

Article

From Private Cars to Micromobility: Network Modeling and Environmental Assessment of Short-Distance Trips in Izmir

Emre Ogutveren ^{1,*}  and Soner Haldenbilen ²¹ Department of Transportation Services, Balikesir University, Balikesir 10440, Turkey² Department of Civil Engineering, Faculty of Engineering, Pamukkale University, Denizli 20160, Turkey; shaldenbilen@pau.edu.tr

* Correspondence: emre.ogutveren@balikesir.edu.tr

Abstract

Urban transportation systems face increasing sustainability challenges due to the dominance of private-car use, particularly for short-distance trips. This study investigates the potential of micromobility to replace private-car travel on short-distance journeys and evaluates the resulting impacts on urban transportation networks and environmental sustainability. The analysis focuses on the Bornova district of Izmir and is based on a face-to-face survey conducted with 502 private-vehicle users. Survey data were analyzed using descriptive statistics, chi-square tests and a binary logit regression model to identify factors influencing the willingness to adopt micromobility. Within the surveyed sample of private-car users, modal-shift rates were estimated as 35% for trips up to 5 km and 33% for trips between 5 and 10 km. These rates were applied to the private-car demand and distance matrices developed for the year 2030 within the scope of the Izmir Transportation Master Plan, resulting in a revised private-car demand matrix and a separate demand matrix representing potential micromobility users. Network assignments were performed in the PTV VISUM modeling environment. Assignment results demonstrate notable network-level changes following micromobility integration. The total length of road segments with micromobility traffic volumes exceeding a threshold of 10 veh/h was calculated at 292.5 km. Environmental impacts were evaluated using a life-cycle assessment (LCA) framework, revealing an approximate 5.5% reduction in total life-cycle CO₂ emissions. Overall, the findings provide quantitative evidence supporting micromobility as an effective component of sustainable urban transport strategies and offer guidance for local governments in infrastructure planning and policy development.

Keywords: micromobility; modal shift; network modeling; sustainable urban transport; life-cycle assessment; infrastructure planning; PTV VISUM



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1. Introduction

The rapid growth of private-car ownership poses significant challenges to urban livability and sustainability. The most important of these problems are the factors that reduce the quality of urban life such as increased traffic delays, environmental pollution and the decrease in green and public living spaces. A substantial share of private-vehicle trips consists of short-distance travel. In the United States, European Union countries and many metropolitan cities in China, the proportion of short-distance journeys varies between 50% and 65% [1–4]. High rates of private-vehicle use for short distances have serious consequences in terms of both traffic density and environmental impacts. Therefore, in

line with environmental sustainability, which is one of the basic components of sustainable transportation goals, micromobility solutions (electric scooters, electric bicycles, etc.) that can provide an alternative to individual motor vehicles for short-distance journeys are becoming increasingly important. According to the Institute for Transport and Development Policies (ITDP), the concept of micromobility is defined as “small lightweight devices operating at speeds typically below 25 km/h and ideal for the trips up to 10 km” [5]. Similarly, the International Transport Forum (ITF) categorizes micromobility vehicles into four types based on speed and weight thresholds, with types A and B limited to 25 km/h and types C and D ranging between 25 and 45 km/h [6]. In practical terms, micromobility includes a range of shared and privately operated modes such as shared bicycles, shared electric bicycles (e-bikes), electric scooters and other small electric vehicles. These modes differ in operational characteristics, infrastructure dependency, travel range and user demographics. Shared bicycle and e-bike systems have demonstrated considerable potential for modal substitution and first-last-mile integration in many urban contexts, while dockless e-scooter systems have gained rapid popularity due to their operational flexibility and ease of use. Despite these differences, micromobility modes collectively attract attention due to their relatively low carbon emissions, flexible usage patterns and lower costs compared to private motor vehicles. Particularly in large cities, micromobility systems often operate in integration with public transportation networks, contributing to multimodal connectivity and improved urban mobility efficiency.

Although the effects of micromobility vehicles on the urban traffic network have been increasingly investigated in the literature in recent years, studies in this area are still limited [7–18]. One of the first steps to understand the effects of new modes of transportation on urban life and the transportation system is to determine the demographic and socioeconomic characteristics of the individuals using these vehicles. In this context, the profiles of micromobility users have been examined in studies conducted in different cities [19–23]. The findings of these studies reveal that micromobility users are largely male, middle-aged, have a higher education level, are in full-time employment and have above-average income [24–27]. When the purposes of use were examined, most of the micromobility vehicles were used for commuting to work and school or for fun/recreation purposes [28–30]. The increasing adoption of micromobility is also associated with shifts in travel behavior, particularly through the substitution of private-car trips over short distances [31,32]. Evidence from the United States suggests that approximately 45% of micromobility users would have traveled by private vehicles if micromobility options had not been available [33]. However, accurately identifying such modal shifts requires a clear understanding of travel distances and durations, as these factors play a decisive role in determining under which conditions private-vehicle users are willing to switch to micromobility.

In the literature, many studies reveal the potential effects of micromobility vehicles with qualitative data, but the use of macro-level simulation programs to determine the distance- and time-based effects of these vehicles on transportation networks due to modal shifts is quite limited. Addressing this gap, the present study utilizes the PTV VISUM 23 transportation modeling software to analyze modal shifts and to identify resulting infrastructure requirements at the network level.

The main contribution of this study is the development of an integrated analytical framework that converts modal-shift behavior into micromobility demand, corridor-level infrastructure needs and associated environmental outcomes. Moving beyond conventional survey-based assessments, the study translates empirically derived modal-shift rates from private vehicles into dedicated micromobility demand matrices and embeds them within a macroscopic transportation network model. Through PTV VISUM-based assignment,

spatially concentrated micromobility corridors are identified, enabling a direct evaluation of infrastructure prioritization needs. In parallel, a life-cycle assessment grounded in total travel distances is employed to quantify the environmental implications of these modal shifts in terms of CO₂ emissions. By jointly assessing behavioral responses, network-level impacts and environmental performance, the study offers a novel approach for integrating micromobility into sustainable urban transport planning.

The rest of this paper is structured as follows: Section 2 reviews the existing literature and defines research gaps. Section 3 details the methodology and data, while Section 4 describes the field of study. Section 5 provides an analysis of the data, and finally, Section 6 summarizes key conclusions and suggests directions for future research.

2. Literature Review

Micromobility is a relatively new concept. However, studies in this field have increased rapidly in recent years. The existing literature can be broadly classified according to micromobility types, primarily focusing on (i) e-scooters, (ii) e-bikes and electric-bike-sharing systems and (iii) environmental and system-level assessments.

2.1. E-Scooters

2.1.1. User Characteristics and Usage Patterns

One of the most comprehensive statistical studies on the characteristics of e-scooter users in Europe was conducted in France [24]. Based on an online survey of 4382 users from different cities, the study found that 66% of users were male, 28% were aged between 25 and 34 and the majority were employed, well-educated and wealthier than the national average. In terms of usage frequency, 38% of respondents reported using e-scooters at least once a week. Key motivations for use included enjoyment, time savings and the ability to travel door-to-door.

Similar patterns have been observed in other European cities. In Brussels, a survey conducted with 1181 participants revealed that 66% of users were male and 44% were aged between 25 and 34, while most were employed (76%) and highly educated [34]. Nearly half of private e-scooter owners (47%) were regular users, compared to 23% among shared e-scooter users. Frequent users primarily employed e-scooters for commuting (30%), leisure (22%) and access to public transport stops (22%), citing time savings, intermodal accessibility and enjoyment as the main reasons for use. Comparable findings were reported in Oslo, where 70% of users were male, 69% were under the age of 40 and 76% were employed [35]. Studies conducted in Vienna also indicate that young men are significantly more likely to use e-scooters [20]. In a survey of 430 respondents across Spanish cities, Aguilera-García et al. [36] identified age, education level and travel-related variables as the primary factors influencing e-scooter usage frequency.

Across these studies, safety consistently emerges as the most critical concern among e-scooter users. In the French study, perceived lack of safety, high rental costs and adverse weather conditions were identified as the main disadvantages of e-scooter use [24]. Similarly, users in Brussels reported that feelings of insecurity (28%), high prices (23%), unfavorable weather conditions (11%) and difficulties in carrying loads (11%) negatively affected their use of e-scooters [34]. Inadequate infrastructure, exposure to motor vehicle traffic and unpredictable behavior of other road users were also highlighted as major challenges.

Infrastructure-related barriers have been further emphasized in city-specific studies. Research conducted by Markvica et al. [37] in Vienna showed that 65% of users considered the lack of dedicated lanes to be the primary obstacle, followed by heavy traffic on

main roads. Narrow sidewalks and high pedestrian densities were also found to increase perceived risk.

2.1.2. Built Environment and Network-Level Effects

Spatial analyses have demonstrated that the built environment plays a crucial role in shaping e-scooter use. Caspi et al. [38] found in a spatial analysis conducted in Austin, Texas, that the most important physical environmental factors affecting e-scooter use are the presence of bike lanes, proximity to bus stops and high-employment areas. Bai and Jiao [39] stated that proximity to the city center, access to public transport and land-use diversity are positively associated with e-scooter use. On the other hand, in a multi-city analysis conducted by Huo et al. [7], proximity to the city center was negatively associated with trip frequency.

Network-level studies further highlight the interaction between micromobility and existing transport systems. Smith and Schwieterman [40] observed that e-scooter trip volumes were lower in areas with limited public transport infrastructure in Chicago. Huo et al. [7] similarly reported positive correlations between e-scooter usage and population density, employment density and bus stop density, emphasizing the role of urban form and transit accessibility in shaping micromobility demand.

2.1.3. Modal Substitution Effects

The integration of e-scooters into urban transport systems has also led to observable modal shifts. Several studies indicate differences between privately owned and shared e-scooter users. In Vienna, both groups primarily substituted walking and public transport trips, although private e-scooter owners exhibited a notable shift away from private-car use [20]. In France, modal shifts were found to occur mainly from walking (44%) and public transport (30%), followed by private or shared bicycles (12%) [24]. In Brussels, 70% of users stated that they would have used public transport if e-scooters were unavailable, while 44% would have walked and 26% would have traveled by private car [34]. Comparable results were reported in Oslo, where 60% of users would have walked, 23% would have used public transport and 8% would have relied on private cars or taxis in the absence of e-scooters [35]. Overall, these findings suggest that e-scooters mainly substitute active and public transport modes, while also contributing to a measurable reduction in private-car use, particularly for short-distance trips.

