban mobility"*, Cities, 147, 104785. https://doi.org/https://doi.org/10.1016/j.cities.2023.104785

Bachand-Marleau, J., Lee, B.H.Y., El-Geneidy, A.M.: (2012), *"Better Understanding of Factors Influencing Likelihood of Using Shared Bicycle Systems and Frequency of Use"*, Transportation Research Record, 2314(1), 66–71. https://doi.org/10.3141/2314-09

Ben-Akiva, M., Lerman, S.: (1985), *"Discrete choice analysis: theory and application to travel demand"*. In *MIT Press*. https://doi.org/10.1016/0191-2607(88)90064-7

Cao, Z., Zhang, X., Chua, K., Yu, H., Zhao, J.: (2021), *"E-scooter sharing to serve shortdistance transit trips: A Singapore case"*, Transportation Research Part A: Policy and Practice, 147, 177–196. https://doi.org/10.1016/J.TRA.2021.03.004

Christoforou, Z., Gioldasis, C., de Bortoli, A., Seidowsky, R.: (2021), *"Who is using escooters and how? Evidence from Paris"*, Transportation Research Part D: Transport and Environment, 92(January), 102708. https://doi.org/10.1016/j.trd.2021.102708

Deng, H., Zhou, Y., Wang, L., Zhang C.: (2021), "*Ensemble learning for the early prediction of neonatal jaundice with genetic features"*, BMC Medical Informatics and Decision Making 21:338. https://doi.org/10.1186/s12911-021-01701-9

Donges N.: (2024), "Random Forest: A Complete Guide for Machine Learning", Availible at: https://builtin.com/data-science/random-forest-algorithm, Last

Access: 21.01.2025.

Dündar, S.: (2022), *"Investigating the Service Quality of Kocaeli Tram Service Using Artificial Neural Networks"*, Teknik Dergi, 33(5), 12429-12456, https://doi.org/10.18400/tekderg.783110.

Dündar, S., Günay, G., Yardım, M.S., Yaşar, I., Akgöl, A.C.: (2024), *"Elektrikli skuterların İstanbul trafiğine ve çevreye olan etkilerinin belirlenmesi, en uygun işletme ortamı, koşulları ve kurallarının saptanması – 1. Ara Rapor",* TÜBİTAK 1001 Project, 123M063.

Dündar, S., Gökaşar, I.i Tanyel, S.: (2021), *"Sürücüsüz Karayolu Taşıtlarının Karma Trafiğe Olası Etkilerinin Araştırılması ve Kesintisiz Akım Koşulları Altında Trafik Degişkenlerini En İyileyecek Şekilde İşletilmesinin Sağlanması"*, TÜBİTAK 3501 Program, Project Final Report No. 217M283.

Esztergár-Kiss, D., Tordai, D., Lopez Lizarraga, J.C.: (2022), *"Assessment of travel behavior related to e-scooters using a stated preference experiment"*, Transportation Research Part A: Policy and Practice, 166, 389–405. https://doi.org/https://doi.org/10.1016/j.tra.2022.11.010

Esztergár-Kiss, D., Lopez Lizarraga, J.C.: (2021), *"Exploring user requirements and service features of e-micromobility in five European cities"*, Case Studies on Transport Policy, 9(4), 1531–1541. https://doi.org/https://doi.org/10.1016/j.cstp.2021.08.003

Fox, N., Hunn, A., Mathers, N.: (2007), *"Sampling and Sample Size Calculation"*. The NIHR Research Design Service for the East Midlands, MHS.

Google: (2025), "Google Maps directions for driving from Bostancı, to Selamiçeşme. Availible at: https://www.google.com.tr/maps, Last Access: 21.01.2025.

Gökaşar, I., Günay, G.: (2017), *"Mode choice behavior modeling of ground access to airports: A case study in Istanbul, Turkey"*, Journal of Air Transport Management, 59, 1-7. https://doi.org/10.1016/j.jairtraman.2016.11.003

Günay, G., Ergün, G., Gökaşar, I.: (2016), *"Conditional Freight Trip Generation Modelling"*. Journal of Transport Geography, 54, 102–111. https://doi.org/http://dx.doi.org/10.1016/j.jtrangeo.2016.05.013

Günay, G., Gökaşar, I.: (2021), *"Market segmentation analysis for airport access mode choice modeling with mixed logit",* Journal of Air Transport Management, 91, 102001. https://doi.org/10.1016/J.JAIRTRAMAN.2020.102001

Hensher, D.A., Greene, W.H.: (2003), *"The mixed logit model: The state of practice"*, transportation, 30, 133-176. https://doi.org/10.1023/A:1022558715350

Ibrahim, M.: (2024), *"An Introduction to Gradient Boosted Trees for Machine Learning"*, Availible at: https://wandb.ai/mostafaibrahim17/ml-articles/reports/An-Introduction-to-Gradient-Boosted-Trees-for-Machine-Learning--Vmlldzo2NTQ4NzYx, Last Access: 21.01.2025.

