

INVESTIGATING TRAVEL BEHAVIOR PATTERNS OF DIFFERENT
URBAN SUBREGIONS TO SUPPORT NEW ACTIVITY BASED MODEL
DEVELOPMENT

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DEVELOPMENT**

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ABSTRACT

INVESTIGATING TRAVEL BEHAVIOR PATTERNS OF DIFFERENT URBAN SUBREGIONS TO SUPPORT NEW ACTIVITY BASED MODEL DEVELOPMENT

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Transportation plays a vital role in shaping mobility patterns and access to opportunities in cities; it is important to forecast the travel patterns, when planning a city and its transportation infrastructure. Compared to traditional Four-Step travel demand forecasting, nowadays Activity-Based Model (ABM) approaches are preferred more, as they can better capture real travel behaviour (such as touring, activity scheduling, etc.). In case of data availability problems, a simplistic rule-ABM aims defining travel decisions (i.e. travel making, departure time, destination distance, travel time, etc.), obtained from a household travel survey (HHTS) results, used for trip/activity pattern generation. For large metropolitan areas, a main problem is definition of modelling region(s) for rule generation, as subregions can show different characteristics (i.e. share of commute trips, departure times, mode choices, etc.). This study investigates the need for developing subregion-specific ABM rules in a city, as an alternative to general rules. To test the hypothesis, three subregions from the northern corridor of İzmir Functional Urban Area (FUA) are selected to study as i) Karşıyaka Vicinity subregion with city characteristics, ii) a transitional region of Menemen District, and iii) remotely located mono-centric subregion of Aliğa District. The findings reveal significant differences by region,

especially in terms of departure times, trip lengths, mode preferences, and travel probabilities, which supports the need to develop ABM rules for different urban subregions to better represent the urban travel demand generation.

Keywords: Travel Demand Modelling, Activity Based Model, Trip Length, Trip Departure Time, Urban Commute Trips.



ÖZ

YENİ AKTİVİTE TABANLI MODEL GELİŞTİRMEYİ DESTEKLEMELİK İÇİN FARKLI KENTSEL ALT BÖLGELERİN SEYAHAT DAVRANIŞ ÖRÜNTÜLERİNİN İNCELENMESİ

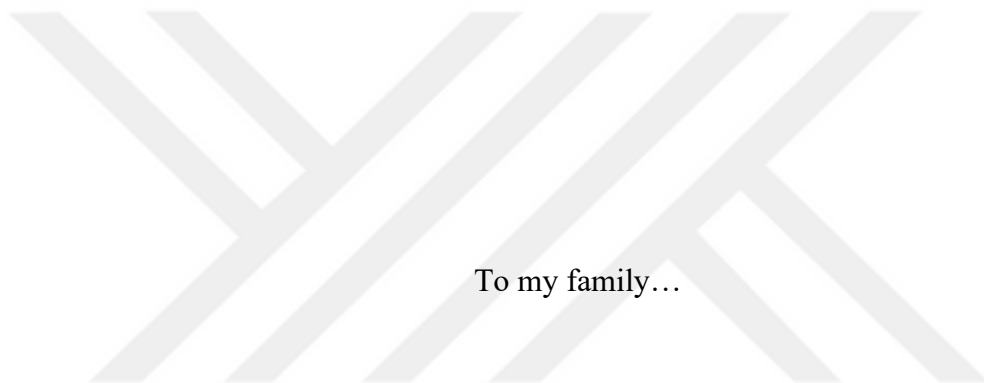
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Ulaşım, şehirlerdeki hareketlilik modellerini ve fırsatlara erişimi şekillendirmede hayati bir rol oynar; bir şehri ve ulaşım altyapısını planlarken seyahat modellerini tahmin etmek önemlidir. Geleneksel Dört Adımlı seyahat talebi tahminine kıyasla, günümüzde Aktivite Tabanlı Model (ABM) yaklaşımları daha çok tercih edilmektedir, çünkü gerçek seyahat davranışlarını (tur, aktivite planlama vb.) daha iyi yakalayabilmektedir. Veri kullanılabilirliği sorunları durumunda, basit bir kural-ABM, seyahat kararlarını (yani seyahat yapma, hareket saati, varış noktası mesafesi, seyahat süresi vb.) tanımlamayı amaçlar ve bu, seyahat/aktivite modeli oluşturmak için kullanılan bir hanehalkı seyahat anketi (HHTS) sonuçlarından elde edilir. Büyük metropol alanları için, ana sorun kural oluşturma için modelleme bölgesinin/bölgelerinin tanımlanmasıdır, çünkü alt bölgeler farklı özellikler gösterebilir (yani işe gidip gelme yolculuklarının payı, hareket saatleri, mod seçimleri vb.). Bu çalışma, genel kurallara alternatif olarak bir şehirde alt bölgeye özgü ABM kurallarının geliştirilmesi ihtiyacını araştırmaktadır. Hipotezi test etmek için, İzmir Fonksiyonel Kentsel Alanı'nın (FUA) kuzey koridorundan i) Kent

özelliklerine sahip Karşıyaka Civarı alt bölgesi, ii) geçiş bölgesi olan Menemen İlçesi ve iii) uzakta tek merkezli alt bölgesi olan Aliğa İlçesi'nin üzere üç alt bölge incelenmek üzere seçilmiştir. Bulgular, özellikle hareket saatleri, seyahat uzunlukları, mod tercihleri ve seyahat olasılıkları açısından bölgelere göre önemli farklılıklar ortaya koymaktadır ve bu da kentsel seyahat talebi üretimini daha iyi temsil etmek için farklı kentsel alt bölgeler için ABM kurallarının geliştirilmesi ihtiyacını desteklemektedir.

Anahtar Kelimeler: Seyahat Talebi Modelleme, Aktivite Tabanlı Model, Seyahat Uzunluğu, Seyahat Kalkış Saati, Şehir İçi Yolculuklar.



To my family...

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CHAPTER 1

INTRODUCTION

Transportation system is backbone of urban life, serving the need for many activities including daily routines, as well as many city-based services. It gives access to many amenities such as education, employment, healthcare, emergency medical care, and etc. Before any major transportation investment of planning the future of the city, it is necessary to forecast the relation between the travel demand and supply (the network) and perform a network assignment according to accepted assignment principles. This way, transportation engineers, urban planners and policymakers, can have a comprehensive understanding of current situations and assess the potential changes. By simulating the impacts of infrastructure investments, policy changes, and demographic changes, transportation models provide insights to guide long-term urban development. They help address pressing challenges such as congestion, accessibility, and sustainability, ensuring cities remain livable and functional in the face of growth and change. Using these models, cities can develop strategies that prioritize efficiency, equity, and resilience in their transportation networks.

The traditional four-step approach included separate mathematical representation of i) trip generation, ii) trip distribution, iii) mode choice and iv) traffic assignment problem. The first three steps heavily depend on household travel surveys (HHTS), a survey which addressed the trips of every person in a household. While the main focus was to capture the major dynamics in travel demand and the potential reflection in the traffic network, four step model is found to produce unrealistic models due to lack of transition between modelling steps, not capturing the true nature of integrated decision making (i.e. deciding the mode and destination of a trip) which led to more realistic and data driven models, such as Activity-Based Modeling (ABM).

1.1 Motivation

ABM has become increasingly preferred in recent years due to its ability to simulate individual-level travel behavior and capture daily activity patterns. However, the widespread implementation of ABM comes with significant data requirements. As in the traditional approach, ABM models also benefit from a HHTS data which is capable of capturing daily tours and activity recognition. The simplistic ABM approach can rely on a set of rules (hence called rule-based) describing the process of activity and trip generation, which are again driven from a HHTS. Such travel patterns should be derived directly from observed data and reflect the dimensions such as

- temporal distribution of trips (e.g., departure times, time-of-day variations)
- spatial characteristics of trips (e.g., trip lengths, regional destinations)
- mode choices depending on person type and region
- trip purposes across different socio-demographic groups
- probability of being a traveler based on person type and location

A critical question arises in the context of metropolitan regions such as İstanbul, Ankara and İzmir, where the urban sprawl spans over very large areas causing long commute trips (such longer than 30-45 minutes). If most jobs start at almost the same time (for example 8.30-9.00), long commute to city center or industrial may start earlier in the outskirts or the suburbs of the city than city neighborhoods. This raises the question of if a single, unified rule set could be applied across the entire metropolitan area, or should ABM rules be developed separately for geographically spread out subregions? How does the modal availability among these subregions affect the activity generation, as some regions may have rapid transit options (such as metro, light rail transit, etc.)? This is a fundamental methodological challenge. In large, heterogeneous urban areas where access to transport infrastructure, proximity to the city center, and socio-economic structures vary significantly across regions a one-size-fits-all rule set may fail to capture the true diversity of travel behavior.

1.2 Objective of the Thesis

This study aims to investigate how findings from a regional HHTS can be translated into behavioral rules for travel or activity-based modeling. More specifically, it addresses determining which travel patterns can be extracted from HHTS data and how these patterns can be effectively translated into rule-based structures for modeling daily travel behavior.

The main focus of the study is to examine whether a unified, city-wide rule framework is sufficient for large metropolitan areas or whether it is more appropriate to develop specific model versions tailored to the characteristics of geographically distinct sub-regions in a city. In this context, the study aims to test the validity and effectiveness of both approaches and to highlight the importance of incorporating spatial, socio-demographic and infrastructural diversity into rule-based travel demand modeling.

1.3 Scope of the Study

This study focuses on analyzing the distribution of trip generation, mode choice behavior, and traveler characteristics across three distinct urban contexts: the urban core, urban transition zones, and suburban areas. These categories represent various levels of density, accessibility, and transportation infrastructure that are expected to affect individual travel behavior in different ways. The analysis is based on data from the HHTS conducted in the Izmir metropolitan area. In this dataset, three representative study areas corresponding to one of the above-mentioned urban forms were selected for detailed examination.

With this approach, the study identifies and documents spatial and temporal differences in travel behavior across different urban typologies. These findings provide a basis for understanding how such differences can inform rule inference for activity-based modeling and ensure that region-specific travel patterns are accurately reflected in the model structure.

1.4 Layout of Thesis

This thesis is divided into six chapters to systematically address the research objectives. Following this introduction, Chapter 2 provides the literature review section, providing information on transportation models and travel demand forecasting approaches. As this thesis tests the proposed statements using data from İzmir Sustainable Urban Mobility Plan (SUMP), Chapter 3 provides a background on the project to support the proposed methodology presented in Chapter 4. Numerical results supporting the need for subregion-specific ABM rule development are presented in Chapter 5. The final conclusions and further recommendations are presented in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

2.1 Approaches in Travel Demand Modelling

History of transportation includes use various methods to estimate both current and forecast future demand. The traditional travel demand forecast model is the Four-step model, which simply divides the forecasting into four separate mathematical models. Over the years, ABM models have been developed to address the inherited problems of the Four-Step model, aiming to reach a more realism in the modeling and future predictions.

2.1.1 Traditional Four-Step Models

The Four-Step Model emerged in the 1950s as a fundamental methodology for modeling transportation demand, first implemented during the Chicago Area Transportation Study (CATS, 1962). It was developed to meet the growing need for systematic and comprehensive tools to assess transportation infrastructure projects in the context of postwar urbanization and economic expansion. This methodology provided a framework for estimating travel demand and analyzing the impacts of traffic flow, primarily focusing on improvements related to highways (McNally, 2000).

The main reason why it is called the Four-Step model is that the method used consists of 4 different steps, which are called;

- Trip generation,
- Trip Distribution,

- Mode Choice,
- Network Assignment.

Figure 2.1. shows the general framework for the four step transport models.

The trip generation stage generates trips for each TAZ to both origin and destination. Trips produced for origin are called production, while trips produced for destination are called attraction. In the Trip Distribution stage, Origin-Destination (O-D) matrices are created by distributing the trips produced in the previous step. The mode selection stage is a step used to decide which transportation mode the generated and distributed trips will be used with. In this step, the mode of each trip is assigned. For example, while a private vehicle preference is selected for a trip from zone A to zone B, public transportation can be selected for another trip. The network assignment stage is the process of reflecting the current situation of the TAZs of the city where the model study is conducted, the road network and the create O-D matrices. Demand matrices are assigned to the network according to the transportation mode they have, and thus the private vehicle volume in the network is estimated for each road.

A trip is described as a single journey that an individual undertakes from a starting point to a destination for a particular reason. For instance, commuting from home to work is an example of a trip. Trips can typically be classified by their purpose, which includes:

- Home-Based Work (HBW): Trips from home to the workplace.
- Home-Based Other (HBO): Trips from home to destinations that are not work-related (e.g., shopping, leisure).
- Non-Home-Based (NHB): Trips where neither the origin nor the destination is home.

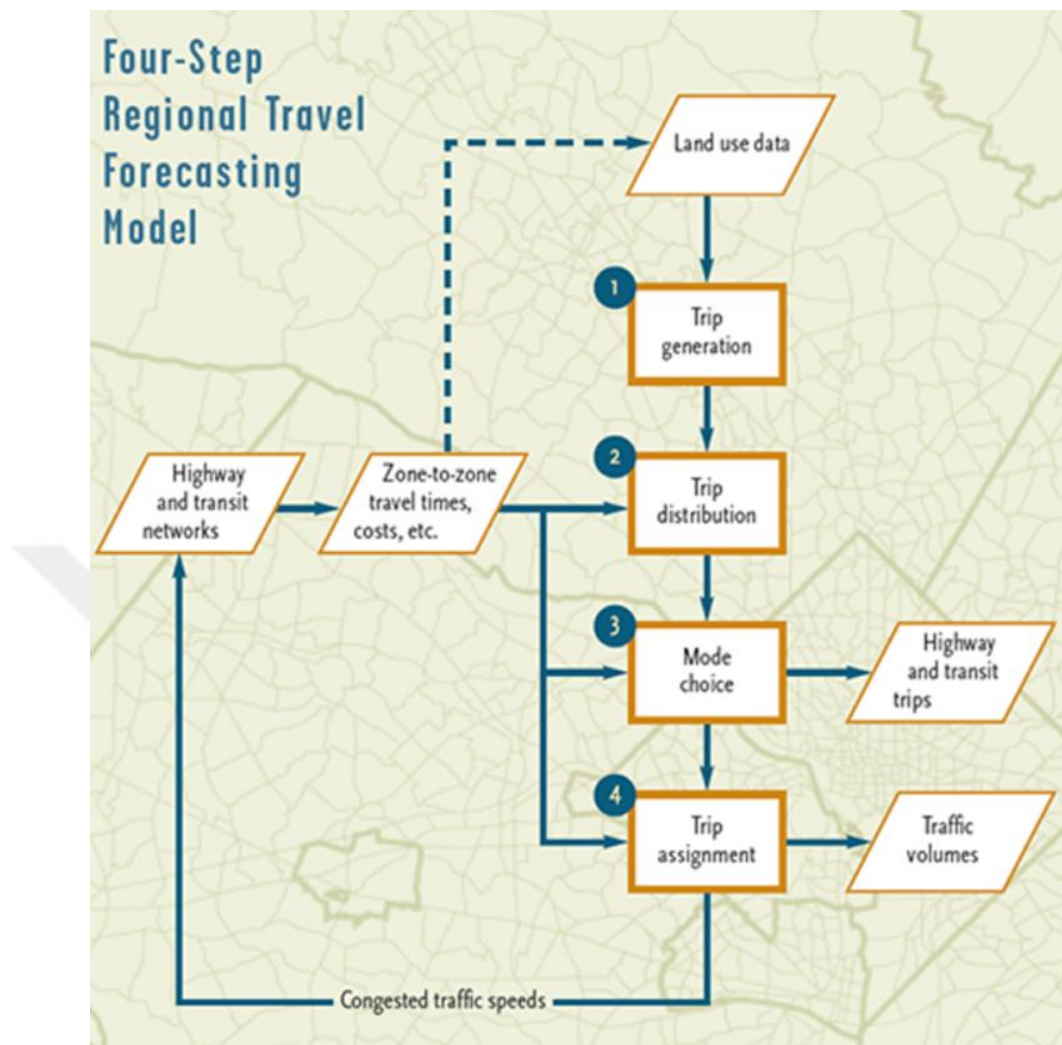


Figure 2.1. Four-Step Modelling Framework (Chicago Area Transportation Study (CATS, 1962))

In the 1960s, the model was institutionalized through federal legislation that mandated urban transportation planning to be “continuous, comprehensive, and collaborative,” thereby embedding the Four-Step Model within policy structures. Over the following decades, its applicability expanded to include multimodal planning and environmental considerations, although its limitations in addressing complex policy scenarios and intricate infrastructure management issues became apparent. As a result, iterative enhancements to the model introduced methods for

discrete demand estimation and balance assignment to improve its analytical capabilities. The evolution of the Four-Step Model demonstrates the responsiveness of transportation analysis to changing societal needs while tackling challenges related to data, institutional contexts, and computational abilities. Its widespread adoption underscores its crucial role in shaping contemporary practices in transportation planning (McNally, 2000).

2.1.2 Activity-Based Modelling Approach

In conventional travel-based frameworks, such as the Four-Step Model, each trip is regarded as a separate unit for analysis, often neglecting the larger context of the traveler's activities or sequences of trips. A tour consists of a series of interconnected trips that commence and conclude at the same location, usually the traveler's residence or workplace. Tours offer a more comprehensive view of travel behavior, incorporating all activities and stops undertaken during an entire trip. For example:

- A tour that starts at home, travels to the workplace, makes a stop at a grocery store, and returns home is classified as a home-based tour.
- Likewise, a tour that begins and ends at the workplace, with visits to a meeting site and a restaurant in between, is identified as a work-based tour.
- Tours play an essential role in activity-based models that highlight the links between activities and travel choices, providing a more realistic and behaviorally consistent method for understanding travel behaviors.

By focusing on tours instead of individual trips, researchers can more effectively capture the intricate connections between travel decisions, activity timelines, and spatial interactions. ABM Approaches in the World.

The ABM is structured around daily travel "tours" for individuals and incorporates sophisticated modeling techniques for time-of-day choices, travel modes, and activity locations. The model classifies the population into distinct person types (e.g., full-time workers, part-time workers, students) and takes into account intra-

household interactions that influence joint travel decisions and car-sharing behaviors. Notably, this ABM is designed to support policy analysis on various fronts, including the assessment of high-occupancy toll (HOT) lanes, changes in transit accessibility, and the emergence of mobility services such as ride-sharing. The activity-based approach enables the model to capture complex behavioral dynamics, including shifts in travel times in response to congestion, as well as the evaluation of non-motorized travel options (e.g., walking and biking) alongside traditional motorized modes. (See Figure 2.2)

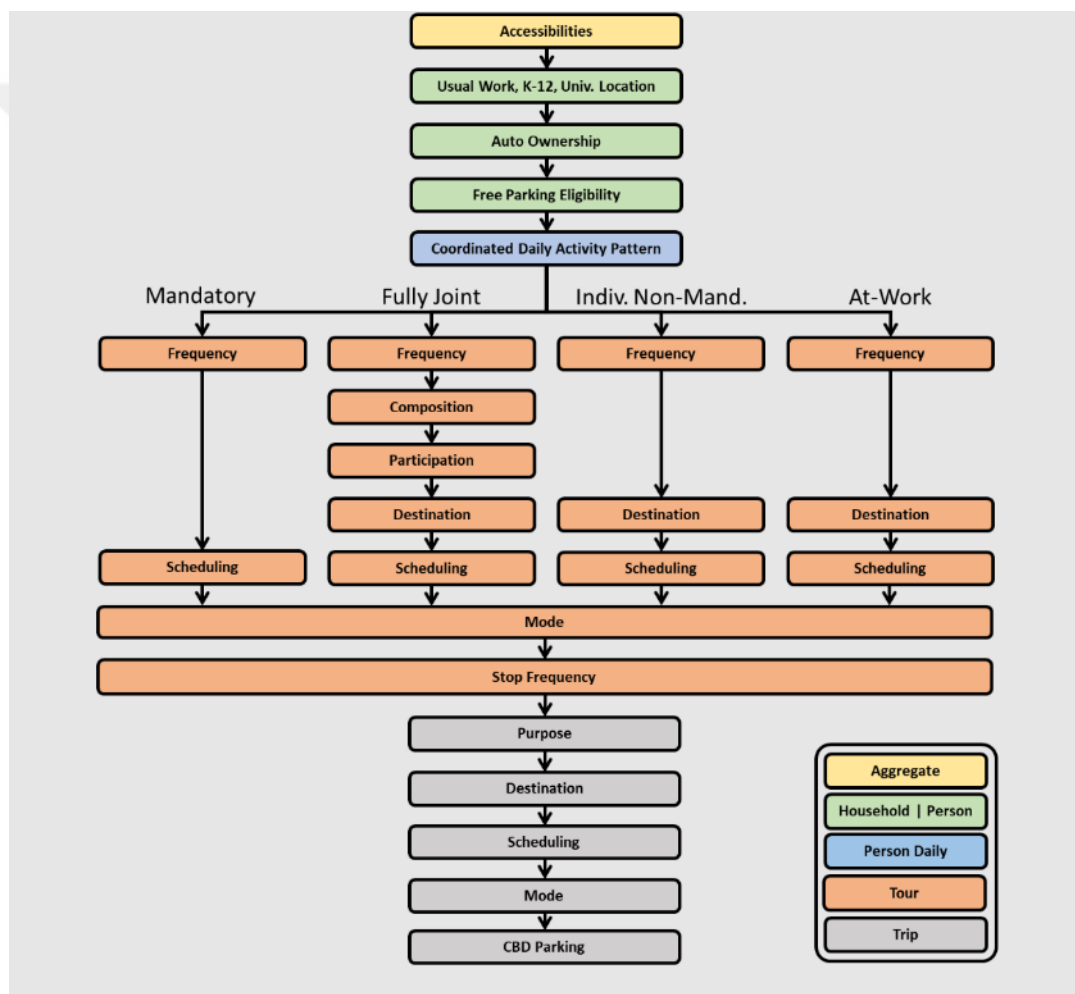


Figure 2.2. Gen3 Model Design Plan (RSG, 2020)

2.2 ABM Experience in Travel Demand Modeling

In the development of the Metropolitan Washington Council of Governments (MWCOG) Generation 3 Model Design Plan (Resource System Group (RSG), 2020), the team synthesized a comprehensive population dataset utilizing census and survey data. This process involved the creation of virtual households and individuals characterized by attributes such as age, employment status, income, and vehicle ownership. The establishment of this synthetic population is fundamental for an ABM, as it facilitates realistic simulations of daily activities and travel behaviors. The team employed the ActivitySim platform, an open-source framework specifically designed for regional and state-level activity-based modeling. Additionally, the development of the synthetic population was carefully aligned with regional demographic distributions to accurately represent the diverse socio-demographic factors influencing travel patterns within the metropolitan area.

The accomplishments of the team with the Generation 3 model include the creation of a highly detailed simulation of travel demand, capable of addressing intricate policy questions and planning scenarios. Validation processes were conducted by comparing model outputs, such as mode choice and trip distribution, against observed data from regional travel surveys and traffic counts. The model demonstrated sensitivity to variables like peak-period congestion and transit crowding, thereby providing valuable insights into its effectiveness in representing real-world behaviors. Furthermore, the validation of time-of-day choices ensured that the model accurately simulates both peak and off-peak travel patterns, which is a critical component for evaluating the impacts of time-based travel policies.

The SIMBA MOBi model, developed by the Swiss Federal Railways (SBB) as presented in Scherr et al. (2019), delineates the construction of a synthetic population integrated within an ABM framework aimed at forecasting travel demand across Switzerland. This research, presented at the European Association for Research in Transportation (hEART) 2019 conference, underscores the critical role of comprehensive socio-demographic and travel behavior data in formulating detailed,

individual-based travel models. The synergy of synthetic population generation and ABM methodology facilitates an intricate representation of individual travel decisions and constraints, thereby addressing the limitations inherent in traditional, aggregated travel demand models (Scherr et al., 2019). The synthetic population encompassed in the SIMBA MOBi model represents the entire residential population of Switzerland, with each individual characterized as an agent possessing attributes such as age, employment status, and car ownership. This synthetic population framework is intentionally designed to reflect the diversity of traveler behaviors across various contexts, including urban, rural, and intercity environments. Key destinations such as workplaces and educational institutions are allocated to individuals based on their specific characteristics, while the frequency and nature of daily activities are generated using discrete-choice models that replicate actual socio-demographic trends (Scherr et al., 2019). This approach builds upon prior advancements in ABM research, integrating established concepts such as time budgets and activity preferences as articulated by Bowman and Ben-Akiva (2001) and Castiglione et al. (2015).

The activity-based travel demand segment, referred to as MOBi.plans (See Figure 2.3 and Figure 2.4), systematically forecasts travel intentions for each agent by aligning personal preferences with inherent constraints. Preferences, including choices concerning travel modes and destinations, are encapsulated within discrete-choice frameworks, while constraints such as time budgets ensure a pragmatic scheduling of activities. The model delineates daily travel behaviors as organized sequences of tours, incorporating primary activities (e.g., work and education) alongside secondary stops (e.g., shopping and leisure). Accordingly, the ABM effectively captures the interaction between travel decisions and activity schedules, allowing for adjustments in travel modes and timing in response to prevailing network conditions (Scherr et al., 2019).

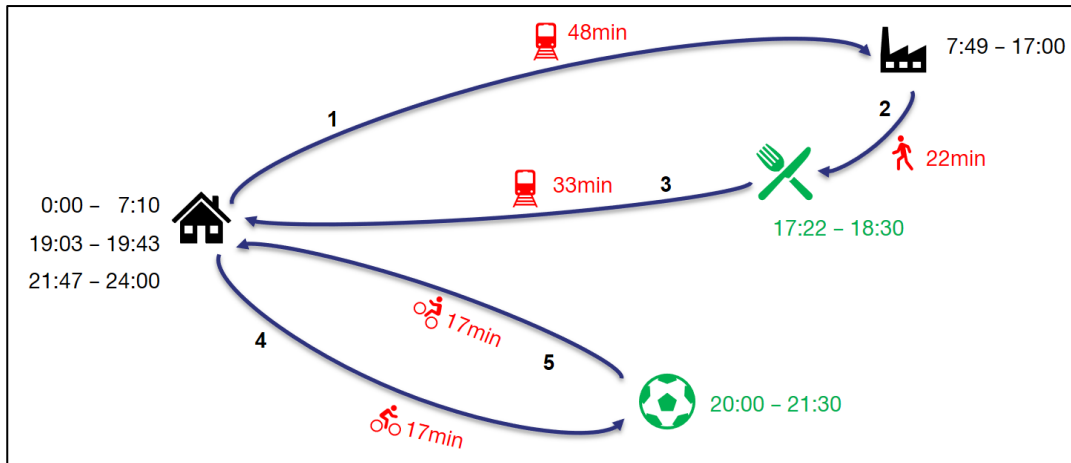


Figure 2.3. Example of a Full day Plan (Scherr et al., 2019)

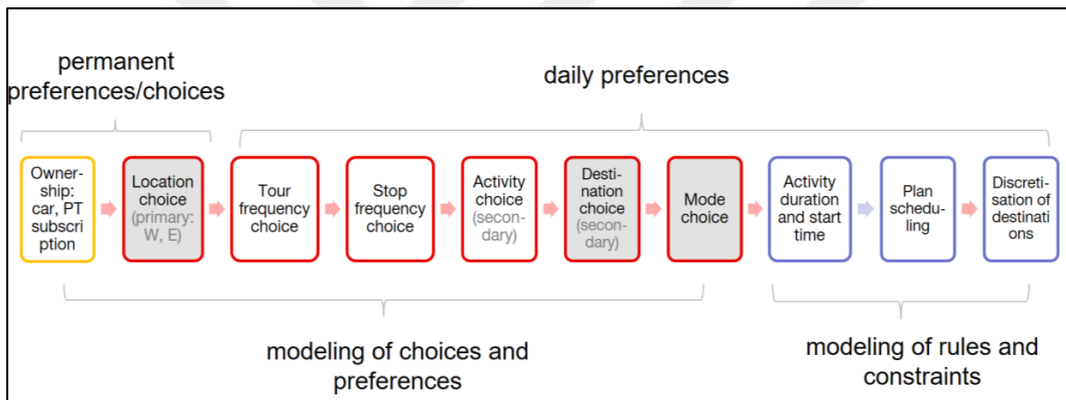


Figure 2.4. Mobi.plans Model Steps (Scherr et al., 2019)

2.2.1 Occurrence and Types of Activity-Based Models

The conceptual foundations of activity-based travel modeling were laid in the late 1980s and early 1990s, when researchers sought to overcome the behavioral shortcomings of trip-based models. One of the seminal early works by Jones, Koppelman, and Orfeuil (1990) outlined the "state of the art and future directions" for activity-based approaches, advocating a focus on entire activity patterns rather

than individual trips. Around the same time, Axhausen and Gärling (1992) provided a comprehensive review of conceptual frameworks and models for activity-based analysis, solidifying the theoretical justification for treating travel as a derived demand and identifying research challenges for implementing such models. These and other early contributions (e.g., Pas, 1985; Kitamura, 1988) established the origin of ABMs as a response to policy needs (e.g., the 1990 Clean Air Act in the United States) that required more behaviorally realistic forecasts. By the mid-1990s, the first prototype models began to emerge. In particular, Bowman and Ben-Akiva developed an integrated activity-based model system that uses nested discrete choice structures to estimate an individual's entire daily activity schedule. Their framework, first presented in 1995 and later published in 2001, showed that it is possible to model complex daily activity-travel patterns within a utility-maximizing paradigm (i.e., treating each possible daily schedule as an alternative in a choice set). This utility-based ABM approach uses econometric discrete choice models to capture activity participation and travel preferences, assuming that individuals choose the schedule that maximizes their overall utility for the day.

In parallel, another school of thought pursued rule-based ABMs, also known as computational process models. Drawing on theories of bounded rationality and decision heuristics, these models assumed that people construct activity schedules by following a set of decision rules or constraints rather than comparing the utility of all possible schedules. Rule-based ABMs typically use sequential decision making; for example, scheduling mandatory activities (work, school) first, then adding flexible activities (shopping, entertainment) to the remaining time slots subject to temporal, spatial, and household constraints. Early examples of this approach include the work of Vause (1997), who proposed a rule-based model of activity planning behavior, and the research of Kitamura and colleagues. In the late 1990s, Kitamura's team developed an Activity Mobility Simulator (AMOS) that included a rule-based algorithm to adjust individuals' activity travel patterns in response to policies. In AMOS, instead of choosing an optimal schedule, the model reads a person's observed baseline schedule and applies decision rules to determine

reasonable changes (e.g., travel schedule changes or activity substitutions) under new conditions. This reflects the assumption of “satisficing” behavior of travelers are assumed to find the first satisfactory solution that meets their needs and constraints rather than optimizing globally. The researchers argued that this process-oriented paradigm can better mimic real-world human decision-making, which often relies on heuristics when faced with complex schedule choices.

In the early 2000s, activity-based modeling was divided into two main methodological types: utility-maximizing (econometric) models and rule-based (process-oriented) models. Utility-based models (e.g., the framework of Bowman and Ben-Akiva, later embodied in systems such as CEMDAP and CT-RAMP) use statistical estimation and the principle of utility optimization to predict activity participation, timing, mode, and location choices. Figure 2.5 shows the framework of the model. In contrast, rule-based models (e.g., ALBATROSS) use decision trees or if-then rules derived from data to simulate how people construct daily activity plans without assuming global optima. Both approaches use microsimulation of individual agents, but their decision logics are fundamentally different.

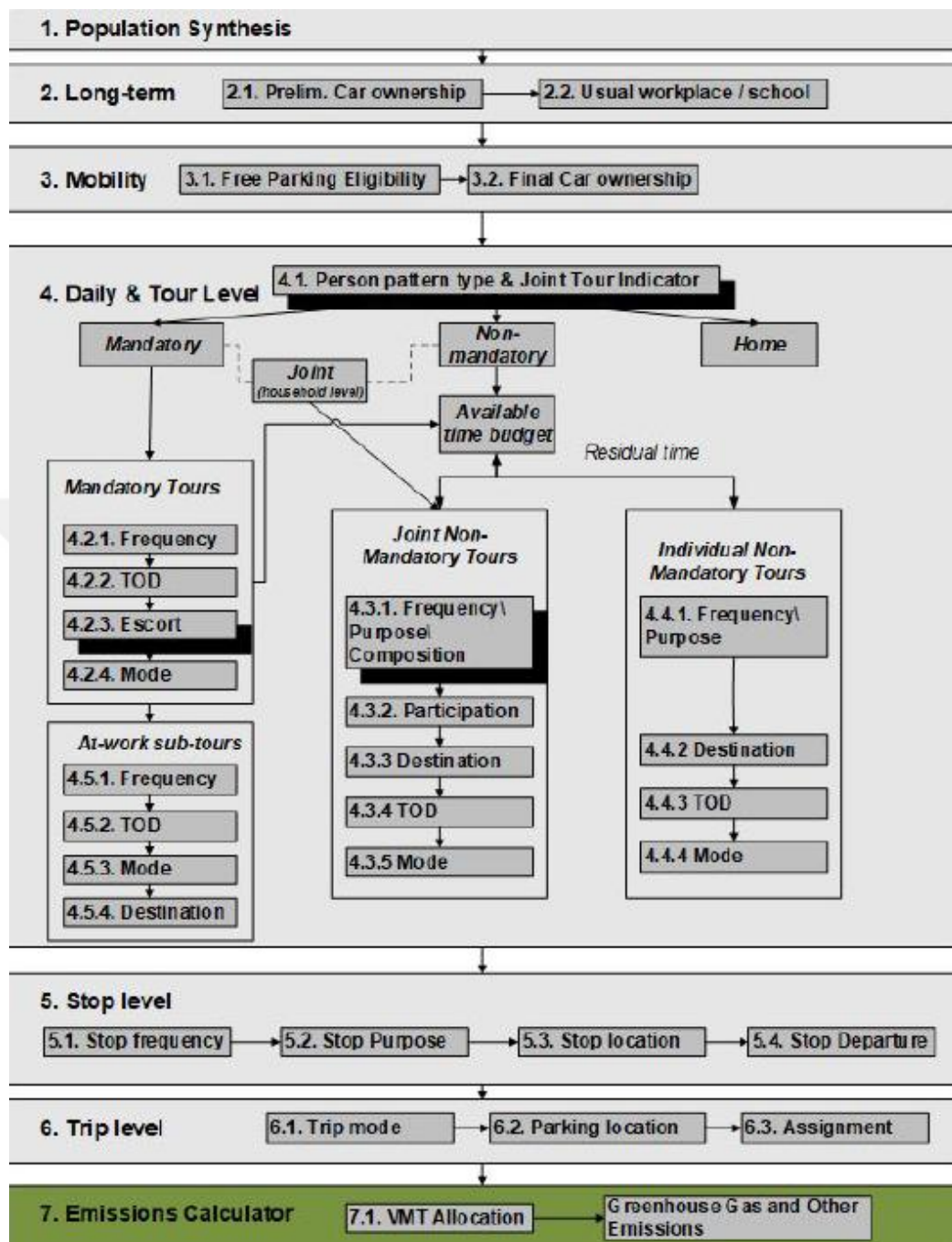


Figure 2.5. CT-RAMP Model Framework (Bowman and Akiva, 2000)

2.2.2 Applications of Rule-Based ABMs

Rule-based ABM approaches have been applied (and studied) in a number of countries, each time adapted to local data and planning questions. In Europe, outside the Netherlands and Belgium, there were research applications in the United Kingdom and elsewhere that made use of similar principles. The ALBATROSS model itself was referenced or partially adapted for research purposes in the United Kingdom and Germany and influenced later European Union projects. It focused on activity planning and time use. An important extension was the integration of environmental impacts: Arentze et al. showed that combining ALBATROSS with emission models (the AURORA air quality model) allowed hour-by-hour pollution estimates, highlighting the breadth of analysis provided by ABMs. In the Figure 2.6, framework of the ALBATROSS is given.

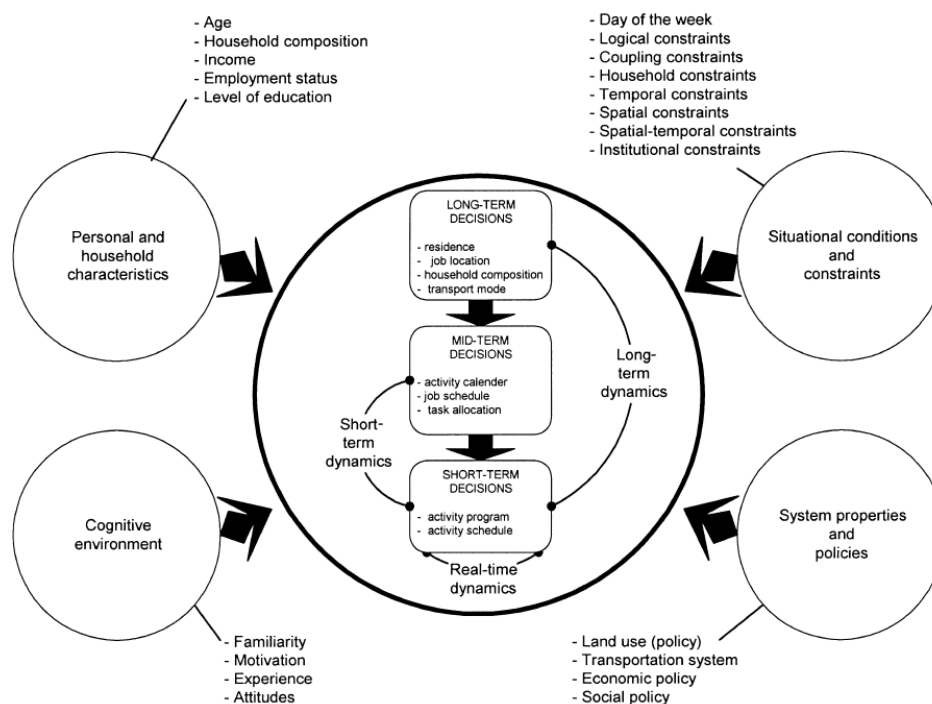


Figure 2.6. Conceptual Framework for ALBATROSS (Arentze et al, 2000)

In North America, many metropolitan planning organizations (MPOs) switched to activity-based models in the 2000s, but these applications (e.g. New York, Los Angeles, Dallas, Atlanta) mostly used utility-based frameworks. An exception is the Toronto model TASHA, which explicitly adopts a rule-based, computational process approach to household planning. The development and subsequent validation of TASHA (See Figure 2.7, to see the class structure) provided a proof of concept that rule-based ABM could work with travel diary data (which is less detailed than multiweek time-use surveys in Europe) found in typical North American cities. It showed that even with simpler data, intuitive scheduling rules (for example, a rule that ensures all household members eventually reunite at home at the end of the day or a rule that limits overlapping use of the family car) could be calibrated to fit observed travel patterns. This was an important step in convincing practitioners of the practicality of rule-based models.

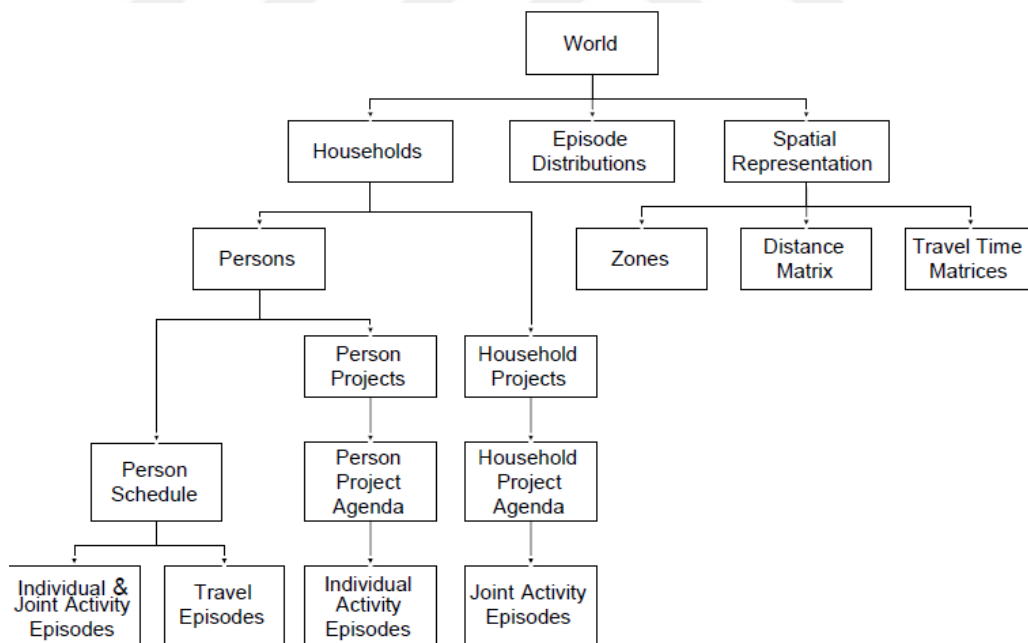


Figure 2.7. Object-oriented class structure (Miller and Roorda, 2003)

In Asia and emerging economies, the adoption of full-fledged ABMs has been slower, mainly due to data and resource constraints. However, the need for behaviorally robust models is perhaps more urgent in these contexts due to the high variability in travel behavior and rapid changes in transportation provision. Researchers in Japan were among the pioneers: Ryuichi Kitamura's work on station location and dynamic activity-travel modeling in the 1990s contributed to the ideas of rule-based simulation (the PCATS mentioned above was tested in Japanese cities). More recently, interest in ABMs has increased for megacities such as Beijing, Mumbai, and Jakarta.