2.2. E-Bikes and Electric-Bike-Sharing Systems

Differences between micromobility modes are also evident in terms of travel distance and duration. According to the findings of various studies, the average distance traveled by e-scooter is shorter compared to that of e-bike trips. Jiao and Bai [41] studied e-scooter trips over a 10-month period in Austin, Texas. In the study, 6000 scooters were active each month and an average of 117,000 miles were traveled. The mean travel distance of e-scooter trips was calculated as 0.77 miles and the mean travel duration was calculated as 7.55 min. It was observed that regions with high population density and educational level had a positive relationship with e-scooter use. In the literature, it has been found that the average e-scooter trip distance is mostly between 0.72 and 2.4 km and the average duration is between 7 and 12 min [8,10,13,28]. In contrast, the average distance of e-bike trips ranged from 1.6 km to 11.4 km, while average durations ranged from 15 min to 32.2 min [8,42–44].

Evidence from e-cycling research also supports that e-bike users tend to travel longer distances than conventional cyclists. A scoping review synthesizing findings across multiple contexts reported longer trip distances and durations for e-bikes relative to conventional bicycles, indicating that electric assistance can expand the feasible range of cycling and strengthen its substitution potential for motorized trips [45].

Beyond privately owned e-bikes, shared bicycle and electric-bike-sharing systems have been widely examined as key components of micromobility ecosystems. Station-level and area-based studies consistently show that bike-sharing demand is shaped by the surrounding built environment, including population and job density, proximity to public transport stops, cycling infrastructure availability and local activity patterns [46]. In medium-sized, car-oriented urban contexts, recent evidence similarly highlights that local urban form and accessibility conditions play a decisive role in explaining bike-sharing usage patterns [47].

The literature also points to differences in mode substitution between conventional bike-sharing and electric-bike-sharing. For shared e-bike systems, empirical evidence indicates strong interaction with public transport and first/last-mile usage patterns. A before–after evaluation using matched surveys reported that shared e-bike trips primarily substituted public transport and acted as a first/last-mile connectors rather than directly replacing car trips [48]. However, evidence from dockless e-bike-share also suggests that car substitution can be substantial in certain operational settings; for example, a study estimating vehicle-miles traveled (VMT) reductions reported meaningful weekday car substitution and associated VMT reductions attributable to dockless e-bike-share use [49].

Recent work further emphasizes that electric-bike-sharing demand determinants are not spatially homogeneous and may vary across spatial scales and travel-distance segments. Using operational order data in a small/medium-sized city and applying a multi-scale geographically weighted approach, one study shows that the effects of built environment and accessibility variables differ across spatial scales and across short- vs. longer-distance riding groups, implying that single-scale models may mask localized mechanisms and that infrastructure and deployment strategies should be tailored to heterogeneous demand patterns [50].

Overall, these findings suggest that e-bikes and shared bicycle/e-bike-sharing systems tend to serve longer distances than e-scooters and may exhibit stronger substitution potential for private-vehicle travel under supportive infrastructure and operational conditions. At the same time, the scale-dependent heterogeneity reported in bike-sharing and e-bike-sharing studies indicates that micromobility demand drivers can vary substantially across districts and corridors, reinforcing the value of network-based approaches that capture spatial concentration and localized infrastructure needs.

2.3. Environmental and Life-Cycle Assessment of Micromobility

There have also been studies in the literature on whether e-scooters are a climate-friendly means of transportation. Kazmaier and Taefi [51] calculated the global warming potential of e-scooters as 165 g CO₂-eq/km, mostly due to materials and production (73% of the impact). Their findings suggest that global warming potential could be reduced by 12% by switching to e-scooter models with replaceable batteries. It is thought that extending the life of e-scooters, changing the charging system and using electricity with low global warming potential for production and charging will reduce the global warming potential of e-scooters to 46 g CO₂-eq/km. Moreau et al. [52] evaluated the environmental impacts of modal shifts induced by e-scooter use in Brussels with a specific focus on global warming potential. Their results indicate that, under current operating conditions, shared e-scooters generate 131 g CO₂-eq per passenger-kilometer, while the transport modes displaced by e-scooter trips are associated with a lower emission intensity of 110 g CO₂-eq per passenger-kilometer. In contrast, the global warming potential of personal e-scooters was estimated at 67 g CO₂-eq/km. The authors concluded that the climate performance of e-scooters can be substantially improved as the market matures, particularly through extending vehicle lifetimes and optimizing system operations.

More recent evidence further highlights the strong dependence of micromobility life-cycle emissions on operational and contextual factors. Jia and Gao [53] developed a data-driven life-cycle assessment based on operational data from 100 European cities, incorporating ride frequency, average trip length, charging and idle energy consumption and country-specific electricity generation mixes. Their study reports that life-cycle greenhouse gas emissions of shared e-scooter systems—covering production, logistics, operation and end-of-life processes—vary widely across urban contexts, ranging from 30 to 124 g CO₂-eq/km.

Overall, the literature indicates that e-scooters are increasingly integrated into urban transportation systems and are predominantly used by young, male, educated and higher-income individuals. Time savings, convenience and enjoyment are consistently identified as key drivers of adoption, while safety concerns, weather conditions and high costs remain major barriers. Spatial analyses highlight the importance of infrastructure quality, public transport accessibility and urban density in shaping usage patterns. At the same time, environmental assessments suggest that the climate performance of micromobility can be significantly improved through longer vehicle lifetimes and more sustainable operational practices.

When the literature is examined, micromobility vehicles are widely recognized for their potential to deliver time savings and environmental benefits, particularly when substituting private-car trips over short distances. While existing studies have extensively addressed user demographics, safety perceptions and environmental outcomes, the majority of this work remains centered on qualitative assessments or descriptive analyses. As a result, integrated approaches that combine behavioral determinants with network-level infrastructure implications are still limited. Addressing this gap, the present study focuses exclusively on private-car users and adopts a multi-stage analytical framework. First, statistical analyses are employed to identify the key socio-demographic, travel-related and perceptual factors influencing the willingness to shift to micromobility. Based on the empirically observed modal-shift rates, micromobility demand matrices are subsequently constructed and assigned to the Bornova transportation network using PTV VISUM to determine infrastructure requirements and identify priority corridors. Finally, total vehicle-kilometer values obtained from the network assignments are used to conduct a life-cycle assessment, allowing the environmental implications of the identified modal shifts to be quantified. Through this integrated approach, the study provides an applied contribution by linking behavioral insights with spatial infrastructure needs and environmental performance at the urban network scale.

3. Methodology and Data

This study was conducted by adopting a quantitative research method to examine the impact of micromobility vehicles on urban transportation habits. Within the scope of the study, the transportation preferences of individuals using private vehicles, their attitudes towards micromobility vehicles and the changes that will occur in the transportation network if they start using these vehicles were evaluated. The research approach is shown in Figure 1.

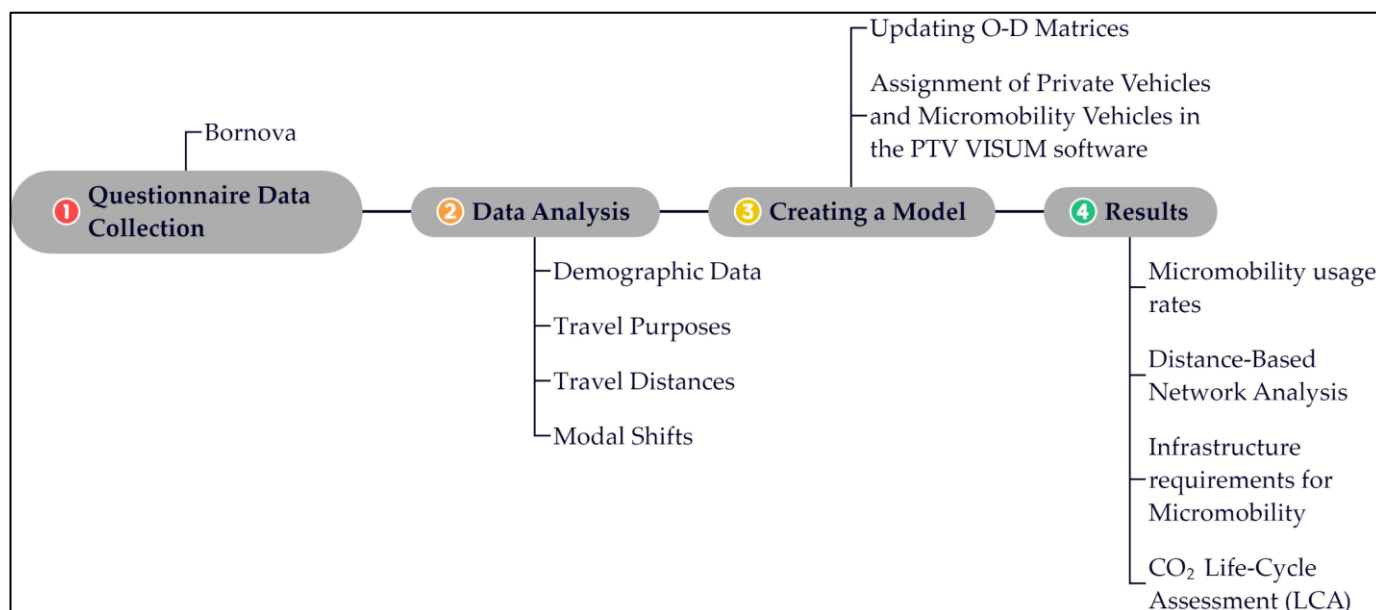


Figure 1. Research approach.

3.1. Data Collection and Sampling Procedure

The data were collected through a structured questionnaire developed by the researcher. Although the questionnaire was prepared online using Google Forms, it was administered face-to-face in the field in collaboration with a professional survey company to ensure data quality, respondent verification and controlled survey conditions.

The field survey was conducted within the administrative boundaries of the Bornova district of Izmir. Data collection was carried out on both weekdays and weekends and during different time intervals (peak and off-peak hours) in order to capture potential variations in travel behavior. All participants were private-car users. Only individuals who had arrived at the survey locations by private vehicle were invited to participate.

To determine the participants, a predefined sampling frame was not used; instead, individuals suitable for the purpose of the study were directly targeted in specific locations such as shopping malls, street parking areas, gas stations, university surroundings and high-activity urban corridors. These locations were strategically selected to ensure access to active private-vehicle users. In this regard, a non-probability purposive sampling method was adopted in the study.

Participants were required to meet the following inclusion criteria:

- (i) being 18 years of age or older;
- (ii) using a private vehicle as their primary mode of transportation;
- (iii) residing in or regularly traveling within the Bornova district.