Ilahi, A., Belgiawan, P.F., Balac, M., Axhausen, K.W.: (2021), *"Understanding travel and mode choice with emerging modes; a pooled SP and RP model in Greater Jakarta, Indonesia"*, Transportation Research Part A: Policy and Practice, 150, 398–422. https://doi.org/https://doi.org/10.1016/j.tra.2021.06.023

İstanbul Büyükşehir Belediyesi (İBB): (2023a), *"İstanbul Büyükşehir Belediyesi Ücret Tarifesi"*, Availible at: https://tuhim.ibb.gov.tr/media/2571/uecret-yayını.pdf, Last Access: 21.01.2025.

İstanbul Büyükşehir Belediyesi (İBB): (2023b), *"İstanbul Büyükşehir Belediyesi Taksi Ücret Tarifesi"*, Availible at: /https://tuhim.ibb.gov.tr/media/2573/taksi-yayınlama.pdf Last Access: 21.01.2025.

İstanbul Büyükşehir Belediyesi (İBB) Ulaşım Yönetim Merkezi (UYM): (2021), "*Ukome'den Scootere Çekidüzen*", Availible at: https://uym.ibb.gov.tr/kurumsal/haberler-ve-duyurular/ukome-den-scootere-%C3%A7ekid%C3%BCzen. Last access: 21.01.2025.

James, O., Swiderski, J.I., Hicks, J., Teoman, D., Buehler, R.: (2019), *"Pedestrians and escooters: An initial look at e-scooter parking and perceptions by riders and non-riders"*. Sustainability (Switzerland), 11(20). https://doi.org/10.3390/su11205591

Kipf, T.N., Welling, M.: (2017), *"Semi-Supervised Classification With Graph Convolutional Networks",* 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26. https://doi.org/10.48550/arXiv.1609.02907

Kopplin, C.S., Brand, B.M., Reichenberger, Y.: (2021), *"Consumer acceptance of shared escooters for urban and short-distance mobility"*, Transportation Research Part D: Transport and Environment, 91(January), 102680.

https://doi.org/10.1016/j.trd.2020.102680

Kotsiantis, S.B.: (2013), *"Decision trees: a recent overview"*, Artificial Intelligence Review, 39(4), 261-283. https://doi.org/10.1007/s10462-011-9272-4

Kurama, V.:(2020). "An Introduction to Decision Trees", Availible at: https://blog.paperspace.com/decision-trees/. Last access: 21.01.2025.

Laa, B., Leth, U.: (2020), *"Survey of E-scooter users in Vienna: Who they are and how they ride"*, Journal of Transport Geography, 89(August), 102874. https://doi.org/10.1016/j.jtrangeo.2020.102874

Ledziński, L., Grześk, G.: (2023), "Artificial Intelligence Technologies in Cardiology", Journal of Cardiovascular Development and Disease, 10, 202. https://doi.org/10.3390/jcdd10050202

Lee, M., Chow, J.Y.J., Yoon, G., He, B.Y.: (2021), *"Forecasting e-scooter substitution of direct and access trips by mode and distance"*, Transportation Research Part D: Transport and Environment, 96(May), 102892. https://doi.org/10.1016/j.trd.2021.102892

Leger, S.J., Dean, J.L., Edge, S., Casello, J.M.: (2019). *"If I had a regular bicycle, I wouldn't be out riding anymore: Perspectives on the potential of e-bikes to support active living and independent mobility among older adults in Waterloo, Canada"*, Transportation Research Part A: Policy and Practice, 123, 240–254. https://doi.org/https://doi.org/10.1016/j.tra.2018.10.009

Luo, H., Zhang, Z., Gkritza, K., Cai, H.: (2021), *"Are shared electric scooters competing with buses? a case study in Indianapolis"*, Transportation Research Part D: Transport and Environment, 97(June), 102877. https://doi.org/10.1016/j.trd.2021.102877

Mcfadden, D., Train, K.: (2000), *"Mixed MNL Models for Discrete Response"*, Journal of Applied Econmetrics , 15, 447–470.