For example, in India, Nayak and Pandit (2022) conducted a comprehensive review and concluded that ABMs are necessary to address the "population heterogeneity, multiple modes, mixed land-use environment, and changing traffic conditions" characteristic of Indian cities, where four-step models struggle. Although they note that very few operational ABMs are currently in use in India, they recommend the gradual development of an activity-based framework, starting with potentially simpler rule-based components to ensure applicability with limited local survey data. This reflects a sensible strategy for data-scarce regions: rule-based models can sometimes be easier to implement initially because they can draw directly from expert knowledge and observed patterns, whereas utility-based models require extensive estimation of many parameters. Indeed, one of the practical appeals of rule-based ABM is its relative transparency and interpretability model developers and stakeholders can understand the decision rules and thus have confidence in the model's responses to new scenarios. In the Figure 2.8, India rule-based-ABM framework is given.

as extensions of the rule-based philosophy, as they do not assume global optima but instead build solutions step by step. At the same time, advanced data-driven methods (such as deep learning) are being attempted to generate activity plans, but these often require large datasets and can act as “black boxes.” In this context, rule-based ABMs still offer a valuable balance between behavioral insight and computational tractability. They allow modelers to code qualitative insights (e.g., “people usually don’t go shopping at 3 a.m.”) directly into the model. This can be particularly useful when extrapolating beyond observed data, for example, when simulating the impact of entirely new policies or technologies (autonomous vehicles, radical work-from-home scenarios, etc.), where human behavior may not follow historical utility tradeoffs but may be driven by new norms or rules. In the Figure 2.9, input and output requirements are given for rule-based ABM.

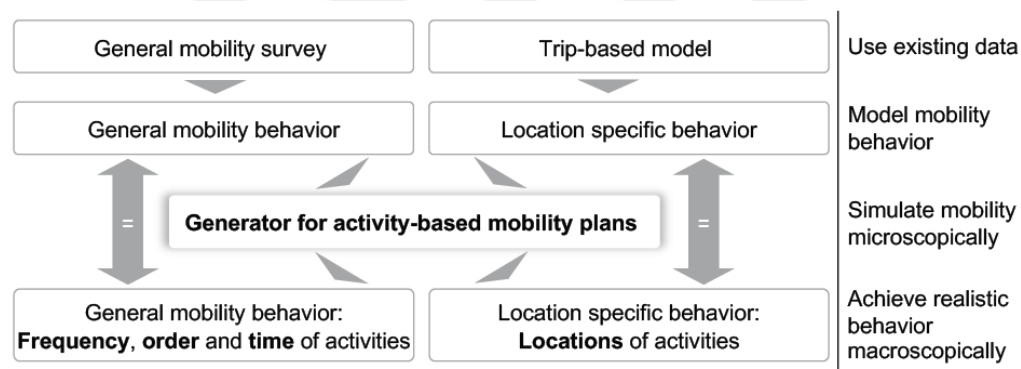


Figure 2.9. Overview of input and output requirements on methodology. (Adenaw and Bachmeier, 2022)

In summary, rule-based activity-based models have established themselves as a fundamental approach in the travel demand modeling literature. They emerged from a need to better represent realistic travel behavior and have evolved through a global dialogue from early conceptual work in the United States and Europe, to operational models in Europe and North America, and now to increasing interest in Asia and other regions. Methodologically, they complement the focus of utility-based models on preferences and trade-offs by emphasizing the importance of decision processes

and constraints in travel modeling. Many modern ABM systems blend elements of both, taking advantage of the strengths of both: the theoretical rigor of discrete choice and the behavioral richness of rule-based simulation. As data availability and computational power continue to increase, we can expect future ABMs to become even more detailed and dynamic, potentially incorporating real-time data and adapting rules through learning algorithms. However, the fundamental contributions of rule-based models, their focus on activities, constraints, and realistic decision-making methods, will continue to be highly relevant in ensuring that travel forecasts are consistent with how people organize their daily lives.

2.2.4 Population Synthesis

Synthetic populations serve as essential components for activity-based models, particularly within agent-based frameworks where individual-level data is imperative. Traditional four-step modeling approaches, frequently employed in transportation planning, do not furnish the level of detailed representation required to accurately simulate the interactions among diverse travel behaviors and multimodal transport services. Conversely, ABMs provide this granularity by capturing individual-level activity patterns, travel behaviors, and socio-demographic characteristics (Balac & Hörl, 2021). Consequently, ABMs derive significant advantages from synthetic populations, which facilitate a comprehensive analysis of dynamic interactions and emergent mobility behaviors, such as car-sharing and multi-modal transit solutions. A more detailed discussion of population synthesis is given in Appendix A.

2.3 Comparison of Traditional and ABM Approaches

Traditional travel demand models have long been trip-based and use a four-step process: trip generation, trip distribution, mode selection, and route assignment. In trip-based models, travel is modeled at the level of individual trips, often aggregated

by region, without explicitly linking trips made by the same person or household. This approach treats each trip independently and does not capture the ordering or dependencies of trips. As a result, important behavioral aspects, such as how multiple stops are organized into a single tour or how one trip may affect another, are ignored. For example, a trip-based model cannot easily distinguish between a one-stop trip from home and a multi-stop trip (tour) that involves additional work. This limitation has led to the recognition of behavioral inconsistencies in trip-based methods, motivating the development of improved frameworks.

Tour-based models emerged as an intermediate step that grouped trips into tours (closed sequences of trips that begin and end at home or work). By treating the entire tour as the unit of analysis, these models consider connections within a tour, such as mode coherence and purpose sequencing. For example, early tour-based formulations introduced models for stop generation and tour formation (e.g., Wen and Koppelman, 1999) and applied sophisticated discrete choice structures to capture mode choice within a tour (e.g., the cross-nested logit by Vovsha, 1997). Tour-based approaches have made significant progress by recognizing that trips are often interrelated parts of a larger activity pattern (trip chain). However, they still fall short of modeling a person's entire activity and travel day in an integrated manner.

This realization paved the way for ABMs, which represents a paradigm shift in travel demand modeling. ABMs view travel as derived demand from people's needs to participate in activities across locations. Instead of predicting travel in isolation, ABMs simulate daily activity schedules for individuals, detailing which activities are performed at what times, for how long, where, and with whom, and the travel required to facilitate those activities. The underlying assumption is that travel behavior is best understood in the context of activity participation; thus, the focus is on sequences of activities (and associated travel) over a full day or longer. Compared to travel-based models, ABMs operate at a much finer level of detail: they typically use a synthetic population of individual travelers and households, preserving heterogeneity and allowing for behavioral rules at the person level.

This higher level of detail allows analysts to examine complex policies (for example, pricing, land-use changes, or remote work) by seeing how individuals might reorganize their activities, rather than simply changing one-time decisions. In summary, ABMs offer richer behavioral realism by addressing many limitations of four-step models by taking into account activity-travel interdependencies and constraints across the day.

From Trip to Activities in Travel Demand Modelling

As the field of travel demand modeling shifted toward an activity focus in the 1990s, researchers explored different formalisms to represent individuals' planning behavior. The rule-based approach emerged from the idea that human decision-making in organizing daily activities is often driven by simplified heuristics and constraints rather than strict utility maximization. In daily travel, people tend to follow habitual patterns and “satisfy” that is, they choose an option that is good enough rather than exhaustively searching for the absolute best schedule. Rule-based ABMs explicitly embrace this idea. They model the activity planning decision process as a set of conditional rules, much like an expert system, and reflect how a person might go about planning their day. For example, a rule-based ABM might start by scheduling mandatory activities (work, school) in fixed time intervals, then allocate the remaining time to maintenance activities (errands, appointments), and finally to discretionary activities (social or leisure). Figure 2.10 shows the trip to activity transformation framework. This prioritization mimics common-sense behavior. Each decision (whether to include an activity, which type, when, where, etc.) is guided by rules derived from observed patterns in the survey data. These rules can be learned using algorithms (e.g. decision tree induction as in ALBATROSS) or formulated from domain knowledge. Most importantly, the model respects the feasibility constraints at each step: time window availability, spatial proximity, opening times of destinations, and travel time budgets. Structurally, a rule-based model generates daily activity-travel schedules that are internally consistent and

feasible across time and space, without requiring an individual to compare every possible combination of activities.

One of the oldest and most comprehensive rule-based ABMs is ALBATROSS, developed by Arentze and Timmermans in the Netherlands in 2000. ALBATROSS uses a library of decision trees to represent choice heuristics for a set of sub-decisions in an activity schedule (whether to run an activity, what type, when to start, how long to last, mode of travel, etc.). These decision trees are derived from detailed activity log data using the CHAID algorithm, effectively inferring if-then rules that replicate the observed behavior. For example, one rule might be: “IF an employee with small children, THEN add a trip from home to daycare before going to work.” Another might determine the timing of a shopping trip based on available time slots between work and picking up the child. During the simulation, ALBATROSS classifies each synthetic individual (with certain attributes) via decision trees to stochastically generate an activity schedule that satisfies all constraints. This rule-based mechanism was shown to reproduce the observed patterns with a high degree of realism and, more importantly, provided a transparent behavioral explanation for each simulated decision (through the logic of the rules). The success of ALBATROSS in the Dutch context (used to test transportation policies for the Dutch Ministry of Transport) demonstrated that rule-based ABM is a feasible and powerful approach.

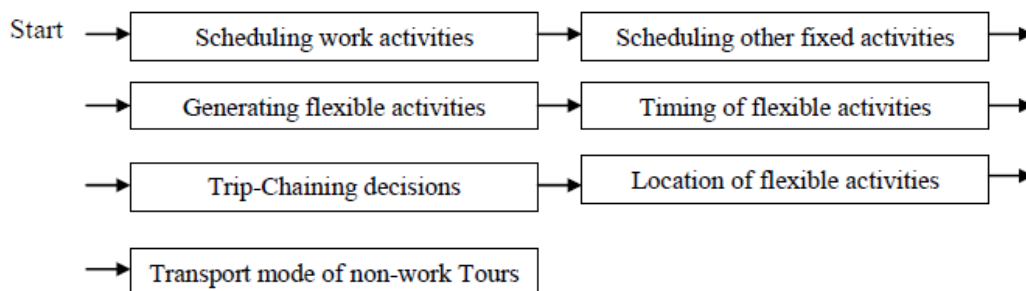


Figure 2.10. Main steps in the Transforming from Trip to Activities (Hofman, Mourik & Timmermans, 2000)

The rule-based philosophy was later adopted and extended in other contexts. In Belgium, the FEATHERS framework was created as a direct evolution of ALBATROSS for Flanders. FEATHERS retained the core rule-based planning engine but added capabilities for policy scenario analysis and later dynamic replanning (to account for daily learning and long-term adjustments). Rule-based models have also influenced hybrid approaches – for example, the Florida Activity Mobility Simulator (FAMOS) combined a rule-based component (the Prism Constrained Activity Travel Simulator, PCATS) with advanced population synthesis and network simulation. Originally developed by Kitamura and co-authors, PCATS uses time-space prisms to establish rules for which activity sequences are achievable given time constraints and transportation network conditions. Pendyala et al. By calibrating such a model for Florida (2005), they were able to show that even in a complex multimodal urban area, a rule-based framework can realistically predict travel behavior and respond to policy changes (such as adding public transit service or telecommuting incentives). These applications highlight a key strength of rule-based ABMs: their rich policy sensitivity. Because the models explicitly account for how people allocate time and adjust activities, they can capture the effects of policies that affect planning (such as congestion pricing that causes people to leave earlier or later, or land-use changes that create new activity opportunities) in more behavioral detail than travel-based models.

CHAPTER 3

OVERVIEW OF İZMİR HOUSEHOLD TRAVEL SURVEY (HHTS)

İzmir HHTS was conducted as a part of İzmir Sustainable Urban Mobility Plan (SUMP) project, which included development of an ABM travel demand model for the Functional Urban Area (FUA) region, which was also defined within the project scope. Due to limited budget and time of the project, the HHTS was conducted for at different sampling rates for different FUA level regions. A rule-based ABM was developed which also required population synthesis using the available sociodemographic data, while developing the daily origin-destination (O-D) matrices

3.1 SUMP İzmir Functional Urban Area (FUA) Zoning

Functional Urban Area (FUA)

The FUA zoning was established to describe the project study area, which was determined through a hierarchical leveling approach, starting from the city center and extending towards the periphery, while also incorporating the İZBAN (İzmir suburban) railway line as a key factor. For instance, central districts such as Karşıyaka were classified as FUA Level 1, whereas peripheral regions like Bayındır and Kiraz were categorized into subsequent levels, namely FUA Levels 2, 3, and 4, based on their relative location and functional characteristics (see Figure 3.1.).

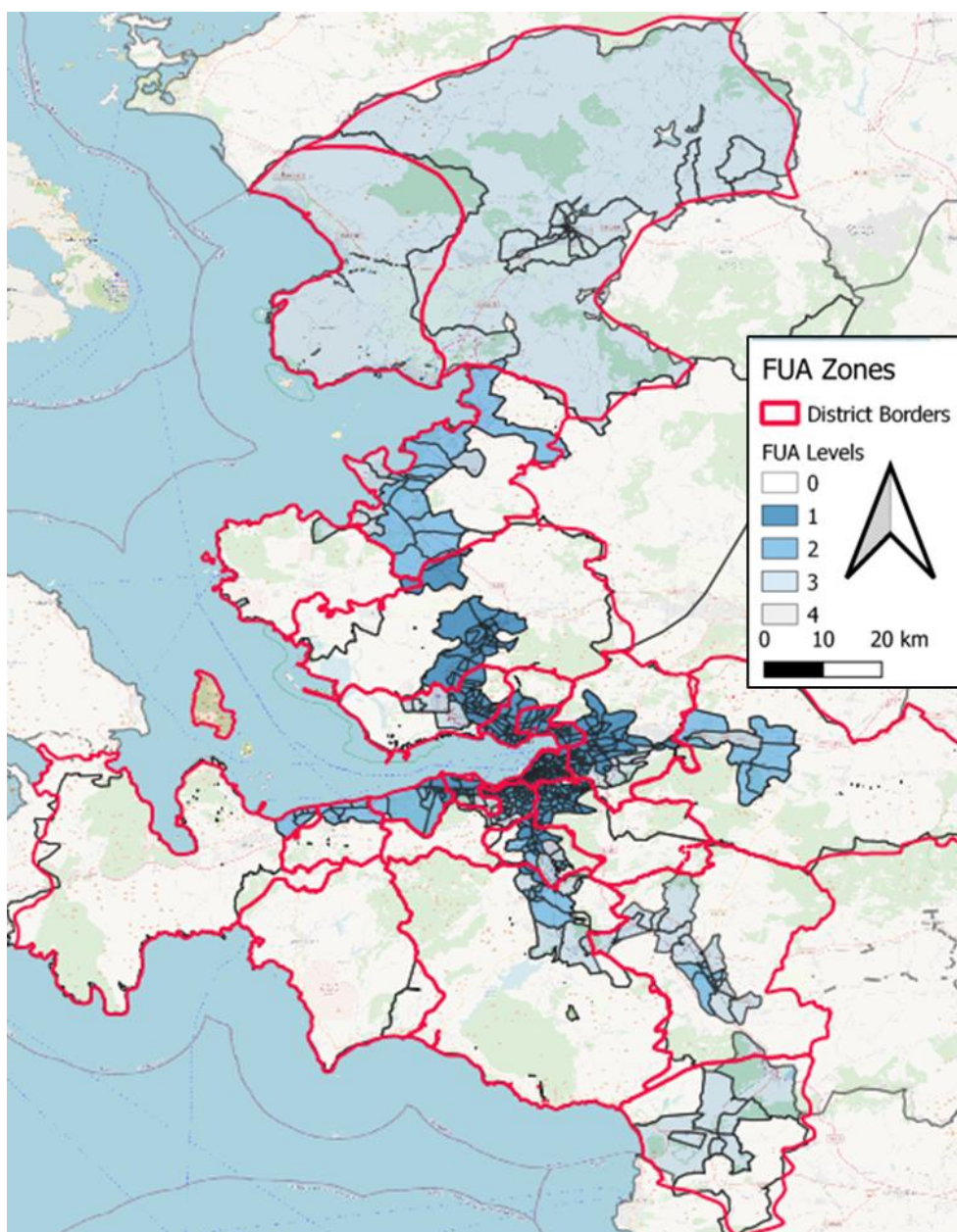


Figure 3.1. FUA Levels

3.2 SUMP İzmir HHTS

The primary objective of the HHTS was to generate critical input data for the development of an ABM, which played a central role in planning sustainable transportation solutions for the city. The survey included four innovative sections designed to capture comprehensive insights into urban mobility dynamics.

- i. “Mobility-Based Activity/ Trip Questions” section focused on understanding the frequency of individuals’ daily travel activities.
- ii. “Shared Trip Information” section examined the use of shared transportation services and their influence on mobility behaviors, representing a notable innovation in the survey design.
- iii. “Micro Mobility Information” section explored the adoption of emerging transportation modes, such as electric scooters and bicycles.
- iv. “Walking’ analysis segment gathered data on the role of walking in daily transportation practices, highlighting its importance as a sustainable mode of mobility.

These four thematic areas were meticulously designed to provide a holistic understanding of urban sustainable mobility and to inform future transportation planning efforts.

In the HHTS study, sample data was obtained from TURKSTAT. The Cluster Sampling method was used for sample collection. This method is a sampling method where the population is divided into clusters, and a random sample of clusters is selected. Data is then collected from all individuals within each selected cluster. Thus, a total of 36,660 samples were obtained. The scope of the survey questions is given in Table 3.1.

Table 3.1. İzmir Household Travel Survey Data Questions Details

Category	Question Description
Household Information	Location, House Type, Interview Information, Household Size, Household Representative (Name-Surname & Mobile Number)
Individual Profile Information	Age, Gender, Degree of Closeness of Family Members, Education Status, Driving License, Smart Card Ownership (Transport Smartcard), Working Status, Working Hours, Working Sector, Working Type, Number of Vehicles Owned
Vehicle Ownership Information	Vehicle Brand, Vehicle Model & Age, Vehicle Fuel Type, Vehicle Parking Location
Activity & Trip Information	Trip and Leg Number, Trip Sharing, Trip Purpose, Transport Mode, Trip Start/End Time, Trip Start/End Location, Trip Cost
Other Household Information	House Ownership Status, Monthly Income, Vehicle Purchase Plan, Transportation Problems of Household Members

The project required varying sampling rates across the defined FUA levels. A sampling rate of 3% was applied in FUA Levels 1 and 2, while a 1% rate was utilized for FUA Levels 3 and 4. The sampling rates for the HHTS were determined based on both the location of the İZBAN railway line and the primary central core areas of İzmir. Given that İZBAN serves as an important public transport corridor, the surrounding areas were prioritized in the sampling process to ensure comprehensive data collection for future transportation planning and potential investment assessments. A 3% sampling rate was applied to FUA Levels 1 and 2, which cover the city core and areas with strong connections to İZBAN, reflecting their importance in urban mobility. In contrast, a 1% sampling rate was allocated to FUA Levels 3 and 4, where population densities and direct access to major public transport infrastructure are lower.

3.3 Northern FUA Corridor

The northern corridor of the FUA region was included to study the effect and connection via the İZBAN Suburban Rail corridor, which includes three specific regions (see Figure 3.2.)

- i) Aliağa District
- ii) Menemen District
- iii) Karşıyaka Vicinity (denoted as Karşıyaka*), which included the KARŞIKAYA District as well as parts of neighboring district, which is geographically isolated in the eastern border.

The areas around Aliağa, Menemen and Karşıyaka* play an important role in the process of creating a synthetic population for transportation modeling. These intersections are crucial in mapping synthetic population data from neighborhood and district levels to the Transportation Analysis Area (TAZ) level. The boundaries shown on the maps are important because they ensure that synthetic population data generated at the neighborhood and district levels can be accurately transferred to the relevant TAZ boundaries. This precise drawing of boundaries is important to ensure consistency in data analysis and to obtain reliable results in subsequent transportation modeling stages. The maps also visually verify that the intersections of neighborhoods, districts and TAZ boundaries are properly aligned, facilitating accurate and seamless integration of data across geographic units. The detailed structures including Districts, Neighborhoods and TAZs are shown in Figure 3.3.

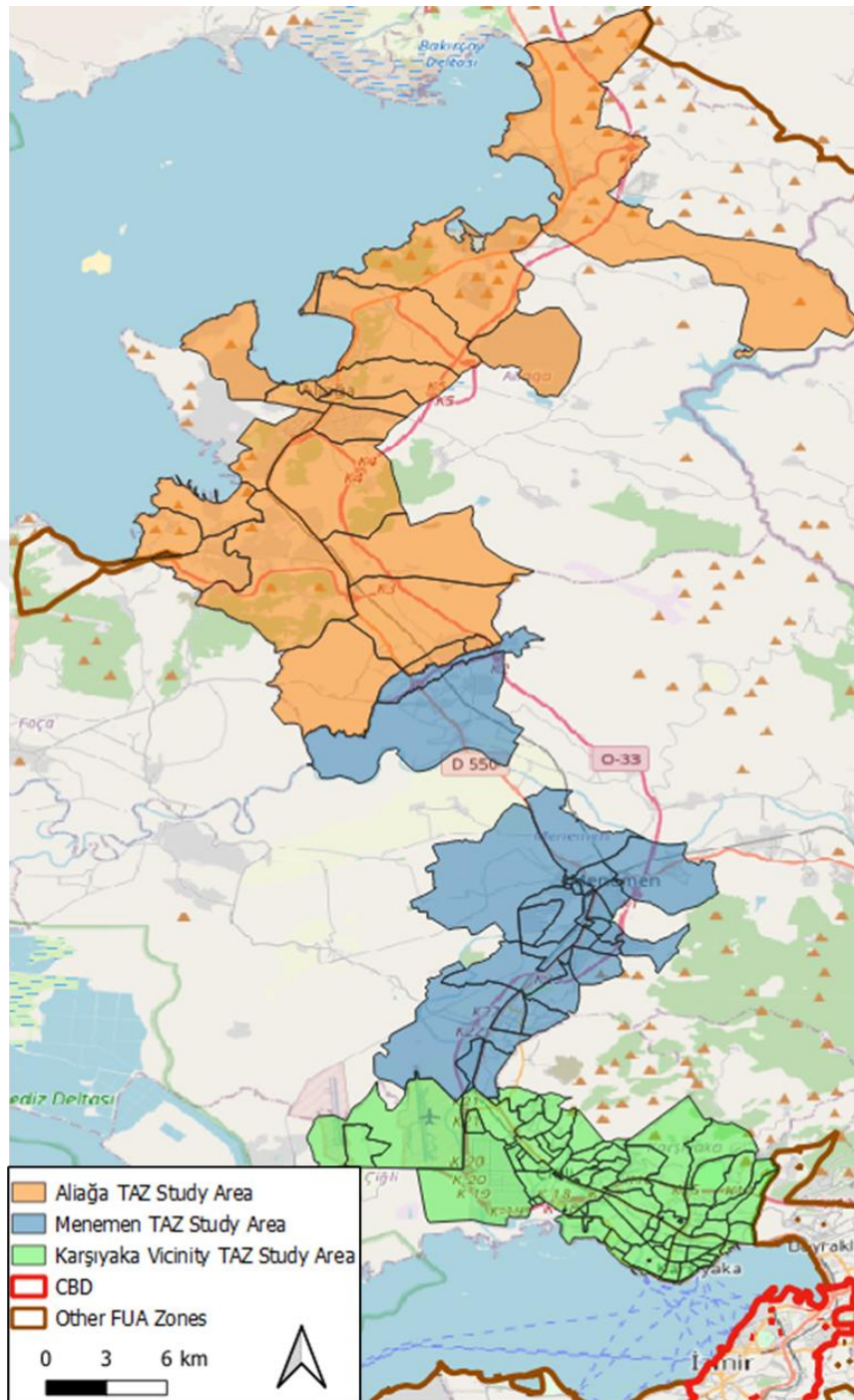


Figure 3.2. Northern FUA Corridor Map

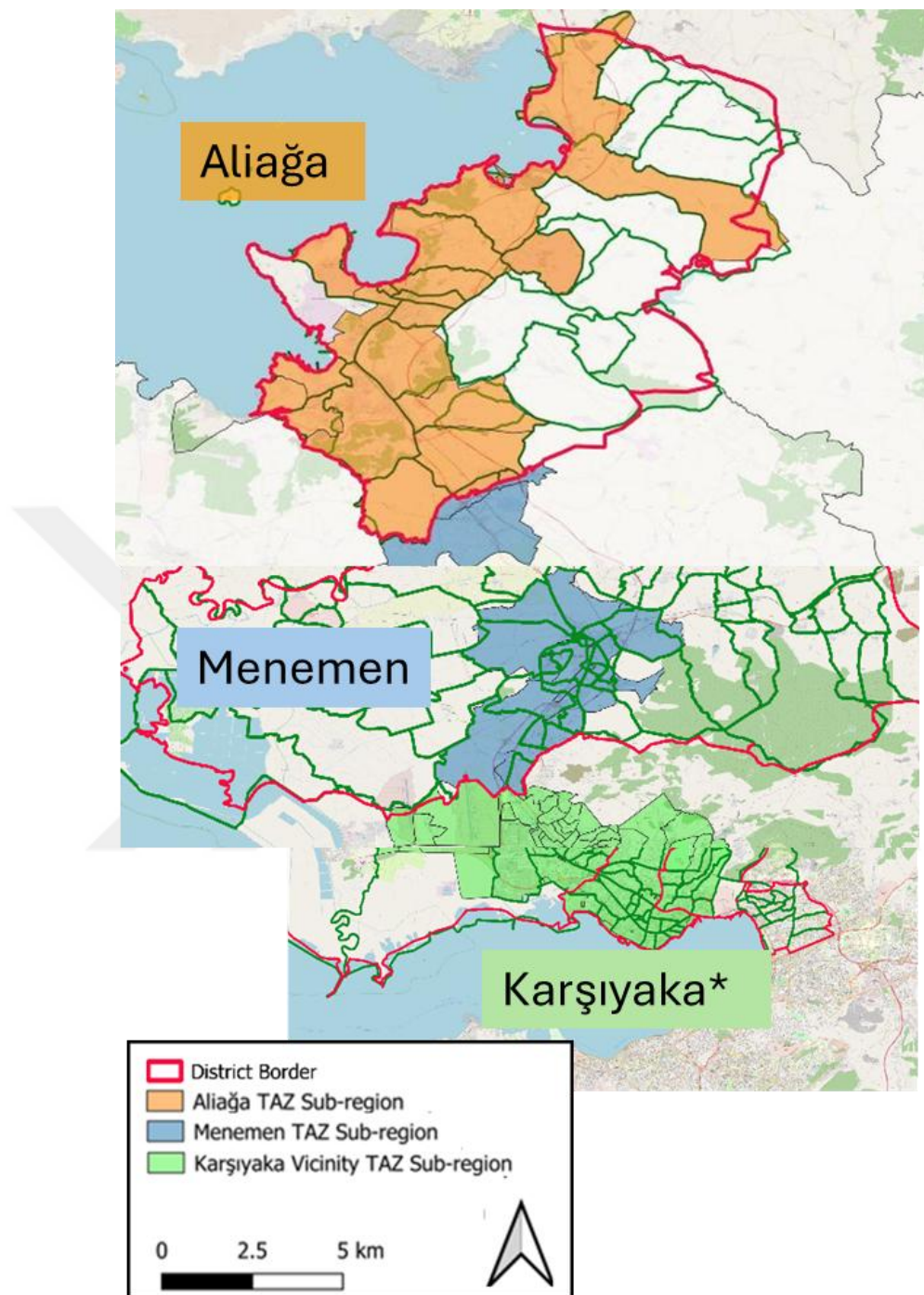


Figure 3.3. District, Neighborhood and TAZ Border Intersections for Northern Corridor

The subregions in the northern corridor show significant differences in terms of total number of neighborhoods, population and households. While Aliğa and Menemen study areas correspond to their own district borders, Karşıyaka* covers three districts: Bayraklı, Çiğli and Karşıyaka. In terms of neighborhood coverage, Aliğa consists of 19 neighborhoods, Menemen consists of 29 neighborhoods and Karşıyaka consists of a total of 55 neighborhoods* in three districts. The differences in population size and number of households reflect the distinct urban and demographic structures of these areas. The detailed distribution of neighborhoods, households and population figures in the study areas is presented in Table 3.2.

Table 3.2. Northern Corridor District, Neighborhood, Household and Population Details

Sub Region	District	N*. NEIG	N*. HH	Population
Aliğa	Aliğa	19	29188	89410
Menemen	Menemen	29	51523	172278
Karşıyaka Vicinity	Bayraklı	8	32953	106789
Karşıyaka Vicinity	Çiğli	22	66429	188927
Karşıyaka Vicinity	Karşıyaka	25	133793	346700
*Sign represents the number of explanation in the table				

Aliğa Sub-region

Aliğa is located on the northernmost border of İzmir and is characterized by significant industrial activities. One of the terminal stations of the İZBAN railway is located in the district, making it a strategic location for both industrial logistics and commuter travel. Bus routes operate to complement the İZBAN service, facilitating connectivity between rural and central areas. The presence of 533 household survey points highlights the diversity in the population structure of Aliğa, shaped by various economic sectors and resulting in different travel and settlement patterns. (See Figure 3.4). Table 3.3 shows the neighborhoods within the Aliğa and the total number of households, population, and number of males and females belonging to those neighborhoods.

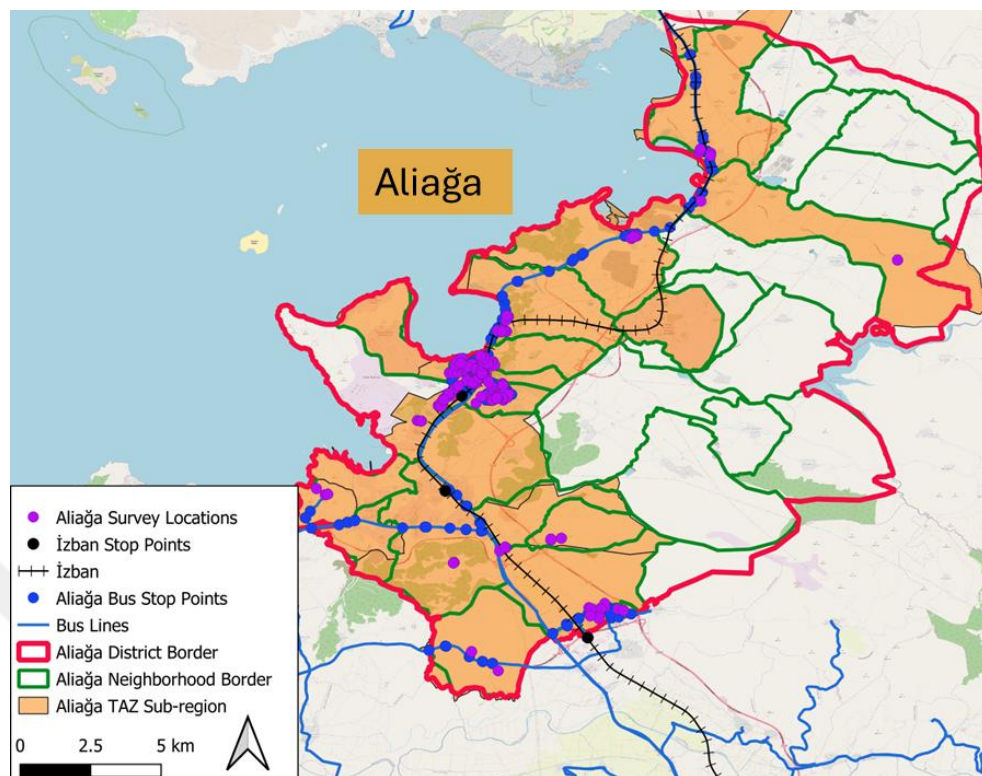


Figure 3.4. Aliaga Sub-region Details

Table 3.3. Aliğa Sub-region Details

District	Neighborhood	Household	Population	Sample	%
Aliğa	Atatürk	2698	8608	47	1.7
	Kazim Dirik	2805	8151	50	1.8
	Kurtuluş	2733	8356	50	1.8
	Kültür	2749	8440	46	1.7
	Siteler	4474	13430	81	1.8
	Yali	1180	3345	19	1.6
	Yeni	6963	23383	131	1.9
	Yukari şehitkemal	128	706	5	3.9
	B.hayrettin Paşa	481	1384	5	1.0
	Fatih	669	1999	15	2.2
	Mimar sinan	438	1318	5	1.1
	Yenişakran	2035	5492	40	2.0
	Bozköy	208	560	5	2.4
	Çakmakli	330	780	5	1.5
	Çaltidere	282	693	10	3.5
	Çitak	234	517	5	2.1
	Haciömerli	326	828	11	3.4
	Karakuzu	230	574	5	2.2
	Şehitkemal	225	846	5	2.2

Menemen Sub-region

Menemen is located on the northern axis of Izmir, encompassing both agricultural and urban areas. The İZBAN railway line runs through the district, serving as a critical public transport backbone connecting Menemen to Izmir city centre and other northern areas. Bus and minibus services are also operated, providing additional travel options for residents. A total of 1,950 household survey points (HHTS) were collected in Menemen, capturing the diverse socio-economic profiles present throughout the district, including urban transformation areas, suburban development and agricultural hinterlands. (See Figure 3.5). Table 3.4 shows the neighborhoods within the Menemen sub-region, and the total number of households, population, and number of males and females belonging to those neighborhoods.

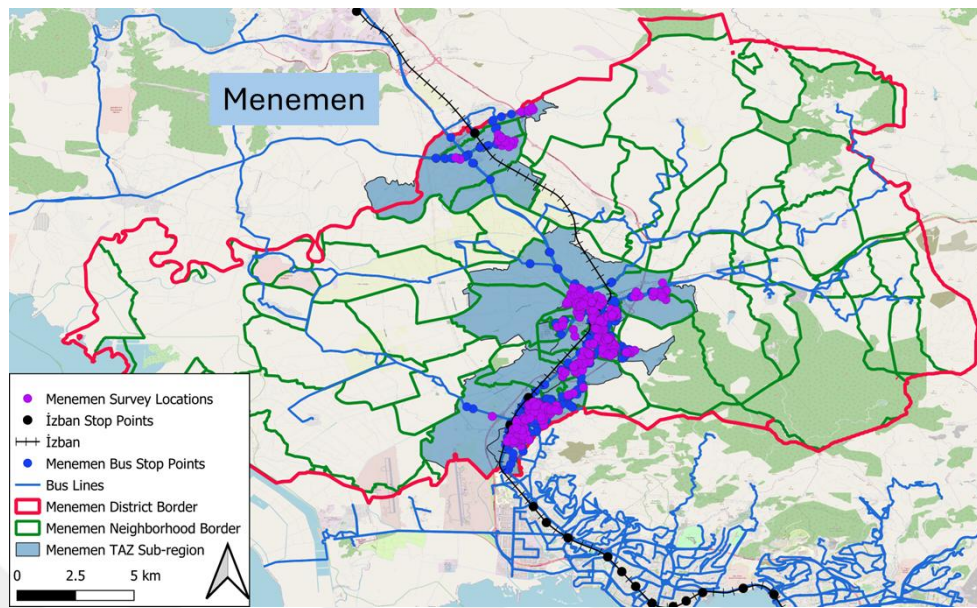


Figure 3.5. Menemen Sub-region Details

Table 3.4. Menemen Study Area Details

District	Neighborhood	Household	Population	Sample	%
Menemen	Ahıhıdır	630	2158	19	3.0
	Atatürk	886	2727	42	4.7
	Camiikebir	463	1316	10	2.2
	Esatpaşa	3092	9423	110	3.6
	İsmet inönü	3336	12174	120	3.6
	Kasimpaşa	4888	15047	165	3.4
	Kazimpaşa	851	3144	32	3.8
	Mermerli	2769	8142	90	3.3
	Tülbentli	583	1673	20	3.4
	Uğur mumcu	4378	15134	150	3.4
	Zafer	432	1308	10	2.3
	Gölcük	1524	7262	61	4.0
	Irmak	1840	7878	62	3.4
	İncirli pınar	1099	5215	42	3.8
	Yeşil pınar	1149	4385	40	3.5
	Zeytinlik	704	2581	20	2.8
	Kemal atatürk	1329	4745	49	3.7
	Cumhuriyet	1129	3339	30	2.7
	Gazi	1182	3726	50	4.2
	Ulus	938	3248	30	3.2
	Fatih	398	1246	28	7.0
	Yıldırım	436	1291	10	2.3
	29 ekim	2171	6395	82	3.8
	30 ağustos	5939	18281	201	3.4
	9 eylül	3192	9194	111	3.5
	Yayla	302	837	10	3.3
	İstiklal	4285	12725	151	3.5
	Hatundere	400	3122	11	2.8
	Yahşelli	1198	4562	42	3.5
Other	-	5313	13103	183	3.4

Karşıyaka* Vicinity Sub-region

Karşıyaka* consists of three different districts which are Karşıyaka (25 neighborhoods), Çiğli (22 neighborhoods) and Bayraklı (8 neighborhoods). Karşıyaka* and its surroundings serve as an important urban center of İzmir, with a high density of residential, commercial and service-oriented activities. Multiple modes of public transportation, including tram, bus, minibus and İZBAN, are available, providing a variety of options for the region's significant daily travel demand. Due to its proximity to the city center, Karşıyaka's coastal corridor is frequently used for work, education and social trips. A total of 9,161 household survey points were collected in this area, reflecting the significant population and travel needs and providing valuable data for ongoing and future transportation planning initiatives. (See Figure 3.6). Table 3.5 and Table 3.6 show the neighborhoods within the Karşıyaka* sub-region and the total number of households, population, and number of males and females belonging to those neighborhoods.