Individuals who did not meet these criteria were excluded from the survey.

To determine the appropriate sample size, the formula in Equation (1), which is widely used for limited population, was used as a basis:

$$n = \left(N \times t^2 \times p \times q \right) / \left(d^2 \times (N - 1) + t^2 \times p \times q \right) \quad (1)$$

- n : Sample size.
- t : Theoretical value (for 95% confidence interval, 1.96).
- p : The frequency of occurrence of the event under investigation.
- q : The frequency of non-occurrence of the event under investigation (1- p).
- d : Margin of error (0.05 at 95% confidence interval).

- N : Population size.

Using this formula, the minimum required sample size was calculated as 384. To enhance the statistical robustness of the analysis and reduce potential sampling error, data collection was extended beyond this threshold. A total of 548 questionnaires were initially collected through face-to-face interviews.

Prior to statistical analysis, the dataset was carefully screened for completeness, internal consistency and logical plausibility. Cross-checks were conducted for key travel-related variables, such as daily travel duration and travel distance, to ensure consistency across responses. Questionnaires containing substantial missing information or internally inconsistent answers were excluded from the dataset. Following this data cleaning process, 502 valid observations were retained for subsequent statistical analyses.

The questionnaire consisted of four main sections. The first section captured participants' demographic and socioeconomic characteristics, including age, gender, educational level, income status and vehicle ownership. The second section focused on daily travel behavior, including primary transport modes, trip frequency and trip purposes. The third section assessed participants' awareness, usage experience and perceptions of micromobility vehicles. The final section examined the respondents' potential willingness to shift from private-car use to micromobility and the key barriers preventing such a transition.

A non-probability purposive sampling strategy was employed due to the absence of a comprehensive sampling frame for active private-car users at the district level. This approach enabled the targeted inclusion of individuals relevant to the research objectives; however, it does not allow for strict statistical representativeness. As a result, potential sampling bias cannot be entirely ruled out, particularly given that participants were recruited in high-activity urban locations and through voluntary face-to-face participation.

It is important to note that the primary objective of this research is not to generate population-level prevalence estimates, but rather to identify behavioral transition mechanisms and integrate these mechanisms into a transport network modeling framework. Accordingly, the study prioritizes internal analytical validity over broad statistical generalization. The survey data are used to estimate behavioral relationships and derive scenario-based modal-shift parameters, rather than to produce deterministic population-level transition probabilities.

Although efforts were made to enhance sample heterogeneity by collecting data across different locations, days and time periods, the findings should be interpreted within the spatial and contextual boundaries of the Bornova district. Consequently, the external validity of the results is inherently limited and future research employing probability-based or stratified sampling designs may further strengthen the generalizability of micromobility adoption estimates.

3.2. Survey Statistical Analyses

All statistical analyses were conducted using IBM SPSS Statistics 2024. This stage aimed to identify the determinants of micromobility adoption intention among private-car users through a progressive analytical approach, combining descriptive, bivariate and multivariate methods.

In the first step, descriptive statistics were applied to characterize the sample and to summarize general travel behavior patterns. Frequency and percentage distributions were used for categorical variables, while mean values and standard deviations were calculated for Likert scale statements. Based on respondents' stated preferences, preliminary modal-shift rates from private vehicles to micromobility were derived under a hypothetical adoption scenario. These rates provided an initial behavioral insight and served as an intermediate input for subsequent network modeling.

In the second step, the chi-square (χ^2) test of independence was employed to examine the association between micromobility adoption intention and socio-demographic characteristics such as age, gender, education level and income. This method was selected because both the dependent variable and the explanatory variables are categorical. The chi-square statistic is defined as

$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(O_{ij} - E_{ij})^2}{E_{ij}} \quad (2)$$

where O_{ij} denotes the observed frequency in cell (i,j) and E_{ij} represents the expected frequency under the null hypothesis of independence.

Statistical significance was assessed at the 95% confidence level ($p < 0.05$). This analysis enabled the identification of demographic groups exhibiting statistically significant differences in micromobility adoption tendencies.

In addition, the reasons for not using micromobility vehicles were evaluated using five-point Likert scale statements and mean scores were calculated to rank the relative importance of perceived barriers and user concerns.

In the final step, to estimate the independent effects of explanatory variables while controlling for potential confounding factors, a binary logistic regression model was developed. Micromobility adoption intention was defined as a binary outcome variable:

$$Y_i = \begin{cases} 1, & \text{if individual } i \text{ intends to adopt micromobility} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Based on random utility theory, the latent utility difference is expressed as

$$U_i = \beta_0 + \beta' X_i + \varepsilon_i \quad (4)$$

where X_i represents a vector of socio-demographic attributes, travel characteristics and perceived barriers; β_0 is the intercept; β is the parameter vector to be estimated; and ε_i is a stochastic error term assumed to follow a logistic distribution.

Under this assumption, the probability of micromobility adoption is given by the logistic function:

$$P_i = \frac{1}{1 + \exp[-(\beta_0 + \beta' X_i)]} \quad (5)$$

or equivalently in log-odds form:

$$\ln\left(\frac{P_i}{1 - P_i}\right) = \beta_0 + \beta' X_i \quad (6)$$

Model parameters were estimated using maximum likelihood estimation (MLE) and the estimated coefficients were interpreted through odds ratios, allowing the magnitude and direction of each variables effect on micromobility adoption likelihood to be quantified.

3.3. Transport Network Modeling Framework

To translate individual-level micromobility adoption behavior into system-wide transport impacts, a strategic transport network modeling framework was implemented. Within this framework, travel demand matrices are restructured and network performance indicators are evaluated based on separate traffic assignments conducted under alternative modal split conditions.

The analysis was conducted using PTV VISUM, a macroscopic transport planning software widely applied in strategic travel demand modeling and policy evaluation. The

modeling framework follows a baseline-scenario comparison logic, ensuring that all impacts are measured relative to a common reference state.

The baseline scenario represents the future reference condition of the study area and is based on origin–destination (OD) demand and distance matrices developed within the scope of the Izmir Transportation Master Plan for the year 2030. These matrices describe private-vehicle travel demand at the metropolitan scale and were spatially disaggregated and calibrated to the Bornova district to reflect local travel patterns.

The baseline private-vehicle OD demand structure is expressed as

$$Q^0 = \{Q_{ij}^0\} \quad (7)$$

where Q_{ij}^0 represents the number of trips from origin i to destination j . Using this matrix, a baseline traffic assignment was performed to obtain reference values for network flows, total vehicle kilometers traveled and average travel speeds.

Micromobility adoption was explicitly modeled as a distance-sensitive modal substitution process. Based on empirical findings from the survey analysis, modal-shift rates were defined for two distance classes: up to 5 km (0–5 km) and 5–10 km trips. These distance bands reflect the operational range within which micromobility modes are considered a feasible substitute for private-vehicle travel.

For each OD pair (i, j) , a distance-dependent shift coefficient α_d was applied, yielding a reallocation of trips between private vehicles and micromobility modes. The resulting demand matrices are defined as

$$Q_{ij}^{\text{micro}} = \alpha_d \cdot Q_{ij}^0 \quad (8)$$

$$Q_{ij}^{\text{car}} = (1 - \alpha_d) \cdot Q_{ij}^0 \quad (9)$$

where $\alpha_d \in [0, 1]$ denotes the modal-shift rate associated with distance band d . This formulation preserves total travel demand while allowing systematic redistribution across modes.

The restructured demand matrices were assigned to the Bornova transport network using mode-specific assignment principles. Private-vehicle trips were assigned using a stochastic user equilibrium approach, allowing for probabilistic route choice behavior and congestion feedback effects. In contrast, micromobility trips were assigned using a system-based deterministic shortest-path routing logic. This distinction reflects both modal characteristics and empirical findings in the literature. Studies on e-scooter and bicycle usage indicate that micromobility users tend to prioritize route directness, perceived safety and infrastructure continuity rather than marginal travel time differences caused by congestion redistribution [38,39]. Unlike motor vehicles, micromobility flows interact only weakly with network-wide congestion dynamics at the strategic planning scale. Therefore, deterministic assignment provides a conceptually consistent and computationally efficient representation of micromobility routing behavior for scenario-based network analysis.

This differentiated assignment strategy enables the joint evaluation of congestion effects, route redistribution and speed changes induced by modal shifts. Model outputs include link-level flows, total vehicle kilometers traveled and average network speeds for each scenario.

In addition, the spatial distribution of micromobility flows was used to derive desire lines and identify corridors with elevated micromobility demand, providing indirect evidence for potential infrastructure prioritization.

3.4. Life-Cycle Assessment (LCA) of Emission Impacts

To assess the environmental implications of micromobility adoption, a life-cycle assessment (LCA) framework was applied, focusing on CO₂-equivalent emissions as the primary

impact indicator. The LCA is formulated as a distance-based impact model, directly linked to network-level travel outcomes generated by the transport assignment.

For each transport mode m , a corresponding life-cycle emission factor EF_m (gCO₂e/km) was defined. These factors represent aggregated emissions associated with vehicle manufacturing, energy production, operation and maintenance stages.

Total emissions are expressed as a linear function of traveled distance:

$$E = \sum_m VKT_m \cdot EF_m \quad (10)$$

where VKT_m denotes total vehicle kilometers traveled by mode m .

Using the vehicle kilometers traveled obtained from the transport model, total emissions were computed separately for the baseline and micromobility adoption scenarios:

$$E^0 = \sum_m VKT_m^0 \cdot EF_m \quad (11)$$

$$E^s = \sum_m VKT_m^s \cdot EF_m \quad (12)$$

where superscripts 0 and s denote baseline and scenario conditions, respectively.

The net environmental impact of micromobility adoption is quantified as the difference between baseline and scenario emissions:

$$\Delta E = E^0 - E^s \quad (13)$$

To facilitate comparison across scenarios, relative emission change is defined as

$$\Delta E\% = \frac{\Delta E}{E^0} \times 100 \quad (14)$$

This formulation ensures that emission impacts are attributed exclusively to changes in network-level travel distances and modal composition, rather than to exogenous assumptions.

The adopted framework establishes analytical loop between behavioral intention, network performance and environmental impact. Survey-based modal-shift tendencies are used to restructure origin–destination (OD) matrices. Network assignment then translates these demand changes into vehicle kilometers traveled and identifies priority infrastructure needs for micromobility, while the LCA model converts distance-based outputs into life-cycle emission estimates.