Meltzer, R.: (2023), *"What Is Random Forest?"*, Availible at: https://careerfoundry.com/en/blog/data-analytics/what-is-random-forest/ Last Access: 27.11.2024.

Meyer, J.T.: (1979), *"Fundamental Research Statistics for the Behavioural Sciences"*, Holt, Rinehart & Winston.

Mo, B., Wang, Q.Y., Moody, J., Shen, Y., Zhao, J.: (2021), *"Impacts of subjective* *evaluations and inertia from existing travel modes on adoption of autonomous mobility on-demand"*, Transportation Research Part C: Emerging Technologies, 130, 103281. https://doi.org/https://doi.org/10.1016/j.trc.2021.103281

Muradoğlu, C.: (2021), *"Elektrikli scooter paylaşım girişimi Martı'nın kullanıcı sayısı 5 milyonu geçti.",* Availible at: https://webrazzi.com/2021/01/14/elektrikli-scooter-paylasim-girisimi-marti-nin-kullanici-sayisi-5-milyonu-gecti/, Last Access: 12.12.2024.

Murat, Y.Ş.: (2006), "Comparison of fuzzy logic and artificial neural networks approaches in vehicle delay modeling", Transportation Research Part C, 14, 316–334. https://doi.org/10.1016/j.trc.2006.08.003

Nikiforiadis, A., Paschalidis, E., Stamatiadis, N., Raptopoulou, A., Kostareli, A., Basbas, S.: (2021), *"Analysis of attitudes and engagement of shared e-scooter users"*, Transportation Research Part D: Transport and Environment, 94(March), 102790. https://doi.org/10.1016/j.trd.2021.102790

NTV: (2023), *"İSPARK Ücretleri Ne Kadar Oldu?"*, Availible at: https://www.ntv.com.tr/turkiye/ispark-ucretleri-ne-kadar-oldu-iste-ekim-2023-guncel-ispark-tarifesi,aukiggueC0aes4uOzs8WNg, Last access: 21.01.2025.

OPET: (2023), *"OPET Benzin Fiyatları Arşivi"*, Availible at: https://www.opet.com.tr/akaryakit-fiyatlari-arsivi, Last access: 21.01.2025.

Pishue, B.: (2025), "*INRIX Global Traffic Scorecard Reveals Return to Office Drives Congestion and Trips to Downtown*", Availible at: https://inrix.com/blog/inrix-global-traffic-scorecard-reveals-return-to-office-drives-congestion-and-trips-to-downtown/. Last access: 21.01.2025.

Polat, A., Adalıoğlu, İ., Ceyhan Erdoğan, M., Bozatlı, S., Sarısoy, G.: (2023),. *"Paylaşımlı Elektrikli Skuter Kullanımının Araştırılması: İstanbul İli Örneği"*, Gazi Journal of Engineering Sciences, 9(2), 360-379. https://doi.org/10.30855/gmbd.0705077

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A.V., Gulin, A.: (2018), *"CatBoost: unbiased boosting with categorical features"*, 32nd Conference on Neural Information Processing Systems (NeurIPS 2018), Montréal, Canada. Availible at: https://proceedings.neurips.cc/paper/2018/file/14491b756b3a51daac41c2486328

5549-Paper.pdf, Last access: 21.01.2025.

Psarrou Kalakoni, A.M., Christoforou, Z., Gioldasis, C.: (2024). *"The ambivalent relationship of e-scooters and public transport: Evidence from France"*, Transport Policy, 159, 215–229. https://doi.org/10.1016/J.TRANPOL.2024.10.023

Reck, D.J., Haitao, H., Guidon, S., Axhausen, K.W.: (2021), *"Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland"*, Transportation Research Part C: Emerging Technologies, 124, 102947. https://doi.org/https://doi.org/10.1016/j.trc.2020.102947

Roig-Costa, O., Miralles-Guasch, C., Marquet, O.: (2024). "Shared bikes vs. private escooters. Understanding patterns of use and demand in a policy-constrained micromobility environment", Transport Policy, 146, 116–125. https://doi.org/10.1016/J.TRANPOL.2023.11.010

Şengül, B., Mostofi, H.: (2021),. *"Impacts of e-micromobility on the sustainability of urban transportation—a systematic review*". Applied Sciences, 11(13). https://doi.org/10.3390/app11135851

T.C. Resmi Gazete: (2021), "*Elektrikli Skuter Yönetmeliği*". 14.04.2021. Sayı: 31454, T.C. Cumhurbaşkanlığı İdari İşler Başkanlığı Hukuk ve Mevzuat Genel Müdürlüğü, Ankara.