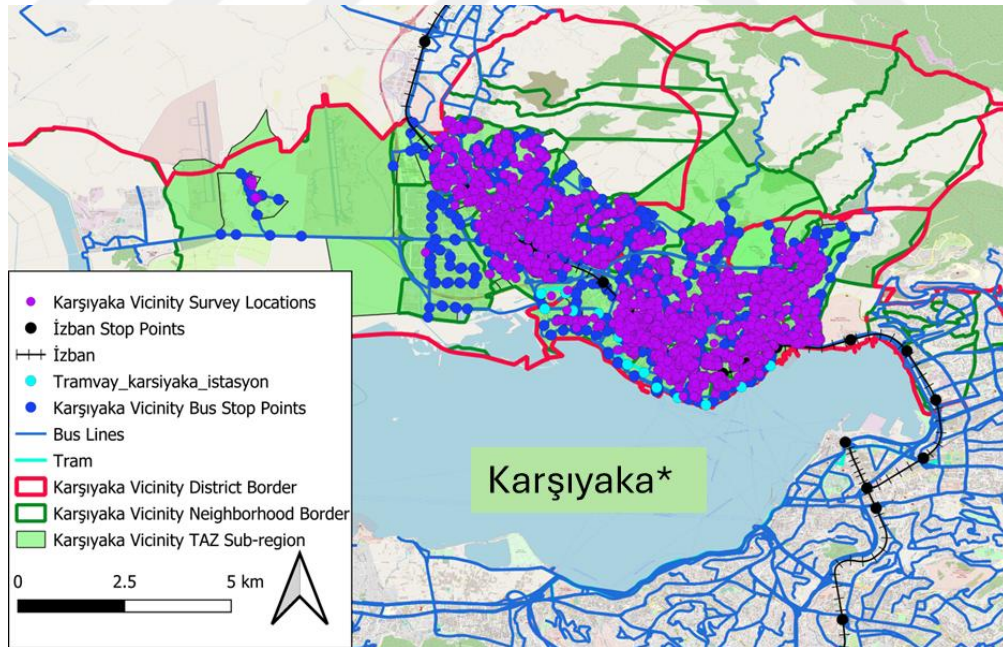


Figure 3.6. Karşıyaka* Study Area Details

Table 3.5. Karşıyaka* Sub-region Details – Karşıyaka District

District	Neighborhood	Household	Population	Sample	%
Karşıyaka	Aksoy	5089	11436	149	2.9
	Alaybey	3152	7156	79	2.5
	Atakent	2805	6921	85	3.0
	Bahariye	4933	12287	133	2.7
	Bahçelievler	9809	25955	269	2.7
	Bahriye üçok	5174	12537	143	2.8
	Bostanlı	13234	31187	364	2.8
	Cumhuriyet	4797	13665	146	3.0
	Dedebaşı	7800	20272	216	2.8
	Demirköprü	2709	6754	86	3.2
	Donanmacı	4373	10180	115	2.6
	Fikri altay	2965	8126	98	3.3
	Goncılar	3640	9229	90	2.5
	İmbatlı	2838	7265	81	2.9
	Mavişehir	5126	14129	142	2.8
	Nergiz	3263	8042	93	2.9
	Örnekköy	8554	23938	246	2.9
	Şemikler	10972	28956	299	2.7
	Tersane	2810	6573	79	2.8
	Tuna	2584	5750	71	2.7
	Yalı	14179	37588	396	2.8
	İnönü	3184	8261	90	2.8
	Zübeyde hanım	5610	17667	154	2.7
	Mustafa kemal	3512	10584	102	2.9
	Latife hanım	681	2242	20	2.9

Table 3.6. Karşıyaka* Sub-region Details Other Districts

District	Neighborhood	Household	Population	Sample	%
Çiğli	Ahmet taner kişlali	2514	6627	70	2.8
	Atatürk	4382	12502	103	2.4
	Aydinlikevler	1308	4063	45	3.4
	Balatçik	5444	16008	174	3.2
	Çağdaş	2215	6479	60	2.7
	Egekent	3074	8480	120	3.9
	Esentepe	1980	5509	53	2.7
	Evka-2	1540	4371	64	4.2
	Evka-5	4732	13095	174	3.7
	Evka-6	907	2319	30	3.3
	Güzeltepe	2075	6623	58	2.8
	Ataşehir	10237	28560	319	3.1
	İzkent	2387	6450	71	3.0
	Kaklıç	463	1676	10	2.2
	Köyiçi	1478	4049	48	3.2
	Küçük çiğli	7147	21016	211	3.0
	Maltepe	1311	4023	44	3.4
	Şirintepe	2989	8540	85	2.8
	Uğur mumcu	1830	5456	51	2.8
	Yakakent	3419	9729	118	3.5
	Yeni mahalle	4567	12177	139	3.0
	Ahmet efendi	430	1175	16	3.7
Bayraklı	Emek	4126	12361	141	3.4
	Gümüşpala	5302	15597	190	3.6
	Onur	4130	15763	130	3.1
	Org.nafiz gürman	4005	14255	110	2.7
	Postacılar	3926	12879	130	3.3
	Soğukkuyu	4063	12148	134	3.3
	Yamanlar	5239	18268	169	3.2
	Körfez	2162	5518	71	3.3
Other	-	70663	210826	2373	3.4

3.4 Socio-Demographic Structure of the Northern Corridor Sub-regions

The socio-demographic characteristics of the northern subregions (Aliğa, Menemen and Karşıyaka*) were analyzed using two separate datasets: the TURKSTAT dataset representing official population statistics and the Sample dataset reflecting data collected through the HHTS. While the TURKSTAT dataset provides an overview of the total population and household distribution in each region, the sample dataset provides a proportional representation of these characteristics according to the surveyed population. By comparing these datasets, insights were gained into the population composition, household types, age distributions and education levels in the three regions.

A general review of the data reveals that the number of households and individual populations varies significantly across regions. As shown in Table 3.9, Aliğa has a relatively smaller population size; 29,188 households were recorded in the TURKSTAT dataset and a corresponding sample of 533 households in the sample dataset. In contrast, Menemen, presented in Table 3.9, has a significantly larger population with 56,390 households and 1,950 sampled households in the TURKSTAT dataset. The most urban district among the three, Karşıyaka*, stands out with a significantly higher number of households, reaching 233,175 in the TURKSTAT dataset and 9,161 in the sample dataset, as shown in Table 3.10. Sample rate column represents the TURKSTAT data values divided by sample data values. In table there is “*” sign which represents the there is no available data at the neighbourhood level from TURKSTAT.

Key Differences Between Regions

Age Distribution

Age group distributions show significant differences between regions. In Aliğa and Menemen, a significant portion of the population falls into the younger, working-age groups (25-44 years), while in Karşıyaka* the population is more evenly distributed across different age ranges. This difference may be due to the industrial nature of Aliğa and the suburban nature of Menemen, which tends to attract a young working population. In contrast, Karşıyaka*, with its established residential areas and urban infrastructure, hosts a higher proportion of older residents, as reflected in the higher proportion of individuals aged 65 and over compared to the other two regions.

Education Level

Education levels in the three regions show significant differences that can be related to the socio-economic structure of each region. In Aliğa, a significant proportion of the population has completed lower levels of education, and relatively fewer individuals have attained a higher education degree. Menemen shows a slightly more balanced education distribution, reflecting its mixed urban-rural character. In contrast, Karşıyaka* stands out with a significantly higher proportion of individuals with a tertiary degree, consistent with the district's urban character and socio-economic development. This distinction suggests that Karşıyaka* attracts more highly educated residents, probably due to better access to white-collar employment opportunities and educational institutions.

Table 3.7 and Table 3.8 show the definitions of household types and education level definitions.

Table 3.7. Household Type Definitions

Household Type	Definition
HHTYPE1	One Person Household
HHTYPE2	Household consisting of spouses
HHTYPE3A	Household consisting of mother and children
HHTYPE3B	Household consisting of Father and children
HHTYPE4	Household consisting of parents and children
HHTYPE5	Household consisting of At Least One Extended Family and Other Persons
HHTYPE6	Household consisting of non-family members

Table 3.8. Education Level Definitions

Education Level	Definition
EDU0	Unknown
EDU1	Illiterate
EDU2	Literate Without Going to School
EDU3	Primary school graduate
EDU4	Primary education graduate
EDU5	Middle school or equivalent graduate
EDU6	High school or equivalent graduate
EDU7	MSc / PhD

Table 3.9. Aliğa and Menemen Descriptive Analysis

	Aliğa			Menemen		
	TURKSTAT	HHTS		TURKSTAT	HHTS	
	Pop.	Sample	%	Pop.	Sample	%
N_HH	29188	533	2.0	56836	1950	3.0
NPer	89410	1457	2.0	185381	4954	3.0
N_HHTYPE1	*	66	*	*	373	*
N_HHTYPE2	*	147	*	*	596	*
N_HHTYPE3A	*	29	*	*	113	*
N_HHTYPE3B	*	14	*	*	43	*
N_HHTYPE4	*	243	*	*	651	*
N_HHTYPE5	*	29	*	*	144	*
N_HHTYPE6	*	5	*	*	30	*
NPer_AGE0-4	6488	69	1.0	14119	171	1.0
NPer_AGE5-9	7176	72	1.0	15351	233	2.0
NPer_AGE10-14	6391	67	1.0	13634	251	2.0
NPer_AGE15-19	5179	81	2.0	11929	348	3.0
NPer_AGE20-24	5420	103	2.0	13451	373	3.0
NPer_AGE25-29	7255	117	2.0	15586	426	3.0
NPer_AGE30-34	8043	137	2.0	16056	415	3.0
NPer_AGE35-39	8320	131	2.0	15834	375	2.0
NPer_AGE40-44	7776	98	1.0	15738	364	2.0
NPer_AGE45-49	6016	107	2.0	12930	327	3.0
NPer_AGE50-54	5241	101	2.0	10185	375	4.0
NPer_AGE55-59	5129	110	2.0	9806	260	3.0
NPer_AGE60-64	3938	93	2.0	7208	334	5.0
NPer_AGE65+	7038	171	2.0	13554	702	5.0
NPer_EDU0	8699	95	1.0	18937	221	1.0
NPer_EDU1	606	22	4.0	1909	220	12.0
NPer_EDU2	7156	100	1.0	17599	339	2.0
NPer_EDU3	21831	406	2.0	48747	1482	3.0
NPer_EDU4	12802	154	1.0	29648	660	2.0
NPer_EDU5	20673	395	2.0	36815	1351	4.0
NPer_EDU6	16245	279	2.0	28648	654	2.0
NPer_EDU7	1398	6	0.0	3078	27	1.0
N_Male	45682	736	2.0	94505	2540	3.0
N_Female	43728	721	2.0	90876	2414	3.0

Table 3.10. Karşıyaka* Descriptive Analysis

Karşıyaka*	TURKSTAT	Sample	%
N_HH	233175	9161	3
NPer	642416	21993	3
N_HHTYPE1	*	2007	*
N_HHTYPE2	*	2560	*
N_HHTYPE3A	*	551	*
N_HHTYPE3B	*	274	*
N_HHTYPE4	*	2897	*
N_HHTYPE5	*	663	*
N_HHTYPE6	*	209	*
NPer_AGE0-4	31737	657	2
NPer_AGE5-9	38130	735	1
NPer_AGE10-14	36937	989	2
NPer_AGE15-19	34219	1324	3
NPer_AGE20-24	38617	1384	3
NPer_AGE25-29	43800	1566	3
NPer_AGE30-34	49905	1700	3
NPer_AGE35-39	54650	1770	2
NPer_AGE40-44	58306	1697	2
NPer_AGE45-49	51222	1695	2
NPer_AGE50-54	43875	1576	3
NPer_AGE55-59	41408	872	2
NPer_AGE60-64	35163	1607	4
NPer_AGE65+	84447	4421	4
NPer_EDU0	50633	874	1
NPer_EDU1	5369	542	7
NPer_EDU2	40430	1034	2
NPer_EDU3	130357	5291	3
NPer_EDU4	84716	2736	2
NPer_EDU5	149137	5950	3
NPer_EDU6	156177	5290	3
NPer_EDU7	25597	276	1
N_Male	309906	10405	3
N_Female	332510	11588	3

CHAPTER 4

METHODOLOGY

4.1 Framework

To investigate the travel behavior patterns of different urban sub-regions in search for insights regarding the support of a regionally sensitive rule-based ABM, it is critical to develop a systematic search and evaluation framework. This integrated look should include the aspects to be compared as well as the criteria and methods to shed light into detection of region-sensitive measure/features as shown in Figure 4.1.

Step 1: Preprocessing of Izmir HHTS

The first step is the preprocessing of the available HHTS data, as travel characteristics would be most realistically depicted via HHTS, despite its high cost and labor work. In this regard, HHTS data was pre-processed to ensure analytical consistency. This included data cleaning, filtering missing records, and classifying individuals into person types (PT1–PT6) based on socio-demographic characteristics such as employment, age, and education status. Also, time periods are assigned to the each trip according the departure time. Moreover, this step includes the defining of trip origin and destination locations. Lastly, mode and purpose transformations are done by the aim of the study.

Step 2a: Determining Trip Generation Probabilities

In this step, trip generation probabilities were calculated to determine whether individuals traveled and to measure person type-specific travel probabilities. The output of this step forms the basis of traveler probability rules in subsequent modeling stages.

Step 2b: Determining Travel Characteristics

Detailed travel characteristics were determined, including trip purposes, activity chains, mode choices, travel distances, and destination choices. These characteristics were evaluated for each person type to reveal travel behavior trends among different population segments.

Step 3: Comparative Analyses of Study Areas

A comparative analysis was conducted for three selected regions (Aliğa, Menemen, and Karşıyaka*) to investigate temporal and spatial differences. Regional differences in mode preference, departure time, travel distance, and activity composition were assessed to determine the extent of behavioral variation across subregions.

Step 4: ABM Rule Development Recommendations

Based on the findings, region-based recommendations were formulated to inform ABM rule development. These recommendations reflect observed differences in traveler probabilities, travel purposes, modes, and time-of-day patterns across both person types and geographic contexts. The goal is to guide future ABM designs to incorporate regionally and demographically differentiated rule structures rather than relying on city-wide assumptions.

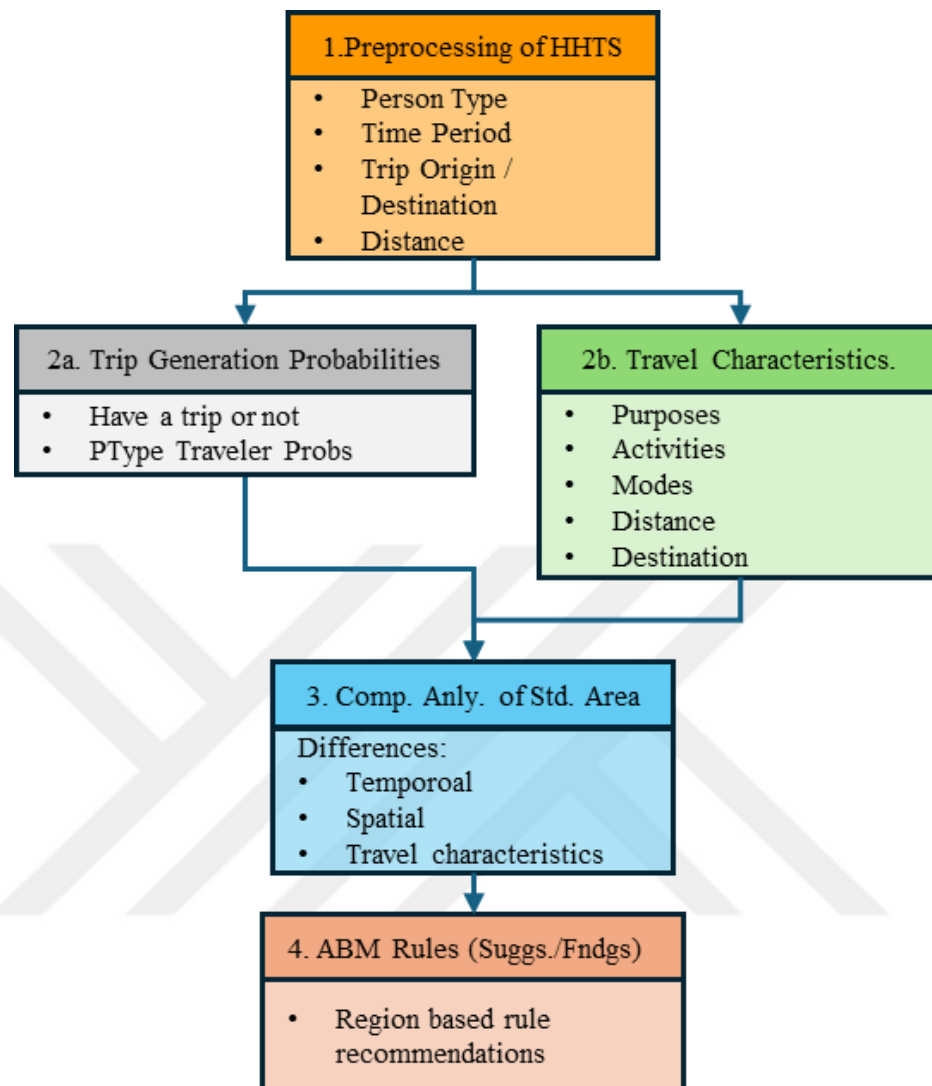


Figure 4.1. Framework for Methodology

4.2 Sociodemographic Variables

To define person types, socio-demographic attributes derived from the HHTS were utilized. This classification was essential to segment the population into meaningful behavioral groups for subsequent travel demand analysis. The person types were developed based on key variables including age, employment status, and current

student status. These attributes were chosen due to their strong influence on daily mobility patterns, travel necessity, and activity participation.

By categorizing individuals into predefined person types, it was possible to establish a foundation for modeling critical behavioral decisions such as the likelihood of travel, trip purpose, mode choice, and departure time period. This segmentation not only ensures consistency in the rule-based ABM framework but also reflects the diversity of travel needs and constraints across different population groups.

The person type classification table is provided in Table 4.1., summarizing the rules used to assign individuals to specific categories based on their socio-demographic profiles. This structure forms a crucial layer in the modeling logic and directly supports the probabilistic rule development process in subsequent stages of the study.

Table 4.1. Person Type Definitions

Variable Name	Short Name	Explanation
PT1	Full Time Employee	Full time employee and 18+
PT2	Part-Time Employee	Part time employee and 18+
PT3	University Student	University Student
PT4	Unemployed Adult	Unemployment person and 18+
PT5	Retired	Retired people
PT6	Student	Non-university student

4.3 Trip Related Variables

To ensure that activity and travel behaviors can be comprehensively analyzed over a full day, the study defined a series of discrete time periods spanning the 24-h cycle. Temporal resolution is critical to capture variation in travel departure times and to ensure that time-dependent travel decisions such as peak and off-peak movements are accurately modeled.

Accordingly, the day was divided into seven discrete time periods, each representing a specific part of the day with behavioral significance (e.g., morning peak, evening return, late night travel). This stratification supports the rule-based ABM framework by allowing travel and activity patterns to be expressed probabilistically over time periods rather than as fixed or average values.

The defined time periods and their corresponding time intervals are presented in Table 4.2. These intervals form a temporal structure for modeling not only departure times but also purpose-mode interactions and time-dependent analyses throughout the study. This temporal segmentation is particularly important in regions with diverse activity schedules and helps reflect realistic and dynamic urban mobility patterns.

Table 4.2. Time Period Definitions

Variable Name	Description
TP1	Morning (06:00-09:00)
TP2	Late Morning (09:00-12:00)
TP3	Noon (12:00-13:30)
TP4	Afternoon (13:30-16:30)
TP5	Evening (16:30-19:30)
TP6	Late Evening (19:30-21:00)
TP7	Night (21:00-06:00)

As part of the preprocessing step, a mode recategorization process was conducted to align the travel mode classifications in HHTS with the modal structure defined in this study. The original HHTS dataset included several specific modes, such as bicycle, scooter, rideshare, and car, which were aggregated into broader mode groups based on functional similarities.

These recategorized mode groups were organized into three main categories used in the study:

- **AcT (Active Transport):** includes walking and micromobility modes (bicycle, scooter)
- **PuT (Public Transport):** includes bus, minibus, metro/tram, commuter train, and ferry
- **PrT (Private Transport):** includes service, private vehicle, rideshare, car, and taxi

The matching process is illustrated in Figure 4.2, which shows the relationship between the HHTS mode categories, and the modes defined in the study. This step was important to ensure analytical consistency when comparing mode choice behaviors across different subregions and person types.

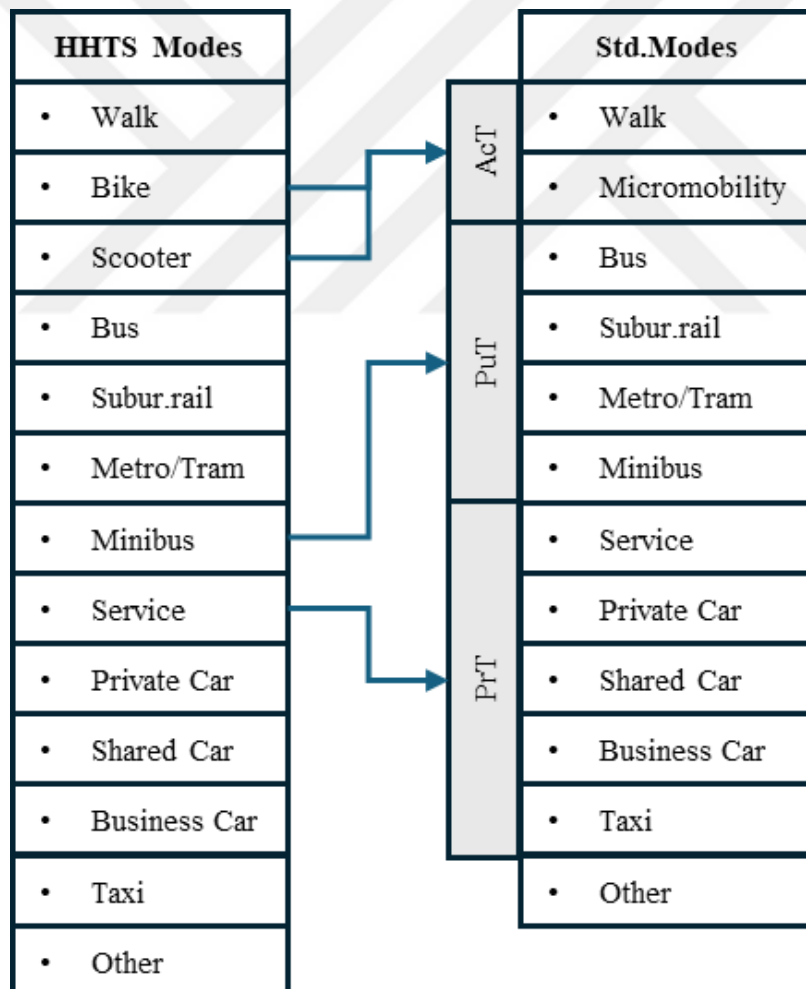


Figure 4.2. Mode Acceptances from HHTS to Study

In addition to the mode recategorization, a trip purpose transformation was also performed to align the detailed HHTS purpose categories with the purpose structure used in this study. Several original purposes that were functionally similar or low in frequency were combined into broader categories to simplify the analysis and support consistent comparison across regions and person types. As shown in Figure 4.3, the following transformations were performed:

- “Friends and Family” and “Recreational” purposes were grouped under “Social”
- “Work” and “Health” purposes were included under “Other”

Main purposes such as “Work”, “School”, “Pick-Up and Drop-Off”, and Shopping were retained as separate categories due to their distinct behavioral importance and high representation in the data set.

This purpose recoding process was important to reduce fragmentation in the data and increase the clarity of behavioral interpretation in later stages of the study.

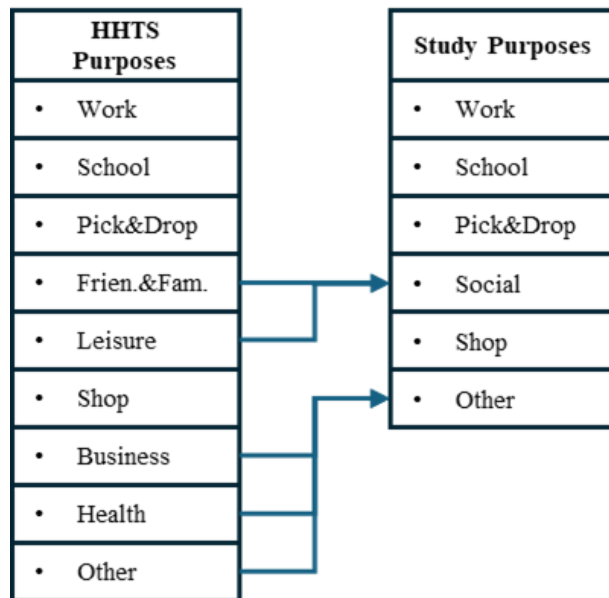


Figure 4.3. Trip Purpose Classification for the Study based on HHTS

4.4 Study Locations

To implement the proposed methodology, the area defined as the Northern Corridor, previously introduced in 3.3, was selected as the study region. These regions were selected for two key reasons: first, the survey data was collected at the FUA level; second, the chosen areas collectively represent a comprehensive mobility pattern, encompassing movements from the northern parts of İzmir to the city center. This selection facilitates an analysis of both intra-city mobility within the urban core and the diverse travel patterns observed in areas farther from the city center.

By analyzing these three distinct yet interconnected regions, the study aims to capture region-specific differences in travel dynamics, for example, differences in travel departure timing, destination preferences, and modal accessibility. This spatial differentiation is important for testing the applicability and robustness of a region-based rule-generation approach. The selected Northern Corridor therefore provides a representative microcosm of urban mobility diversity in metropolitan areas such as İzmir, enabling a more detailed and behaviorally grounded analysis of travel demand. Figure 4.4. show the selected study locations for the O-D analysis.

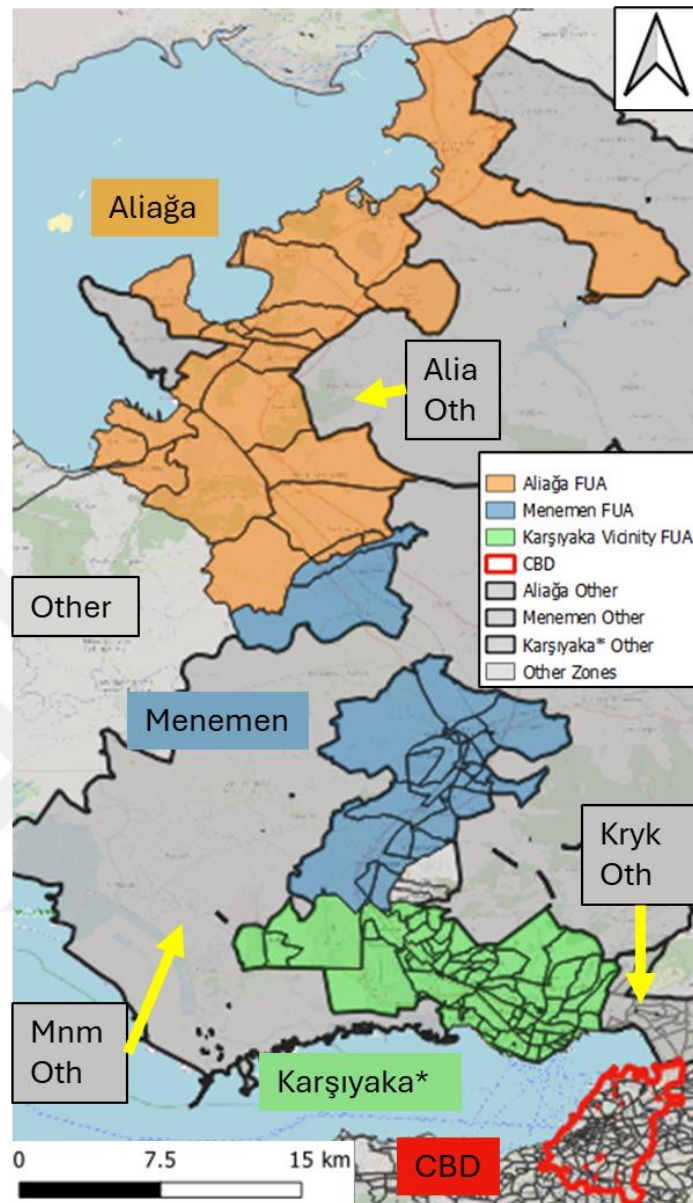


Figure 4.4. Study Locations

4.5 Comparison Dimensions

A set of key travel characteristics were systematically analyzed to evaluate and compare the selected study area regions. These comparative analyses aimed to identify both spatial and temporal differences in mobility behavior across

subregions. The dimensions examined included time period distribution, travel purposes, mode choice, activity participation, trip lengths, reported travel times, origin-destination patterns, and OD-based spatial representations.

As a first step, travel probabilities by person type were analyzed to determine the probability of an individual to travel. These probabilities form the basis for determining the behavioral role of socio-demographic profiles in travel decisions. An example of this analysis is presented in Table 4.3. Next, the focus shifted to daily activity chains, allowing the calculation of average activity numbers per person type. This approach allows for a more detailed understanding of how different demographic segments participate in daily mobility. A representative table of these findings is presented in Table 4.4.

Table 4.3. Example Travel Probability Table for different Person Types

		Travel Probabilities	
Person Type	Definition	Travel	No-Travel
PT1	Full_Time Worker		
PT2	Part_Time		
PT3	Uni_Std.		
PT4	Non_Emp.		
PT5	Retired		
PT6	Student		

Table 4.4. Example Activity Patterns Starting for Different Person Types

Activity Patterns	PT1	PT2	PT3	PT4	PT5	PT6
Home ->Work ->Home						
Home ->School ->Home						
Home ->Pick&Drop ->Work ->Home						
Home ->Pick&Drop ->Home						
Home ->Shop ->Home						
Home ->Social ->Home						
Home ->Other ->Home						

Next, the temporal distribution of trips was assessed by purpose and mode over seven defined time periods in Table 4.2. These results help to reveal peak periods and purpose-mode relationships throughout the day. Descriptive results are shown in Table 4.5, while visualizations of the distributions are provided in Figure 4.5. The analysis is then extended to mode-purpose intersections, providing insights into typical mode choices made for specific travel purposes. A sample output is summarized in Table 4.6.

In addition, the destination patterns of trips originating from each study area were assessed. These were disaggregated by time period, purpose, and mode, revealing how spatial interactions vary according to context. Representative outputs are presented in Table 4.7, Table 4.8 and Figure 4.6.

Table 4.5. Example Trip Distribution for Trips Table Starting in a Study Region for Different Time Periods

		Time Periods						
		TP1	TP2	TP3	TP4	TP5	TP6	TP7
From								
Trips								
Work								
School								
....								
Other								
Home								
AcT	Walk							
	Micromobility							
PuT	Bus							
								
	Minibus							
PrT	Private Car							
	...							
	Taxi							
	Other							

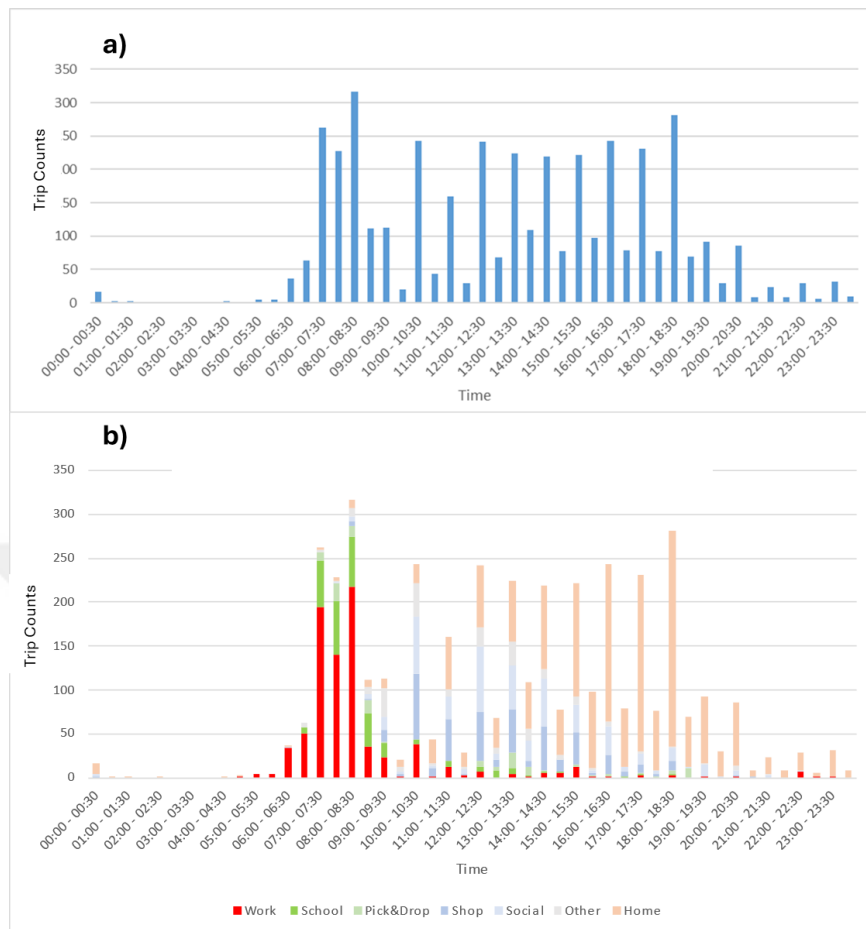


Figure 4.5. Daily Profile of a) Trip Departure Time for a) all trips and b) various trip purposes

Table 4.6. Example of Trip Mode and Purpose Cross Tables

	From a Region	Work	School	...	Other		Home
AcT	Walk						
	Micromobility						
PuT	Bus						
	...						
	Minibus						
PrT	Private Car						
	...						
	Taxi						
	Other						

Table 4.7. Explanations of Destination Locations

	Destinations	Explanations
Aliğa	FUA	Study Area
	Other	Other places in Aliğa except study area
Menemen	FUA	Study Area
	Other	Other places in Menemen except study area
Karşıyaka*	FUA	Study Area
	Other	Other places in Karşıyaka* except study area
İzmir	CBD	Central business district of İzmir
	Other	Other places in İzmir except above areas

Table 4.8. Example of Destination Analysis Table

		Destinations								
		Aliğa		Menemen		Karşıyaka*		İzmir		Total
		FUA	Oth	FUA	Oth.	FUA	Oth	CBD	Oth	
Time Periods	TP1									
	...									
	TP7									
Trip Purp.	Work									
										
	Home									
AcT	Walk									
	MicroMob.									
PuT	Bus									
	...									
	Minibus									
PrT	Private Car									
	...									
	Taxi									
	Other									

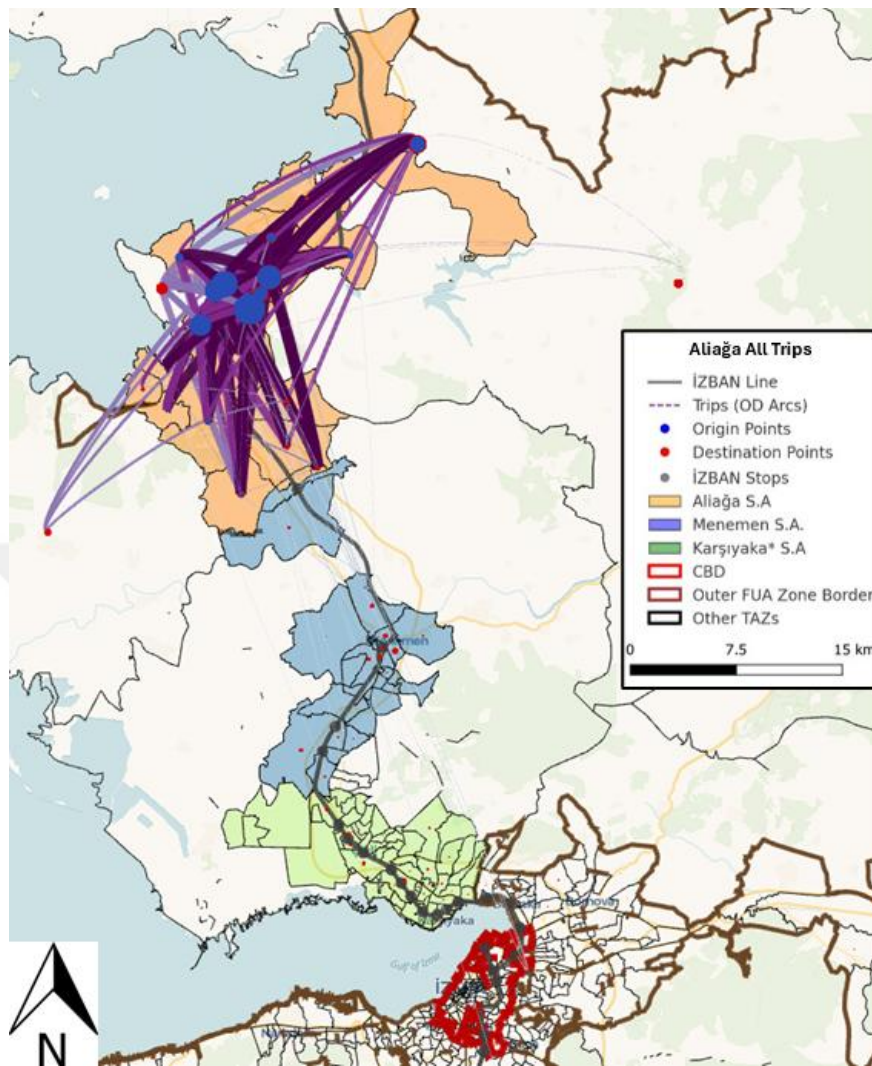


Figure 4.6. Example GIS Based O-D Analysis

Finally, travel times and travel lengths were analyzed in detail to identify changes in travel behavior across multiple dimensions. These metrics were examined in aggregate and by transportation mode, travel purpose, and person type to provide an overview of travel patterns in each study area.

By considering travel times and distances together, it was possible to assess the spatial and temporal efficiency of different travel modes and to understand how mobility needs vary between mandatory and discretionary activities. Furthermore, analyzing these variables by person type provides insights into how

sociodemographic characteristics affect the distance and time individuals are willing or required to travel. Figure 4.7 show example of the graphs.

These multidimensional comparisons support the identification of spatial-temporal travel behavior differences and provide a basis for defining region-specific rules.

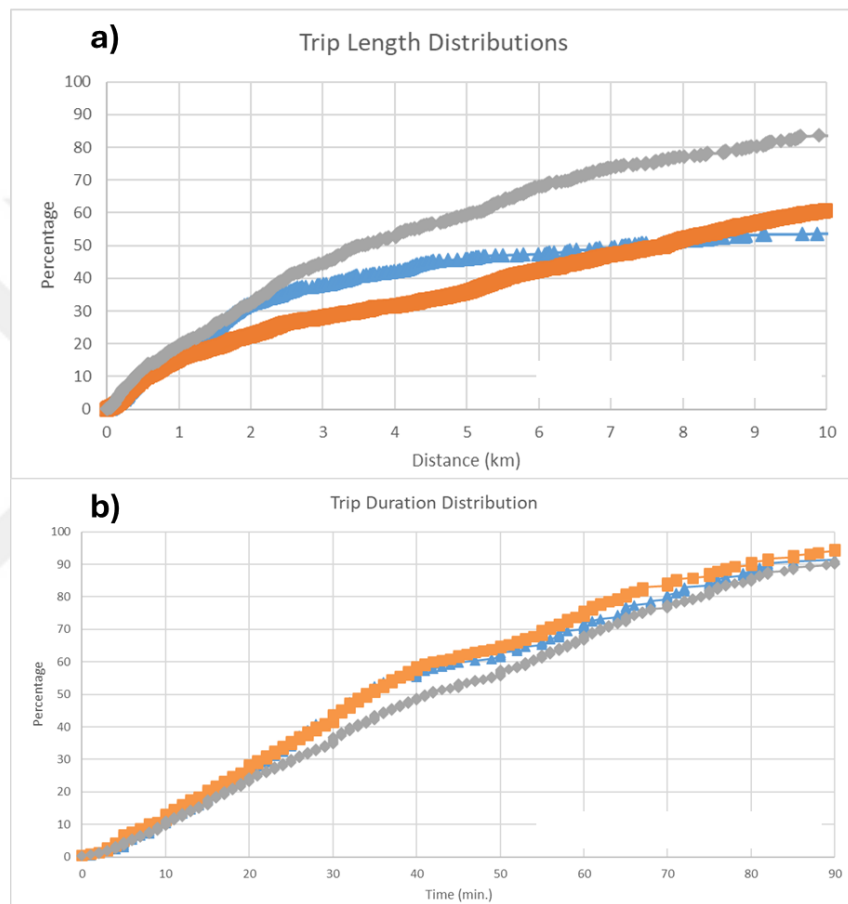


Figure 4.7. Example of Distribution of a) Trip Length and b) Stated Trip Duration

CHAPTER 5

INVESTIGATING TRAVEL BEHAVIOR PATTERNS

5.1 Urban Travel Characteristics of Aliaga FUA Region

Travel Distribution

All of the rules determined and used in this step come from the household survey. In determining the rules, the household survey was decided by grouping according to person types. By using these probabilistic distribution, travel or no-travel situation was assigned. Table 5.1. shows the travel probabilities for the Aliaga citizens according to the person types.