As a result, environmental impacts are not inferred directly from stated preferences; instead, they are generated through network interactions, congestion effects and route adjustments captured by the transport modeling framework.

4. Study Area

As the third largest city in Türkiye, Izmir has a well-developed transportation infrastructure in terms of both public transportation and micromobility. The public transportation system includes various modes such as IZBAN, metro, three separate tram lines (Konak, Karşıyaka, Çiğli), ESHOT buses and sea transportation. Road transportation is supported by the Izmir–Istanbul, Izmir–Aydın and Izmir–Ankara highways. However, especially in the central districts (Alsancak, Konak, Bornova), traffic congestion occurs during rush hours.

According to the Transportation Master Plan, prepared by the Izmir Metropolitan Municipality with a target of 2030, the majority of trips in the city are for work and school purposes. In the projected distribution for 2030, private-vehicle use is stated as

25.54%, public transportation use as 31.09% and pedestrian transportation as 32.76%. The mean duration of trips by private vehicles is 35.99 min and the mean distance is 15.03 km. Approximately 70% of these trips last less than 40 min and 50% are less than 10 km. The report offers various recommendations for transition from private-vehicle use to other means of transportation to reduce traffic congestion, especially during peak hours. Micromobility is thought to become an important alternative for short-distance trips made with private vehicles [54].

In line with the goal of promoting sustainability in urban transportation, the use of micromobility vehicles has been steadily increasing in Izmir. While BİSİM bicycle rental stations along the coastal corridor are heavily used, e-scooter services provided by private companies such as Martı and BinBin are particularly preferred in areas with a high concentration of young population. This trend is consistent with international studies showing that younger users demonstrate a stronger inclination toward e-scooter systems [25,26]. There are bicycle and pedestrian paths along the coastline and micromobility infrastructure is expanding throughout the city.

An examination of e-scooter usage data in Izmir provided by the Izmir Metropolitan Municipality Transportation Department shows that the areas with the highest micromobility activity include the coastal corridors of Konak and Karabağlar, as well as the districts of Karşıyaka, Bornova, Bayraklı, Buca, Çiğli and Balçova. The concentration of e-scooter trips in these regions is associated with the presence of a young population, the tendency of the working class and vibrant social activity zones. These spatial patterns are consistent with findings reported in international literature [20,38,39]. Figure 2 visualizes the origin and destination points of e-scooter trips across these districts based on the dataset obtained from the Izmir Metropolitan Municipality Transportation Department [55].

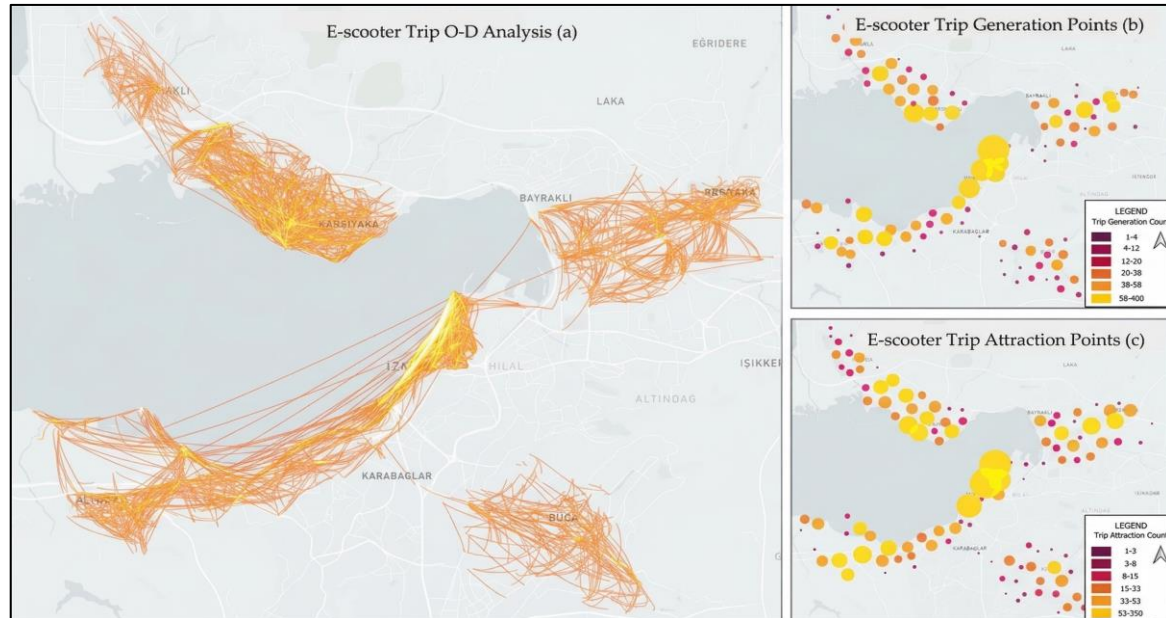


Figure 2. (a) E-scooter trip O-D analysis in Izmir; (b) Trip generation points with counts; (c) Trip attraction points with counts.

Bornova district, which was selected as the study area, is one of the exemplary areas in Türkiye where e-scooter systems were first implemented and regulated by the local government. Areas such as the Ege University Campus, Small Park (Küçük Park) and Large Park (Büyük Park) in the district are important travel production and attraction centers. As of 2023, it is the third most populous district of Izmir with a population of 447,553

(TSI, 2023). The number of BİSİM (bicycle-sharing system operating in İzmir, Türkiye) stations in the district has increased over time and stations have been established in new locations such as Bornova Metro, Fethi Sekin Park, Cumhuriyet Park and Bornova Stadium. Additionally, there are four shopping malls, five hospitals and two university campuses (Ege University, Yaşar University) in the district. With these features, Bornova is a strategic exemplary area in terms of micromobility and therefore was determined as the study area.

5. Findings

5.1. Statistical Analyses

The survey administered to private-vehicle users begins with an overview of respondents' socio-demographic characteristics. A total of 502 individuals participated in the survey, comprising 199 females (39.6%) and 303 males (60.4%). The age distribution of the sample is relatively balanced, with 22.3% of respondents aged 15–25, 22.7% aged 26–35, 25.6% aged 36–45 and 25.4% aged 46–64, while individuals aged 65 and above represent a smaller proportion of the sample (3.7%). In terms of educational attainment, university graduates form the largest group (41.2%), followed by high school graduates (28.8%). Regarding employment status, the majority of respondents are full-time employees (65.3%), whereas students account for 13.9% of the sample. Income distribution indicates that nearly 70% of participants report a monthly income between 5000 and 40,000 TL. Furthermore, approximately 71% of respondents incur monthly transportation expenditures ranging from 1000 to 5000 TL.

Following the presentation of the socio-demographic characteristics, the survey results provide detailed insights into the underlying motivations behind private-car use. The findings indicate that time efficiency and travel comfort are the most prominent factors shaping private-vehicle preferences. A substantial share of respondents emphasized the ability to reach destinations more quickly as a primary motivation, while an equally large proportion highlighted the convenience and comfort associated with private-car travel. These results suggest that private vehicles are perceived as offering a superior balance between speed and personal comfort compared to alternative transport modes.

In addition to these factors, flexibility and independence emerged as important considerations, reflecting users' preference for travel options that allow unrestricted departure times and routes without dependence on fixed schedules. Furthermore, a notable segment of participants reported relying on private vehicles due to the lack of viable alternatives, indicating potential deficiencies in the availability or accessibility of other transport options. By contrast, functional attributes such as carriage capacity and luggage space were identified as relatively less influential in shaping private-car preferences (see Figure 3a).

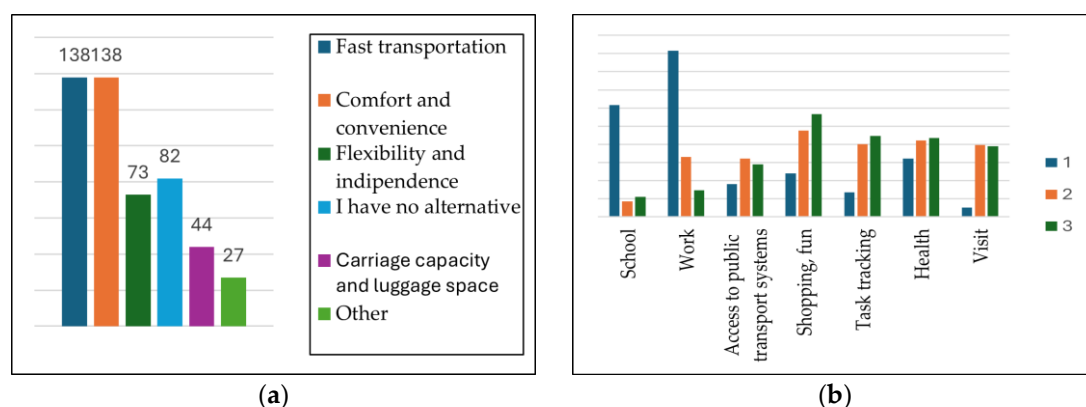


Figure 3. (a) Reasons for preferring a private car; (b) Travel purposes.

The travel purposes of private-vehicle users were also analyzed in the questionnaires. In this context, the participants were asked to rank their top 3 preferences. The resulting ranking is given in Figure 3b. When the graph is examined, it is seen that using private cars for the purpose of “commuting” is clearly prominent. This category reached the highest number of participants with 183, revealing a serious trend towards using private vehicles to travel to work. There is also a remarkable rate of using private vehicles for the purpose of “going to and from school” (123 participants). This shows that parents who take their children to school or students tend to use this type of transportation.

Micromobility vehicles are considered an important alternative for short-distance trips. Therefore, private-vehicle users were asked about their daily mean travel distances and an attempt was made to identify potential micromobility users. The results indicate that the largest share of respondents (200 participants) reported daily travel distances between 11 and 20 km, followed by those traveling 6–10 km (130 participants). A smaller group of respondents (37 participants) indicated travel distances of 0–5 km. Based on these responses, the daily mean travel distance was calculated as approximately 19 km. As stated in Section 4, which is the third part of the study, the mean travel distance was determined as 15.03 km in the Izmir Transportation Master Plan prepared by the Izmir Metropolitan Municipality. In addition to daily mean travel distance, the daily mean travel duration is also an important parameter to be used in the analysis. In the Izmir Transportation Master Plan, the mean travel duration of private-vehicle users was calculated as 35.99 min. In this study, the majority of respondents reported travel durations of 31–45 min (187 participants), followed by 16–30 min (178 participants). According to the data obtained, the mean travel duration was calculated as approximately 34 min. When these results are compared with the Izmir Transportation Master Plan, it is seen that the data is consistent. The daily mean travel distance distribution is given in Figure 4a and the mean travel duration distribution is given in Figure 4b.