Torun, H.: (2022). *"Karar Ağacı (Decision Tree)"*, Availible at: https://hakan.io/karar-agaci-decision-tree/. Last access: 27.11.2024.

Türkiye İstatistik Kurumu (TÜİK): (2024), "*Adrese Dayalı Nüfus Kayıt Sistemi Sonuçları, 2023*", Availible at: https://data.tuik.gov.tr/Bulten/Index?p=Adrese-Dayali-Nufus-Kayit-Sistemi-Sonuclari-2023-49684. Last access: 21.01.2025.

Varol Malkoçoğlu, A.B., Orman, Z., Şamlı, R.: (2022), *"Comparison of Different Heuristics Integrated with Neural Networks: A Case Study for Earthquake Damage Estimation"*, ACTA INFOLOGICA 2022;6(2):265-281. https://doi.org/1 10.26650/acin.1146097

Yang, H., Kitamura, R., Jovanis, P.P., Vaughn, K.M., Abdel-Aty, M.A.: (1993), *"Exploration of route choice behavior with advanced traveler information using neural network concepts"*, transportation, 20(2), 199–223.

https://doi.org/10.1007/BF01307059

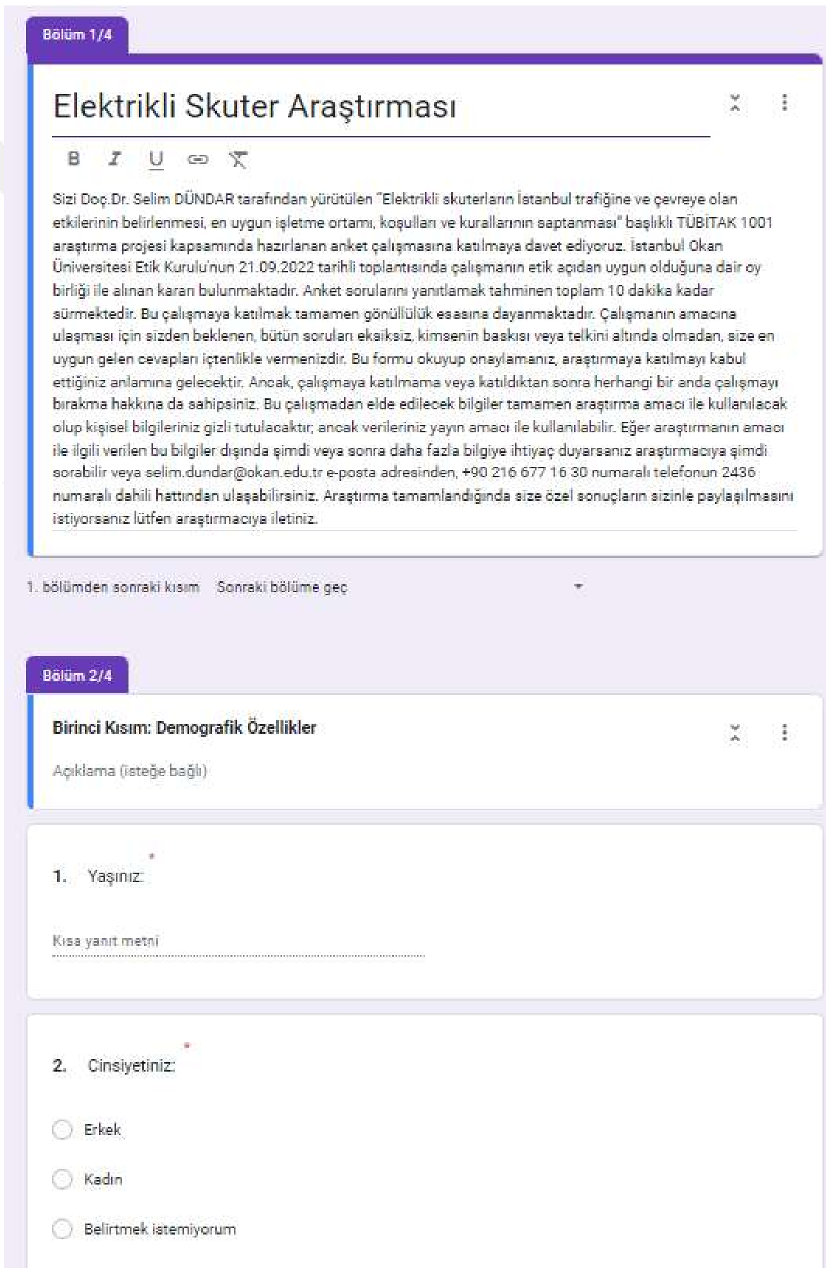
Yazdani, H., Doostizadeh, M., Aminifar, F.: (2023), "Forecast-aided power and flexibility trading of prosumers in peer to peer markets", IET Renewable Power Generation, 17(4), 920-934. https://doi.org/10.1049/rpg2.12645