Table 5.1. Travel Probabilities for Aliaga by Person Types

	From Aliaga	Travel Probabilities (%)	
Person Type	Definition	Travele	No-Travele
PT1	Full_Time Work	83	17
PT2	Part_Time	85	15
PT3	Uni_Std.	42	58
PT4	Non_Emp.	28	72
PT5	Retired	39	61
PT6	Student	53	47

Activity Pattern Distribution

The Table 3.1 shows the activity patterns by person type in Aliaga highlights strong differences in travel behavior that are tightly linked to socio-demographic roles. These patterns are critical for rule development in an ABM because they indicate which activity types are dominant and how complex daily tours are depending on person type. <

- PT1 is overwhelmingly associated with Home → Work → Home chains (470 trips), indicating a predominance of mandatory, single-purpose trips during the week. A smaller share also engages in shopping, social, and other discretionary activities, indicating some multipurpose travel.
- PT2 also engage primarily in work-based touring, albeit to a lesser extent (90 trips). Activity chains are more diverse, with moderate participation in shopping and social trips reflecting greater schedule flexibility.
- PT3 and PT6 engage primarily in Home → School → Home trips. PT6 is dominated by 175 such chains, reinforcing their strong attachment to educational travel and predictable daily routines.
- PT4 and PT5 engage primarily in discretionary activities, particularly shopping (PT5: 57 trips), social (PT5: 51 trips), and other purposes (PT5: 42 trips). PT4 shows similar but less frequent patterns.

Table 5.2. Activity Pattern Distribution by Person Types in Aliaga

Activities From Aliaga	PT1	PT2	PT3	PT4	PT5	PT6
Home ->Work ->Home	470	90	0	0	0	7
Home ->School ->Home	0	4	17	5	0	175
Home ->Pick&Drop ->Work ->Home	1	0	0	0	0	0
Home ->Pick&Drop ->Home	2	0	1	8	0	0
Home ->Shop ->Home	8	3	5	57	22	4
Home ->Social ->Home	6	8	6	51	20	4
Home ->Other ->Home	11	2	3	42	10	5

Time Period Analysis by Purpose and Mode

Based on HHTS data for the Aliaga study area, a detailed analysis (See Table 5.3) was conducted to understand the temporal, modal and purpose-based characteristics of the observed trips, which will inform the development of rules within the rule-based ABM. The majority of trips occur during TP1 and TP5, reflecting typical commuting patterns associated with work and school activities. Work-related trips are largely concentrated in TP1, while return trips are distributed between TP5 and TP7, indicating the presence of both standard and non-standard work schedules.

School trips also show a similar pattern with high activity in TP1 and return flows in TP4. Social and shopping trips are more frequent in TP4 and TP5, indicating that they act as secondary or discretionary activities. In terms of mode choice, private cars and shuttles are the dominant modes, especially during TP1 and TP5, while walking and micromobility modes are more common between TP2 and TP5 and are generally applicable for lunch and short-distance trips.

The use of public transportation vehicles such as buses and minibuses appear to be at a moderate level, while the use of taxis and metro/trams remains at a minimum level. These findings provide critical inputs for defining probabilistic rules regarding travel time, travel purpose, and vehicle choice, enabling the development of a behaviorally based and context-specific rule set for individuals residing in Aliaga. Figure 5.1 shows the trip departure time distributions in Aliaga.

Table 5.3. Trip Distribution by Time Periods for Purpose and Mode (Aliaga)

		Time Periods						
From Aliaga		TP1	TP2	TP3	TP4	TP5	TP6	TP7
Trips		483	171	53	313	454	52	155
Work		282	33	2	12	6	2	18
School		117	14	5	7	1	0	7
Pick&Drop		40	6	3	11	12	0	11
Social		3	16	7	20	4	0	9
Shop		0	36	10	21	12	0	8
Other		19	23	9	9	2	0	4
Home		22	43	17	233	417	50	98
AcT	Walk	138	100	32	150	108	9	64
	Micromobility	0	0	0	0	0	0	0
PuT	Bus	13	9	1	6	7	1	1
	Subur.rail	20	11	1	13	27	6	7
	Metro/Tram	0	0	0	0	0	0	0
	Ferry	0	0	0	0	0	0	0
	Minibus	19	13	4	33	18	1	10
PrT	Service	156	7	6	42	147	17	26
	Private Car	116	28	9	62	122	16	44
	Shared Car	3	1	0	0	4	1	0
	Business Car	11	1	0	4	18	1	1
	Taxi	1	0	0	1	0	0	1
	Other	6	1	0	2	2	0	1

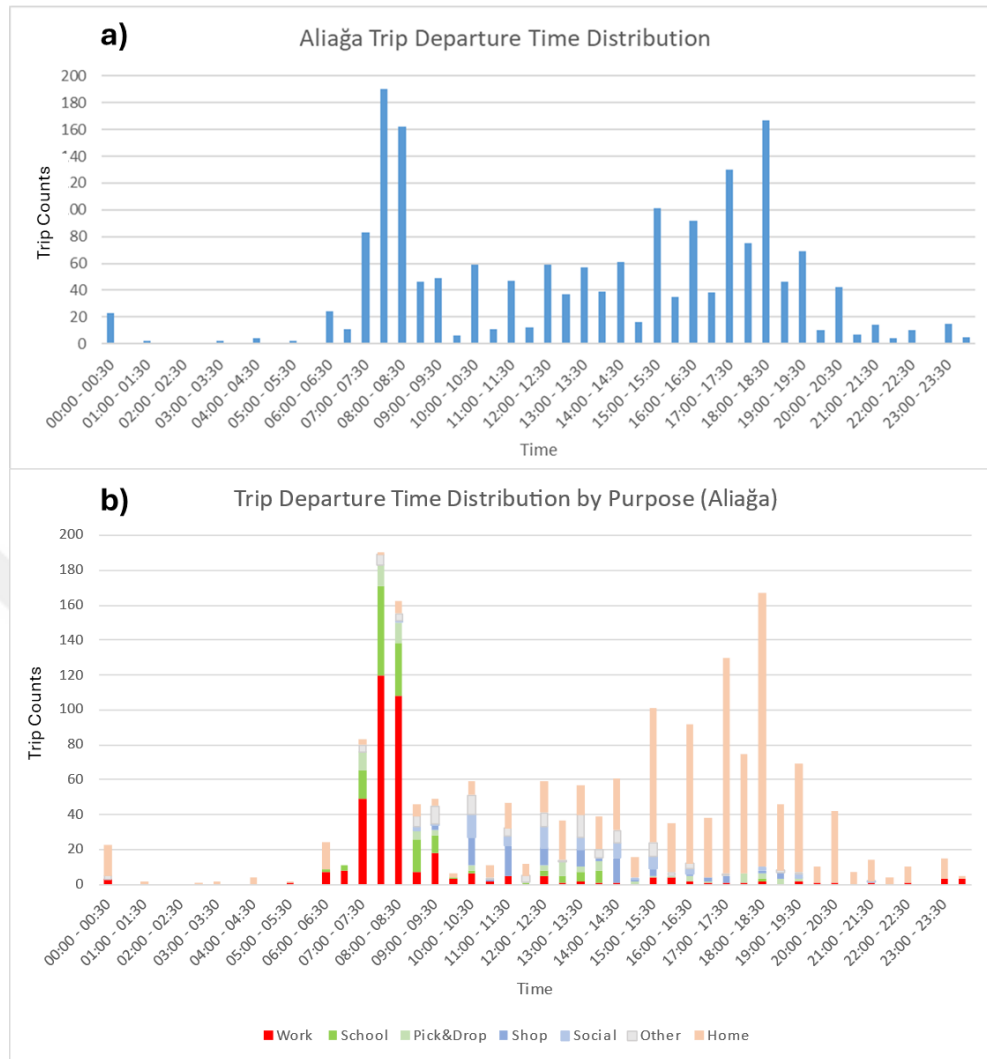


Figure 5.1. Aliaga Trip Departure Time Distribution for a) all trips and b) by Purpose

Analysis by Travel Modes

Active Modes:

The analysis of the mode-purpose matrix for trips originating from the Aliaga study area reveals clear relationships between specific travel purposes and preferred modes of transportation. Table 5.4 show the distribution of modes by purposes. Walking and micromobility modes are the most frequently used modes overall, accounting

for 293 trips, with the highest usage being for home (return), school, work, and shopping purposes. These modes dominate shorter, intra-city trips, consistent with the compact spatial structure of the Aliaga.

Public Transport:

Public transport modes show modest usage, making a total of 113 trips when combined. The minibus, in particular, serves a range of purposes including work (13), school (8) and other discretionary activities, indicating its role as a complementary public transport mode. The sub urban (44 trips) is used primarily for work (22) and social/shopping activities, indicating that rail connections are used for regional access beyond Aliaga. Bus use is more limited but consistently present for school and home-related trips.

Private Modes:

Service vehicles are the next most frequently used mode with 217 trips, and are strongly associated with work (143 trips) and school (41 trips) purposes. This suggests that employer- or institution-provided transportation plays a critical role in facilitating structured daily travel for work and education, especially in commuting densities. Private cars also have a high share (218 trips) and are distributed across a variety of purposes: work (79), pick-up/drop-off (42), shopping (33), and home (61), indicating their use for both mandatory and discretionary activities. This reflects the flexibility and accessibility of private vehicle use for multi-purpose daily travel. Less commonly used modes such as shared cars, business cars, motorcycles and taxis together account for a small proportion of total trips but show specific usage patterns. For example, business cars (24 trips) are associated with work, while motorcycles (5 trips) and taxis (1 trip) are marginally used for work or round-trip trips.

This mode-purpose analysis provides a strong empirical basis for assigning probabilistic mode choices based on travel purpose. For example, rules can be defined such that a school trip from Aliaga is more likely to walk, use a service or a private car, while work trips are more likely to use a service, a private car or a

commuter train. Similarly, shopping and social trips tend to prefer private modes or walking depending on distance. These findings enrich the behavioral realism of rule-based ABM and ensure that travel decisions reflect the mobility patterns observed in the Aliğa study area. Table 5.4 is showing the trip distribution by modes and purposes.

Table 5.4. Trip Distribution by Mode and Purpose for Aliğa Study Area

	From Aliğa	Trip Purposes						Home
		Work	School	Pick up & Drop off	Social	Shop	Other	
AcT	Walk	71	90	40	29	61	17	293
	Micromobility	0	0	0	0	0	0	0
PuT	Bus	6	6	0	1	0	5	20
	Subur.rail	22	4	0	4	5	6	44
	Metro/Tram	0	0	0	0	0	0	0
	Ferry	0	0	0	0	0	0	0
	Minibus	13	8	1	8	8	11	49
PrT	Service	143	41	0	0	0	0	217
	Private Car	79	1	42	17	13	27	218
	Shared Car	3	0	0	0	0	0	6
	Business Car	12	0	0	0	0	0	24
	Taxi	0	1	0	0	0	0	2
	Other	6	0	0	0	0	0	6

Destination Analysis Total Trip Distribution

The majority of trips from the Aliğa study area (1,259 out of 1,681 total trips, approximately 75%) are internal trips within the Aliğa Functional Urban Area (Alia_FUA). This confirms a strong internal mobility within the area and indicates a relatively self-sufficient urban structure. External destinations include nearby districts such as Karşıyaka_FUA (Karşıyaka Vicinity) (107 trips) and Menemen_FUA (Menemen Study Area) (95 trips), as well as the Izmir CBD (34 trips), the outer regions (68 trips) and areas within the Aliğa, Menemen and

Karşıyaka districts but outside the defined FUA boundaries. Among these, Karşıyaka_FUA is the most prominent external attractor, closely followed by Menemen_FUA. Figure 5.2, Figure 5.3, Figure 5.4, Figure 5.5, Figure 5.6, Figure 5.7, Figure 5.8, Figure 5.9, and Figure 5.10 show the O-D maps for Aliağa.

Temporal Distribution of Travel by Destination

In terms of time zones, the highest travel volume occurs in TP1 (06:00–09:00) with 483 trips, indicating a strong morning peak consisting mainly of outbound work and school trips. For outbound destinations, Karşıyaka_FUA and Menemen_FUA receive most of their trips in TP1 and TP5 (16:30–19:30), consistent with commuting and return-home patterns. Notably, Menemen_FUA sees a high volume of return trips in TP5 (46 trips), while Karşıyaka_FUA is more balanced, showing both morning and evening movement. The İzmir CBD and outer regions are visited at a much lower frequency, typically spread over the peak periods in TP1 and TP5. These patterns highlight the functional role of neighboring districts in providing employment and education opportunities, and time-of-day preferences reflect typical daily schedules.

Travel Mode Distribution by Destination and Time Period

Travel mode usage shows a clear relationship with travel distance and purpose. Walking and micromobility modes (601 trips) are dominant for domestic travel within Alia_FUA, indicating a compact urban structure where non-motorized modes are applicable. These trips are most frequent during TP2 to TP5, indicating usage for discretionary or lunchtime activities. In contrast, private cars (397 trips) and shuttles (401 trips) are dominant for trips to Menemen and Karşıyaka, especially during TP1 and TP5. Karşıyaka_FUA, in particular, is heavily dependent on the use of private cars (42 trips) and shuttles (26 trips), probably for commuting. Public transportation usage (bus, minibus, and suburban-rail) is generally limited, but shows modest usage, especially during TP1, towards Menemen and İzmir CBD. For example, the commuter train sees 29 trips towards Karşıyaka_FUA and 16 trips towards İzmir CBD, which is consistent with morning trips.

Distribution of Travel Purpose by Destination and Time Period

A clear pattern emerges when analyzing travel purpose by destination and time. Work trips (355 in total) are largely distributed across Karşıyaka_FUA (42 trips), Alia_Other and Menemen districts, with a strong concentration in TP1, reflecting morning commutes. School trips (151 in total) follow a similar spatial pattern, but are slightly more limited in Alia_FUA and neighboring areas, peaking in TP1. Pick-up/drop-off and shopping trips mostly occur within Alia_FUA and occur during the afternoon hours (TP4 and TP5), while social trips are fewer in number but likely directed slightly further out during the low season. Return trips home (880 total) cover a wider time range but are concentrated in TP4 and TP5, consistent with return patterns. Destinations for return trips home include Karşıyaka_FUA (85 trips), outer regions (54), and Menemen_FUA (77), indicating a strong return flow to Aliğa from adjacent employment and service centers.

These findings (See Table 5.5.) provide a solid foundation for defining destination-related rules within a rule-based ABM framework for Aliğa. Trip distributions provide probabilistic weights for where people travel, when they travel based on time of day, how they travel based on distance and purpose, and why they travel based on activity type. This multidimensional assessment supports the creation of context-specific, behaviorally realistic rules to simulate travel decisions with high spatial and temporal fidelity in the Aliğa study area.

Table 5.5. Aliğa Study Area Trip Destination Details

	Destinations								
From Aliğa	Aliğa		Menemen		Karşıyaka*		İzmir		Total
	FUA	Oth	FUA	Oth	FUA	Oth	CBD	Oth	
Trips	1259	77	95	30	107	11	34	68	1681
TP1	378	40	12	19	11	1	6	16	483
TP2	146	1	6	0	5	1	7	5	171
TP3	49	1	0	2	1	0	0	0	53
TP4	251	15	10	5	17	0	7	8	313
TP5	297	9	46	3	53	8	10	28	454
TP6	24	0	13	1	8	0	2	4	52
TP7	114	11	8	0	12	1	2	7	155
Work	251	47	12	21	10	2	5	7	355
School	141	2	5	0	0	0	0	3	151
Pick&Drop	81	2	0	0	0	0	0	0	83
Social	46	0	0	2	6	0	2	3	59
Shop	81	0	0	2	3	0	1	0	87
Other	51	0	1	0	3	0	10	1	66
Home	608	26	77	5	85	9	16	54	880
Walk	591	10	0	0	0	0	0	0	601
	0	0	0	0	0	0	0	0	0
Bus	31	1	2	0	1	0	0	3	38
Subur.rail	2	1	23	4	29	3	16	7	85
Metro/Tram	0	0	0	0	0	0	0	0	0
Ferry	0	0	0	0	0	0	0	0	0
Minibus	90	4	3	0	0	0	1	0	98
Service	232	39	51	18	26	6	5	24	401
Private Car	278	20	14	7	42	1	11	24	397
Shared Car	4	0	0	1	1	1	0	2	9
Business Car	19	2	2	0	7	0	1	5	36
Taxi	3	0	0	0	0	0	0	0	3
Other	9	0	0	0	0	0	0	3	12

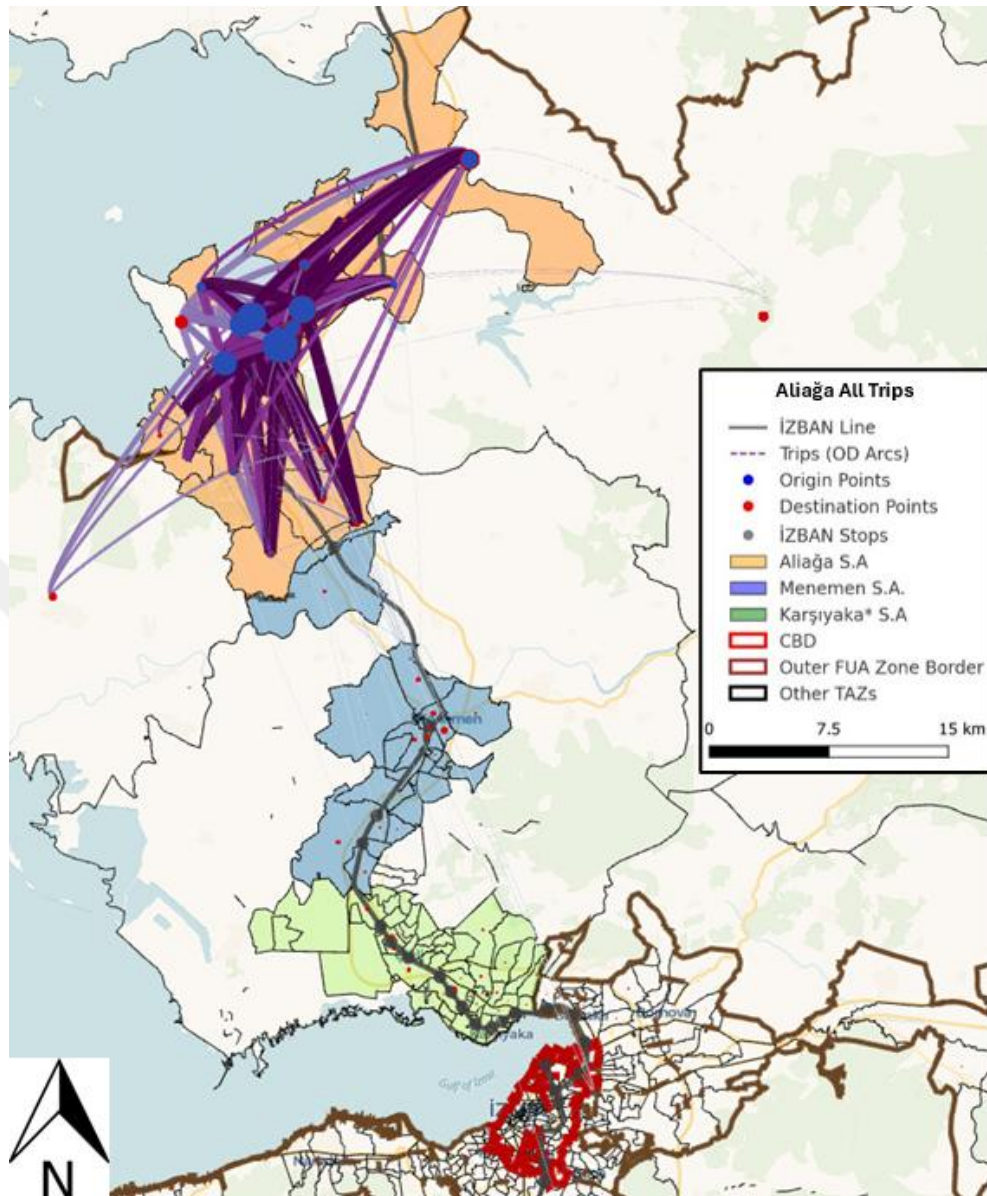


Figure 5.2. Aliğa Study Area All Trips

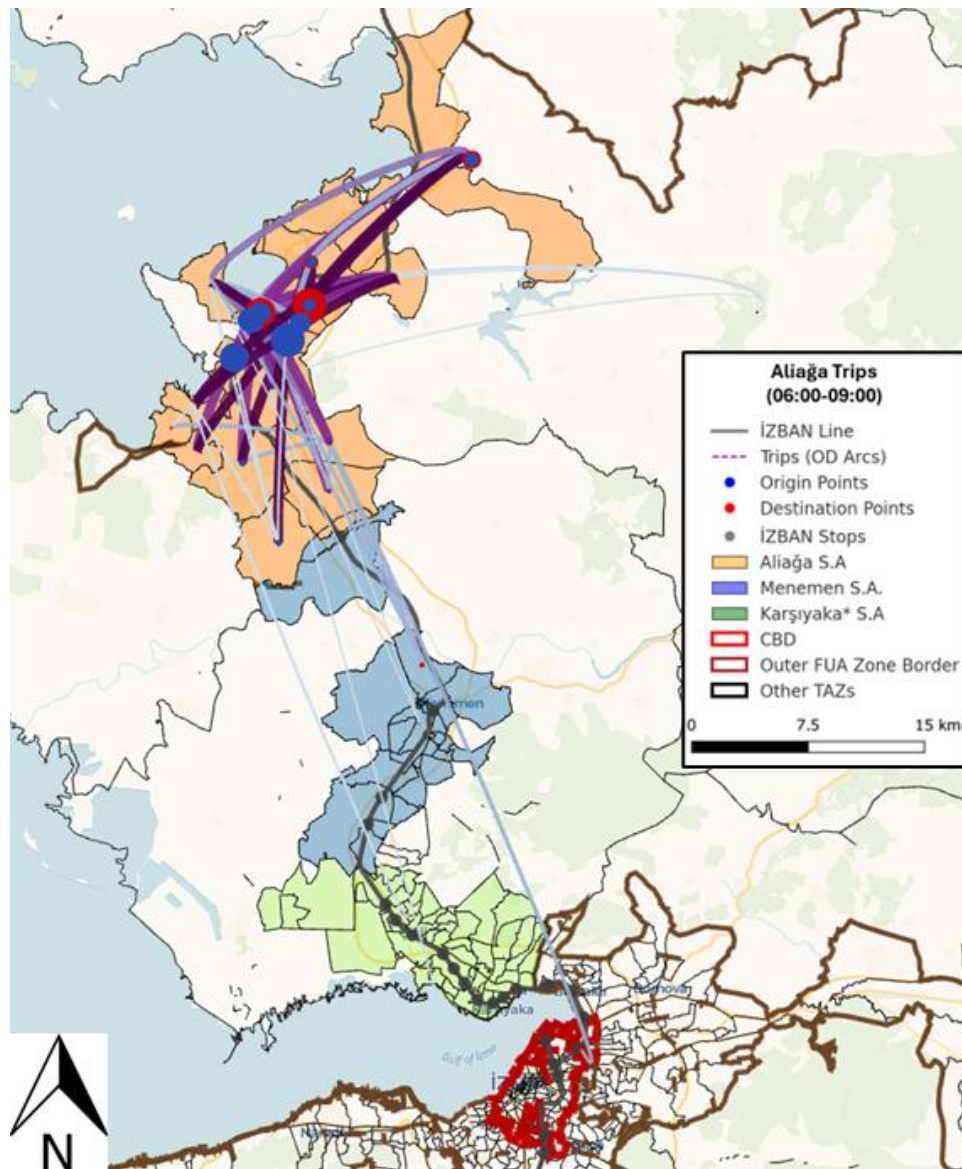


Figure 5.3. Aliğa Study Area All Trips (06:00-09:00)

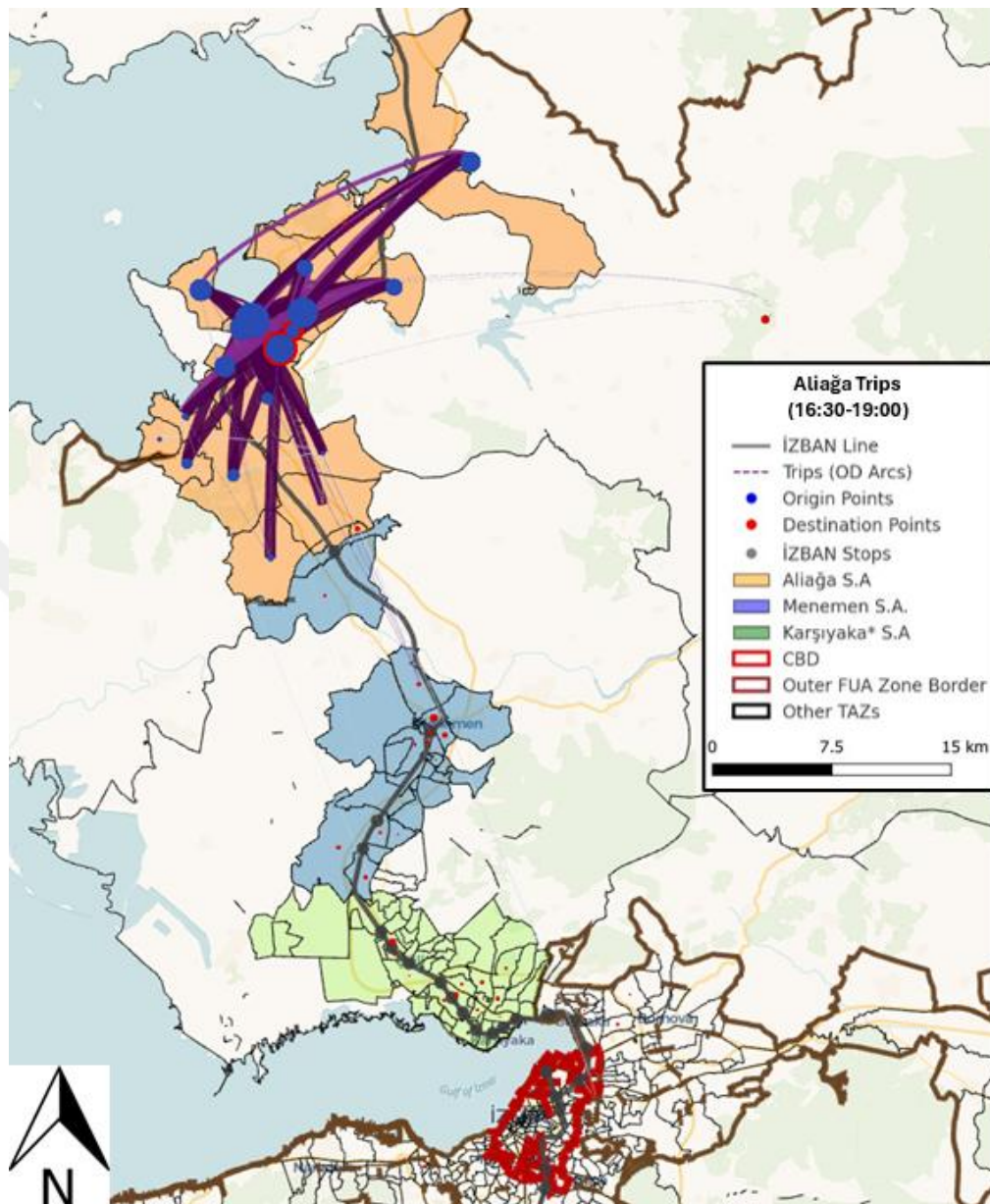


Figure 5.4. Aliğa All Trips (16:30-19:00)

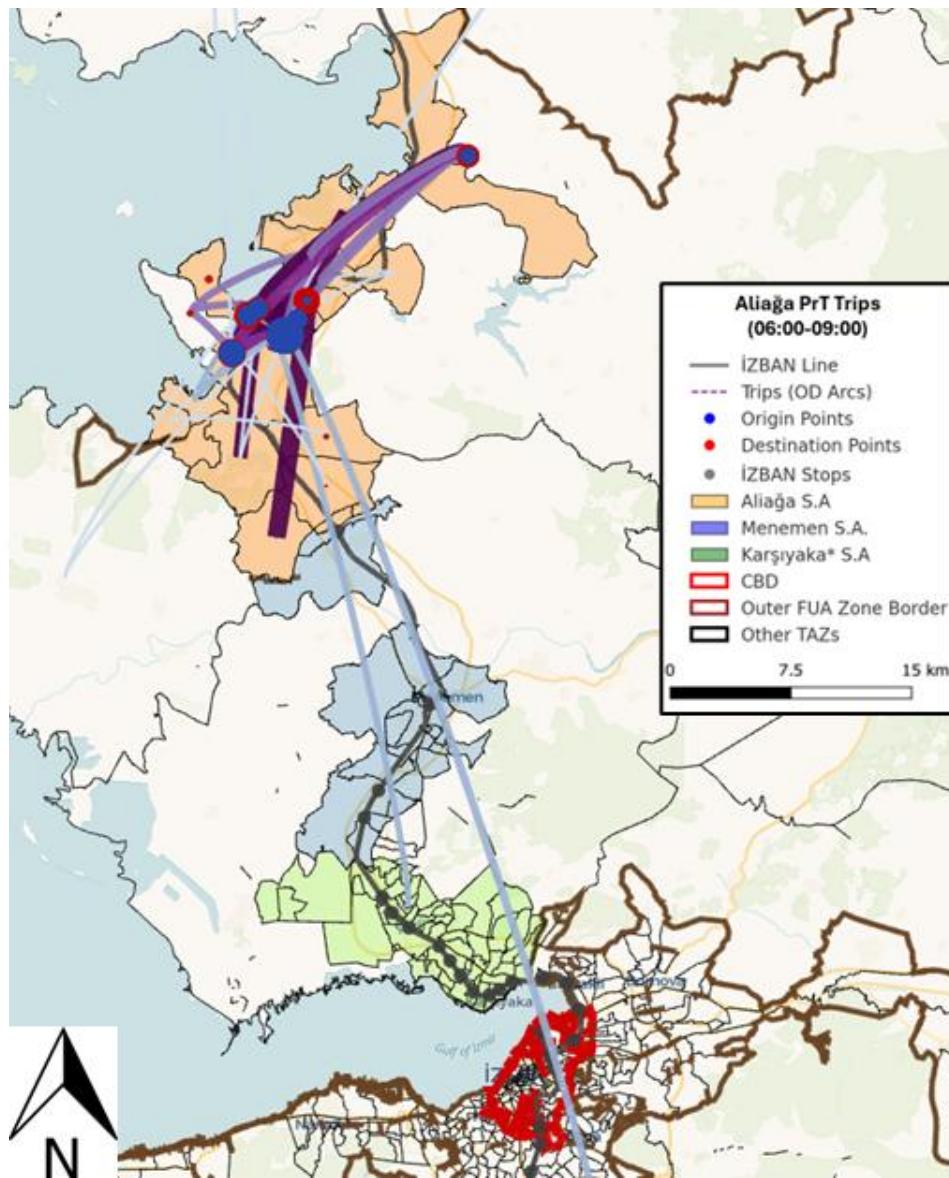


Figure 5.5. Aliğa PrT Trips (06:00-09:00)

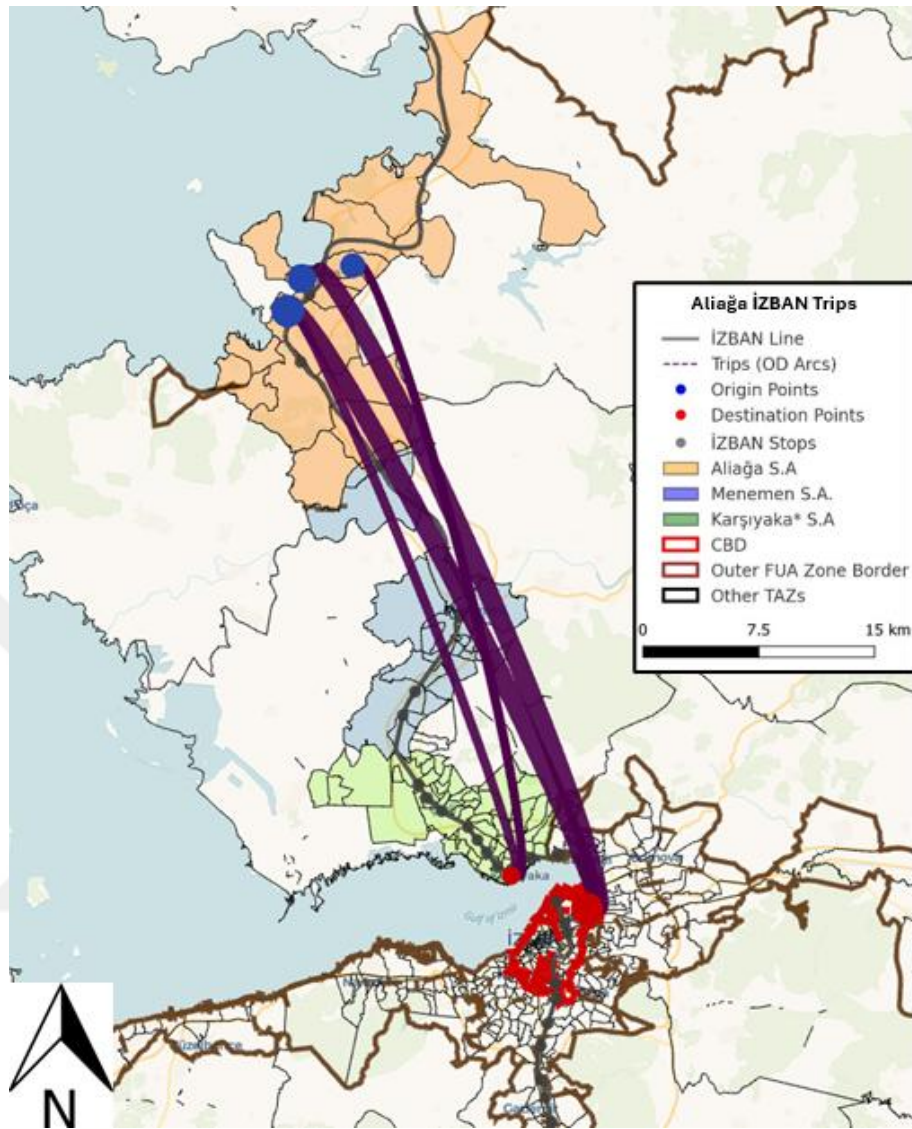


Figure 5.6. Aliğa İZBAN Trips

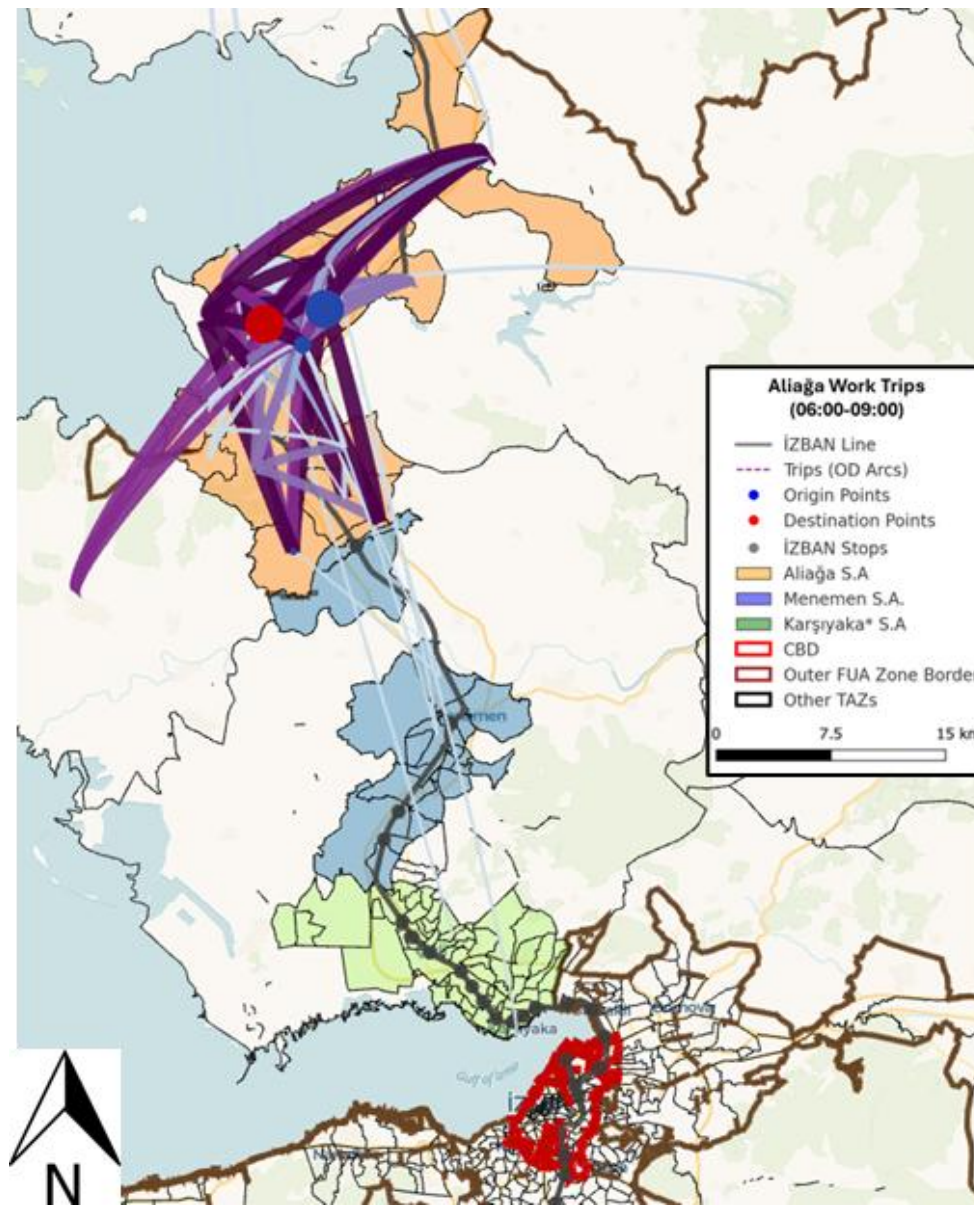


Figure 5.7. Aliğa Work Trips (06:00-09:00)

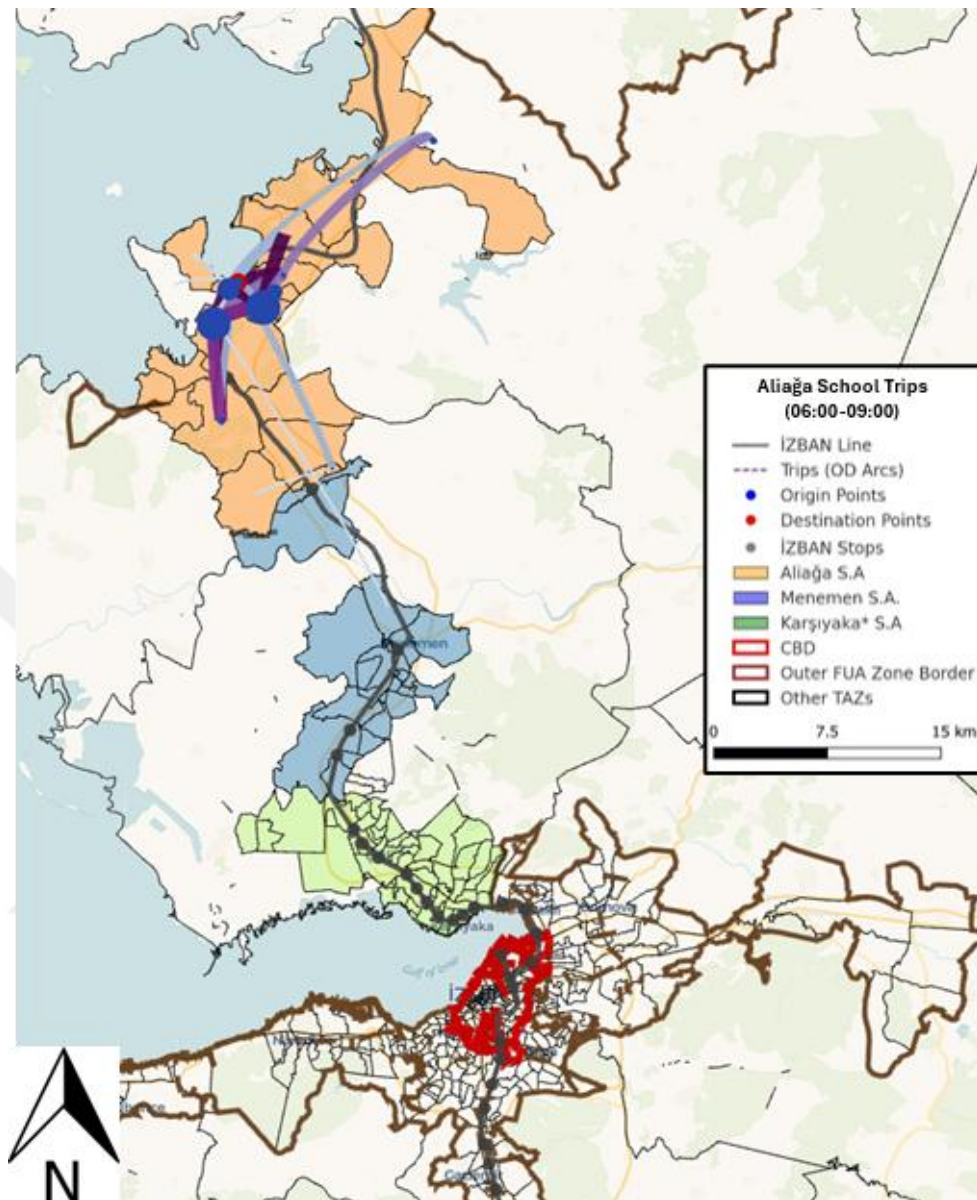


Figure 5.8. Aliğa School Trips (06:00-09:00)