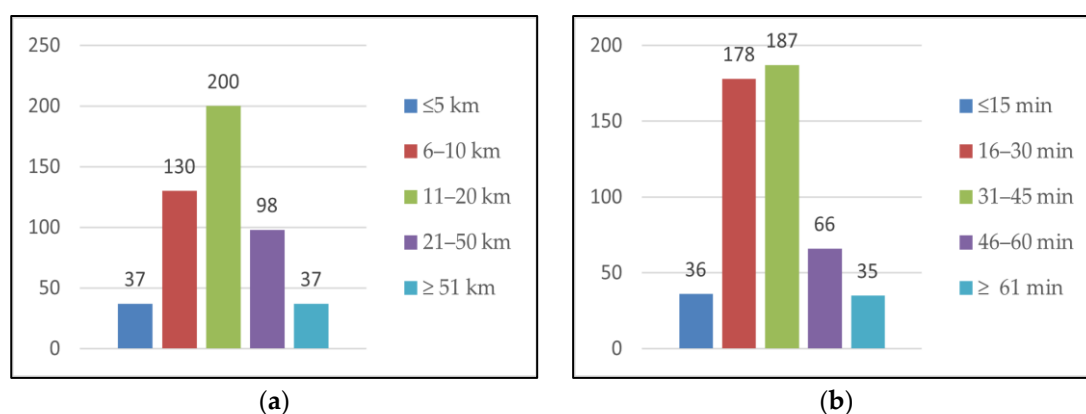


Figure 4. (a) Distribution of daily mean travel distances; (b) Distribution of daily mean travel duration.

Daily mean travel distance and duration data provided an important basis for identifying potential micromobility users. However, understanding the reasons why private-vehicle users do not prefer micromobility vehicles is of great importance in terms of analyzing the factors affecting the spread of this alternative transportation type. For this purpose, opinions of the participants were obtained using a Likert scale based on various criteria. On this scale, 1 means “Strongly Disagree” and 5 means “Strongly Agree”. The results show that the most important criteria are “Exposure to bad weather conditions” (3.73, SD = 1.18) and “Long travel distance” (3.67 St 1.17). Mean and std deviation values of other determined parameters are given in Table 1.

Table 1. Weighted mean and std deviation of reasons for not using micromobility vehicles.

Criteria	Descriptive Statistics					N	Mean	Std Deviation
	1	2	3	4	5			
Inadequate infrastructure	88	70	82	176	86	502	3.203	1.356
I do not find it safe	75	114	51	103	159	502	3.313	1.484
Scooters are not maintained properly and are broken	49	83	60	194	116	502	3.488	1.277
High usage fee	66	79	65	159	133	502	3.426	1.372
Limited coverage areas	48	75	61	197	121	502	3.534	1.268
Low number of scooters	52	101	80	157	112	502	3.351	1.304
Exposure to adverse weather conditions	29	64	71	189	149	502	3.727	1.182
Long travel distance	25	80	66	194	137	502	3.673	1.177
Having too much stuff when traveling	29	89	59	190	135	502	3.624	1.215
Parking problems	82	105	47	150	118	502	3.233	1.432
Valid N (listwise)						502		

To assess the potential transition from private-vehicle use to micromobility modes, respondents' stated willingness to substitute their private-car trips with micromobility alternatives was analyzed. The results indicate that 165 participants (32%) expressed a willingness to shift their trips from private vehicles to micromobility modes. The detailed distribution of respondents indicating a transition to micromobility is presented in Table 2. To further examine the relationship between socio-demographic characteristics and modal-shift tendencies, a chi-square analysis was conducted, enabling the identification of statistically significant associations between demographic variables and the likelihood of transitioning to micromobility.

Table 2. Demographic data and modal-shift statistical analysis.

Demographic Data		N	Percentage	Modal Shift to Micromobility		Chi-Square	Degree of Freedom (df)	p-Value
				Yes	No			
Gender	Male	303	0.60	108	195	2.668	1	0.102
	Female	199	0.40	57	142			
Age	15–25	112	0.22	52	60	30.743	4	$p < 0.001$
	26–35	114	0.23	46	68			
	36–45	129	0.26	41	88			
	46–64	128	0.25	26	102			
	65 and over	19	0.04	0	19			
Educational Level	Primary school	18	0.04	0	18	12.219	5	0.032
	High school	145	0.29	44	101			
	Associate degree	103	0.21	40	63			
	University	207	0.41	72	135			
	Postgraduate	27	0.05	9	18			
	Other	2	0.00	0	2			
Working Status	Full-time employee	328	0.65	106	222	33.043	5	$p < 0.001$
	Part-time employee	22	0.04	9	13			
	Student	70	0.14	39	31			
	Retired	37	0.07	3	34			
	I do not work	35	0.07	5	30			
	Other	10	0.02	3	7			
Monthly Income Level	0–5000 TL	23	0.05	12	11	13.453	4	0.009
	5001–20,000 TL	166	0.33	61	105			
	20,001–40,000 TL	185	0.37	63	122			
	40,001–60,000 TL	80	0.16	22	58			
	60,001 and above	48	0.10	7	41			
Monthly Transportation Expenses	Less than 1000 TL	87	0.17	29	58	14.829	3	0.002
	1001–3000 TL	244	0.49	92	152			
	3001–5000 TL	111	0.22	37	74			
	5001 TL and above	60	0.12	7	53			

According to the chi-square analysis between the demographic data given in Table 2 and the users who expressed willingness to make their trips with micromobility vehicles, the following observations can be made:

- There is no statistically significant relationship between the gender variable and the shifts (chi-square = 2.668; $df = 1$; $p = 0.102$), showing that the observed differences were random and that the shifts did not differ significantly according to gender.
- There is a statistically significant relationship between the age variable and the shifts (chi-square = 30.743; $df = 4$; $p < 0.001$). According to this result, it is seen that the shifts towards micromobility occurred largely among users between the ages of 15–45.
- There is a significant relationship between educational level and the shifts (chi-square = 12.219; $df = 5$; $p = 0.032$), showing that educational level is an effective factor in the transition tendency of private-vehicle users to micromobility.
- There is a statistically significant relationship between working status and the shifts (chi-square = 33.043; $df = 5$; $p < 0.001$). This reveals that individuals' transition tendencies to micromobility varied according to their working status.
- There is a significant relationship between monthly income level and the shifts (chi-square = 13.453; $df = 4$; $p = 0.009$). According to this result, the income level of users was an important variable affecting micromobility preference.
- There is a significant relationship between monthly transportation expenses and the shifts (chi-square = 14.829; $df = 3$; $p = 0.002$). Accordingly, the shifts from private-vehicle users varied depending on monthly transportation expenses.

The chi-square analysis presented in Table 2 provides an initial descriptive assessment of the relationship between socio-demographic characteristics and the willingness of private-car users to shift to micromobility. While these bivariate results reveal which variables are associated with modal-shift tendencies, they do not account for the simultaneous influence of multiple factors nor control for potential confounding effects among variables. In particular, demographic characteristics, travel-related attributes and perceived barriers are likely to interact in shaping individuals' transition decisions. Therefore, to move beyond pairwise associations and to identify the independent and relative effects of these factors on the likelihood of shifting to micromobility, a multivariate modeling approach is required. In this context, a binary logistic regression model was estimated, incorporating demographic variables, travel duration and perceived barriers into a single analytical framework. This approach allows for a more robust examination of micromobility adoption behavior by controlling for interdependencies between variables and by quantifying the direction and magnitude of each factors effect on transition probability.

Spearman's rank correlation analysis was conducted among the independent variables to assess potential monotonic associations prior to regression modeling. The correlation coefficients generally remained below 0.60. The maximum observed correlation ($r_s \approx 0.63$) occurred between the perceptual constraints "Long travel distance" and "Having too much stuff when traveling", reflecting conceptually related travel characteristics. Since this value does not exceed commonly accepted multicollinearity thresholds ($|r| \geq 0.70$), the independence assumption required for regression estimation is considered satisfied.

To enhance the statistical robustness and interpretability of the model, selected demographic variables were reclassified based on theoretical considerations and empirical distributions. Educational attainment was grouped into three categories: low education (primary school, high school and other), medium education (associate degree) and high education (undergraduate and postgraduate degrees). Similarly, working status was consolidated into three groups: employed (full-time and part-time workers), students, and non-working individuals (retired, unemployed and other); the logistic regression results are given in Table 3.

Table 3. Binary logistic regression predictions.

Variable	Coeff.	SE	z	p
(Intercept)	0.531	0.75	0.707	-
Employed (<i>ref: Not Employed</i>)	0.908	0.390	2.326	0.020
Student (<i>ref: Not Employed</i>)	1.381	0.500	2.764	0.006
Travel Duration	−0.298	0.128	−2.321	0.020
Inadequate Infrastructure	−0.215	0.105	−2.042	0.041
Safety	−0.306	0.107	−2.849	0.004

Note: Nagelkerke R^2 : 0.254.

The regression results indicate that working status plays a significant role in explaining micromobility transition behavior. Students and employed individuals demonstrate a stronger willingness to transition compared to non-working respondents. This suggests that individuals with active daily mobility patterns—particularly those related to work and education—are more inclined to consider micromobility as a viable transportation alternative. Although education level was included in the model, it did not exhibit an independent statistically significant effect on transition probability.

Travel duration also emerged as a significant explanatory variable with a negative coefficient, indicating that longer daily travel times reduce the likelihood of shifting to micromobility. This finding supports the view that micromobility is perceived as more suitable for short-distance trips, where time efficiency and flexibility offer clear advantages. Accordingly, private-car users with shorter travel durations constitute the segment with the highest modal-shift potential.

Among perceived barriers, safety concerns and perceived infrastructure inadequacy exert statistically significant and negative effects on transition probability ($p = 0.004$ and $p = 0.041$, respectively). These findings underscore the importance of safe, continuous and well-designed infrastructure as fundamental prerequisites for encouraging a shift toward micromobility.

Prior to model estimation, certain independent variables were regrouped due to low-frequency subcategories that could generate unstable coefficient estimates and inflated standard errors in logistic regression. Conceptually similar categories were merged to ensure sufficient observations within each group, thereby improving parameter stability while preserving theoretical coherence.