Zuniga-Garcia, N., Ruiz Juri, N., Perrine, K.A., Machemehl, R.B.: (2021), *"E-scooters in urban infrastructure: Understanding sidewalk, bike lane, and roadway usage from trajectory data"*, Case Studies on Transport Policy, 9(3), 983–994. https://doi.org/10.1016/j.cstp.2021.04.004

Zuniga-Garcia, N., Tec, M., Scott, J.G., Machemehl, R.B.: (2022), *"Evaluation of e-scooters as transit last-mile solution"*, Transportation Research Part C: Emerging Technologies, 139, 103660. https://doi.org/10.1016/J.TRC.2022.103660

APPENDICES

APPENDIX A QUESTIONNAIRES



Bölüm 1/4

Elektrikli Skuter Araştırması

Sizi Doç.Dr. Selim DÜNDAR tarafından yürütülen "Elektrikli skuterların İstanbul trafiğine ve çevreye olan etkilerinin belirlenmesi, en uygun işletme ortamı, koşulları ve kurallarının saptanması" başlıklı TÜBİTAK 1001 araştırma projesi kapsamında hazırlanan anket çalışmasına katılmaya davet ediyoruz. İstanbul Okan Üniversitesi Etik Kurulu'nun 21.09.2022 tarihli toplantısında çalışmanın etik açıdan uygun olduğuna dair oy birliği ile alınan kararı bulunmaktadır. Anket sorularını yanıtlamak tahminen toplam 10 dakika kadar sürmektedir. Bu çalışmaya katılmak tamamen gönüllülük esasına dayanmaktadır. Çalışmanın amacına ulaşması için sizden beklenen, bütün soruları eksiksiz, kimsenin baskısı veya telkini altında olmadan, size en uygun gelen cevapları içtenlikle vermenizdir. Bu formu okuyup onaylamanız, araştırmaya katılmayı kabul ettiğiniz anlamına gelecektir. Ancak, çalışmaya katılmama veya katıldıktan sonra herhangi bir anda çalışmayı bırakma hakkına da sahipsiniz. Bu çalışmadan elde edilecek bilgiler tamamen araştırma amacı ile kullanılacak olup kişisel bilgileriniz gizli tutulacaktır; ancak verileriniz yayın amacı ile kullanılabilir. Eğer araştırmanın amacı ile ilgili verilen bu bilgiler dışında şimdi veya sonra daha fazla bilgiye ihtiyaç duyarsanız araştırmacıya şimdi sorabilir veya selim.dundar@okan.edu.tr e-posta adresinden, +90 216 677 16 30 numaralı telefonun 2436 numaralı dahili hattından ulaşabilirsiniz. Araştırma tamamlandığında size özel sonuçların sizinle paylaşılmasını istiyorsanız lütfen araştırmacıya iletiniz.

1. bölümden sonraki kısım Sonraki bölüme geç

Bölüm 2/4

Birinci Kısım: Demografik Özellikler

Açıklama (isteğe bağlı)