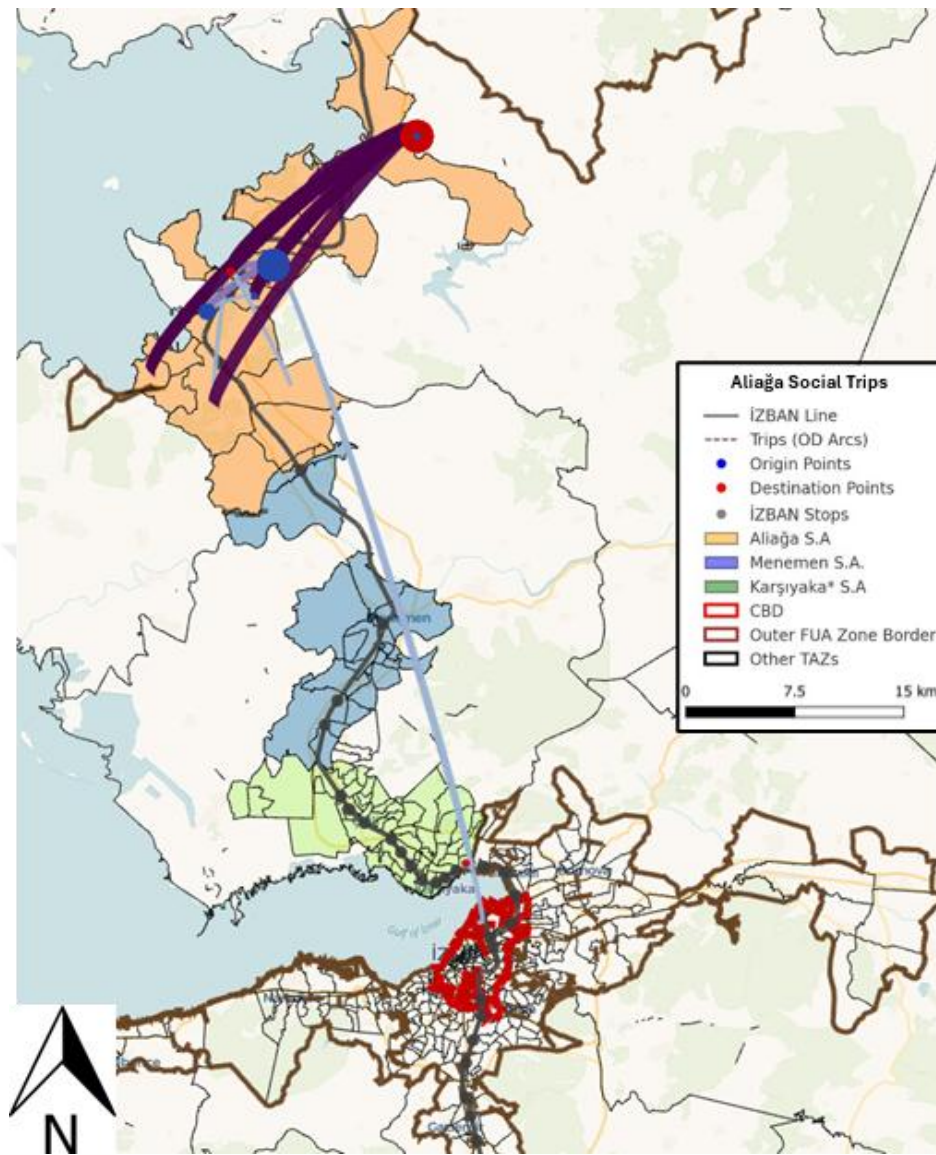


Figure 5.9. Aliğa Social Trips

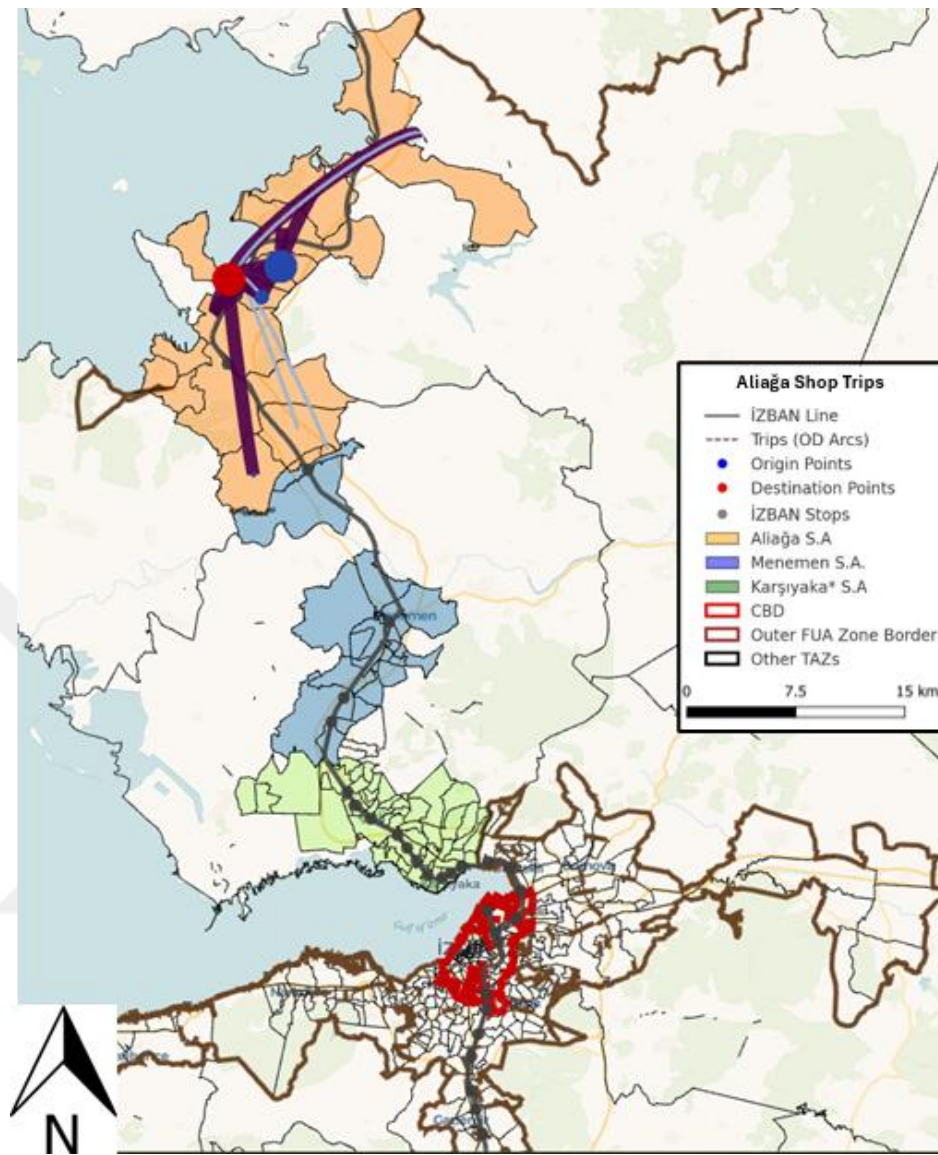


Figure 5.10. Aliğa Social Trips

5.2 Urban Travel Characteristics of Menemen FUA Region

Travel Distribution

All the guidelines established and utilized in this phase are derived from the household survey. The formulation of these guidelines was achieved by categorizing individuals based on their types. By applying these probabilistic distributions, the classification of individuals as either travelers or non-travelers was conducted. Table 5.6 presents the probabilities of travelers among the citizens of Menemen, categorized by person types.

Table 5.6. Travel Probabilities for Menemen by Person Types

	From Menemen	Travel Probabilities (%)	
Person Type	Definition	Travel	No-Travel
PT1	Full_Time	77	23
PT2	Part_Time	73	27
PT3	Uni_Std.	36	65
PT4	Non_Emp.	32	68
PT5	Retired	46	54
PT6	PStudent	36	64

Activity Pattern Distribution

The analysis of the Menemen study area provides vital behavioral insights for rule-based ABM by revealing clear distinctions in daily activity chains between person types (See Table 5.7). The table presents the number of observed Home-based tours, which are sequences that start and end at home, classified by activity purpose and person type. This allows identifying which person types participate in which types of activities and when.

- PT1 overwhelmingly follows the Home → Work → Home pattern (837 trips), confirming a strong association with essential work travel. PT2 also

shows significant participation in this chain (157 trips), with the remaining person types contributing minimally.

- PT6 almost exclusively participates in Home → School → Home chains (275 trips), indicating a fairly consistent and routine activity structure. PT3 and PT4 also participate in school-related travel, but at significantly lower volumes.
- PT5 and PT4 exhibit strong participation in discretionary activities, particularly Home → Shop → Home (PT5: 94, PT4: 213) and Home → Social → Home (PT5: 77, PT4: 217). These person types also show a significant presence in Home → Other → Home trips, reflecting a wider flexibility and variability in travel behavior.
- Pick & Drop chains are minimal but are seen in PT1, PT2 and PT4, usually as shorter or auxiliary trip chains.
- PT3 and PT6 have limited participation in extracurricular activities, while PT1 and PT2 occasionally participate in shopping, social and other trips beyond their work-related patterns.

Table 5.7. Activity Schedule Distribution by Person Types in Menemen

Activities From Menemen	PT1	PT2	PT3	PT4	PT5	PT6
Home ->Work ->Home	837	157	5	0	0	18
Home ->School ->Home	7	0	26	16	0	275
Home ->Pick&Drop ->Work ->Home	2	1	0	0	0	0
Home ->Pick&Drop ->Home	1	0	2	16	1	0
Home ->Shop ->Home	69	8	10	213	94	16
Home ->Social ->Home	69	12	25	217	77	31
Home ->Other ->Home	34	11	9	95	49	10

• *Time Period Analysis by Purpose and Mode*

Based on HHTS data for the Menemen study area, a detailed analysis (See Table 5.8 was conducted to understand the temporal, modal and purpose-based characteristics

of the observed trips, which will inform the development of rules within the rule-based ABM. Most trips occur during TP1 (06:00–09:00) and TP5 (16:30–19:30), reflecting the dominant commuting peaks. Work-related trips are highly concentrated in TP1 (623 trips), and return trips are distributed between TP5 and TP7, indicating the presence of both standard and late shift schedules. School trips are similarly concentrated in TP1, with moderate return flows in TP4. Social and shopping trips show increased activity in TP3, TP4 and TP5, reflecting their discretionary nature and their compatibility with trips in the afternoon and early evening. In particular, shopping trips peak during TP2 (09:00-12:00) and TP4 (13:30-16:30), while social trips are spread throughout the day and have a significant share in TP7 (Night), probably representing leisure or family-related evening activities.

In terms of mode choice, private cars and shuttles dominate travel during the day, especially during TP1 and TP5, with private car use reaching its peak in TP5 (223 trips). Shuttles are heavily used in TP1 (193 trips), indicating structured travel arrangements for work and school purposes. Walking and micromobility modes are frequently used, especially in TP2 to TP5, highlighting the feasibility of non-motorized travel options for local, short-distance activities in Menemen.

Public transport usage is moderate, bus usage is highest during TP3 and TP4, and commuter rail shows consistent but relatively low volumes across all time periods, suggesting a supporting role in regional mobility. Metro/tram, shared cars, and taxis remain minimal, suggesting limited availability or preference for these modes in the study area.

These findings provide essential inputs for developing travel rules for Menemen residents within the ABM framework. Temporal distributions, mode preferences, and travel purposes provide a detailed behavioral profile that supports probabilistic rule generation for travel duration, mode, and activity planning, ensuring that the model accurately reflects real-world mobility patterns in the Menemen study area. Figure 5.11 shows the trip departure time distributions in Menemen.

Table 5.8. Trip Distribution by Time Periods for Purpose and Mode (Menemen)

		Time Periods						
From Menemen		TP1	TP2	TP3	TP4	TP5	TP6	TP7
Trips		947	509	197	850	759	117	401
Work		623	69	4	23	5	1	28
School		205	23	6	4	4	0	13
Pick&Drop		55	2	15	20	18	0	9
Social		13	101	45	132	53	5	75
Shop		6	135	42	122	28	3	64
Other		21	69	26	44	6	5	26
Home		24	110	59	505	645	103	186
AcT	Walk	273	248	104	425	222	29	176
	Micromobility	2	0	0	0	2	1	2
PuT	Bus	143	101	41	154	148	36	57
	Subur.rail	91	37	10	39	44	11	43
	Metro/Tram	0	0	0	0	0	0	0
	Ferry	0	0	0	0	0	0	0
	Minibus	9	9	3	16	11	1	6
PrT	Service	193	6	0	47	82	9	22
	Private Car	205	101	37	158	223	21	86
	Shared Car	0	3	1	1	4	1	0
	Business Car	25	2	0	2	12	5	2
	Taxi	0	0	0	5	3	0	6
	Other	6	2	0	3	6	3	1

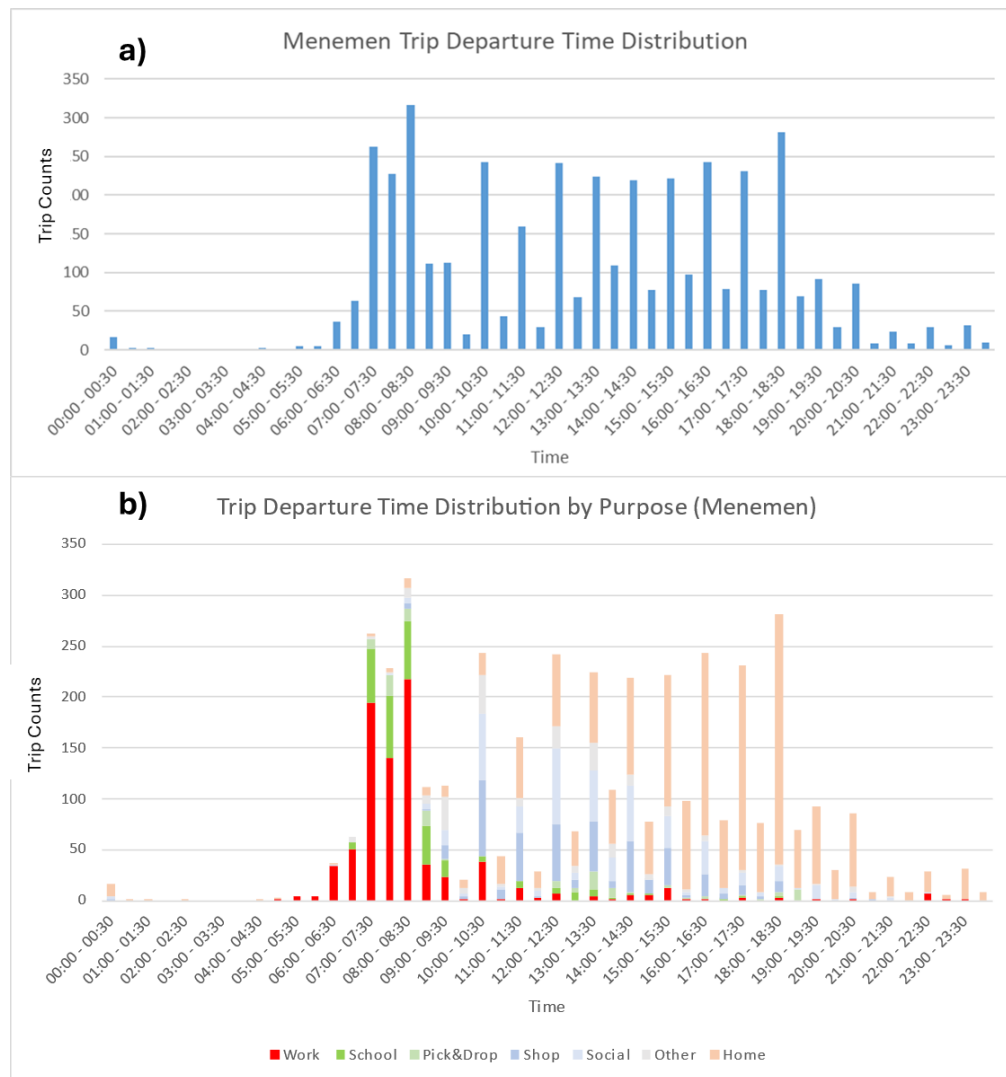


Figure 5.11. Menemen Trip Departure Time Distribution for a) all trips and b) by Purpose

The cross-tabulation of mode choice by travel purpose (See Table 5.9) for the Menemen study area highlights both the functional use of transport modes and the diversity of travel behavior across different activity types. The findings reveal clear patterns consistent with the types of travel and transport categories (AcT, PuT, PrT), which are crucial for defining behavior-based rules in ABM modeling.

Active Modes:

Walking is dominant for a wide range of purposes, especially for school (142), shopping (245), social (161) and work (116) trips. High frequency for discretionary trips indicates good proximity to destinations or a compact urban form. Micromobility modes are hardly used and only isolated trips for work, social and shopping purposes are recorded, reflecting limited infrastructure or adoption in the region.

Public Transport:

Bus is widely used for almost all purposes, especially for work (114) and pick-up and drop-off (84) trips, but also for optional purposes such as shopping and other (64 each), indicating its flexibility in meeting both essential and non-essential travel needs. Suburban-rail is used especially for work (83) and school (17) trips, reflecting a possible dependence on this mode for long-distance or corridor-based essential travel. Metro/Tram and Ferry are not used, indicating a lack of service coverage or connectivity from Menemen. Minibus appears in limited but consistent numbers for work, shopping and other trips, indicating niche but stable use.

Private Modes:

Private car is one of the most frequently used modes, especially for work (198), school (15), social (132) and shopping (56) trips. Its widespread use for both essential and discretionary travel highlights the car dependency in the area. Service vehicles are strongly used for work (197) and school (30) trips, likely reflecting institutional or employer-based transport provisions. Business cars, shared cars and taxis are used minimally, with a small number of vehicles distributed across a range of purposes, suggesting that they are not the dominant options in this area.

Table 5.9. Trip Distribution by Mode and Purpose for Menemen Study Area

		Trip Purposes						Home
From Menemen		Work	School	Pick up & Drop off	Social	Shop	Other	
AcT	Walk	116	142	101	161	245	48	664
	Micromobility	2	0	0	1	1	0	3
PuT	Bus	114	50	0	84	64	64	304
	Subur.rail	83	17	0	36	25	16	98
	Metro/Tram	0	0	0	0	0	0	0
	Ferry	0	0	0	0	0	0	0
	Minibus	8	1	0	2	7	7	30
PrT	Service	197	30	0	0	0	1	131
	Private Car	198	15	18	132	56	53	359
	Shared Car	1	0	0	1	0	2	6
	Business Car	29	0	0	0	0	0	19
	Taxi	0	0	0	4	1	3	6
	Other	5	0	0	2	1	3	10

Destination Analysis Total Trip Distribution

The majority of trips from Menemen are directed to Menemen_FUA (2,428 trips), confirming a strong internal mobility within the functional urban area. The next significant flows are to Karşıyaka_FUA (526 trips) and Menemen_Other (306 trips), indicating frequent intra-district travel. Additionally, İzmir CBD (254 trips) and the outer regions (85 trips) reflect moderate long-distance travel, likely associated with business or institutional functions. Very few trips go to Aliğa FUA (104) or Karşıyaka_Other (64), making them relatively small destinations.

Temporal Distribution of Travel by Destination

The temporal distribution reveals that TP1 (06:00–09:00) and TP5 (16:30–19:30) are the dominant travel periods in all destination areas, consistent with commuting patterns. In particular, Menemen_FUA, Karşıyaka_FUA and İzmir CBD attract the largest number of trips during TP1, highlighting their role as employment and education centers. Conversely, return trips are concentrated in TP5 and TP7 (21:00–

06:00), especially for Menemen_FUA (475 and 235 trips, respectively), suggesting standard and late shift work or extended activity periods. Karşıyaka_FUA also receives a significant number of trips during TP4 and TP5, suggesting interactions occurring in the middle or late hours of the day.

Trip Mode Distribution by Destination and Time Period

The choice of travel mode varies significantly depending on the destination, in line with the length of the trip and the type of activity. Walking and micromobility dominate domestic trips within Menemen_FUA (1,313 trips), reflecting short-distance accessibility and local connectivity. Private cars (392 trips) and public transport (bus: 497; suburban rail: 292) are also used within Menemen, indicating a variety of mobility options even for local trips. For longer-distance trips, such as Karşıyaka_FUA and İzmir CBD, the use of private cars increases significantly (Karşıyaka_FUA: 197; İzmir CBD: 147), shuttles (Karşıyaka_FUA: 75; İzmir CBD: 42), and suburban rail (Karşıyaka_FUA: 127; İzmir CBD: 46). These patterns reflect structured commuting via both private and public transport modes. Bus use is also evident in inter-district travel, especially in the Karşıyaka and Menemen_Other directions.

Transportation vehicles such as metro/tram, taxi and shared vehicles are rarely used, indicating limited infrastructure for travel originating from Menemen.

Distribution of Travel Purpose by Destination and Time Period

Work (753 trips) was the primary purpose, trips were primarily directed to Menemen_FUA (315), Karşıyaka_FUA (156), and Menemen_Other (79), peaking in TP1 and returning in TP5–TP7. School (259 trips) were mostly directed to Menemen_FUA (220), reflecting local educational outreach. Pick-up/drop-off and shopping trips were also concentrated within Menemen, but with some spillover to Karşıyaka and İzmir CBD, particularly during TP4 and TP5. Social trips (370 total) and shopping trips (400 total) were primarily directed to Menemen_FUA,

Karşıyaka_FUA, and İzmir CBD, and occurred mostly during lunch and evening hours (TP4–TP7), consistent with discretionary activity scheduling.

Finally, round-trip trips from home (1,632 total) are distributed across all destinations but are particularly high in Menemen_FUA (1,170) and Karşıyaka_FUA (184), reaching peaks in TP5 and TP7, reflecting the typical end-of-day pattern.

Destination-based travel data from the Menemen study area confirm a predominantly intra-urban and localized mobility pattern with meaningful connections to Karşıyaka and İzmir CBD for work, education, and discretionary purposes. While temporal patterns follow traditional commuting and daily activity schedules, modal preferences vary according to travel distance and purpose. These behavioral insights provide key probabilistic inputs for the generation of rules regarding destination choice, travel timing, mode choice, and activity purpose in rule-based ABM. Such granular, person-level logic enables realistic simulation of daily travel decisions among Menemen residents.

The results presented (refer to Table 5.10.) establish a strong basis for outlining destination-specific guidelines within a rule-based ABM framework for Menemen. Also, Figure 5.12, Figure 5.13, Figure 5.14, Figure 5.15, Figure 5.16, Figure 5.17, Figure 5.18, Figure 5.19, and Figure 5.20 show O-D maps for Menemen.

Table 5.10. Menemen Study Area Trip Destination Details

From Menemen	Destinations								Total
	Aliağa		Menemen		Karşıyaka*		İzmir	Outer	
	FUA	Oth	FUA	Oth	FUA	Oth	CBD	Oth	
Trips	104	13	2428	306	526	64	85	254	3780
TP1	71	10	517	77	157	12	39	64	947
TP2	3	2	336	58	67	3	12	28	509
TP3	1	0	148	15	23	0	0	10	197
TP4	11	0	644	71	78	6	9	31	850
TP5	13	0	475	36	115	23	13	84	759
TP6	1	0	73	3	29	1	0	10	117
TP7	4	1	235	46	57	19	12	27	401
Work	81	11	315	79	156	11	44	56	753
School	3	0	220	6	16	0	4	6	255
Pick&Drop	0	0	97	8	0	1	0	13	119
Social	0	0	216	70	82	1	9	46	424
Shop	1	0	296	37	57	2	5	2	400
Other	1	0	114	24	31	0	3	24	197
Home	18	2	1170	82	184	49	20	107	1632
Walk	0	0	1307	125	9	6	7	23	1477
Micromobility	0	0	6	0	1	0	0	0	7
Bus	2	0	497	52	94	1	2	32	680
Subur.rail	24	1	34	2	127	29	46	12	275
Metro/Tram	0	0	0	0	0	0	0	0	0
Ferry	0	0	0	0	0	0	0	0	0
Minibus	3	0	35	5	6	0	0	6	55
Service	57	5	117	43	75	13	7	42	359
Private Car	15	5	392	72	197	14	17	119	831
Shared Car	1	0	4	2	1	0	1	1	10
Business Car	2	2	16	1	15	1	4	7	48
Taxi	0	0	6	3	1	0	0	4	14
Other	0	0	12	1	0	0	0	8	21

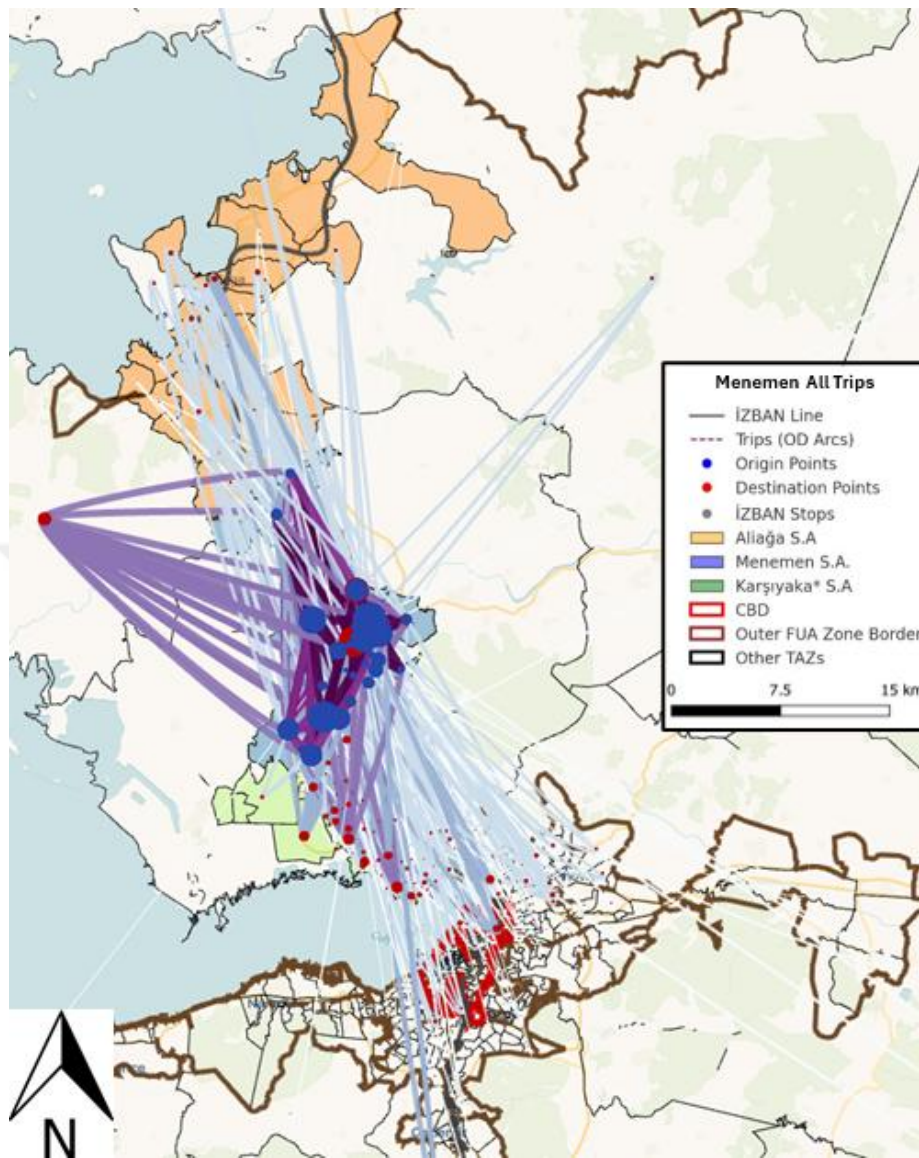


Figure 5.12. Menemen All Trips

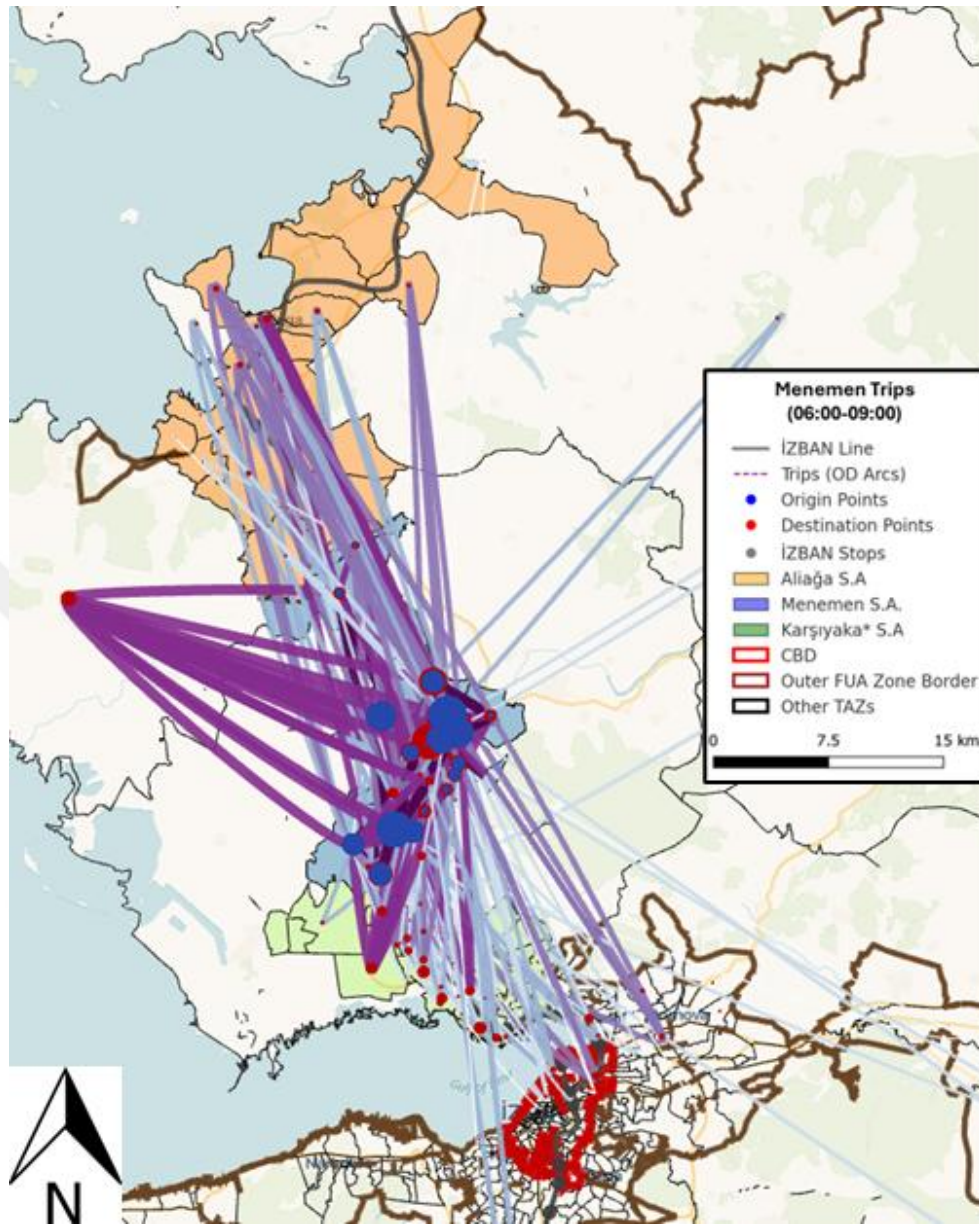


Figure 5.13. Menemen All Trips (06:00-09:00)

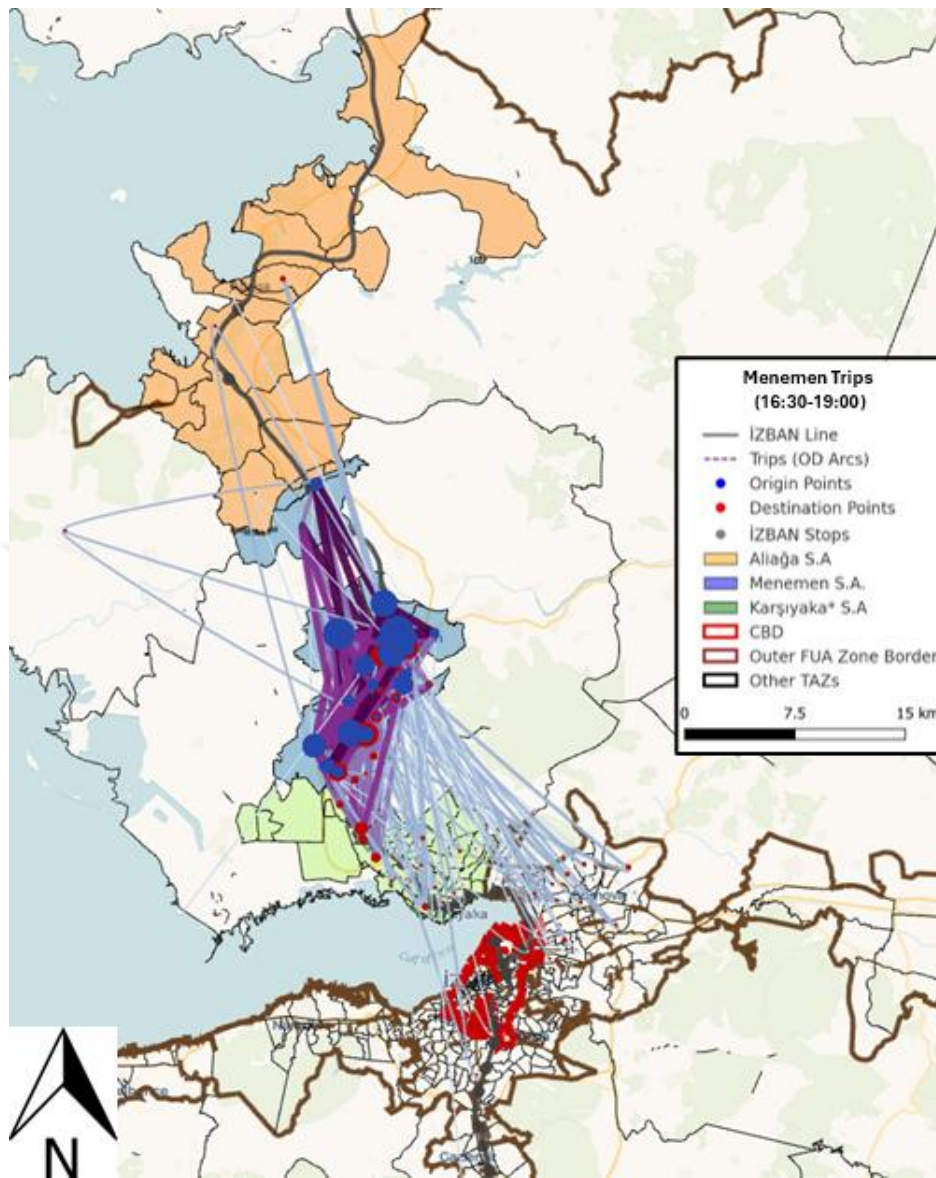


Figure 5.14. Menemen Trips (16:30-19:00)

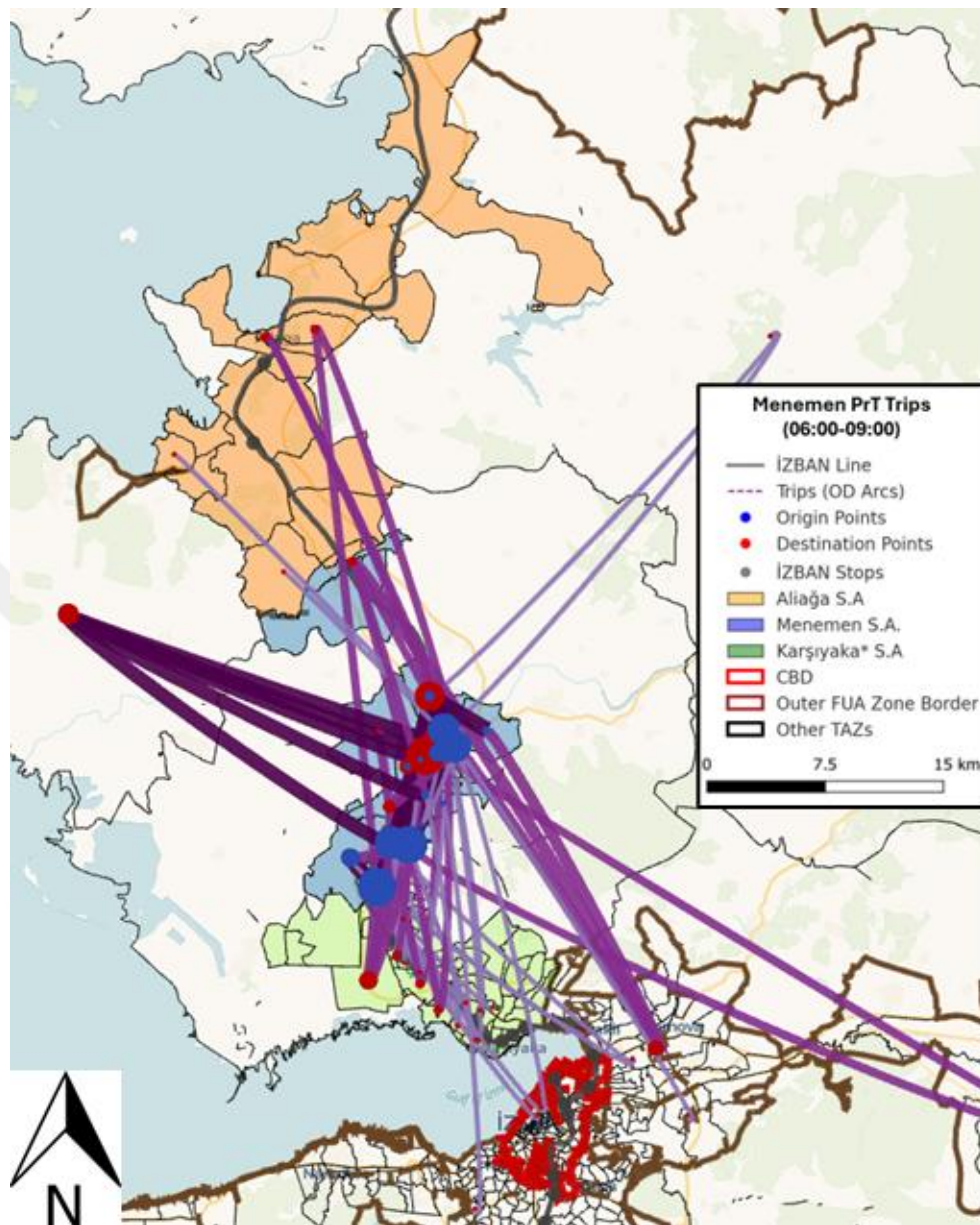


Figure 5.15. Menemen PrT Trips (06:00-09:00)