Model diagnostics further confirm the robustness of the estimation. The Hosmer–Lemeshow goodness-of-fit test ($\chi^2 = 8.326$, $df = 8$, $p = 0.402$) indicates an adequate fit between observed and predicted values. The model correctly classifies 72.5% of observations (cut-off = 0.50) and the ROC analysis yields an Area Under the Curve (AUC) of 0.741, demonstrating good discriminatory power. Although the Nagelkerke R^2 value (0.254) reflects moderate explanatory capacity, such magnitudes are typical in behavioral adoption studies where travel decisions are shaped by multidimensional and context-dependent factors.

The estimated binary logistic regression model is presented in Equation (15):

$$\ln\left(\frac{P_i}{1 - P_i}\right) = 0.531 + 0.908x_1 + 1.381x_2 - 0.298x_3 - 0.215x_4 - 0.306x_5 \quad (15)$$

To complement the multivariate findings, Pearson correlation coefficients were calculated to examine simple bivariate relationships between transition intention and the explanatory variables (Table 4).

The results indicate weak-to-moderate positive associations for employment status ($r = 0.149$), travel duration ($r = 0.148$), infrastructure inadequacy ($r = 0.140$) and safety perception ($r = 0.234$), with safety exhibiting the strongest simple correlation. Student

status, however, does not show a statistically significant bivariate association ($r = -0.027$, $p = 0.585$).

Table 4. Pearson correlation and multicollinearity diagnostics.

Variable	Pearson r	p-Value	Tolerance	VIF
Employed (<i>ref: Not Employed</i>)	0.149	0.002	0.779	1.284
Student (<i>ref: Not Employed</i>)	−0.027	0.585	0.797	1.254
Travel Duration	0.148	0.001	0.962	1.039
Inadequate Infrastructure	0.140	0.002	0.671	1.490
Safety	0.234	<0.001	0.674	1.484

This apparent discrepancy between Pearson and logistic regression results highlights the distinction between simple pairwise associations and multivariate effects. While student status does not display a strong direct correlation with transition intention, it becomes statistically significant once employment status, travel duration and perceived barriers are simultaneously controlled. This confirms that the logistic regression model provides a more reliable interpretation of the independent behavioral determinants of micromobility adoption.

Multicollinearity diagnostics further support model stability. All tolerance values exceed 0.20 and VIF values range between 1.039 and 1.490, remaining well below conservative thresholds. Therefore, the estimated coefficients can be considered statistically stable.

Overall, the findings demonstrate that working-age individuals and students with shorter travel durations exhibit the highest transition potential, while improvements in perceived safety and infrastructure quality constitute critical policy levers. In the subsequent stage of the study, these behavioral insights are integrated into the network modeling framework to identify priority corridors based on projected micromobility traffic volumes.

5.2. Modal Shift and Modeling

Micromobility has the potential to meet different travel purposes over distances shorter than 8 km, accounting for 50% to 60% of total trips in China, the European Union and the United States. Therefore, given that most car journeys are shorter than 8 km, it is thought that micromobility vehicles could largely replace private-car use [56].

In order to evaluate this potential more concretely, private-vehicle users were asked about the distances they would consider using micromobility vehicles for if they chose to use them. The results show that 222 respondents (44.2%) would consider using micromobility for distances of 3–5 km; 152 respondents (30.3%) stated that they would prefer these vehicles for distances of less than 2 km. Additionally, 121 participants (24.1%) stated that they were willing to use micromobility vehicles for trips between 6 and 10 km. When distance preferences are examined in relation to both personal micromobility ownership and shared micromobility use, the findings indicate that micromobility is predominantly favored for trips of up to 10 km. Beyond this threshold, the propensity to use micromobility decreases markedly. The distribution of distance preferences by micromobility ownership and shared micromobility usage status is illustrated in Figure 5.

The participants were asked what changes could enable them to use micromobility vehicles and were asked to rank their top three preferences. Figure 6 shows the participants' primary expectations on this issue.

When the graph is examined, it is seen that the option of "Facilitating access to micromobility vehicles" is the first choice of 175 participants. This reveals that accessibility is an important factor in private-vehicle users' decisions to use micromobility vehicles. When the first choices are examined, access to micromobility vehicles is followed by increasing bicycle and scooter paths and cheaper costs. When the sum of the first three preferences made by the users is examined, it is seen that the infrastructure need is the

most important factor. Increasing parking areas was preferred at significant rates in the second and third preferences. This shows that physical arrangements for infrastructure can directly affect usage rates.

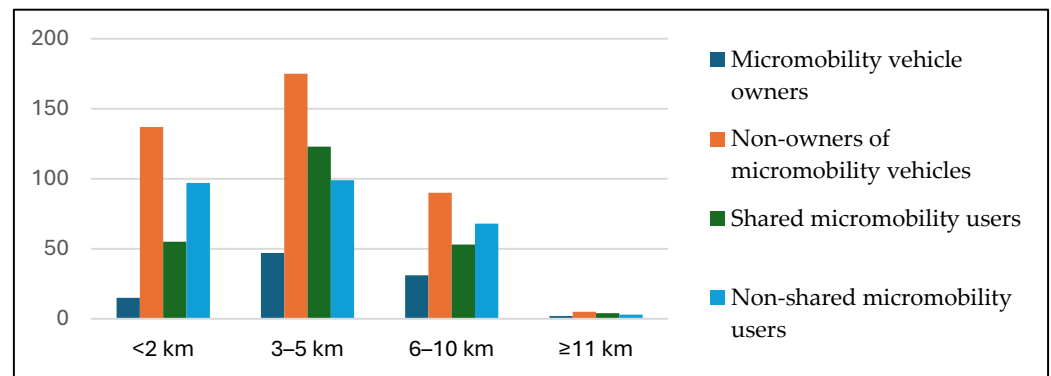


Figure 5. Micromobility usage distances.

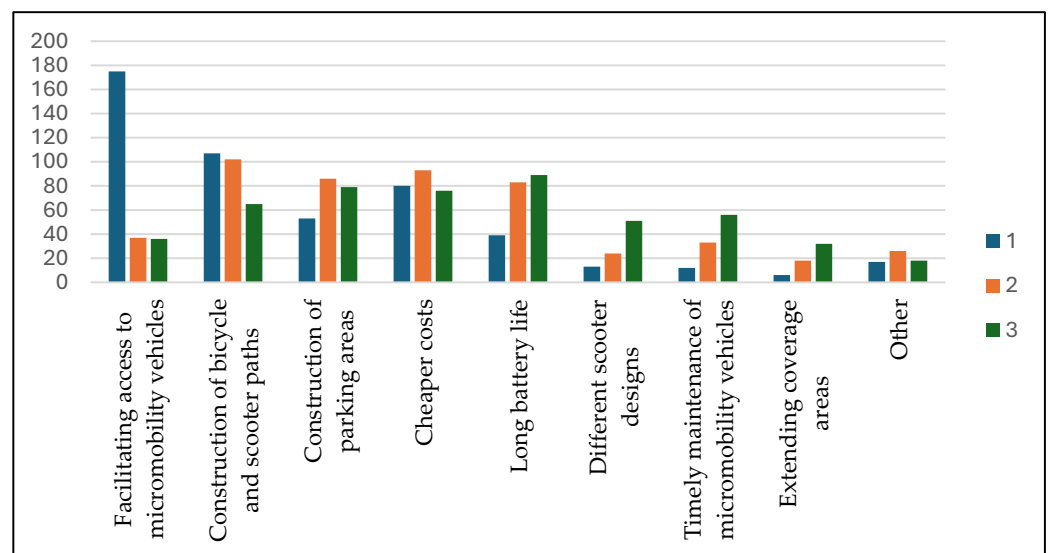


Figure 6. Participants' expectations of change.

Strengthening the physical infrastructure, increasing the accessibility of vehicles and reducing costs stand out as the most critical elements to increase the use of micromobility. These findings reveal the necessity for local governments and service providers to plan transportation infrastructure in line with user demands. In this context, in order to accurately determine the infrastructure needs on the existing transportation network, it is necessary to first accurately identify the possible modal shifts from private vehicles to micromobility vehicles. In line with the obtained rates of shifts, micromobility vehicles were assigned to the transportation network using the PTV VISUM program and infrastructure requirements were spatially determined.

In order to calculate the rates of shifts, the participants were asked whether they would consider using micromobility vehicles for their journeys and 165 people stated that they would transition from private vehicles to micromobility vehicles. It is thought that the 165 people identified here could be potential micromobility users. However, as seen in Figure 5, private-vehicle users preferred to use micromobility vehicles for journeys up to 10 km. In the literature review, it was stated that the usage distance of micromobility vehicles is approximately 8–10 km [5,42,43]. In this study, it was assumed that journeys up to 10 km can be made by micromobility vehicles. In this context, in order to determine

the rates of shifts, the number of private vehicle users whose travel distance was less than 10 km and who accepted transition to micromobility vehicles was determined, as shown in Figure 4a. While 13 out of 37 participants whose travel distance with their private cars was up to 5 km accepted transition to micromobility vehicles, 43 out of 130 participants whose travel distance was 5–10 km accepted transition to micromobility vehicles. The rate of modal shift for distances up to 5 km was calculated as 35% and for 5–10 km as 33%. The rates of modal shift are given in Table 5.

Table 5. Rates of modal shift.

Private-Car Travel Distance	N	Would You Use Micromobility on This Trip?	Rate of Modal Shift
		Yes	
<5 km	37	13	0.35
5–10 km	130	43	0.33

It is important to emphasize that these modal-shift rates are derived from stated preferences within the surveyed sample and do not constitute statistically generalizable adoption probabilities. In the modeling framework, they are operationalized as scenario-based behavioral parameters to explore potential network and environmental outcomes rather than to forecast deterministic district-wide modal redistribution.

Within the scope of the Izmir Transportation Master Plan prepared by the Izmir Metropolitan Municipality, urban transportation analyses were carried out by creating private-vehicle demand and distance matrices for 2030. In this context, private-vehicle-focused demand and distance matrices for the whole Izmir province were filtered and simplified to 59×59 size, specifically for Bornova district. In the analyses performed using this matrix, private-vehicle trips made within <5 km distance were identified in Bornova district and the demand matrices of these trips were reduced in line with the 35% rate of shift determined based on the questionnaire results. Similarly, the demand matrices for trips within 5–10 km distance were determined and reduced by 33% for this group. In order to observe the impact of shifts on private-vehicle traffic, the revised demand matrices were reassigned to the Bornova district transportation network through the PTV VISUM software and this assignment was named Scenario 1.