1. Yaşınız: *

Kısa yanıt metni

2. Cinsiyetiniz: *

- Erkek
- Kadın
- Belirtmek istemiyorum

3. Eğitim Düzeyiniz: *

- İlkokul
- Ortaokul
- Lise
- Üniversite
- Lisansüstü

4. Sürücü belgeniz var mı? *

- Evet
- Hayır

5. Kendinize ait özel otomobiliniz var mı? *

- Evet
- Hayır

6. Hangi ilçede ikamet ediyorsunuz? *

Kısa yanıt metni

7. Yaşadığınız hanede siz dahil kaç kişi var? *

Kısa yanıt metni

8. Yaşadığınız hanede kaç tane otomobil bulunuyor? *

Kısa yanıt metni

9. Çalışma Durumunuz: *

- Kendi işim
- Öğrenciyim
- Özel şirket
- Kamu
- Çalışmıyorum

10. Mesleğiniz: *

Kısa yanıt metni

11. Aylık kişisel gelir düzeyiniz nedir? *

- 0
- 1-Asgari ücret
- Asgari ücret-20000 TL
- 20001-30000 TL
- 30001-40000 TL
- 40001-50000 TL
- 50000 TL'den fazla

12. Yaşadığınız hanenin toplam aylık gelir düzeyi nedir? *

- 0-Asgari ücret
- Asgari ücret-20000 TL
- 20001-30000 TL
- 30001-40000 TL
- 40001-50000 TL
- 50000 TL'den fazLa

13. Kendinize ait bir e-skuteriniz var mı? *

- Evet
- Hayır

2. bölümden sonraki kısım Sonraki bölüme geç

Bölüm 3/4

İkinci Kısım: E-Skuter Hakkındaki Düşünceler ve Tercihler

Açıklama (isteğe bağlı)

1. Oturduğunuz yere 250 m mesafede bisiklet yolu var mı? *

- Evet
- Hayır

2. Günlük yolculuklarda en fazla hangi ulaşım türünü tercih edersiniz? *

- Toplu taşıma
- Özel araç
- Taksi
- Bisiklet
- E-skuter
- Yürüme

3. En fazla hangi amaçla yolculuk yaparsınız? *

- İş
- Okul
- Sağlık
- Alışveriş
- Eğlence
- Diğer

4. E-skuter araçlarını en fazla hangi altyapı türünde kullanmayı tercih edersiniz? *

- Yol
- Kaldırım
- Bisiklet yolu

5. E-skuter araçlarını kaldırımda kullanır mısınız? *

- Evet
- Hayır

6. E-skuter ile yaptığınız yolculuklarda, e-skuter kullanma imkanınız olmazsa, hangi ulaşım türünü kullanırsınız? *

- Toplu taşıma
- Özel araç
- Taksi
- Bisiklet
- Yürüme

7. E-skuter araçlarını hangi trafik sıkışıklık seviyelerinde tercih edersiniz? *

- Açık
- Akıcı
- Yoğun

8. E-skuter araçlarını en fazla kaç dakikalık yolculuklarda tercih edersiniz? *

- 0-5 dk
- 6-10 dk
- 10 dk veya daha fazla

9. E-skuter araçlarını ne kadar güvenli buluyorsunuz? *

- Çok güvenli
- Güvenli
- Orta
- Az güvenli
- Hiç güvenli değil

10. Belli kurallar dahilinde kaldırımda e-skuter kullanımına izin verilmesi konusundaki düşünceniz nedir? *

- Kaldırımda e-skuter kullanılması uygundur
- Kararsızım
- Kaldırımda e-skuter kullanılması yasaklanmalı

11. E-skuter araçlarını trafiğin tek yönlü aktığı yollarda kullanır mısınız? *

- Evet
- Hayır

12. E-skuter araçlarını trafiğin her iki yönde de aktığı yollarda kullanır mısınız? *

- Evet
- Hayır

13. E-skuter araçlarını en fazla nereye park ediyorsunuz? *

- Kaldırıma
- En sağ şerit kenarına
- Bisiklet ve e-skuter park yerlerine
- Kendi aracımı evimde/ofisimde uygun bir yere

14. E-skuter araçlarını, bisiklet ve e-skuter araçları için inşa edilen özel park yerlerine park ediyor musunuz? *

- Evet
- Hayır

15. Eğer üstteki soruya hayır cevabını verdiyseniz, indirimli ücretler, ücretsiz kullanım süresi gibi avantajlar uygulansa bu park yerlerini tercih eder misiniz?