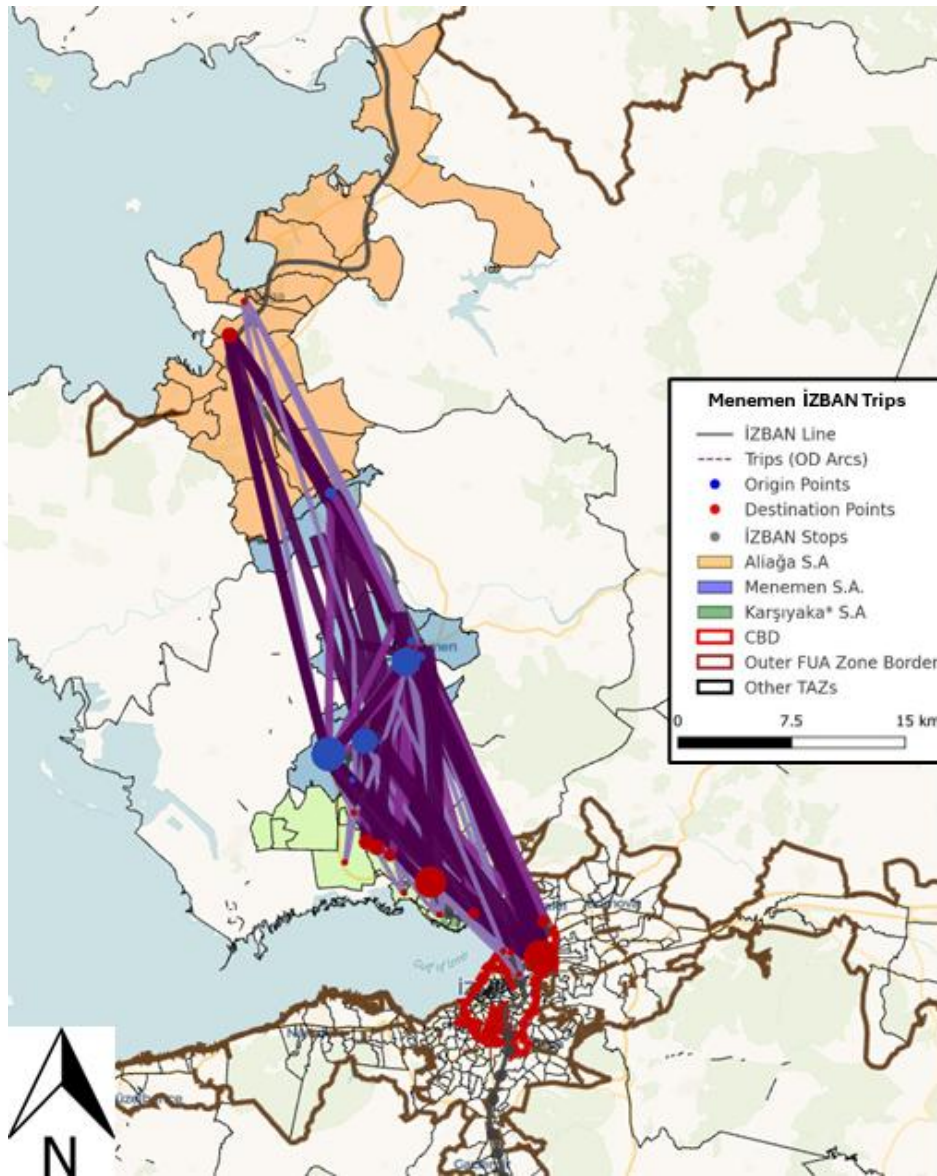


Figure 5.16. Menemen İZBAN Trips

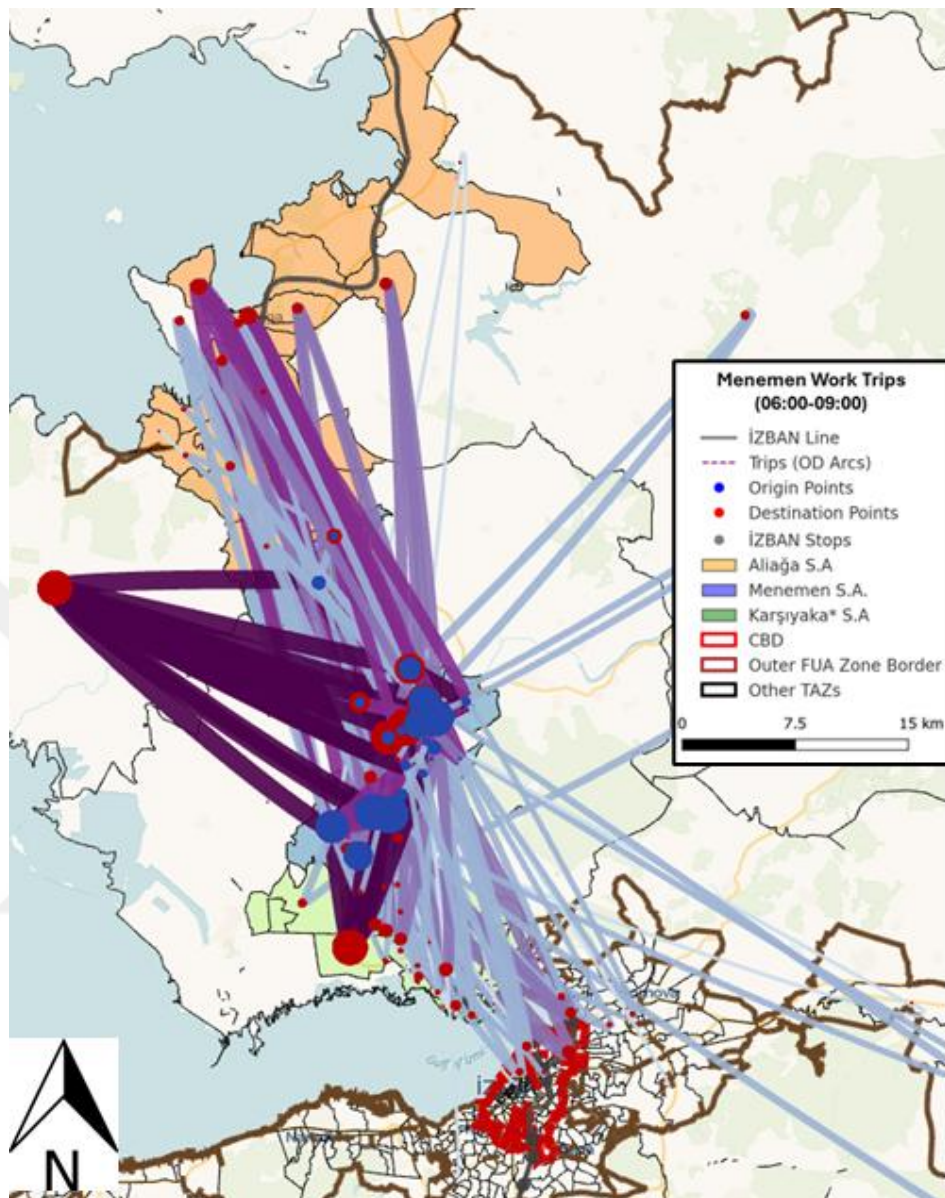


Figure 5.17. Menemen Work Trips (06:00-09:00)

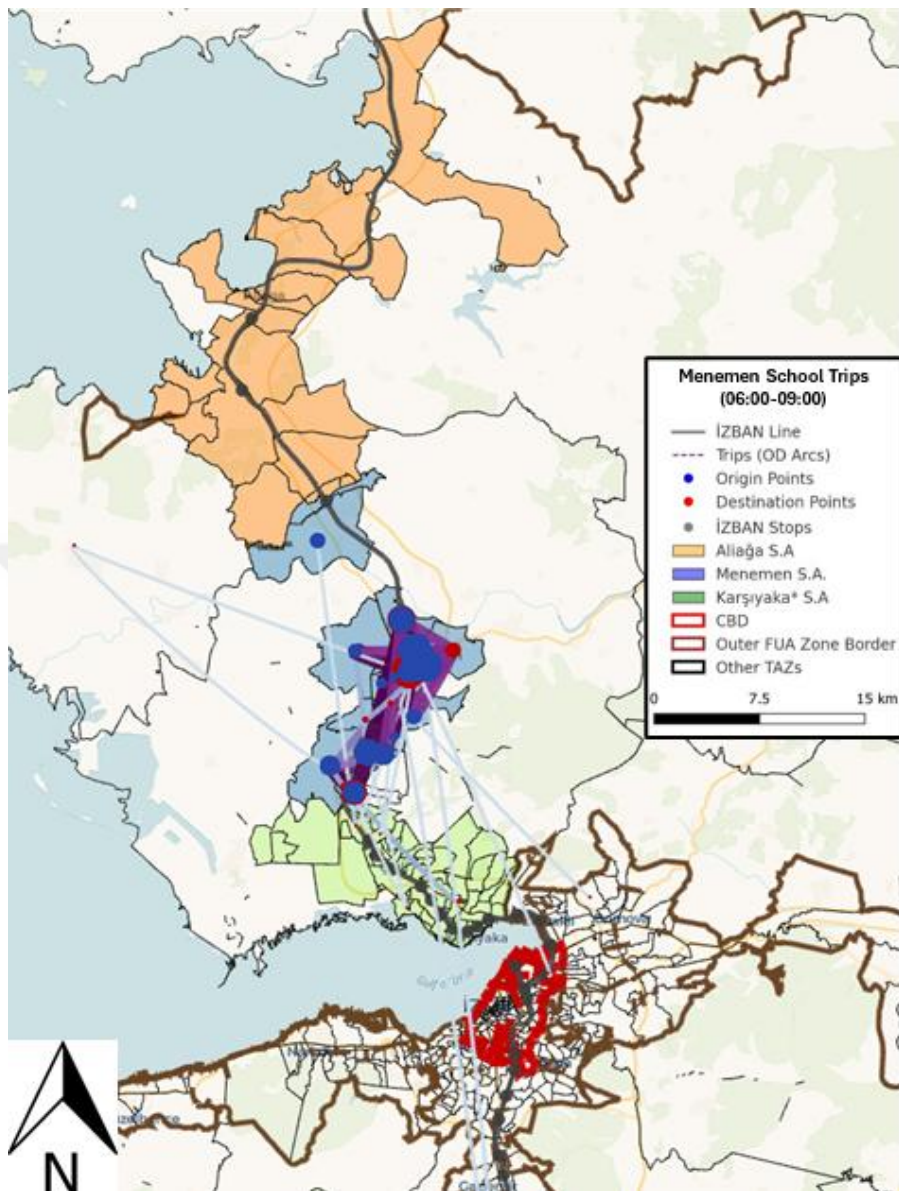


Figure 5.18. Menemen School Trips (06:00-09:00)

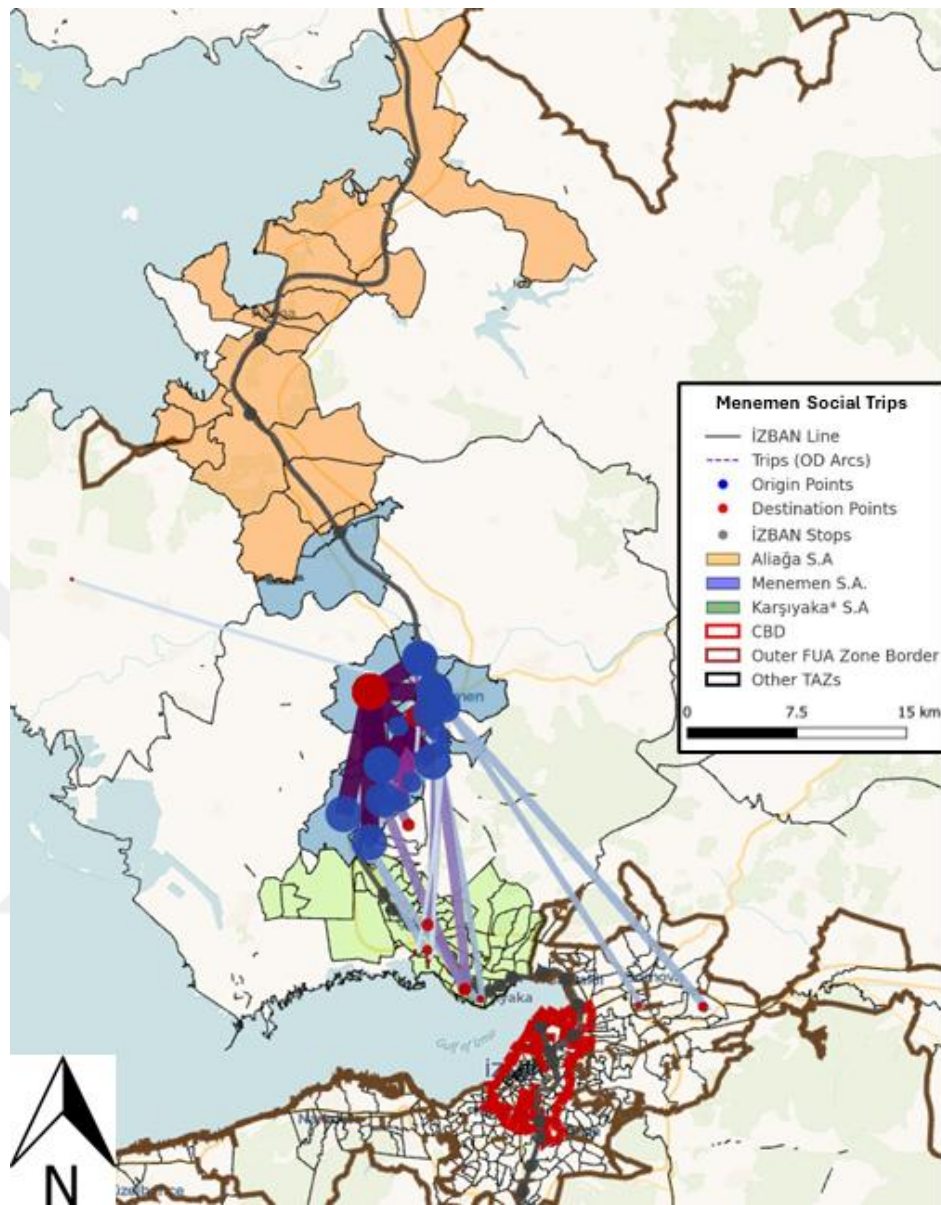


Figure 5.19. Menemen Social Trips

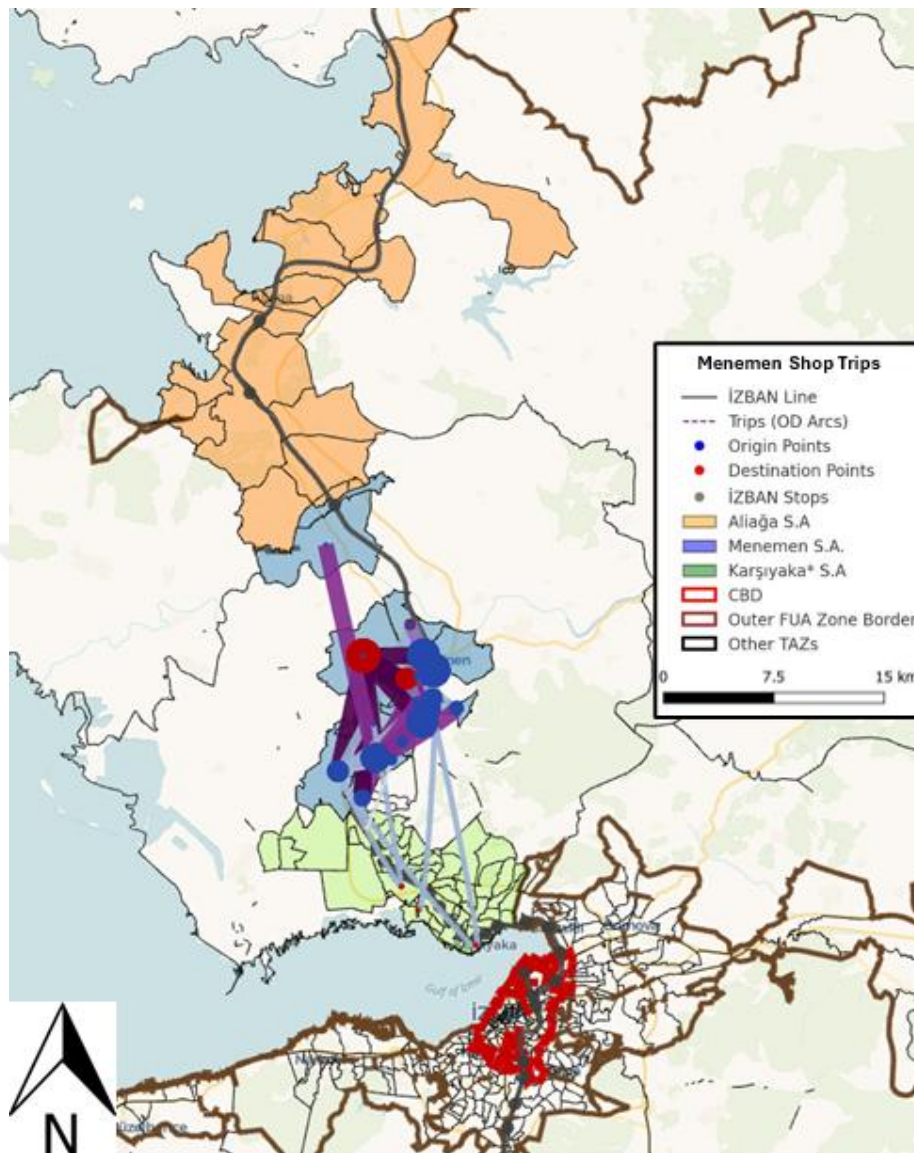


Figure 5.20. Menemen Shop Trips

5.3 Urban Travel Characteristics of Karşıyaka Vicinity FUA Region

Travel Distribution

The guidelines implemented in this phase are based on the household survey data. These guidelines were established by classifying individuals according to their types. Using these probabilistic distributions, individuals were classified as either travelers or non-travelers. The probabilities of individuals being travelers from Karşıyaka*, categorized by person types, are shown in Table 5.11.

Table 5.11. Traveler Probabilities for Karşıyaka Vicinity by Person Types

	From Karşıyaka*	Travel Probabilities (%)	
Person Types	Definitions	Travele	No-Travele
PT1	Full_Time	76	24
PT2	Part_Time	70	30
PT3	Uni_Std.	50	50
PT4	Non_Emp.	38	62
PT5	Retired	49	51
PT6	Student	45	55

Activity Pattern Distribution

The activity patterns which is shown in Table 5.12 observed from the Karşıyaka study area show a wide range of travel behaviors across person types, reflecting the mixed-use, urban character of the area.

- PT1 shows a dominant concentration in Home → Work → Home chains (2,672), followed by PT2 as the second highest contributor (761). This highlights the significant presence of structured, compulsory travel behaviour in the region.
- PT6 is highly concentrated in Home → School → Home chains (840), followed by PT3 (128). This suggests a strong school-based travel routine with clearly defined planning.

- PT4 and PT5 are particularly highly involved in discretionary trips: These person types reflect flexible mobility patterns often seen in older or non-working populations.
- PT3 and PT6 also participate in out-of-school travel, particularly social activities (PT3: 149, PT6: 100), indicating a mix of institutional and social mobility.
- Pick & Drop chains are low in volume but scattered across PT1–PT4, indicating limited but present parental or companion-type responsibilities.

Table 5.12. Activity Schedule Distribution by Person Types in Karşıyaka Vicinity

Activities From Karşıyaka*	PT1	PT2	PT3	PT4	PT5	PT6
Home ->Work ->Home	2672	761	19	0	0	43
Home ->School ->Home	15	10	128	50	1	840
Home ->Pick&Drop ->Work ->Home	7	2	0	0	0	0
Home ->Pick&Drop ->Home	12	8	3	43	9	0
Home ->Shop ->Home	192	99	40	755	558	51
Home ->Social ->Home	309	116	149	727	422	100
Home ->Other ->Home	99	47	23	367	211	32

Time Period Analysis by Purpose and Mode

Based on HHTS data for the Karşıyaka* study area, a comprehensive analysis (See Table 5.15) was conducted to examine the temporal, modal and purpose-based characteristics of the observed trips. These findings are important for the development of travel behavior rules in the rule-based ABM. The trip distribution shows high volumes throughout the day, with significant peaks observed in TP1 (06:00–09:00), TP4 (13:30–16:30) and TP5 (16:30–19:30), reflecting the area's function as both a large settlement and activity center.

The highest number of trips is seen in TP4 (3647 trips), followed by TP5 (3369 trips) and TP1 (3410 trips), indicating a well-distributed and continuous flow of travel demand throughout the day. In TP1, work trips dominate, accounting for 2,248 trips, gradually decreasing towards the evening, but a non-negligible activity continues in

TP7, which may indicate late shifts or flexible working hours. School trips also follow a typical morning pattern, with the majority (663 trips) occurring in TP1, followed by scattered returns in later periods. Social trips are more evenly distributed, peaking during TP4 (592 trips) and TP7 (308 trips), reflecting a strong involvement in discretionary activities in the afternoon and evening periods. Shopping trips follow a similar profile, peaking in TP4 and TP5, while Pick-up/Drop-off activities show activity throughout the day, particularly in TP4 and TP5. These distributions reinforce the need to consider temporal dynamics in assigning activity schedules and purposes in ABM.

In terms of mode choice, private car use is dominant, peaking at 4,461 total trips in TP5 (977 trips) and remaining high throughout all peak periods. This suggests a strong vehicle dependency for both essential and discretionary activities. Walking and micromobility modes also show high usage, particularly from TP2 to TP5, indicating local access and short-distance travel within Karşıyaka*.

Public transport use is significant, with bus (2,508 trips) and commuter train (1,276 trips) contributing significantly. Bus use peaks in TP4 and TP5, while commuter train has a stable presence from TP1 to TP5, reflecting the availability and importance of high-capacity public transport options in the region. Metro/tram use is insignificant but not zero, indicating specific connectivity points. Shuttle vehicles (1,537 trips) are also heavily used, particularly in TP1 and TP5, and are likely linked to institutional or employer-organized transport for work and school.

Return trips home are concentrated in TP4 (2,098 trips) and TP5 (2,828 trips), as expected for post-activity flows. However, significant volumes continue in TP7 (918 trips), indicating flexible or late-evening activity chains, particularly for social and other discretionary purposes. Figure 5.21 show the trip departure time distributions.

Table 5.13. Trip Distribution by Time Periods for Purpose and Mode (Karşıyaka*)

		Time Periods						
From Karşıyaka*		TP1	TP2	TP3	TP4	TP5	TP6	TP7
Trips		3410	2116	900	3647	3369	504	1743
Work		2248	472	39	102	41	12	116
School		663	144	31	31	4	0	39
Pick&Drop		198	42	60	67	64	1	59
Social		64	352	228	592	218	51	308
Shop		23	351	224	581	185	16	227
Other		111	297	81	176	29	1	76
Home		103	458	237	2098	2828	423	918
AcT	Walk	677	912	496	1888	925	109	706
	Micromobility	30	13	6	37	24	4	14
PuT	Bus	603	335	111	501	521	89	229
	Subur.rail	289	128	39	155	277	39	84
	Metro/Tram	0	0	0	0	0	0	0
	Ferry	46	14	10	18	26	4	16
	Minibus	143	54	25	114	132	22	60
PrT	Service	448	41	20	106	279	33	72
	Private Car	945	513	164	692	977	167	461
	Shared Car	13	10	2	13	12	4	5
	Business Car	140	11	1	14	74	14	13
	Taxi	11	25	6	14	20	6	24
	Other	31	31	11	30	38	4	34

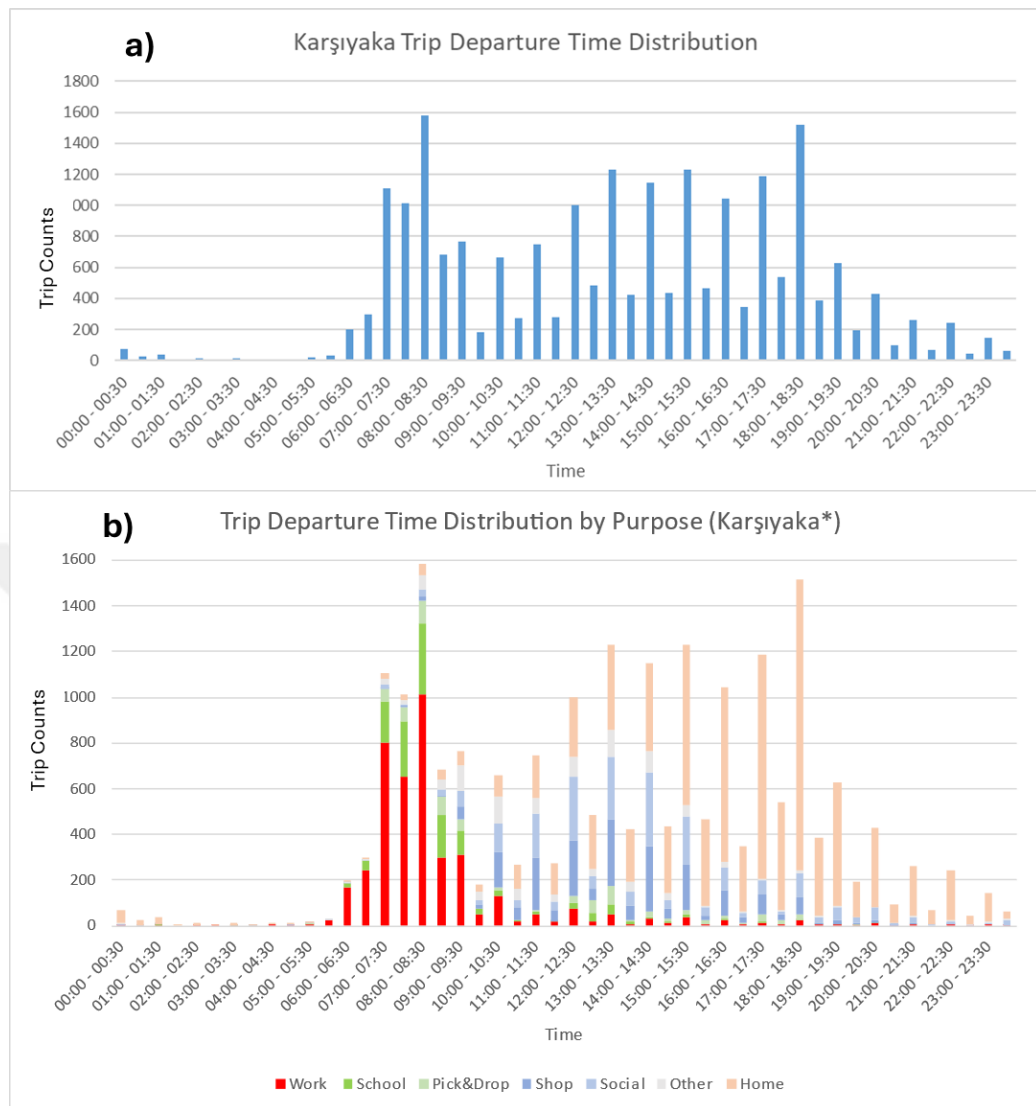


Figure 5.21. Karşıyaka* Trip Departure Time Distribution for a) all trips and b) by Purpose

The distribution of transport modes by travel purpose for Karşıyaka* reveals a relatively balanced use of both active and private modes, with some use of public transport modes, especially for essential trips (See Table 5.11). This pattern is consistent with the urban structure and accessibility of the district.

Active Modes:

Walking is the most prominent active mode, heavily used for school (142) and shopping (245) purposes. It also supports social (161) and work (116) trips, reflecting good access to local destinations. Micromobility appears marginal, with only a few trips (2 in total) for various purposes, consistent with low levels of infrastructure provision or adoption.

Public Transport:

Bus is a well-used mode for work (114), pick-up and drop-off (84) and shopping (64) trips, indicating its role in both essential and discretionary trips. The commuter train is used for work (83) and school (17), suggesting that it is important for structured, longer-distance commuting. There are no Metro/Tram and Ferryboats, suggesting that there is likely a lack of direct connection or use from Karşıyaka* in this dataset. Minibus use is low but consistent across work, shopping and other purposes, and likely fulfills niche or feeder roles.

Private Modes:

Private car use is widespread and significant, particularly for work (198) and social (132) trips, with significant use for school, shopping and other purposes. Shuttles dominate work (197) and school (30) trips, likely reflecting employer or institution-provided transport services. Taxi use appears to be minimal for social and other trips, with business and shared cars present at a low level. The 'Other' mode category covers scattered use but is generally small.

Table 5.14. Trip Distribution by Mode and Purpose for Karşıyaka* Study Area

		Trip Purposes						
		From Karşıyaka*	Work	School	Pick up & Drop off	Social	Shop	Other
AcT	Walk	116	142	101	161	245	48	664
	Micromobility	2	0	0	1	1	0	3
PuT	Bus	114	50	0	84	64	64	304
	Subur.rail	83	17	0	36	25	16	98
	Metro/Tram	0	0	0	0	0	0	0
	Ferry	0	0	0	0	0	0	0
	Minibus	8	1	0	2	7	7	30
PrT	Service	197	30	0	0	0	1	131
	Private Car	198	15	18	132	56	53	359
	Shared Car	1	0	0	1	0	2	6
	Business Car	29	0	0	0	0	0	19
	Taxi	0	0	0	4	1	3	6
	Other	5	0	0	2	1	3	10

Destination Analysis Total Trip Distribution

The majority of trips from Karşıyaka* (11,339) are internal trips occurring within Karşıyaka_FUA, highlighting a strong self-sufficient travel structure. External destinations include İzmir CBD (833 trips), Outer districts (1,513 trips) and Karşıyaka_Other (954 trips), indicating outbound flows to the centre and surrounding areas. The remaining trips are directed to Menemen (912 together) and Aliğa (138 together), indicating modest inter-district movement compared to Aliğa or Menemen. This pattern reinforces Karşıyaka's role as a mixed-use area where most daily needs and activities are met locally.

Temporal Distribution of Trip by Destination

Trip is concentrated in the hours of TP1 (06:00–09:00), TP4 (13:30–16:30) and TP5 (16:30–19:30). In particular, TP1 alone accounts for 3,410 trips reflecting the morning commute, while TP4 and TP5 together contribute to approximately 7,000 trips, suggesting movement in the afternoon and early evening for return trips and

optional activities. Domestic trips to Karşıyaka_FUA dominate in all time periods, but particularly increase in TP4 and TP5. Trips to İzmir CBD and the outer regions also peak in TP1 and TP5, reflecting standard commuting and homecoming patterns. A significant number of TP7 trips (1,743) indicate activity continuing into the late evening and into the night; largely inland, with some trips to the outer regions and the CBD.

Trip Mode Distribution by Destination and Time Period

Walking and micromobility are the most frequently used modes, accounting for 5,841 trips, mostly domestic trips within Karşıyaka_FUA (5,248 trips). This indicates high local accessibility and walkability. Private car use (3,919 trips) is the second most dominant mode, especially for external trips to the outer regions (681 trips), İzmir CBD (211) and Menemen. Shuttle vehicles also account for a large volume (1,793 trips), and are widely used for work or organized commuting, especially to Karşıyaka_FUA (528) and external locations. Public transport use is significant: bus (2,389 trips) and suburban rail (1,300 trips) are used for both domestic and international trips. Suburban train trips mostly target İzmir CBD (278 trips) and Menemen (509 together). Although metro/tram usage is low (25 trips), it is mainly directed to central and high-density areas. Low usage of minibuses, taxis and shared/business cars indicates some niche or last-mile roles but limited modal share overall.

Distribution of Travel Purpose by Destination and Time Period

Work (3,030 trips) and school (912 trips) are the most important travel purposes. Work trips are distributed across Karşıyaka_FUA (1,619), outer regions (559) and İzmir CBD (379), with temporal density in TP1 and return flows in TP5 and TP7. School trips reflect this pattern, with high flows to Karşıyaka_FUA and Menemen, peaking in TP1. Pick-up/drop-off trips (491) and shopping (1,607) or social (1,418) trips are mostly internal but also to the CBD and Menemen, and occur during TP4, TP5 and TP7, in accordance with the discretionary activity timing. Return trips from home (7,065) increased in TP4 and TP5, with the main destinations being

Karşıyaka_FUA (5,261), outer regions (587) and Izmir CBD (164), reflecting strong return flows from all regions.

The findings shown in Table 5.15 provide a solid foundation for developing guidelines tailored to specific destinations within a rule-based ABM framework for Karşıyaka*. Moreover, Figure 5.22, Figure 5.23, Figure 5.24, Figure 5.25, Figure 5.26, Figure 5.27, Figure 5.28, Figure 5.29, and Figure 5.30 show O-D maps for Karşıyaka*



Table 5.15. Karşıyaka Vicinity Study Area Trip Destination Details

	Destinations								
From Karşıyaka*	Aliğa		Menemen		Karşıyaka*		İzmir		Total
	FUA	Oth	FUA	Oth	FUA	Oth	CBD	Oth	
Trips	115	23	510	402	11339	954	833	1513	15689
TP1	54	12	123	126	2084	135	348	528	3410
TP2	10	2	33	87	1476	165	144	199	2116
TP3	0	1	5	31	724	53	30	56	900
TP4	21	6	92	74	2986	188	103	177	3647
TP5	15	0	198	45	2409	248	121	333	3369
TP6	0	0	13	4	371	36	22	58	504
TP7	15	2	46	35	1289	129	65	162	1743
Work	59	14	138	129	1619	133	379	559	3030
School	5	0	15	34	714	23	47	74	912
Pick&Drop	0	0	3	9	443	13	2	21	491
Social	20	1	18	125	1353	32	110	154	1813
Shop	0	0	2	34	1434	52	40	45	1607
Other	11	5	10	35	515	31	91	73	771
Home	20	3	324	36	5261	670	164	587	7065
Walk	1	0	8	81	5132	417	5	69	5713
Micromobility	0	0	0	2	116	3	3	4	128
Bus	1	0	90	64	1717	154	157	206	2389
Subur.rail	27	1	127	8	382	71	278	117	1011
Metro/Tram	0	0	0	0	0	0	0	0	0
Ferry	0	0	0	0	5	0	105	24	134
Minibus	0	0	3	13	442	28	6	58	550
Service	28	9	73	44	528	52	27	238	999
Private Car	39	7	193	153	2430	205	211	681	3919
Shared Car	1	0	2	8	34	1	3	10	59
Business Car	9	1	14	16	119	15	22	71	267
Taxi	0	0	0	5	89	5	2	5	106
Other	8	5	0	4	132	3	8	19	179

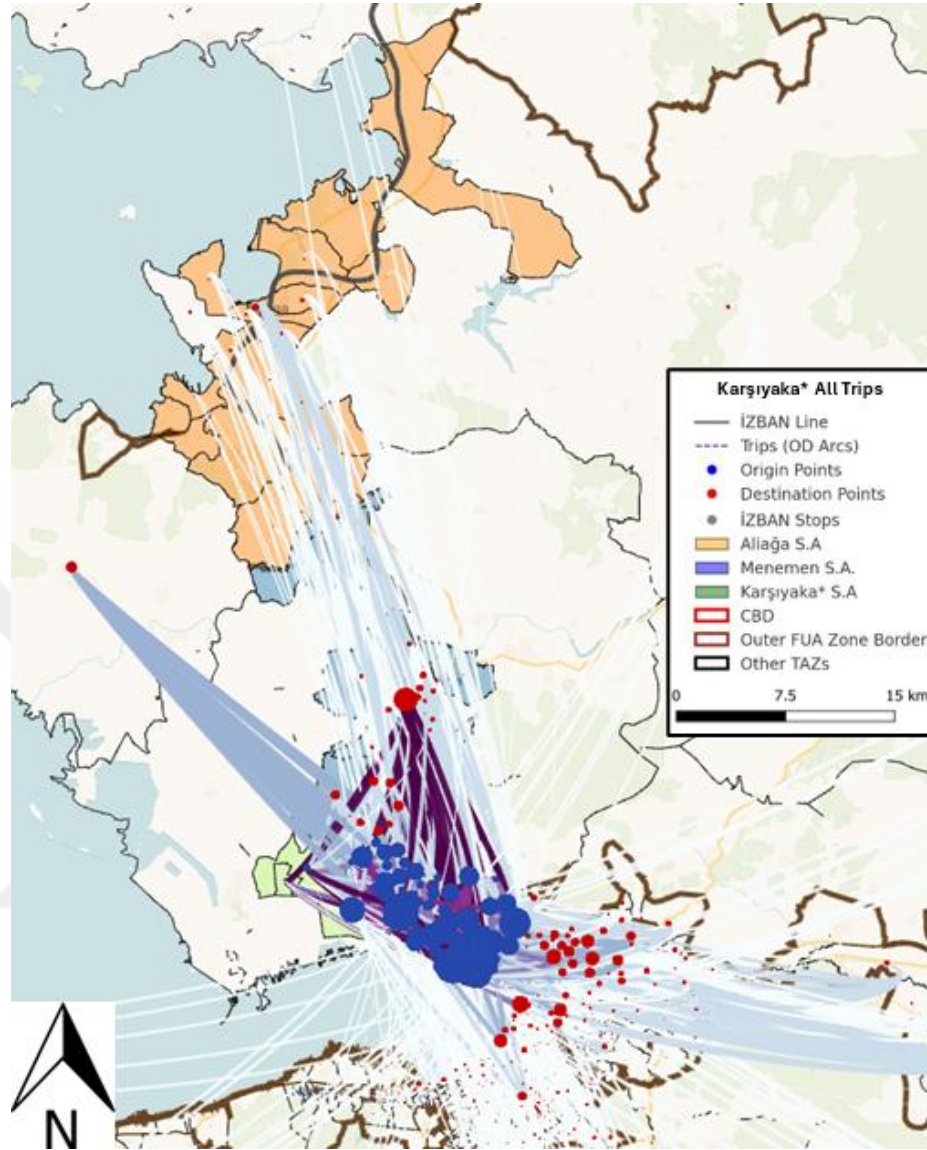


Figure 5.22. Karşıyaka* All Trips

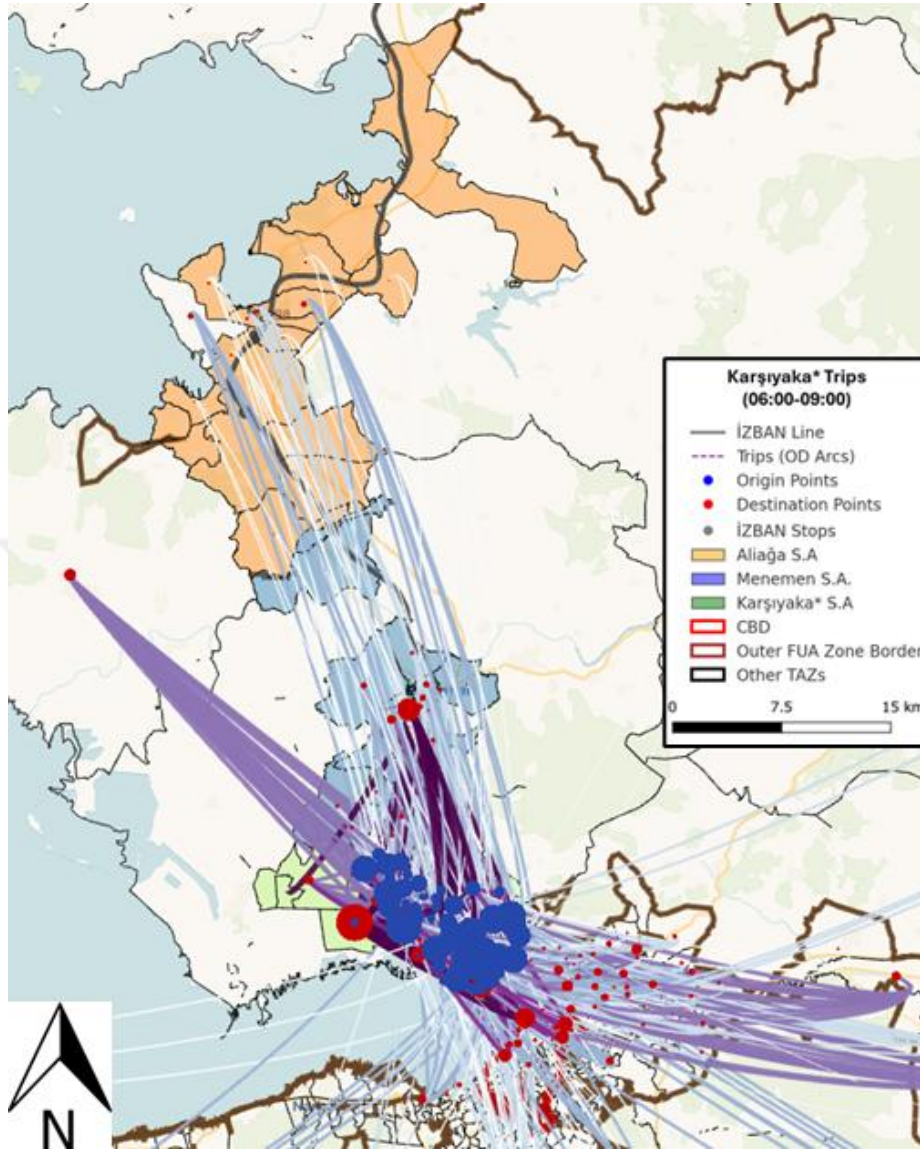


Figure 5.23. Karşıyaka* All Trips (06:00-09:00)