Within the scope of Scenario 2, it is thought that the journeys under 10 km, which will be made by private vehicles in the 2030 projection, will be made by micromobility vehicles in line with the rates of modal shift obtained from the questionnaires. In this direction, a micromobility demand matrix was generated based on the identified modal shifts and an alternative traffic load distribution model was obtained. As noted in the introduction, the maximum operating speed of type A and B micromobility vehicles is 25 km/h, while type C and D vehicles may reach speeds between 25 and 45 km/h under certain conditions. However, in Türkiye, the legally regulated maximum operating speed for electric scooters is limited to 25 km/h. Accordingly, to ensure consistency with national regulatory standards and to maintain a conservative and policy-relevant modeling framework, the average operational speed of micromobility vehicles in Scenario 2 was set at 25 km/h.

Furthermore, due to the physical and operational characteristics of micromobility vehicles, they are able to access certain links that are restricted to private-vehicle traffic. Accordingly, links that were not available for private-vehicle assignment in the Bornova district transportation network were opened for micromobility assignment in Scenario 2. This approach allowed the reassignment process to realistically reflect the network flexibility and spatial accessibility advantages associated with micromobility modes.

The traffic volumes of micromobility vehicles within the Bornova transportation network obtained from the VISUM assignment are presented in Figure 7. The network assignment conducted using the PTV VISUM software enabled the spatial identification of routes where micromobility demand is concentrated, thereby providing guidance for local authorities in planning the necessary infrastructure investments. Through this assignment, the potential impacts of the micromobility trend on transportation demand and network load were analyzed in a spatially explicit manner, allowing infrastructure requirements to be systematically assessed.

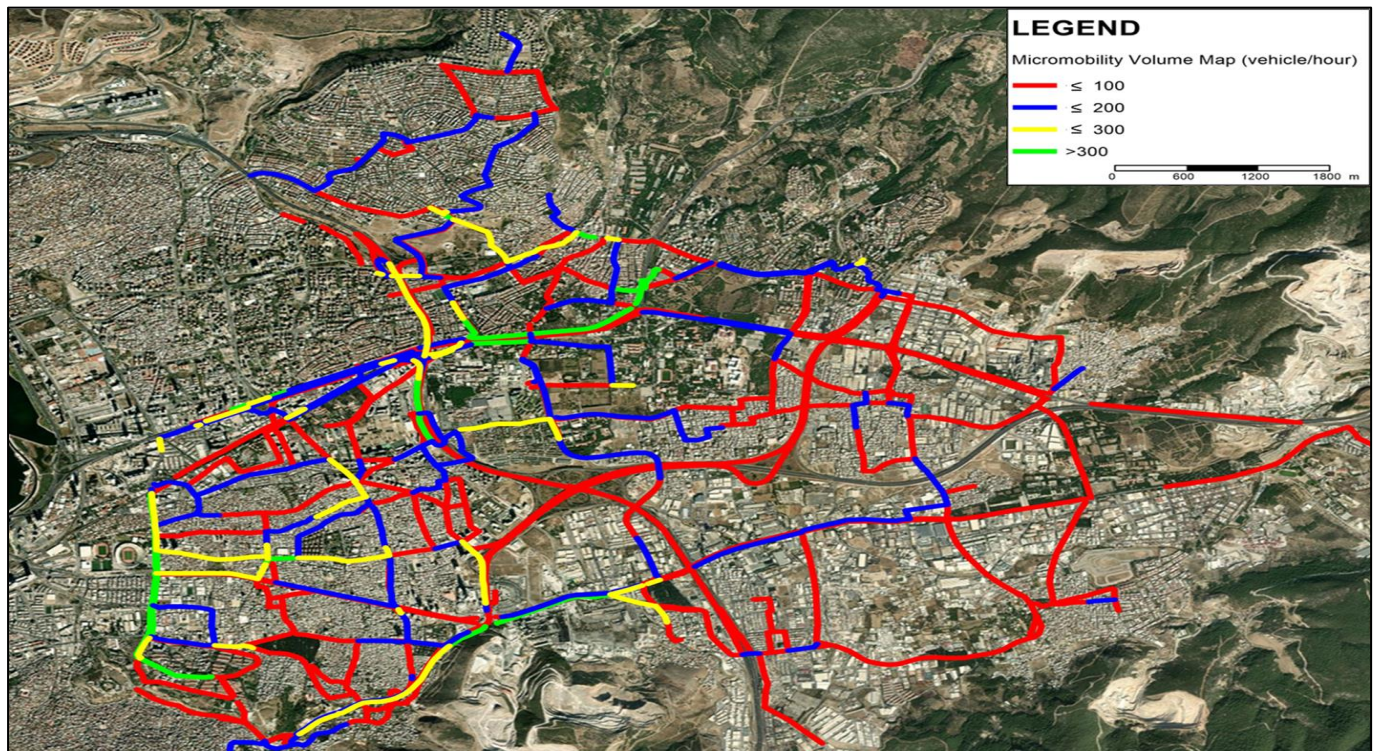


Figure 7. Assignment of micromobility vehicles in Bornova district.

As a result of the modeling, the total length of road segments utilized by micromobility vehicles in the network (as shown in Figure 7) was calculated as 292.5 km. This value represents the overall extent of road infrastructure that could form the primary backbone of a micromobility network in the Bornova district. To further prioritize infrastructure needs, road segments were classified according to micromobility traffic volume thresholds and the corresponding infrastructure requirements are illustrated in Figure 8.

Figure 8a presents the road segments with micromobility traffic volumes exceeding 100 vehicles/hour, with a total length of 80.5 km. These routes indicate areas where micromobility usage is expected to be frequent and where basic infrastructure improvements, such as lane continuity and surface quality, are required. Figure 8b shows road segments with traffic volumes exceeding 200 vehicles/hour, corresponding to a total length of 25 km, highlighting corridors with more intensive micromobility demand that may require dedicated or physically separated infrastructure. Finally, Figure 8c illustrates the most critical routes, where micromobility traffic volumes exceed 300 vehicles/hour. The total length of these high-demand corridors was determined to be 9.9 km, indicating locations where micromobility infrastructure should be treated as a top planning priority.

To further examine the robustness of the uniform speed assumption applied to micromobility vehicles, additional sensitivity analyses were conducted using alternative operational speeds of 20 km/h and 30 km/h. These values reflect plausible lower and up-

per bounds of average micromobility travel speeds observed under varying infrastructure quality and traffic interaction conditions.



Figure 8. (a) Length of roads with traffic volumes over 100 veh/h; (b) Length of roads with traffic volumes over 200 veh/h; (c) Length of roads with traffic volumes over 300 veh/h.

The reassignment results indicate limited variation in aggregate network-level indicators. Total micromobility vehicle-kilometers traveled (VKT) were calculated as 24,900 veh-km under the 20 km/h assumption and 25,493 veh-km under the 30 km/h assumption, suggesting that moderate speed variation does not structurally alter total demand distribution within the network.

Similarly, infrastructure prioritization outcomes remain largely stable across speed scenarios. The total length of road segments exceeding different micromobility traffic thresholds was calculated as follows:

Total length of road: 290.091 km (20 km/h) and 293.42 km (30 km/h).

Traffic volumes >100 veh/h: 81.913 km (20 km/h) and 85.74 km (30 km/h).

Traffic volumes >200 veh/h: 24.889 km (20 km/h) and 25.106 km (30 km/h).

Traffic volumes >300 veh/h: 9.227 km (20 km/h) and 9.39 km (30 km/h).

The observed differences between scenarios remain marginal and do not modify the spatial concentration patterns of high-demand corridors. These findings indicate that the primary modeling results—particularly corridor-level infrastructure prioritization and emission impacts—are robust to moderate variations in assumed micromobility operating

speeds. Therefore, the adoption of 25 km/h as the reference operational speed is considered methodologically appropriate within the strategic planning scope of this study.

Overall, these findings reveal the spatial distribution of routes where micromobility use is expected to be most intensive and demonstrate that infrastructure planning efforts should be concentrated on a limited number of high-demand corridors. By linking micromobility traffic volumes to network-wide infrastructure requirements, the VISUM-based analysis provides a robust and evidence-based framework for prioritizing micromobility investments within the urban transportation system.

The VISUM-based assignment results not only reveal the spatial distribution of micromobility demand and associated infrastructure requirements but also provide a quantitative basis for evaluating the environmental impacts of modal shifts. Specifically, the changes in vehicle-kilometers traveled (VKT) observed across the different scenarios constitute a key input for estimating transport-related carbon emissions. By capturing how private-vehicle travel is reduced and partially replaced by micromobility trips, the VISUM outputs enable a direct linkage between network-level traffic dynamics and emission outcomes. Building on these results, a CO₂ life-cycle emission analysis was conducted to quantify the potential environmental benefits associated with micromobility adoption, taking into account the reduced private-vehicle activity as well as the operational characteristics of micromobility modes. In this way, the traffic assignment results were translated into emission metrics, allowing the assessment of micromobility not only as a network efficiency measure but also as a strategy for mitigating transport-related carbon emissions.

5.3. Life-Cycle (LCA) Analyses

This study assesses the environmental impacts of shifting short-distance trips from private cars to micromobility using a comprehensive life-cycle assessment (LCA) framework. The analysis integrates behavioral changes observed through the user survey with vehicle-kilometers traveled (VKT) outputs from the transport demand model, allowing emissions to be evaluated at the system level.

Before estimating emissions, changes in the fuel type composition of private-vehicle users were examined, as life-cycle greenhouse gas (GHG) intensities differ substantially across vehicle technologies. Figure 9 illustrates the distribution of private-car users by fuel type in the current situation and after the expected modal shift toward micromobility. In the baseline scenario, the sample consists of 194 gasoline, 138 diesel, 98 LPG, 38 battery electric and 34 hybrid electric vehicle users. Following the modal shift, the most pronounced reductions are observed among gasoline (−22 users) and diesel vehicles (−15 users), which are also associated with the highest life-cycle emission intensities.