- Üstteki soruya evet cevabını verdim
- Evet
- Hayır

16. E-skuter kullanırken trafik kurallarına ne düzeyde uyarsınız? *

- Hep uyarım
- Genellikle uyarım
- Bazen uyarım
- Nadiren uyarım
- Hiç uymam

17. E-skuter tercih ettiğiniz yolculuklarınızda bu kararı etkileyen en önemli faktör hangisidir? *

- ◯ Ücret
- ◯ Güvenlik
- ◯ Hız
- ◯ Süre
- ◯ Trafik tıkanıklıkları
- ◯ Erişilebilirlik

18. E-skuter tercih etmediğiniz yolculuklarınızda bu kararı etkileyen en önemli faktör hangisidir? *

- ◯ Ücret
- ◯ Güvenlik
- ◯ Hız
- ◯ Süre
- ◯ Trafik tıkanıklıkları
- ◯ Erişilebilirlik

19. 10 dakikalık e-skuter kullanımı için kaç TL ödemeyi uygun bulursunuz? (Birden fazla seçim yapabilirsiniz) *

- ☐ 0-25 TL
- ☐ 26-50 TL
- ☐ 51-75 TL
- ☐ 76-100 TL
- ☐ 101-125 TL

20. Haftada kaç e-skuter yolculuğu yapıyorsunuz? *

- Hiç kullanmam
- Haftada 1-5 yolculuk
- Haftada 6-10 yolculuk
- Haftada 11-15 yolculuk
- 15 yolculuktan fazla

21. Tek bir e-scooter yolculuğunuzda ortalama kaç dakika yol gidiyorsunuz? (dk/yolculuk) *

- 5 dk'dan az
- 5-10 dk
- 10-15 dk
- 15-20 dk
- 20 dk'dan fazla

22. E-scooter ile günde ortalama kaç kilometre yolculuk yapıyorsunuz? (km/gün) *

- 1 km'den az
- 1-2 km
- 2-4 km
- 4-8 km
- 8-12 km

23. Aşağıdaki hangi hava koşullarında e-skuter kullanırsınız? (Birden fazla seçim yapabilirsiniz) *

- [ ] Güneşli
- [ ] Yağmurlu
- [ ] Bulutlu
- [ ] Rüzgarlı

3. bölümden sonraki kısım Sonraki bölüme geç

3. Kısım: Senaryolar

Açıklama (isteğe bağlı)

Aşağıda 4 km mesafelik bir yolculuk için 4 ulaşım türüne ait maliyet ve süre bilgileri verilmiştir. Toplam 8 farklı senaryo olup her senaryoda ulaşım türleri için farklı ücret kombinasyonları verilmiştir. Her senaryo içerisinde de trafiğin açık, akıcı ve yoğun olma durumları için alt senaryolar vardır. Verilen 8 farklı senaryoyu göz önünde bulundurarak, her senaryo içerisinde açık, akıcı ve yoğun trafik durumları için ayrı ayrı hangi ulaşım türünü seçeceğinizi belirtiniz.

Açıklama (isteğe bağlı)

1. Senaryo

Açıklama (isteğe bağlı)

Trafik Açıkken *

- Özel Araç - 105 TL / 9 dk
- Taksi - 125 TL / 9 dk
- E-skuter - 125 TL / 16 dk
- Toplu Taşıma - 25 TL / 15 dk

Trafik Akıcıyken *

- Özel Araç - 105 TL / 20 dk
- Taksi - 125 TL / 20 dk
- E-skuter - 125 TL / 16 dk
- Toplu Taşıma - 25 TL / 29dk

Trafik Yoğunken *

- Özel Araç - 105 TL / 30 dk
- Taksi - 125 TL / 30 dk
- E-skuter - 125 TL / 16 dk
- Toplu Taşıma - 25 TL / 45 dk

2. Senaryo

Açıklama (isteğe bağlı)

Trafik Açıkken *

- ◯ Özel Araç - 105 TL / 9 dk
- ◯ Taksi - 125 TL / 9 dk
- ◯ E-skuter - 75 TL / 16 dk
- ◯ Toplu Taşıma - 15 TL / 15 dk

Trafik Akıcıyken *

- ◯ Özel Araç - 105 TL / 20 dk
- ◯ Taksi - 125 TL / 20 dk
- ◯ E-skuter - 75 TL / 16 dk
- ◯ Toplu Taşıma - 15 TL / 29 dk

Trafik Yoğunken *

- ◯ Özel Araç - 105 TL / 30 dk
- ◯ Taksi - 125 TL / 30 dk
- ◯ E-skuter - 75 TL / 16 dk
- ◯ Toplu Taşıma - 15 TL / 45 dk

3. Senaryo

Açıklama (isteğe bağlı)

Trafik Açıkken *

- Özel Araç - 105 TL / 9 dk
- Taksi - 75 TL / 9 dk
- E-skuter - 125 TL / 16 dk
- Toplu Taşıma - 15 TL / 15 dk