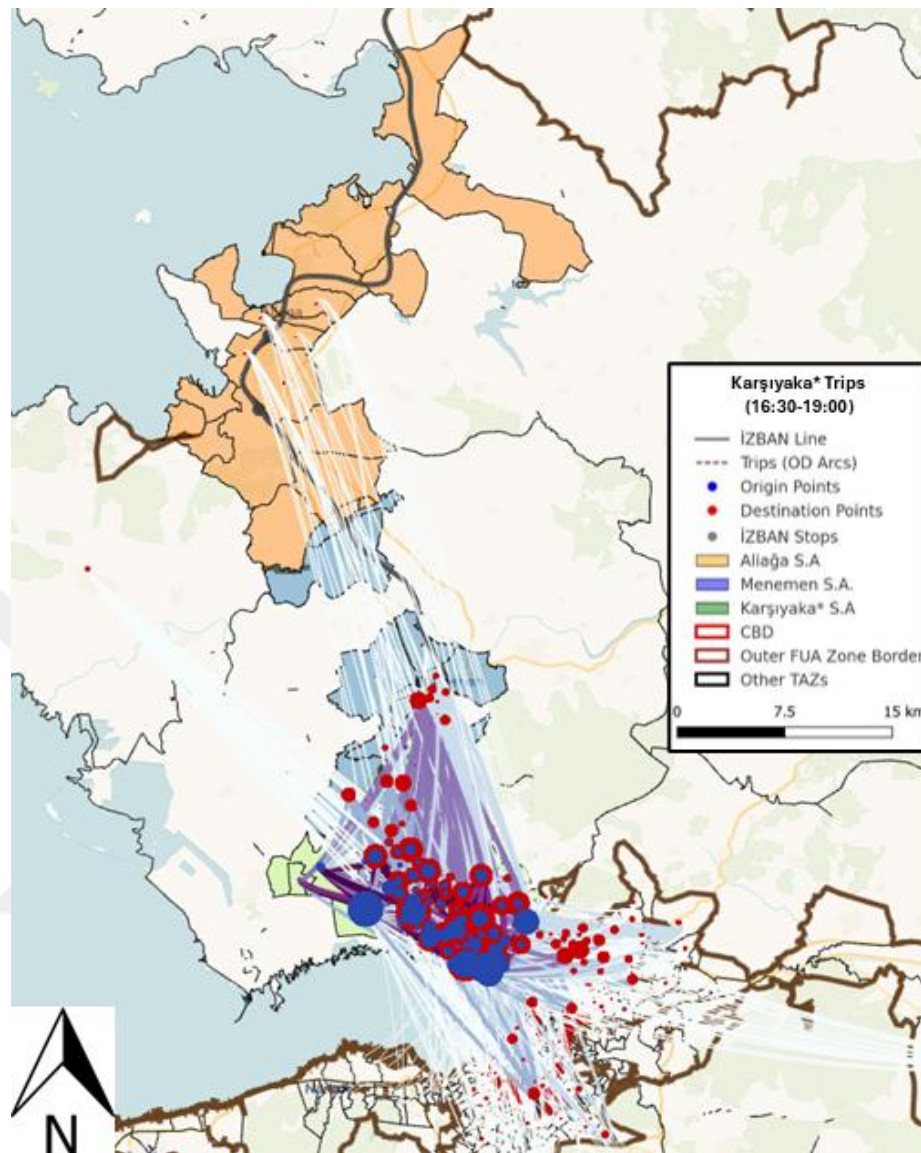


Figure 5.24. Karşıyaka* All Trips (16:30-19:00)

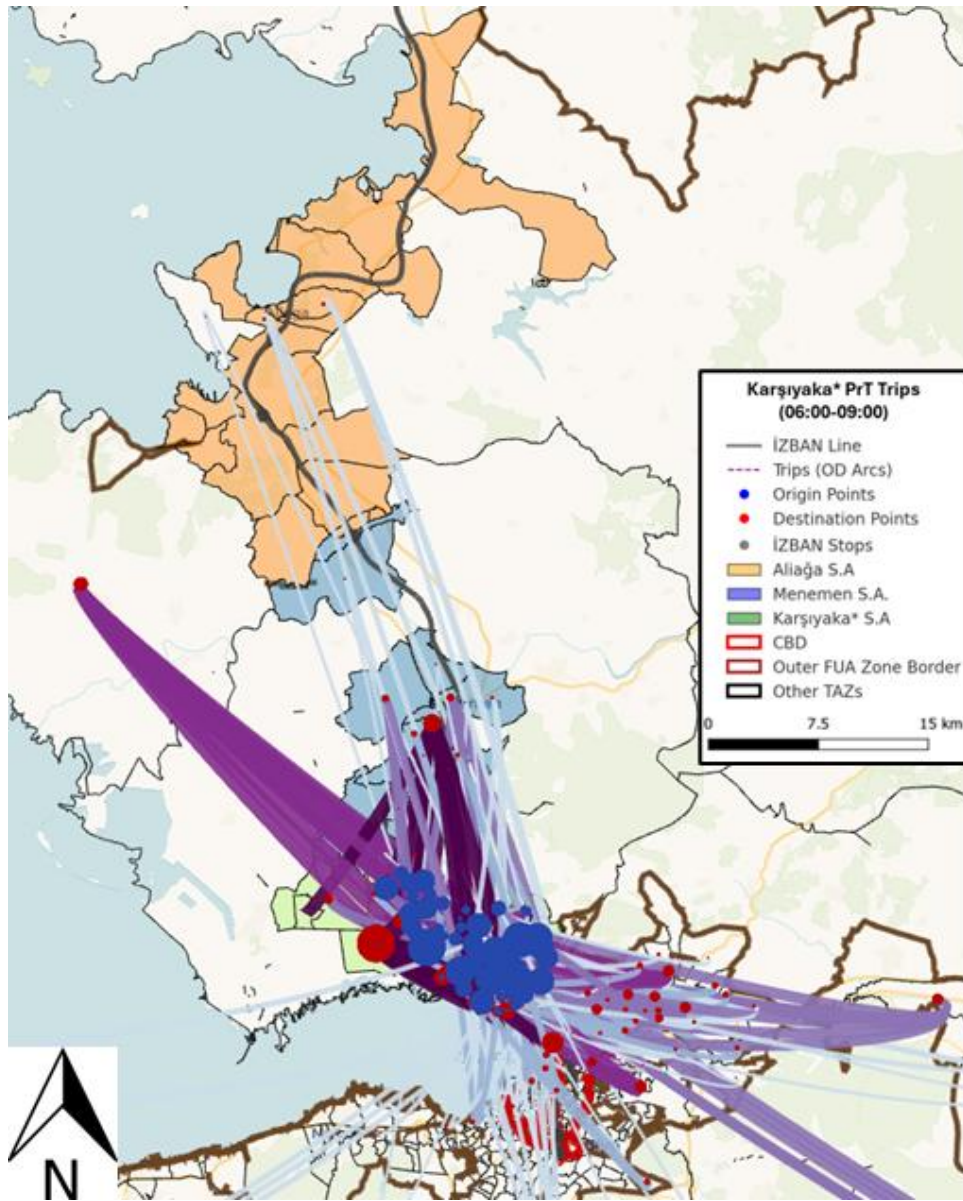


Figure 5.25. Karşıyaka* PrT Trips (06:00-09:00)

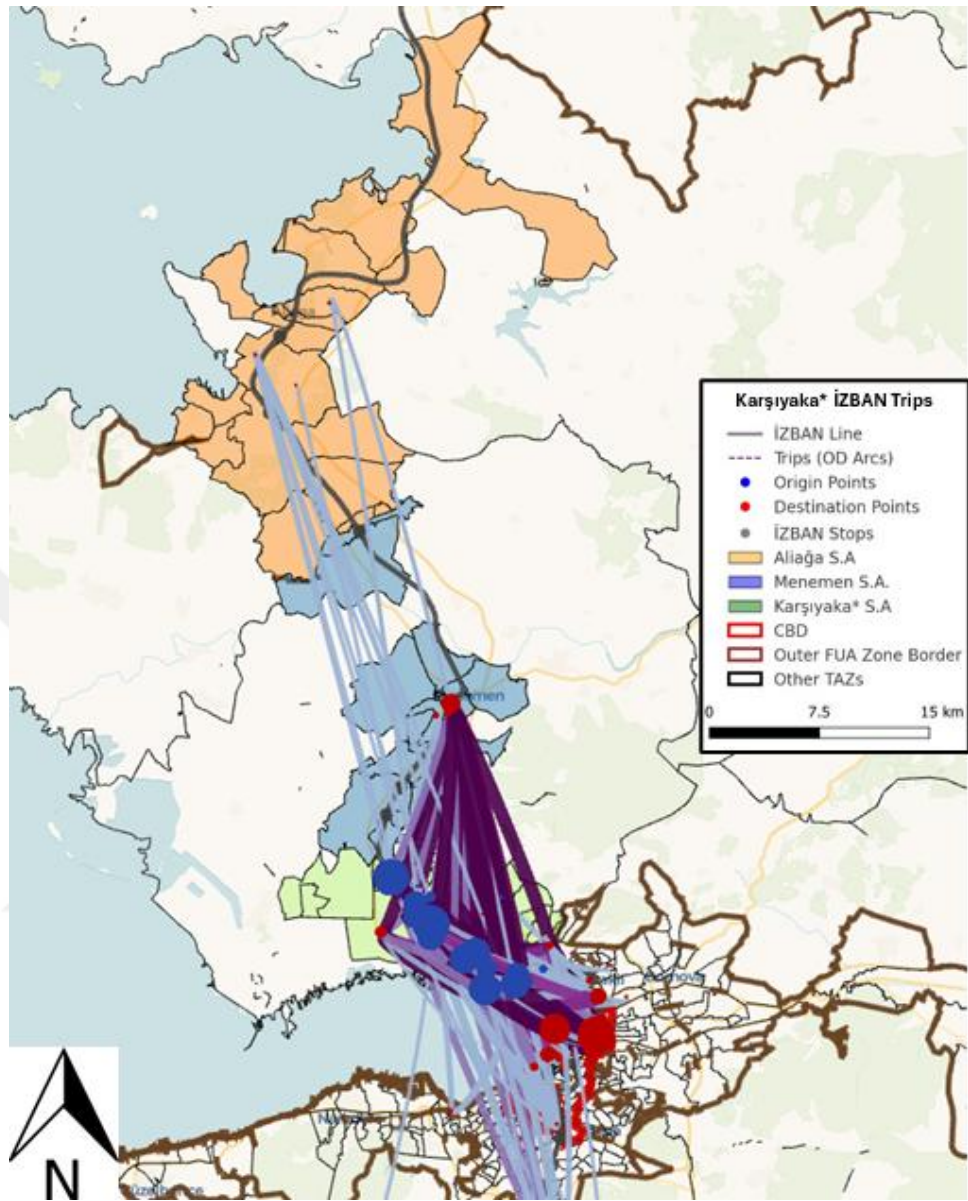


Figure 5.26. Karşıyaka* İZBAN Trips

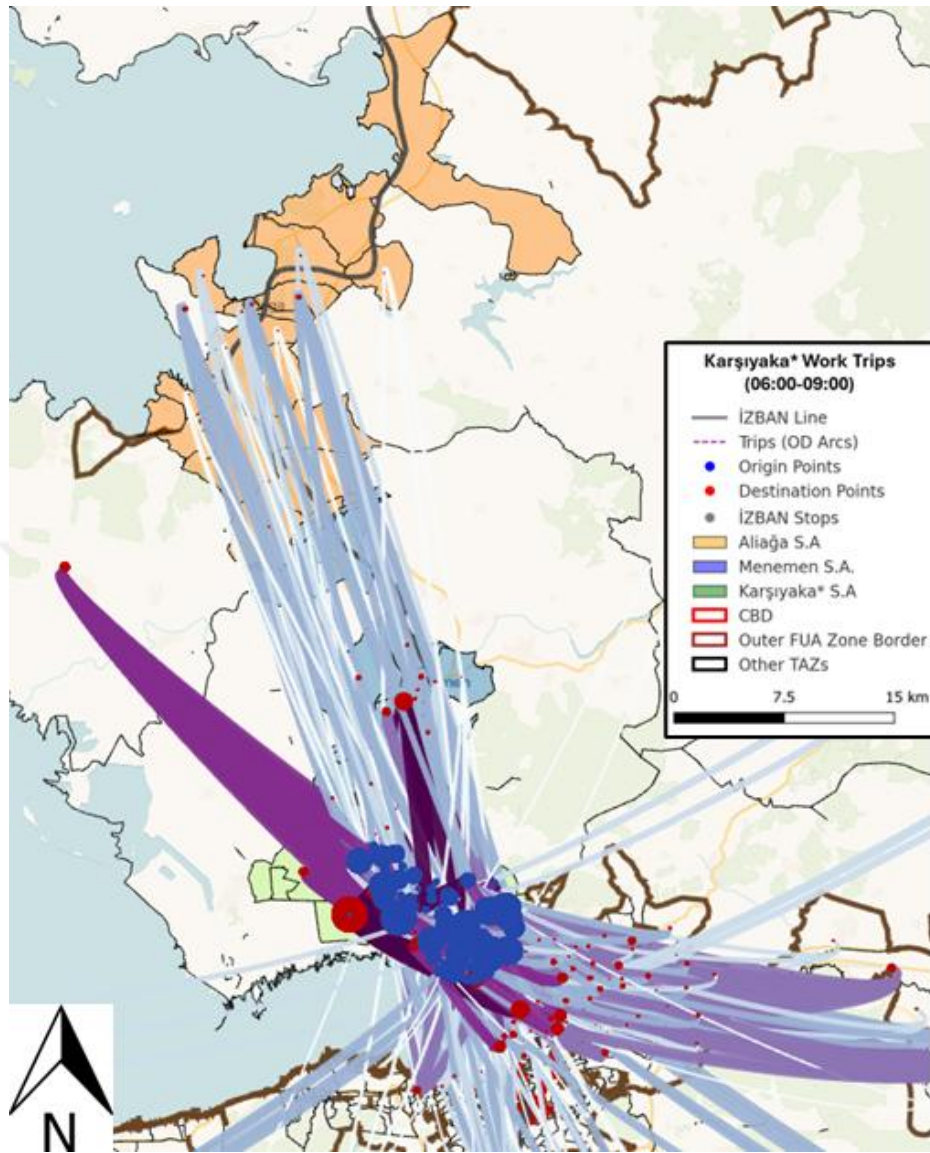


Figure 5.27. Karşıyaka* Work Trips (06:00-09:00)

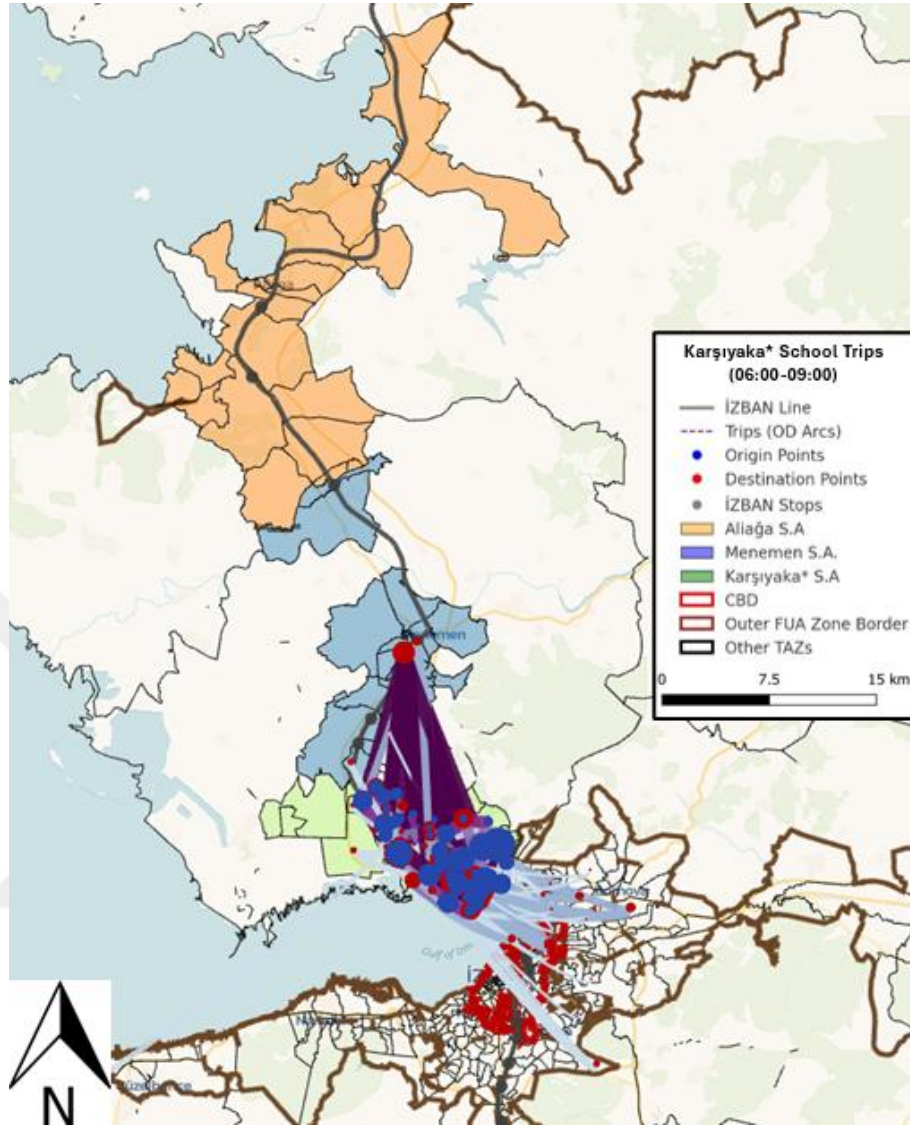


Figure 5.28. Karşıyaka* School Trips (06:00-09:00)

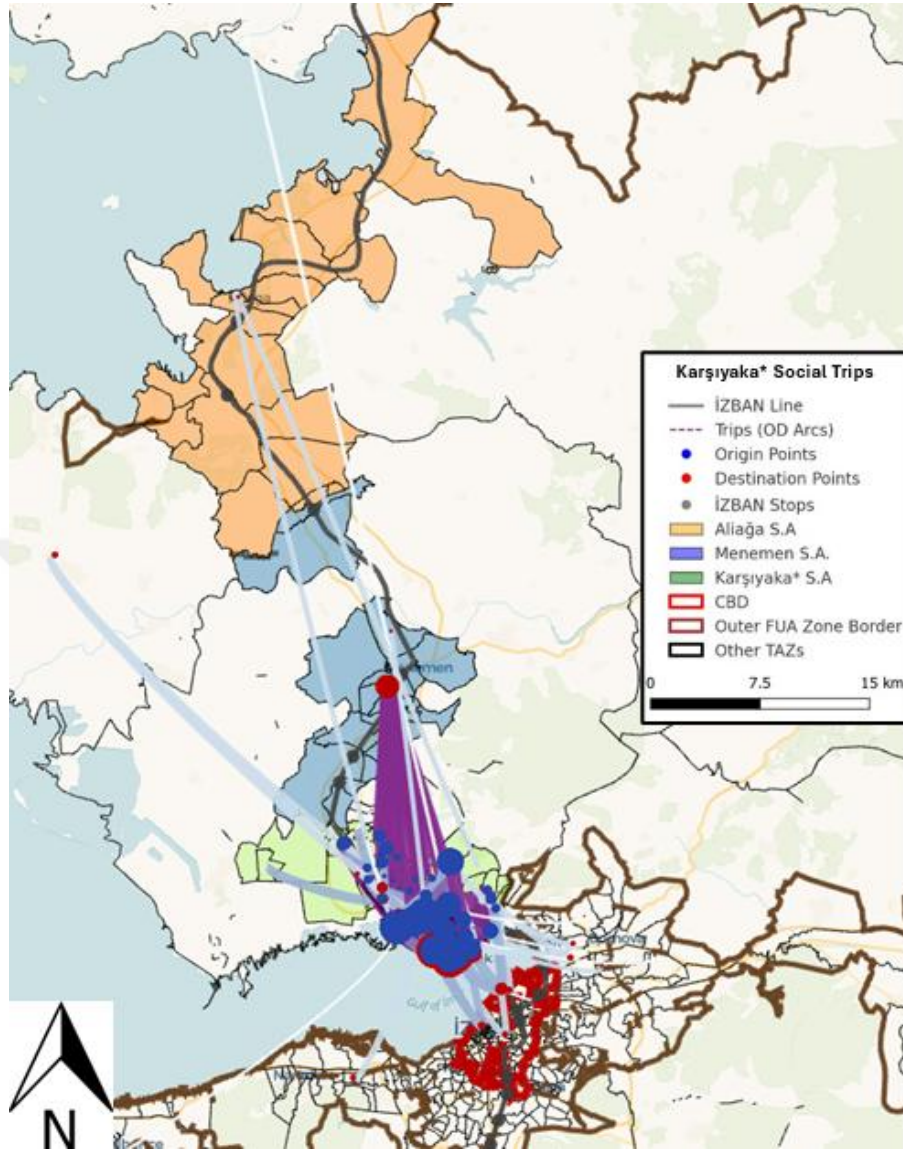


Figure 5.29. Karşıyaka* Social Trips

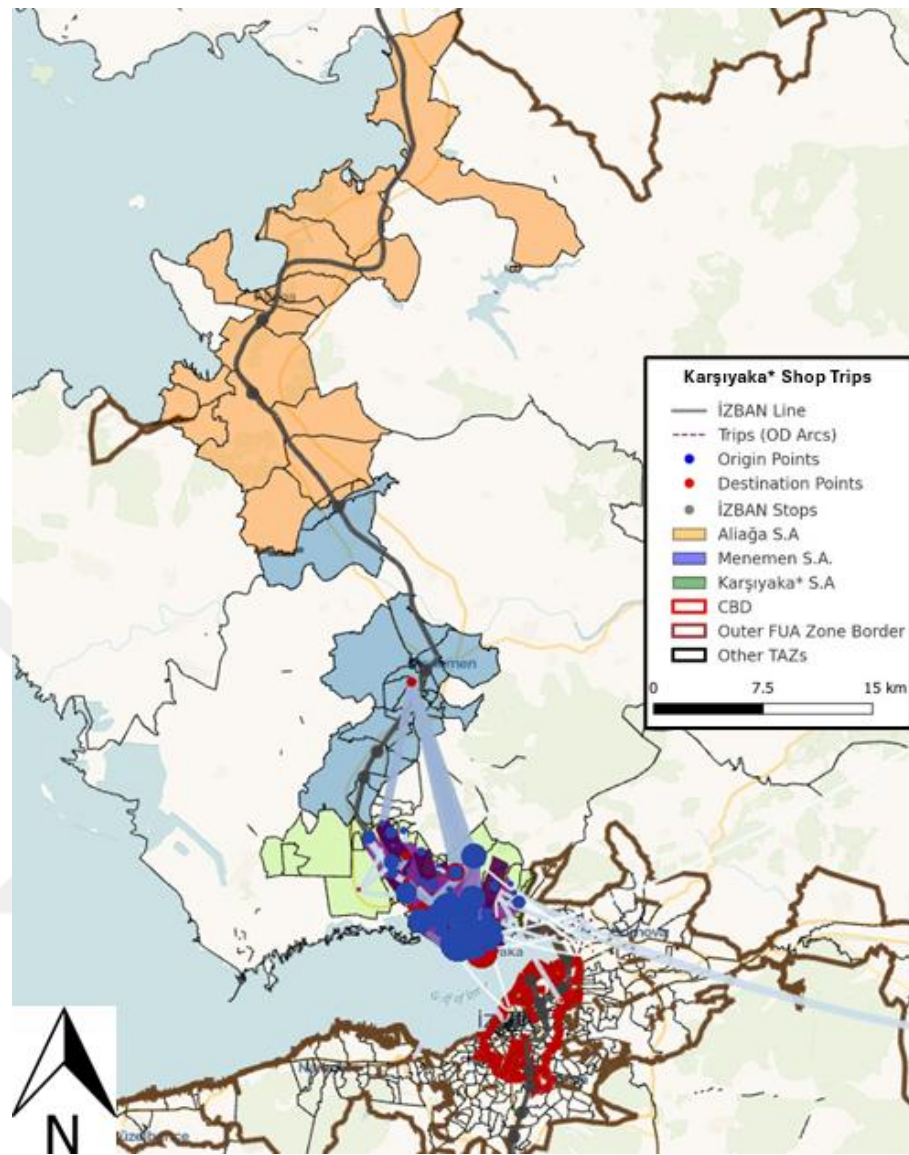


Figure 5.30. Karşıyaka* Shop Trips

5.4 Comparative Analyses of Study Areas

Trip Departure Time Comparison

When examining the distribution of travel departure times (See Figure 5.31) in Aliğa, Menemen and Karşıyaka*, several factors such as local geography, economic structure and demographic structure help explain the observed differences. In Aliğa, a distinct peak in early morning departures is evident, consistent with its status as the northernmost district and centre of industrial activity. The industrial workforce in Aliğa typically follows shift schedules that start early in the day, thus contributing to a higher travel density around 07:00–08:00. In Menemen, a significant increase in trips in the mid-morning (10:00–11:00) suggests that travel patterns are influenced by a mix of agricultural, suburban, and semi-urban lifestyles. Daily routines related to farming, local commerce, and residential work likely shift the start of many trips to slightly later in the morning compared to areas with strong industrial or service sector employment.

In contrast, Karşıyaka*, located closer to the center of İzmir, exhibits a relatively even distribution throughout the day, with a noticeable increase in the evening hours. This pattern reflects Karşıyaka's role as a central district with a higher concentration of retail, entertainment, and service-oriented activities that extend beyond traditional work hours. The demographic profile of the region, marked by diverse socioeconomic backgrounds, also supports a wider range of trip purposes (e.g., shopping, social interactions) later in the day.

Overall, the temporal distribution of trips in each region illustrates how key factors such as industrial and service-based employment, agricultural practices, and proximity to the metropolitan center can shape daily travel behavior. Understanding these local differences is important for designing tailored transportation strategies, from optimizing public transit schedules to developing targeted infrastructure improvements.

Thus, it can be concluded that when rule-based ABM is to be developed, the regional approach may be a more accurate way in terms of journey starts, especially in large cities.

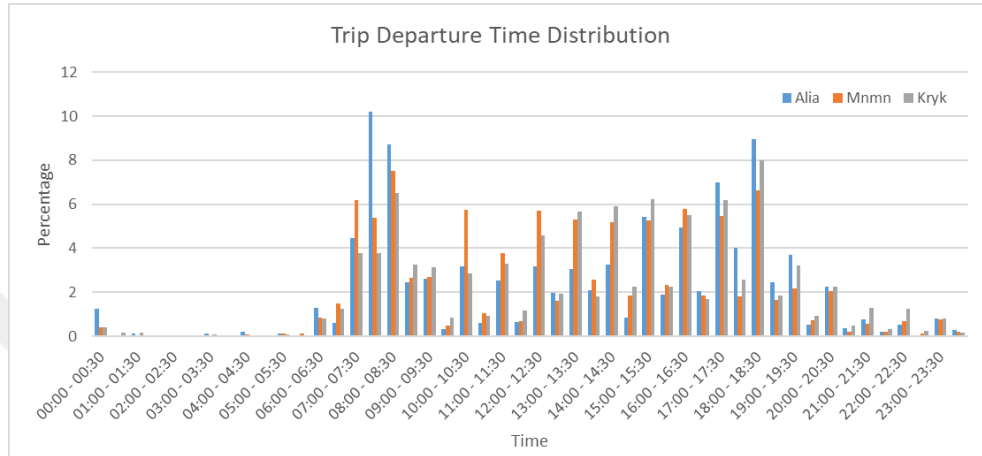


Figure 5.31. Trip Departure Time Distribution for Three Study Areas

Trip Length Distribution

The cumulative trip length distributions presented in Figure 5.31 provides important insights into the spatial characteristics of travel behavior in Aliaga, Menemen, and Karşıyaka*, which should be taken into account in the design of rule-based activity-based models. These models directly influence destination choice behavior, mode choice, and internal and external travel probability, thus serving as key inputs for rule formulation. Figure a, which shows trip lengths up to 60 km, shows that trips originating from Aliaga are significantly longer than those originating from the other two regions. This trend can be attributed to its geographical location, as Aliaga is located further north of the Izmir city center compared to Menemen and Karşıyaka. As a result, trips originating from Aliaga generally require longer distances to reach central destinations or major activity centers. This suggests that in a rule-based ABM, residents of Aliaga may be more likely to make long-distance trips, especially for business or institutional purposes.

Menemen follows Aliğa with moderately longer trips, while Karşıyaka* shows the shortest average trip distances among the three regions. These differences are likely explained by Karşıyaka*'s relative proximity to the city centre and the presence of denser land uses, which favour more localised activity patterns. Therefore, Karşıyaka* residents may be more likely to complete their daily activities over shorter distances; this factor should be reflected in the trip destination rules and internal mobility assumptions in the ABM.

Focusing on trips under 10 km, **Figure b** reveals that a significant proportion of trips occur within this range in all three regions. Notably, nearly half of all trips are completed within 10 km. This reinforces the importance of accounting for internal trips in the model structure, especially in self-sufficient regions such as Karşıyaka* and parts of Menemen. The presence of short-distance travel highlights the need to accurately represent walkability, micromobility and intra-regional travel in the ABM, especially for non-essential and discretionary activities.

The observed trip length distributions highlight the need to include regional distance characteristics in developing rule-based travel behavior guidelines. The longer average trip distances from Aliğa and the prevalence of short-distance travel in Karşıyaka* demonstrate how geographic context shapes mobility. These insights should inform the formulation of destination choice probabilities, distance thresholds, and internal and external travel logic for agents in each study area and ensure spatial realism in the simulation of travel patterns.

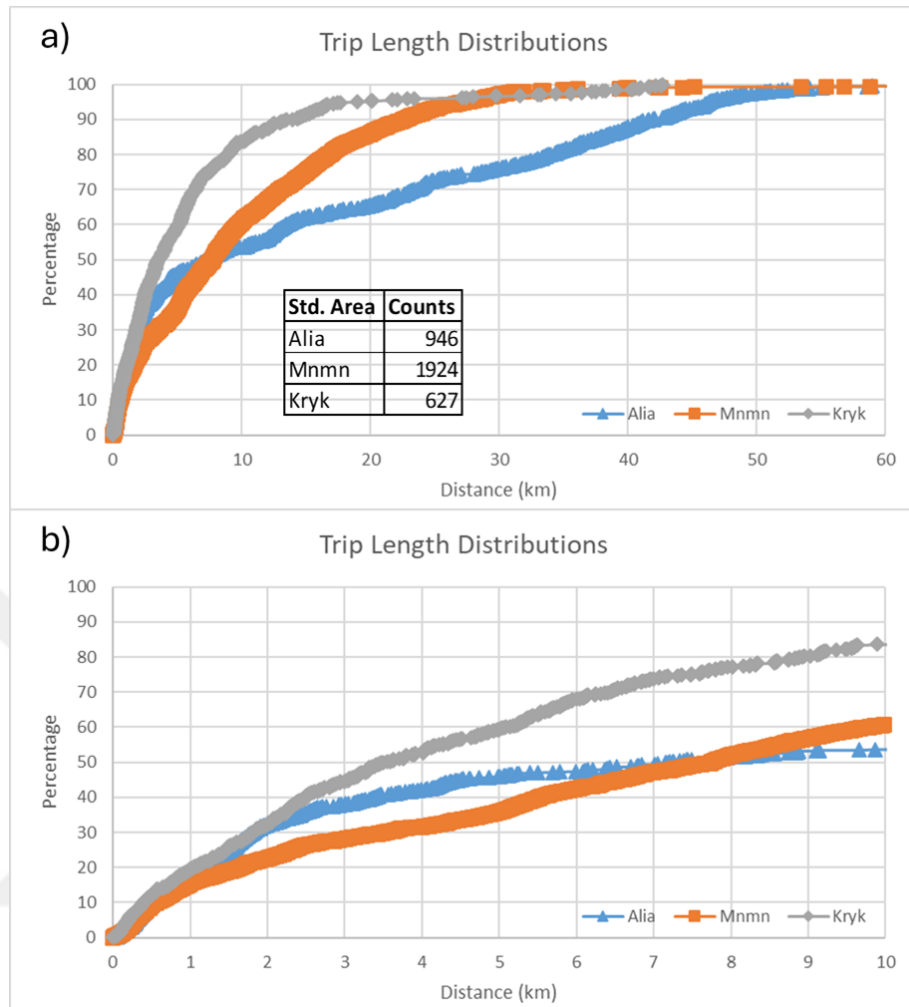


Figure 5.32. Trip Length Dist. for Three Std. Area a)Till the 60km, b)Till the 10km

Walk Trip Length Distribution

The distribution of walk trip lengths (See Figure 5.33) highlights clear regional differences between Aliağa, Menemen and Karşıyaka*, which are important for defining distance-based mode choice rules in a rule-based ABM. It is observed that approximately 50% of walk trips are shorter than 2 km, confirming that walking mode is mostly used for very short distances.

Karşıyaka* shows the highest share of short-distance trips, probably due to its compact urban structure and dense land use. In contrast, Menemen shows longer non-motorized trip distances, while Aliğa lies in between. These differences suggest that regional characteristics should be reflected in the ABM through distance-sensitive thresholds for walk travel. Given the dominance of short trips and regional differences in trip lengths, walk travel should be modeled using location-specific distance thresholds, ensuring realistic mode choice behavior in each study area. In the Figure 5.33, walk trips showing themselves till the 15 km but, this can be due to the wrong statements of the surveyed person. Therefore, after the 2km distances for walk trip, the data can also be treated as an error and removed

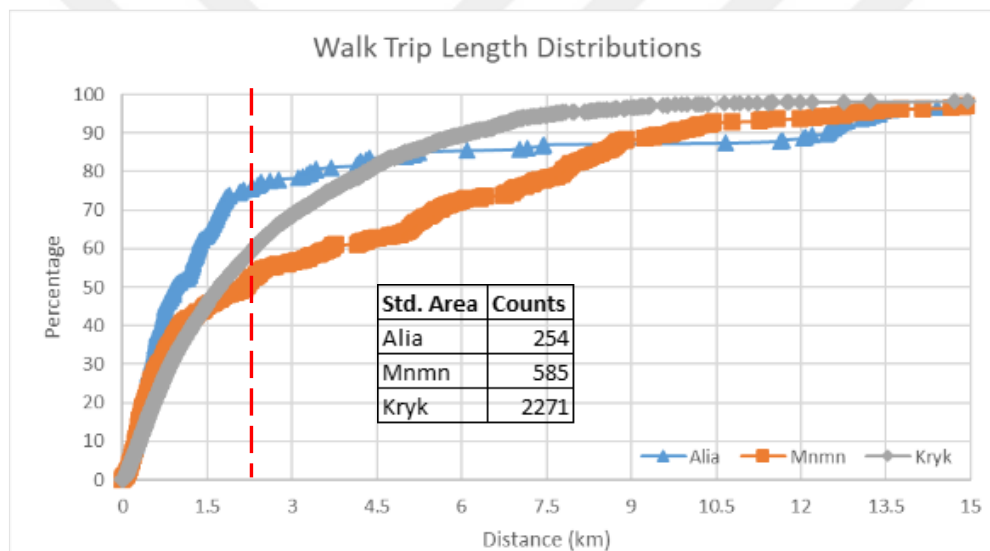


Figure 5.33. Walk Trip Length Distributions for Study Areas

Private Vehicles Trip Length Distribution

The distribution Figure 5.34 of car trip length shows significant regional differences between Aliğa, Menemen, and Karşıyaka*, which has important implications for distance-based travel behavior rules in a rule-based ABM

Aliğa stands out with significantly longer car trips, with over 40% of trips extending beyond 20 km. This reflects the area's geographical location further from the city

center and the need for longer commutes. In contrast, Karşıyaka* exhibits the shortest car trip distances, with over 80% completed within 10 km, indicating a more compact urban structure. Menemen lies between the two, showing moderate car trip distances, the majority of which are under 20 km.

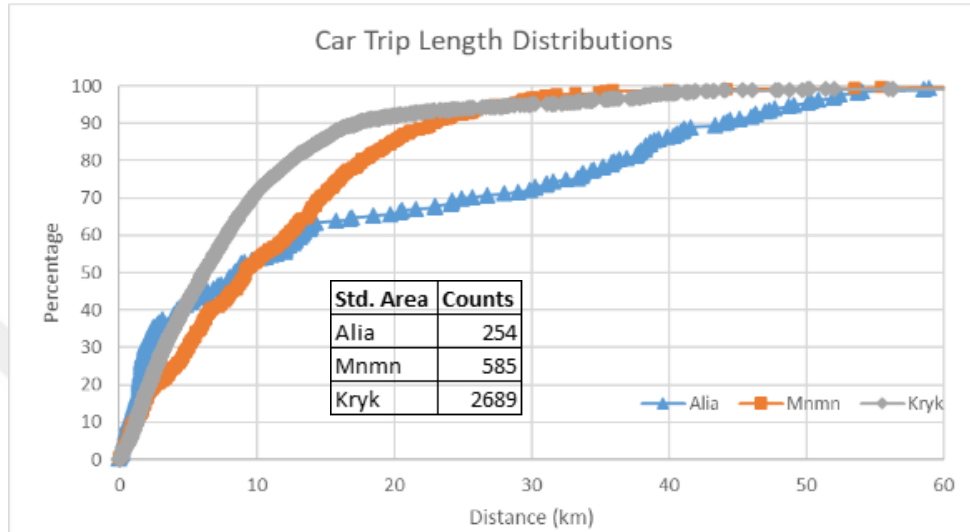


Figure 5.34. Car Trip Length Distributions for Study Areas

Trip Length Distributions by PT Modes

The trip length distributions in Figure 5.35 for public transport modes show significant regional differences between Aliğa, Menemen and Karşıyaka*. These differences are crucial for correctly defining mode-specific distance thresholds and assignment probabilities in rule-based ABM.

Aliğa: In Aliğa, suburban rail trips show the longest trip distances, with a significant share exceeding 40 km, reflecting the peripheral location of the region and its dependence on regional trains to access employment or activity centers further south. In contrast, bus and other PT modes are mostly used for shorter trips, usually within 10 km. The limited use of local PT suggests that PT services in Aliğa may be focused on intercity connectivity rather than local mobility.

Menemen: Bus trips are dominant in Menemen and are relatively short, with most completed within 15 km, suggesting a strong role in local and intra-district travel. Commuter train trips in Menemen are longer, extending up to 40–50 km, consistent with its intermediate location between Aliğa and the Izmir CBD. This pattern suggests that commuter trains are used primarily for regional commuting, while buses and other PT modes serve more local purposes.

Karşıyaka*: -Karşıyaka* exhibits the most balanced and intensive use of all three PT modes. Bus trips are dominant and mostly within 10–15 km, supporting the dense, urban nature of the area and the strong local PT network. Commuter and other PT modes follow a similar distribution, with slightly longer trip intervals, but still largely within 20 km. The high trip volume across all PT modes reflects the region's well-integrated and accessible transport infrastructure.