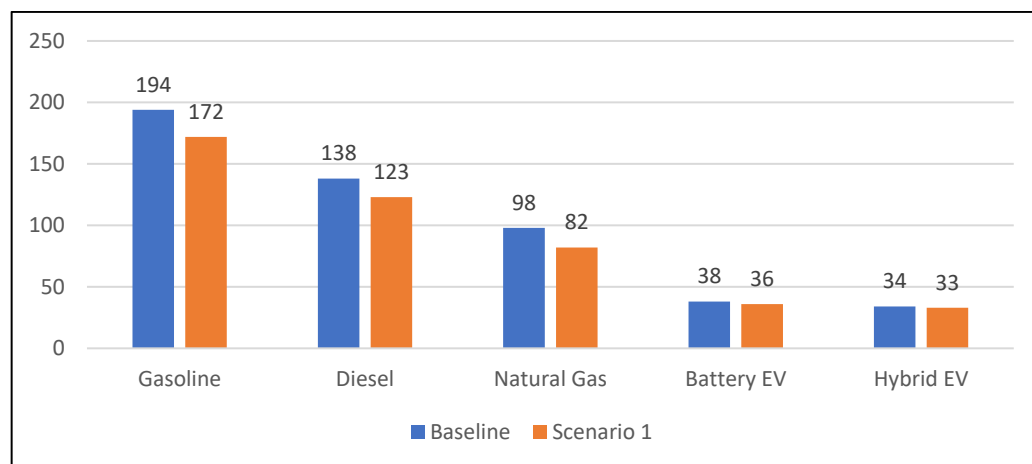


Figure 9. Changes in the distribution of private-vehicle fuel types following modal shift to micromobility.

This pattern is environmentally significant because gasoline and diesel vehicles dominate the private-car fleet and exhibit the largest per-kilometer life-cycle emissions. Although the proportional change in fleet composition remains relatively small, the concentration of modal shift among high-emitting vehicle types amplifies the emission reduction potential of micromobility adoption.

To quantify emissions, private-car VKT values were multiplied by fuel-type-specific life-cycle emission factors derived primarily from the 2025 ICCT [57] database, which includes vehicle manufacturing impacts for the European passenger car fleet. The emission intensities applied in the analysis are 235 gCO₂e/km for gasoline vehicles, 234 gCO₂e/km for diesel vehicles, 210 gCO₂e/km for LPG vehicles (based on literature values), 188 gCO₂e/km for hybrid electric vehicles and 63 gCO₂e/km for battery electric vehicles assuming the 2025 EU electricity mix.

Using the observed fleet composition from the survey, weighted average life-cycle emission factors were calculated for both the baseline and the modal-shift scenarios. The resulting average factor declines marginally from 216 gCO₂e/km in the baseline case to 215 gCO₂e/km after the shift, reflecting the small change in fuel type distribution. The emission calculation framework and its quantitative outcomes are detailed in Table 6.

Table 6. Summary of emission calculation steps.

Variable	Expression	Baseline (0)	Scenario (1)	Unit
Average car EF	EF_{avg}	216	215	gCO ₂ e/km
Car VKT	VKT_{car}	450,904	420,527	veh-km
Car emissions	$VKT_{car} \times EF_{avg}$	97.4	90.4	tCO ₂ e
Micromobility VKT	VKT_{micro}	-	25,140	veh-km
Micro EF	EF_{micro}	-	66	gCO ₂ e/km
Micromobility emissions	$VKT_{micro} \times EF_{micro}$	-	1.66	tCO ₂ e
Total emissions	$E_{car}^{(1)} + E_{micro}$	97.4	92.06	tCO ₂ e
Net reduction	$E^{(0)} - E_{new}$	-	5.34	tCO ₂ e

In the baseline scenario, total private-car travel amounts to 450,904 vehicle-kilometers per day, corresponding to 97.4 tCO₂e of life-cycle emissions. Following the modal shift, private-car VKT decreases to 420,527 km/day, resulting in 90.4 tCO₂e from private-car use.

The shifted trips generate 25,140 km/day of micromobility travel. The environmental impacts of micromobility are assessed using a full life-cycle perspective that includes vehicle and battery production, charging electricity, operational logistics, maintenance and redistribution activities, and end-of-life treatment. Based on a comprehensive life-cycle assessment of shared e-scooter systems across 100 European cities [53], an aggregated emission factor of 66 gCO₂e/km is applied, corresponding to 1.66 tCO₂e of daily micromobility-related emissions.

Accordingly, total system-wide life-cycle emissions after the modal shift amount to 92.06 tCO₂e per day. Compared with the baseline, this represents a net reduction of 5.34 tCO₂e, equivalent to approximately 5.5% of total life-cycle greenhouse gas emissions.

To evaluate the robustness of these findings, a one-way sensitivity analysis was conducted on the micromobility life-cycle emission factor while keeping network-derived VKT values constant. The emission factor was varied between 40 and 120 gCO₂e/km to reflect optimistic and conservative operational assumptions reported in the literature. Even under the most conservative scenario, total system emissions remain approximately 4% below baseline levels, whereas under more realistic assumptions (around 60 gCO₂e/km), the reduction approaches 6%.

Overall, the results indicate that the environmental benefits of micromobility adoption are driven primarily by reductions in private-car VKT rather than by structural changes in fleet composition. The concentration of modal substitution among gasoline and diesel

vehicle users further amplifies emission savings, suggesting that shifting short-distance trips (<10 km) to micromobility yields consistent and meaningful life-cycle GHG reductions, even when production, logistics and end-of-life impacts are fully considered.

Nevertheless, the environmental assessment remains conditional upon several modeling assumptions and selected emission factors. The coefficients applied for both private vehicles and micromobility modes were derived from widely cited secondary sources; however, real-world emission performance may vary depending on fleet composition, vehicle age distribution, electricity generation mix and operational intensity. In particular, micromobility life-cycle emissions may differ across manufacturing processes, battery lifetimes and charging logistics.

Moreover, the adopted system boundary primarily captures direct life-cycle emissions associated with vehicle usage and infrastructure demand, while excluding potential secondary effects such as rebound travel, induced demand, or broader modal spillovers. Accordingly, the reported reductions should be interpreted as scenario-based comparative estimates rather than precise environmental forecasts. Within the defined analytical framework and tested parameter ranges, however, the direction and magnitude of the environmental impact remain structurally consistent.

6. Conclusions and Recommendations

This study evaluated the potential of micromobility to substitute private-car use for short-distance trips in the Bornova district of Izmir by integrating behavioral survey analysis, macroscopic network modeling and life-cycle environmental assessment within a unified analytical framework.

The findings indicate that transition potential is primarily shaped by travel duration, employment status and perceived safety and infrastructure adequacy rather than gender differences, partially diverging from previous literature [20,25,26]. Consistent with studies emphasizing short-distance substitution potential [1,2], trips under 10 km represent the most realistic replacement range. Within this interval, empirically derived modal-shift rates suggest that a meaningful proportion of short-distance car demand can be reallocated under supportive spatial and operational conditions.

When incorporated into the PTV VISUM network model, these transition rates generate an approximately 7% reduction in private-vehicle kilometers traveled and a 5.5% decrease in total CO₂-equivalent emissions. Importantly, micromobility demand is spatially concentrated rather than uniformly distributed. Approximately 80.5 km of road segments exceed 100 veh/h in projected micromobility traffic, indicating that infrastructure requirements are corridor-specific. Accordingly, implementation strategies should prioritize high-demand corridors through phased and targeted investments rather than network-wide expansion.

In alignment with the Izmir Transportation Master Plan (UPI 2030), practical implementation pathways include: (i) development of physically separated micromobility lanes meeting geometric and safety standards; (ii) integration with metro stations and major transfer nodes to enhance first-last-mile connectivity; (iii) expansion of secure parking and docking infrastructure near universities, commercial centers and activity hubs; and (iv) complementary demand management measures, such as parking pricing adjustments to discourage short-distance car use. Such coordinated planning is essential to translate behavioral transition potential into measurable spatial and environmental outcomes.

From an environmental perspective, the life-cycle assessment indicates that emission reductions are primarily driven by decreased private-vehicle activity. However, the environmental performance of shared micromobility systems remains sensitive to operational conditions. Vehicle lifespan, redistribution logistics, charging strategies, electricity genera-

tion mix and maintenance efficiency substantially influence life-cycle emission intensities. Optimized fleet management and low-carbon electricity supply can significantly enhance environmental benefits, whereas inefficient turnover and frequent collection operations may offset potential gains. Therefore, the magnitude of emission reductions identified here should be interpreted as conditional upon sustainable system management.

Beyond environmental considerations, economic implications warrant attention. Reduced private-car dependency may lower household expenditures on fuel, maintenance and parking, while micromobility infrastructure deployment and system operation introduce public investment and maintenance costs. Future research should integrate cost benefit analysis and life-cycle economic evaluation to assess long-term financial feasibility at the district scale.

It is also important to distinguish between transition-oriented micromobility contexts and urban systems where micromobility constitutes a structurally dominant mode. In high-penetration environments, policy challenges extend beyond modal-shift promotion and include sidewalk obstruction, pedestrian conflicts, curb-space competition and traffic flow interactions. By contrast, the present study focuses on a car-oriented district where micromobility represents an emerging complement to short-distance private-car travel. Accordingly, the policy implications primarily address integration and scaling strategies rather than saturation-stage management challenges.

The empirical analysis is context-specific to Bornova, a district characterized by relatively gentle topography, mixed land-use patterns and strong public transport accessibility. Modal-shift parameters should therefore not be interpreted as universally transferable coefficients. Recent research highlights that micromobility demand determinants exhibit multi-scale spatial heterogeneity [50], suggesting that transition dynamics may vary across neighborhoods, districts and metropolitan contexts. Rather than proposing fixed generalizable shift rates, this study offers a transferable analytical framework that can be recalibrated through context-sensitive parameter adjustments and sensitivity analysis.

Finally, several methodological limitations should be acknowledged. The use of purposive non-probability sampling restricts strict statistical representativeness and limits external validity. Moreover, modal-shift rates are derived from stated intentions rather than revealed preference data, which may introduce intention–behavior discrepancies. Certain micro-scale spatial variables—such as slope intensity, intersection geometry and dynamic operational constraints—were not explicitly incorporated into the assignment model. Future research may strengthen robustness by employing probability-based sampling, revealed travel datasets, dynamic traffic assignment methods, slope-sensitive accessibility modeling and equity-oriented evaluation metrics.

In conclusion, the contribution of this research lies not in generalizing Bornova-specific outcomes to all urban contexts, but in demonstrating a replicable and policy-relevant modeling framework that integrates behavioral determinants, spatial infrastructure prioritization, environmental assessment and operational considerations. When strategically aligned with local transport master plans and supported by corridor-focused investment and efficient system management, micromobility can function as an effective complement to urban transport systems in reducing short-distance car dependency at the district scale.

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Data Availability Statement: Since the research includes a quantitative survey examining individuals' personal preferences and circumstances, participants have been informed in advance that the confidentiality of their data will be respected. In this context, we would like to state that the analysis results and findings can be sent and disclosed upon request. However, we prefer not to share the data publicly, as this is important for the confidentiality of the information.

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