Trafik Akıcıyken *

- Özel Araç - 105 TL / 20 dk
- Taksi - 75 TL / 20 dk
- E-skuter - 125 TL / 16 dk
- Toplu Taşıma - 15 TL / 29 dk

Trafik Yoğunken *

- Özel Araç - 105 TL / 30 dk
- Taksi - 75 TL / 30 dk
- E-skuter - 125 TL / 16 dk
- Toplu Taşıma - 15 TL / 45 dk

4. Senaryo

Açıklama (isteğe bağlı)

Trafik Açıkken *

- Özel Araç - 105 TL / 9 dk
- Taksi - 75 TL / 9 dk
- E-skuter - 75 TL / 16 dk
- Toplu Taşıma - 25 TL / 15 dk

Trafik Akıcıyken *

- Özel Araç - 105 TL / 20 dk
- Taksi - 75 TL / 20 dk
- E-skuter - 75 TL / 16 dk
- Toplu Taşıma - 25 TL / 29 dk

Trafik Yoğunken *

- Özel Araç - 105 TL / 30 dk
- Taksi - 75 TL / 30 dk
- E-skuter - 75 TL / 16 dk
- Toplu Taşıma - 25 TL / 45 dk

5. Senaryo

Açıklama (isteğe bağlı)

Trafik Açıkken *

- Özel Araç - 65 TL / 9 dk
- Taksi - 125 TL / 9 dk
- E-skuter - 125 TL / 16 dk
- Toplu Taşıma - 15 TL / 15 dk

Trafik Akıcıyken *

- Özel Araç - 65 TL / 20 dk
- Taksi - 125 TL / 20 dk
- E-skuter - 125 TL / 16 dk
- Toplu Taşıma - 15 TL / 29 dk

Trafik Yoğunken *

- Özel Araç - 65 TL / 30 dk
- Taksi - 125 TL / 30 dk
- E-skuter - 125 TL / 16 dk
- Toplu Taşıma - 15 TL / 45 dk

6. Senaryo

Açıklama (isteğe bağlı)

Trafik Açıkken *

- Özel Araç - 65 TL / 9 dk
- Taksi - 125 TL / 9 dk
- E-skuter - 75 TL / 16 dk
- Toplu Taşıma - 25 TL / 15 dk

Trafik Akıcıyken *

- Özel Araç - 65 TL / 20 dk
- Taksi - 125 TL / 20 dk
- E-skuter - 75 TL / 16 dk
- Toplu Taşıma - 25 TL / 29 dk

Trafik Yoğunken *

- Özel Araç - 65 TL / 30 dk
- Taksi - 125 TL / 30 dk
- E-skuter - 75 TL / 16 dk
- Toplu Taşıma - 25 TL / 45 dk

7. Senaryo

Açıklama (isteğe bağlı)

Trafik Açıkken *

- ◯ Özel Araç - 65 TL / 9 dk
- ◯ Taksi - 75 TL / 9 dk
- ◯ E-skuter - 125 TL / 16 dk
- ◯ Toplu Taşıma - 25 TL / 15 dk

Trafik Akıcıyken *

- ◯ Özel Araç - 65 TL / 20 dk
- ◯ Taksi - 75 TL / 20 dk
- ◯ E-skuter - 125 TL / 16 dk
- ◯ Toplu Taşıma - 25 TL / 29 dk

Trafik Yoğunken *

- ◯ Özel Araç - 65 TL / 30 dk
- ◯ Taksi - 75 TL / 30 dk
- ◯ E-skuter - 125 TL / 16 dk
- ◯ Toplu Taşıma - 25 TL / 45 dk

8. Senaryo

Açıklama (isteğe bağlı)

Trafik Açıkken *

- Özel Araç - 65 TL / 9 dk
- Taksi - 75 TL / 9 dk
- E-skuter - 75 TL / 16 dk
- Toplu Taşıma - 15 TL / 15 dk

Trafik Akıcıyken *

- Özel Araç - 65 TL / 20 dk
- Taksi - 75 TL / 20 dk
- E-skuter - 75 TL / 16 dk
- Toplu Taşıma - 15 TL / 29 dk

Trafik Yoğunken *

- Özel Araç - 65 TL / 30 dk
- Taksi - 75 TL / 30 dk
- E-skuter - 75 TL / 16 dk
- Toplu Taşıma - 15 TL / 45 dk