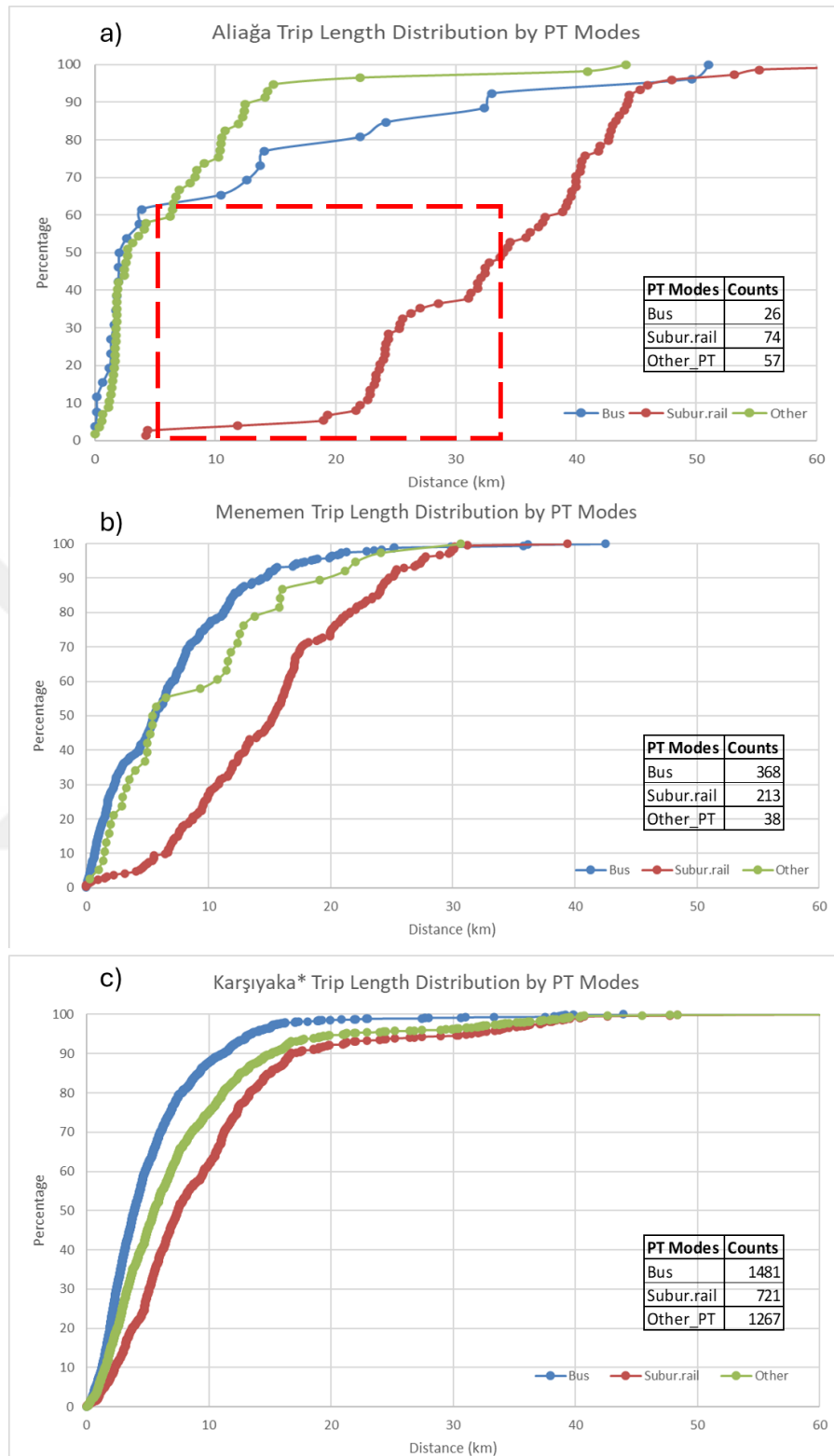


Figure 5.35. Study Areas PT Modes Trip Length Distributions for a) Aliğa, b) Menemen and c) Karşıyaka*

Trip Length Distributions by Purposes

The distribution of work trip lengths (See Figure 5.36) for Aliğa, Menemen and Karşıyaka* highlights the region-specific commuting behavior that is important for defining destination and mode choice rules in a rule-based ABM.

Menemen exhibits the longest work trip distances overall, with a significant portion of trips extending beyond 20 km. This suggests that employees frequently commute to distant employment centers such as the Izmir CBD or outer urban areas. Aliğa follows with slightly shorter but still significant work trip lengths, reflecting its peripheral location relative to large work clusters. In contrast, Karşıyaka* exhibits the most compact work trip pattern, with most trips completed within 10 km, likely due to its urban density and better access to nearby employment opportunities.

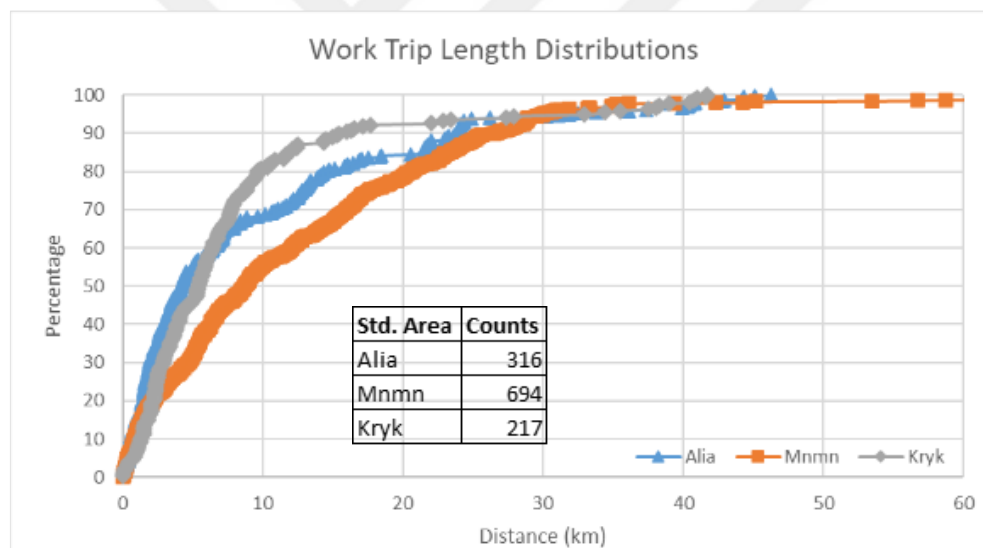


Figure 5.36. Work Trip Length Distributions for Study Areas

The cumulative distribution of shopping trip lengths (See Figure 5.37) reveals significant regional differences between Aliğa, Menemen, and Karşıyaka*, providing important guidance for modeling destination and mode choice behavior in rule-based ABM. Karşıyaka* exhibits the shortest shopping trip distances, with almost all trips completed within 5 km, reflecting the area's dense land use and high

accessibility to retail services. Menemen also exhibits a compact pattern, but trips are slightly longer than Karşıyaka*, with the majority under 10 km. In contrast, Aliğa presents a more dispersed shopping behavior, with many trips extending beyond 10 km and some reaching 35–45 km, likely due to limited local retail opportunities or the need to access regional shopping centers.

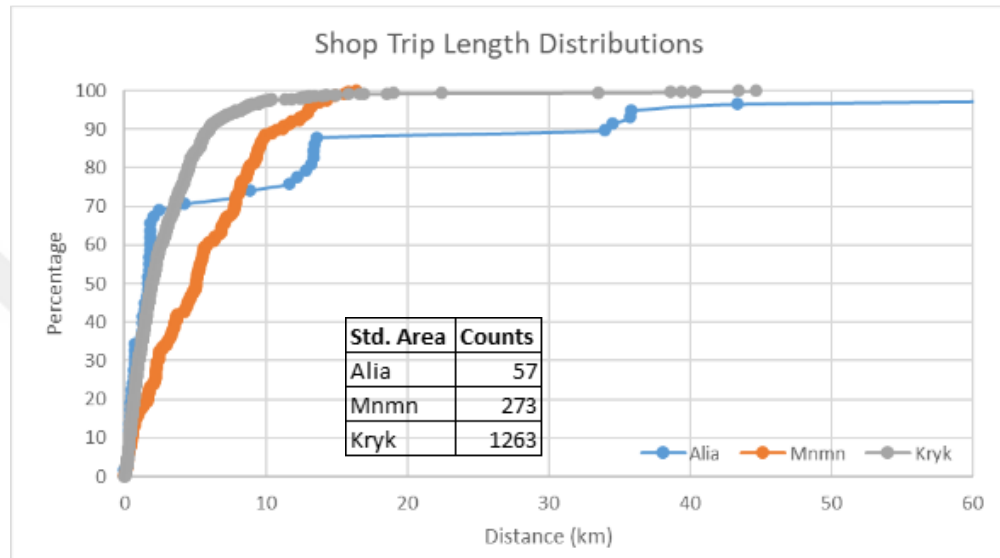


Figure 5.37. Shop Trip Length Distributions for Study Areas

The distribution of social trip lengths (See Figure 5.38) provides important inputs for destination and mode selection rules in rule-based ABM by revealing regional differences in how far individuals travel for social purposes across Aliğa, Menemen, and Karşıyaka*. Karşıyaka* again shows the shortest social trips, with the vast majority completed within 10 km, likely due to the dense urban environment and proximity to social opportunities. Menemen follows with a slightly wider spread, but most trips remain under 15 km. Aliğa shows the longest social trip distances, with a significant number of trips extending beyond 15–20 km, with some reaching as far as 45 km, indicating a need to access social activities outside the immediate area.

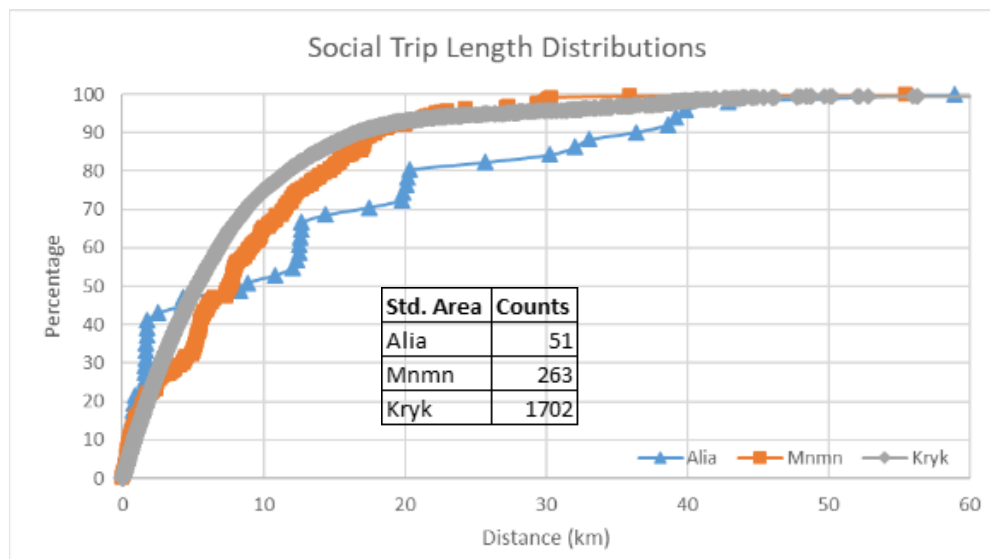


Figure 5.38. Social Trip Length Distributions for Study Areas

Trip Length Distributions by Person Types

The distribution of travel lengths by person type (See Figure 5.39) reveals significant differences across study areas, highlighting the importance of incorporating person type-specific distance behavior rules in rule-based ABMs.

Aliaga: In Aliaga, students (PT6) exhibit the shortest travel lengths, with almost all trips completed within 15 km. In contrast, full-time workers (PT1) and unemployed adults (PT4) exhibit much longer travel distances, with a large proportion exceeding 30 km. This reflects Aliaga's peripheral location and the need for longer trips to access employment or basic services. Retirees (PT5) and university students (PT3) have more compact travel patterns, but are still variable, indicating limited local access to activity destinations.

Menemen: The distribution is more balanced in Menemen. Full-time workers (PT1) and part-time workers (PT2) make relatively longer trips than the other groups, but most trips are still under 25 km. Students (PT6) and retired individuals (PT5) show the shortest travel lengths, with distributions clustered below 10 km. Unemployed individuals (PT4) also tend to travel shorter distances, indicating localized travel behavior driven by discretionary or household breadwinner activities.

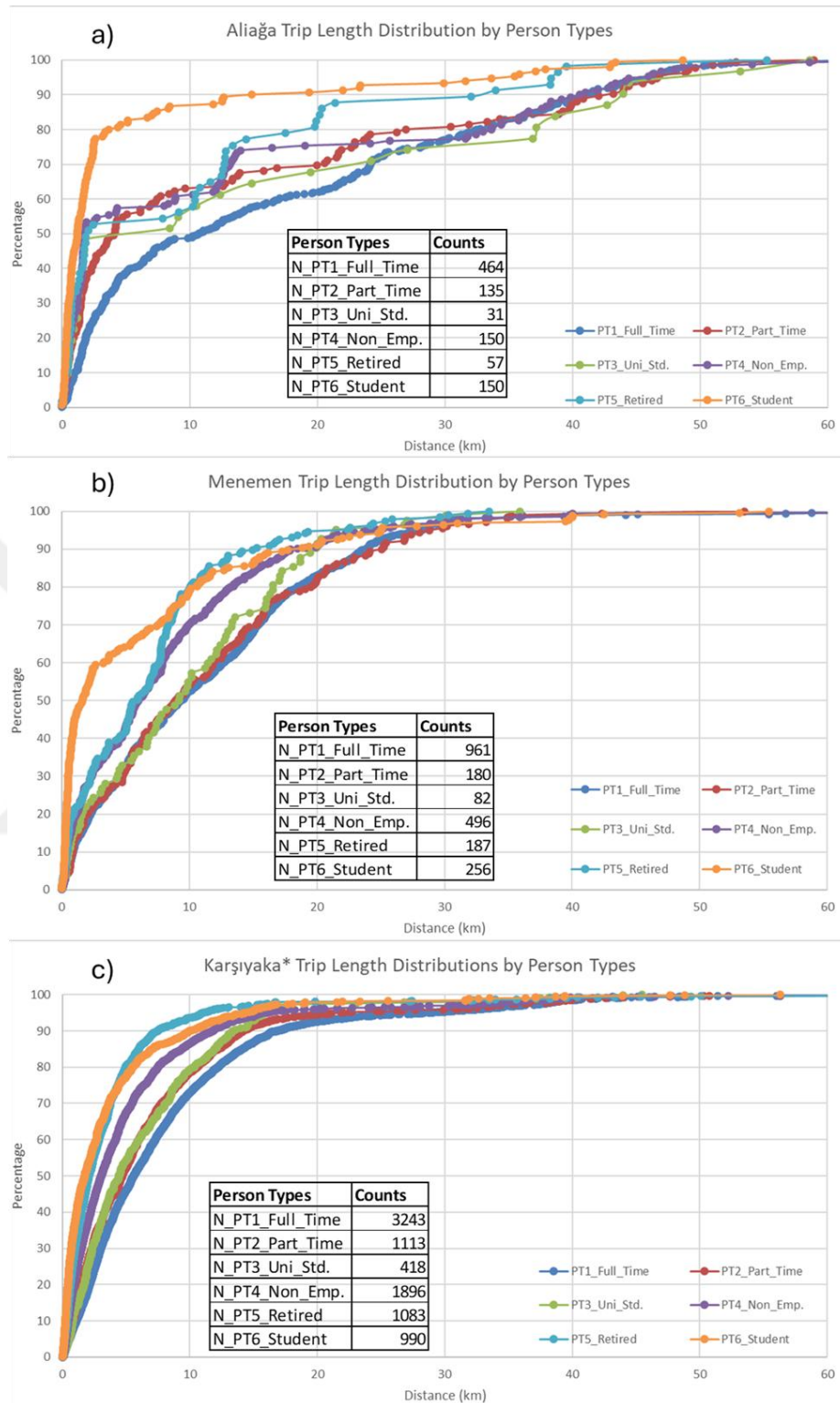


Figure 5.39. Trip Length Distributions by Person Types for a) Aliğa, b) Menemen and c) Karşıyaka*

Karşıyaka*: Figure 5.39 presents the most compact travel patterns among all types of people. Most trips occur within 10-15 km, regardless of socio-demographic group. This uniformity is likely due to the dense land use, high service accessibility, and well-developed public transportation network of the region. Retirees, students, and unemployed individuals show particularly short trips, while full-time and part-time workers maintain relatively limited travel patterns compared to other areas of work.

Trip Duration Distributions

Figure 5.40. presents the cumulative distribution of trip durations reported for all trips (a), work trips (b), and social trips (c) in the three study areas of Aliğa, Menemen, and Karşıyaka*. While these visuals provide an overview of temporal differences in travel patterns, it is important to interpret them with caution. The trip duration data used in this analysis were self-reported by survey participants in the HHTS. Therefore, they are subject to individual variability in time perception and recall accuracy, which may lead to inconsistencies and reduce the precision of the results. Individuals may overestimate or underestimate the time spent traveling, especially on longer or multimodal trips where waiting and transfer times may be misjudged.

Despite these limitations, the results suggest that Aliğa exhibits slightly longer durations for work and social trips, which may be due to its greater distance from major activity centers and limited modal options. Karşıyaka* exhibits generally shorter durations, consistent with its more compact urban structure and higher accessibility.

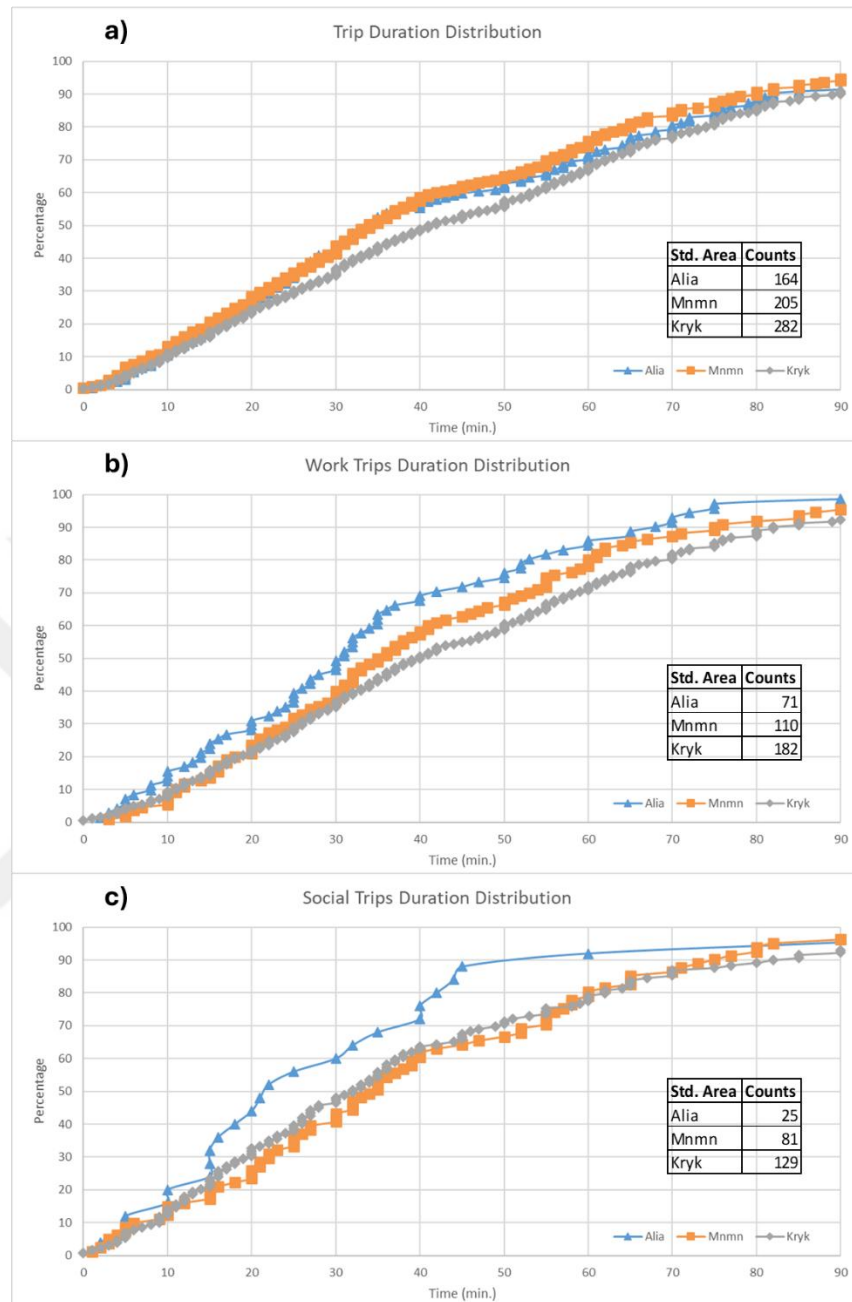


Figure 5.40. Trip Duration Distributions for a) all trips, b) Work Trips, and c) Social trips by Study Areas

5.5 Suggestions for A Rule-Based ABM Methodology for İzmir

Based on the analyses conducted throughout this study, several important issues emerge for the development of a rule-based ABM. One of the most critical findings is the importance of regional variation in rule design. Applying uniform rules to an entire metropolitan area can lead to inaccuracies and miss important differences in travel behavior, especially in large and heterogeneous cities.

Areas located further from the city center, such as Aliğa, exhibit longer travel distances, delayed departure times, and greater reliance on private vehicles or regional public transport modes, mostly due to limited access to dense urban services and frequent public transport. In contrast, central and well-connected areas, such as Karşıyaka*, exhibit more compact travel patterns, shorter trip lengths, and a higher proportion of non-motorized and public transport modes. These regional differences should be explicitly taken into account when defining rules regarding travel purpose, mode choice, departure time, and destination choice.

Moreover, person-type differences play a fundamental role in shaping daily travel behavior. Travel frequency, purposes, and modal preferences differ significantly among full-time employees, students, retirees, and unemployed individuals. For example, full-time workers consistently exhibit high mobility and long-distance commuting patterns, while retirees and unemployed individuals tend to make fewer and shorter discretionary trips. These behavioral differences should be incorporated using person-type-specific rules, particularly regarding traveler probability, activity planning, and distance thresholds.

Furthermore, the trip length distributions analyzed by mode, purpose, and person-type highlight that travel behavior is shaped not only by the socio-demographic and infrastructural context, but also by regional accessibility and spatial structure. For example, while most non-motorized trips are <2 km in all areas, the same cannot be said for car or work trips, which vary significantly by region.

It is therefore recommended to develop regional-level probabilistic rules directly informed by the patterns observed in the HHTS data. Each rule should reflect observed distributions for:

- Traveler probability by person type and region
- Trip purposes, and activity schedules
- Departure time patterns
- Mode choice
- Trip distance.

By embedding these regional and person-specific features into the model rather than the city-wide rules, rule-based ABM can more accurately replicate real-world mobility dynamics and provide more robust outputs for policy and planning applications. In summary, the rule system should go beyond general assumptions and adopt a spatially and demographically sensitive approach driven by empirical distributions derived from observed data.

CHAPTER 6

CONCLUSION AND FURTHER RECOMMENDATIONS

Transportation, and developing travel demand model is important for every country, city and place of living. The steps to be taken, decisions to be made and planning in transportation are very important. There are different methods and purposes applied in the transportation models developed in this planning. The purpose of the study, investigating sub-region based travel patterns to determine the structure of the rule-based ABMs.

6.1 Travel Behavior in Sub-regions of İzmir

The findings of this study highlight the importance of analyzing travel behavior at a sub-regional level rather than relying solely on city-wide averages. Through a comparative assessment of three study areas (Aliağa, Menemen, and Karşıyaka*), significant differences in travel characteristics were identified, which have important implications for travel demand modeling and policy development. The rules to be developed with the inferences summarized below will enable people's travel preferences and patterns to be reflected more accurately.

First, the probability of being a traveler varied significantly not only between regions, but also between different person types defined by basic socio-demographic characteristics such as age, employment status, and educational attainment. For example, working adults in Karşıyaka* consistently exhibited a high probability of taking a daily trip, while the same person type in Aliağa exhibited lower probabilities, likely due to longer distances, limited modal options, or local employment. Similarly, student traveler rates varied between Menemen and Karşıyaka*, reflecting differences in school accessibility and family travel behavior.

These differences in person type behaviors are particularly important for the application of rule-based ABM where individual-level travel decisions are driven by such demographic profiles.

Second, average travel distances varied significantly across regions. Longer average travel distances were observed in Aliğa, primarily due to the spatial separation between residential areas and major activity centers. In contrast, Menemen and Karşıyaka* had shorter travel lengths, consistent with more compact urban forms and better access to services and public transport. Departure time patterns also revealed significant sub-regional distinctions. Aliğa showed significantly earlier morning commutes.

In terms of mode choice, Karşıyaka* residents relied more on public transport and non-motorized modes due to higher public transport service coverage and walkable urban environments. In contrast, greater reliance on private car use was observed in Aliğa, highlighting gaps in public transport accessibility and infrastructure. Menemen showed a mixed pattern, where both public transport and car use were significant depending on the travel purpose and origin-destination pairs.

These results clearly indicate that travel behavior cannot be accurately captured by city-wide generalizations. Instead, subregion-specific behavioral probabilities and person-type-based rules should be created and implemented in transportation modeling frameworks. Incorporating such localized insights ensures that the simulation of travel demand reflects the true diversity of mobility patterns, thereby increasing the reliability of model results and the effectiveness of planning interventions. These differentiated rules can provide a basis for rule-based agent behavior in activity-based models, enabling more realistic scenario testing and improved policy responsiveness at the micro-spatial level.

6.2 Limitations of the Study

One of the main limitations of this study stems from the data requirements associated with ABMs that rely on highly detailed socio-demographic, land-use and travel information at the individual and household level. In the context of Turkey, unlike many European or North American regions where comprehensive census records, household travel surveys and socio-economic databases support the full implementation of ABM frameworks, such detailed datasets are not readily available. While synthetic population techniques help to bridge this gap by approximating population characteristics and improving traditional projection methods, they are still highly dependent on the quality and availability of input data. Given these limitations, this study adopts a rule-based ABM approach, which can be seen as a practical and adaptable alternative. This method offers a balance between data realism and model applicability by focusing on sub-region-specific behavioral rules derived from available survey data. Although it does not cover all the complexities of full-scale ABM, it provides valuable insights into localized travel behavior and supports more informed decision-making under data-limited conditions.

6.3 Further Recommendations

This study has shown that rule-based modeling of travel behavior requires both detailed data inputs and a fragmented approach that accounts for subregional variation. Although data-intensive, using subregion-specific behavioral rules instead of relying solely on city-wide averages can significantly improve the accuracy and policy relevance of transportation models. Therefore, further research efforts should continue to prioritize improving localized travel behavior patterns and incorporating them into activity- or agent-based modeling frameworks.

In particular, walking trips deserve special attention if sustainable transportation outcomes are to be prioritized. This study has revealed that walking behavior varies

not only across subregions, but also across different socio-demographic groups and trip purposes. Therefore, future studies could focus on examining walking trips in more detail by identifying spatial clusters with higher walking shares, assessing infrastructure quality, and developing behavioral rules specific to these contexts. Such insights will support the design of more effective active mobility policies and pedestrian-friendly interventions at the neighborhood level.

Another important area for future improvements concerns the treatment of travel time in the modeling process. Since the travel times used in this study are based on self-reported survey responses, they are inherently subject to individual time perception biases. These perceived times may not always reflect actual network conditions and may lead to inconsistencies when used directly in rule formulation. To address this, future work could incorporate network-based travel time inference methods that use tools such as GIS-based routing algorithms or travel time matrices derived from real or simulated networks to more accurately estimate travel times. This would increase the realism and transferability of the model by ensuring that the rules are based on objective measures of accessibility and network performance.

In summary, while this work has established a strong foundation for rule-based subregional modeling, advancing these approaches through focused analysis of sustainable travel modes and improved estimation of key variables such as travel time would further enhance their application in transportation planning and policy analysis. To improve the quality and applicability of travel demand modelling, socio-demographic data should be prepared and published in more detail, ideally at the neighbourhood (micro) level. The current lack of detailed socio-demographic data limits the ability to accurately define Traffic Analysis Zones (TAZs) and sub-regions and prevents meaningful assessment of the impacts of land use on travel behaviour. To address this, local authorities should take the lead in defining micro-level analysis zones that reflect their land use patterns and transport systems. These micro-regions should be aggregated to form appropriate TAZ structures and sub-regional divisions for strategic planning purposes on a larger scale.

It is also recommended that TURKSTAT begin publishing socio-demographic indicators at the micro-region level. In addition, travel statistics such as travel production rates, vehicle kilometres travelled (VKT) and other key indicators should be published in coordination with municipalities, TURKSTAT or the relevant ministries.

In the long term, establishing this data infrastructure will be essential for the implementation of advanced modelling tools such as ActivitySim. The availability of such detailed and structured datasets will not only support activity-based travel demand forecasting but also increase the accuracy of urban mobility and accessibility analyses.

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APPENDIX

Population Synthesis Literature

Balac and Hörl (2021) established an open-source pipeline for generating synthetic populations entirely based on publicly available data sources, including the U.S. Census, American Community Survey (ACS), California Household Travel Survey (CHTS), and OpenStreetMap. This pipeline emphasizes principles of reproducibility, transparency, and adaptability for application in other geographical regions, thereby addressing a substantial gap in transport research regarding the accessibility of data sources.

The creation process encompasses five principal stages:

1. Household and Individual Generation: Synthetic households and individuals are constructed using demographic and socio-economic data derived from U.S. Census data and Public Use Microdata Sample (PUMS) records, integrating attributes such as age, gender, employment status, income levels, and vehicle ownership.
2. Activity Pattern Assignment Each individual is assigned a daily activity schedule based on CHTS data, incorporating both essential trips (e.g., commuting to work or school) and discretionary activities (e.g., shopping or leisure pursuits).
3. Spatial Imputation of Locations: Home, work, educational, and secondary activity locations are imputed through the use of census tracts and OpenStreetMap data. The methodology employs heuristics to allocate locations within reasonable spatial distances and aligned with activity types.
4. Statistical Matching and Calibration: Synthetic individuals are statistically matched to real-world observational data to ensure an accurate representation

of socio-demographic patterns and travel behaviors. Additionally, the distribution of activities is calibrated to align with observed activity patterns.

5. Validation and Calibration: The outputs generated by the model undergo validation by comparing synthetic population distributions against established data, with a particular emphasis on socio-demographic characteristics and travel patterns.

Balac and Hörl (2021) attained robust validation results for the San Francisco Bay Area and San Diego County by conducting comparative analyses between their synthetic population data and official census data alongside CHTS observations. For instance, the distributions concerning age, gender, income, and employment closely matched empirical data, indicating accurate reproduction of socio-demographic compositions (See Figure A. 1). The model also effectively replicated daily activity patterns, evidenced by the congruence of activity-chain distributions with CHTS data, with deviations typically remaining below one percentage point for the majority of activities (Balac & Hörl, 2021).

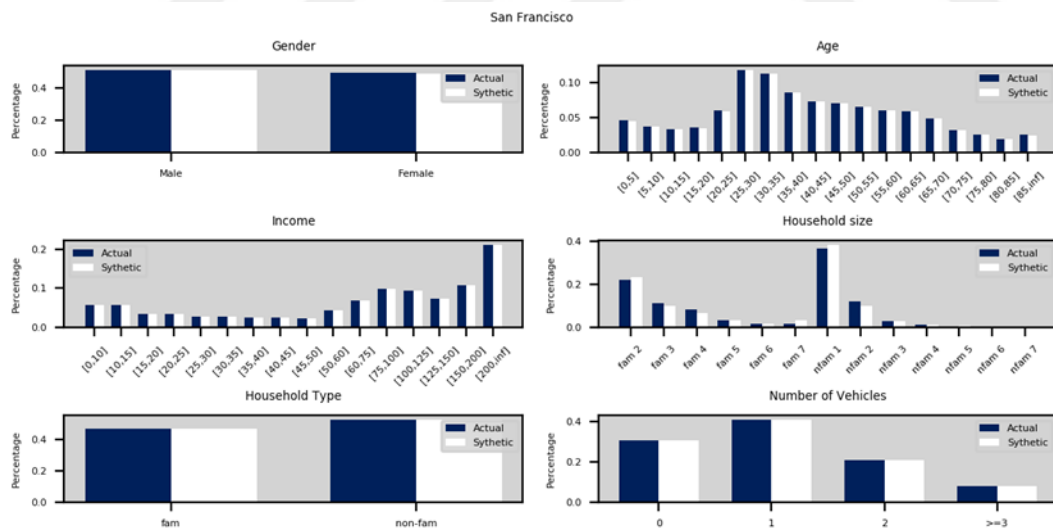


Figure A. 1 Comparison between the Synthetic Population Results and Census Data (Balac & Hörl, 2021)

Validation of activity chains revealed that typical sequences (e.g., home-to-work-to-home) and rates of out-of-home activities corresponded effectively to real-world data for both counties. However, certain discrepancies were identified, particularly within San Diego County, where household and individual demographics exhibited slight deviations from census-based expectations, likely attributable to temporal differences between datasets (Balac & Hörl, 2021). Furthermore, validations of travel distances evidenced the model's accuracy in replicating realistic travel distances, with cumulative distributions demonstrating strong alignment with observed data, except in instances characterized by low sample sizes for specific activities, such as business trips.

Literature on Population Synthesis

“Methodology to Match Distributions of Both Household and Person Attributes in Generation of Synthetic Populations” by Ye et al. (2009) offers a significant advancement in the development of synthetic populations, a structured dataset intended to replicate the demographic characteristics of real populations. This methodology is crucial for the accurate implementation of microsimulation modeling in transportation research, as it allows researchers to examine individual-level behaviors in contexts such as transportation planning, without necessitating comprehensive survey data for each individual.

Ye et al. (2009) introduced the Iterative Proportional Updating (IPU) algorithm, which refines the traditional Iterative Proportional Fitting (IPF) method by incorporating controls for individual-level attributes alongside household-level characteristics. This innovative approach recalibrates household samples drawn from datasets like the Public Use Microdata Sample (PUMS) to harmonize both household and individual distributions within a designated geographic area. The IPU algorithm iteratively adjusts weights for various household types, ensuring that the resultant synthetic population's household and individual distributions are aligned with actual census data, serving as the benchmark for this alignment process.

The implementation of the IPU approach yields a synthetic population encompassing both household characteristics (such as income and household size) and individual traits (including age and gender). This dual alignment significantly enhances the accuracy and relevance of synthetic populations in microsimulation, particularly within activity-based models (ABMs) that rely on comprehensive individual-level data for personal behavior simulations. The primary advantage of this methodology lies in its ability to maintain the accuracy of both household and individual distributions, thereby facilitating realistic travel demand forecasting and policy evaluation at more granular levels.

Ye et al. (2009) mark a notable enhancement in synthetic population generation through the introduction of the IPU algorithm, a sophisticated technique designed for application in activity-based microsimulation models. Their methodology addresses critical limitations in prior approaches by ensuring that both household and individual attributes closely reflect observed demographic distributions. In contrast to conventional methods that predominantly focus on household characteristics, the IPU algorithm achieves a balanced weight allocation across both household and individual dimensions, resulting in synthetic populations that are adept for comprehensive individual-level analyses within the scope of transportation research. A practical application of the IPU algorithm was demonstrated in a case study conducted in Maricopa County, Arizona, where it effectively aligned synthetic data with control data across diverse demographic variables. The utilization of this technique is particularly beneficial in activity-based models, where individual-level data is pivotal for simulating travel behavior, thus leading to more accurate and nuanced modeling of travel demand (Ye et al., 2009).

PopulationSim Software

The development and implementation of PopulationSim, a population synthesizer called "Multi-Level Population Synthesis Using Entropy Maximization," is explained in the paper. Binny Mathew Paul, Jeff Doyle, Ben Stabler, Joel Freedman,

and Alex Bettinardi (2017) developed PopulationSim as part of an open-source project sponsored by the Oregon Department of Transportation (ODOT). It was implemented in Python within the ActivitySim framework and aimed to generate synthetic populations more accurately for use in Activity-Based Models (ABMs). The population synthesizer aimed to address key limitations of existing synthesizers, such as handling multi-level geographic data efficiently, avoiding sequential processing errors, and modifying synthetic populations after creation. PopulationSim's primary innovation involves using entropy maximization and linear programming techniques to eliminate errors commonly found in sequential processing models like PopSynIII. It employs a simultaneous list balancing method to distribute population records across multiple zones simultaneously, ensuring better alignment with geographic controls. This approach, along with a linear programming-based integerizer, reduces Monte Carlo noise and avoids the "large-zone error" problem, which tends to disproportionately affect smaller or last-processed zones, like those with minority populations such as university students. In PopulationSim, mathematical methods like entropy maximization ensure minimal deviation from initial data while satisfying multiple control constraints. Linear programming is used to convert fractional weights to integers, enhancing accuracy, especially for smaller and more diverse population segments. Additionally, PopulationSim offers flexibility in specifying the number of geographic levels, making it adaptable to various modeling scenarios such as statewide population forecasts or traffic impact studies.

Applications of PopulationSim

PopulationSim, a synthetic population generator that utilizes entropy maximization, has been widely applied in various regions. One notable example is its use in the Corvallis-Albany-Lebanon (CALM) modeling region in Oregon, USA, where it was employed to generate a synthetic population comprising 62,041 households and 156,452 individuals, including 17,510 students from Oregon State University. This

implementation was conducted to validate PopulationSim's performance against the PopSynIII synthesizer. The resulting population matched specified demographic controls across different geographic levels, such as Public Use Microdata Areas (PUMAs), Census Tracts, and Traffic Analysis Zones (TAZs). In addition to its regional applications, PopulationSim is designed for flexible use in traffic impact studies, travel demand forecasting, and activity-based modeling (ABM) frameworks, making it a versatile tool for planning and policy assessment.

Performance and Success Rate

PopulationSim's performance was assessed by comparing its outcomes with those produced by PopSynIII using the same input dataset and control specifications. In the CALM region, PopulationSim consistently outperformed PopSynIII, particularly in addressing the "last zone error" issue affecting minority population controls, such as university students. Notably, the model accurately matched the specified OSU student population control, while PopSynIII exhibited larger errors. Validation metrics were computed by evaluating the percentage difference between the control totals and the synthesized totals. PopulationSim achieved a reasonable match for most demographic controls, including household size, income, and occupation, across various geographies. Its ability to enhance matching for smaller, critical population segments underscores its success, particularly in scenarios requiring high accuracy, such as transit ridership modeling and traffic studies.

Mathematical Framework

The PopulationSim algorithm is built around entropy maximization and simultaneous list balancing to ensure accurate population synthesis across multiple geographies. The method aims to minimize the introduction of new information while matching the control distributions, using the following formulations:

1. **List Balancing (Entropy Maximization):** The entropy maximization approach used in PopulationSim seeks to find weights that minimize the

divergence from initial seed weights, while satisfying control totals. The problem is expressed as:

$$\min \sum X_n \ln\left(\frac{X_n}{W_n}\right) \quad (2.1)$$

Subject to:

$$\sum H_{n,i} \times X_n = A_i, \forall i \quad (2.2)$$

Where:

- W_n are the initial weights from the seed data.
- X_n are the final weights assigned to each household record.
- A_i are the control totals.
- $H_{n,i}$ represents the relationship between the household records and the controls.

This optimization problem is solved using the Newton-Raphson method to ensure that the weights closely match the control distributions across different geographic levels.

2. **Simultaneous Integerization:** After list balancing, the fractional weights assigned to each household are converted to integers using a linear programming approach. The residual weights, R_n , are first computed as:

$$R_n = X_n - [X_n] \quad (2.3)$$

These residuals are then treated as binary variables in a new maximum entropy problem formulated as:

$$\min \sum y_n \ln(y_n), \quad y_n \in \{0,1\} \quad (2.4)$$

Subject to:

$$\sum H_{n,i} \times y_n = A_i, \forall_i \quad (2.5)$$

This ensures that the final integer weights assigned to household records still meet the control totals while minimizing errors. The approach improves the fit for minority populations and helps distribute any remaining errors more evenly across zones, preventing them from accumulating in the last processed zones, as observed with previous methods like PopSynIII. By combining entropy maximization with simultaneous list balancing and integerization, PopulationSim offers a robust solution for synthetic population generation, addressing key challenges faced by earlier population synthesizers.

The advantages of PopulationSim include improved accuracy in generating synthetic populations, especially in handling complex, multi-level geographic data, and avoiding sequential processing errors. It is also highly flexible, allowing users to modify or update populations for specific zones and use fewer or more geographic controls. However, there are some disadvantages, including longer processing times, particularly when using simultaneous integerization, due to the higher computational complexity of its methods. The current version also lacks optimization for parallel processing, which may limit its efficiency in larger models or more demanding applications.