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Master's Thesis

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The Impact of Cycling Infrastructure on Shared Dockless E-Scooter Riders' Usage Patterns and Travel Behavior

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Abstract

Shared Dockless E-Scooters (SDES) have emerged as a significant component of urban transportation systems since their introduction just a few years ago. Their ability to facilitate short to medium-distance trips through a flexible, user-friendly platform has led to rapid adoption in cities worldwide. This research examines the relationship between cycling infrastructure and SDES usage patterns in Tel Aviv-Yafo, analysing approximately 1 million trips and 2 million vehicle status transitions recorded in July 2023. The findings indicate that SDES users frequently modify their routes to utilize available cycling infrastructure, with both higher vehicle availability and user demand observed in proximity to these facilities. The study also yields practical insights for SDES parking policy development and cycling infrastructure design optimization.

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1. Introduction

The last few decades have demonstrated that modern cities face an unprecedented transportation crisis stemming from their reliance on private car mobility. While private cars offer individuals maximum flexibility and unrestricted route choices, urban spaces increasingly struggle to accommodate the growing demand. This limitation manifests in severe congestion, lack of parking space availability, and degraded environmental conditions for both residents and visitors. Consequently, researchers and urban planners now prioritize developing sustainable urban mobility alternatives, including public transportation, pedestrian infrastructure, and various two-wheel vehicle (micro-mobility) options.

This research examines an emerging micro-mobility solution in Tel Aviv-Yafo: the Shared Dockless E-Scooter (SDES). These vehicles represent innovation not only through their electric propulsion but also via their shared operational model, which positions them as a promising solution to the "first/last mile" challenge. This study primarily investigates how cycling infrastructure (e.g. bike lanes) affects SDES usage patterns, focusing on two key aspects: riding behavior and trip initiation locations. Specifically, it explores whether cycling infrastructure influences users to modify their routes to utilize these facilities and if vehicles positioned near such infrastructure attract more users.

The thesis comprises seven chapters. Chapter 2 reviews current literature on micro-mobility, SDES systems, cycling infrastructure, and the relationships between these elements. Chapter 3 describes the story of SDES in Tel Aviv-Yafo and its regulatory framework. Chapter 4 outlines the research questions and hypotheses, while Chapter 5 details the methodological approach. Chapter 6 presents the findings, and Chapter 7 discusses these results in relation to the hypotheses and existing literature, acknowledges study limitations, and suggests directions for future research.

2. Literature Review

This literature review provides a comprehensive overview of current knowledge regarding micro-mobility, Shared Dockless E-Scooters (SDES), cycle infrastructure, and the interrelationships among these elements. The review begins by addressing a major urban challenge: traffic congestion dominated by private car usage, resulting in gridlocked, polluted,

and noisy cities that necessitate innovative transportation solutions. It then explores micro-mobility, primarily focusing on non-gasoline-powered two-wheeled vehicles, as a potential solution with numerous benefits. Particular attention is given to SDES as a novel form of shared micro-mobility, examining both its similarities to and differences from other micro-mobility modes. The review also offers a concise yet broad overview of cycle infrastructure, recognizing its role as a key factor in encouraging micro-mobility adoption. Finally, the review explores the connections between infrastructure and the characteristics and usage patterns of micro-mobility and SDES users, providing a holistic understanding of these emerging urban transportation dynamics.

The modern congested city

One of the primary challenges facing modern urban centers is the escalating issue of traffic congestion, which threatens to reach a state of gridlock, hindering the overall mobility within the city. (Downs, 2004). A potential contributing factor to this growing congestion is the predominant reliance on private automobiles. While private vehicles offer a flexible, personal, and multi-purpose mode of transportation, their space requirements and the increasing urban population have rendered them an inefficient mode of transport in densely populated urban areas. (Prieto Curiel et al., 2021). Furthermore, private automobiles are associated with several disadvantages, such as air pollution. (Brand & Hunt, 2018), noise pollution (Patella et al., 2019), and safety concerns (Albalate & Fageda, 2019). Consequently, the imperative to enhance alternative sustainable modes of transportation, including public transit (PT), two-wheel vehicles, and pedestrian infrastructure, has become a crucial priority for urban planners and researchers.

Micro-Mobility: not just a mode of transport

Although the traditional bicycle has existed in the urban space for many years, the concept of micro-mobility is relatively new and developed with the emergence of electric-powered two-wheel vehicles (Orozco-fontalvo et al., 2023). There isn't one definition for the term micro-mobility, but most of the studies use similar features, defining it as light-weighted (<500kg), low-speed (<30km/h), human or electric-powered, eco-friendly, and used for short and medium distances (Eccarius & Lu, 2020; Mcqueen et al., 2021; Orozco-fontalvo et al., 2023). Despite the difficulty of finding one comprehensive definition, which is not challenged by

other vehicles such as small light cars, the term mostly refers to bikes, e-bikes, scooters, segways, skateboards, and similar vehicles.

The advantages of micro-mobility vehicles are numerous, especially in the shade of urban traffic congestion and the efforts to create a sustainable modern city. Its flexibility, cost-effective, relatively easy operating, and on-demand transport, make it an attractive alternative for short-medium distance trips (Abduljabbar et al., 2021). Another benefit is the potential of integration with public transport, by closing the “first/last mile problem”, and allowing people to give up on the private car. (Eom et al., 2023). Additionally, micro-mobility transport also reduces the motorized traffic negative outcomes such as air pollution and noise. (Abduljabbar et al., 2021). Moreover, the benefits do not stop at the roads, and there is evidence for the contribution to the well-being (Gray & Gow, 2020), and even to the feeling of independence of youth(Clanton et al., 2022). Therefore, it is not surprising that many authorities seek ways to encourage the usage of micro-mobility vehicles and shift them to a primal mode of transport, for different purposes, and by varied population groups (Fuller et al., 2021; Kuster, 2019; Minneapolis, 2020; Tel-Aviv-Yafo, 2021).

Shared Micro-Mobility

Shared micro-mobility is a subset of shared mobility, a concept that separates vehicle ownership from ridership by allowing users to rent various modes of transport for short durations. (Shaheen et al., 2019). The shared mobility framework encompasses diverse service models designed to address different mobility demands through various travel modes, with the primary categories being motorized cars (e.g., carsharing, carpooling) and shared micro-mobility (Shaheen et al., 2019).

The evolution of shared micro-mobility can be divided into two main phases. The earlier phase primarily involved docked bikes stationed at various locations throughout the city, where users could retrieve and return vehicles. These systems were typically operated by municipalities or private companies. The latter phase, known as the "dockless" phase, emerged due to technological advancements that enabled users to unlock and lock vehicles using their smartphones, eliminating the need for designated docking stations. (Shaheen et al., 2021). Concurrent developments in electric vehicle technology, particularly in micro-mobility, have made these options more accessible and efficient. Rechargeable batteries now allow for several hours of riding time and decent speeds suitable for urban mobility. (Corti et al., 2024).

Shared Dockless E-Scooter – a new player in the city's mobility

Shared dockless e-scooters (SDES) were first introduced in 2017 and rapidly spread globally. By 2021, SDES systems had been adopted in nearly 900 cities across 60 countries, operated by over 100 companies. (Numo, 2021). The operation is almost the same everywhere, an initial fee is charged to unlock the vehicle, mostly around 1$, then an additional amount every minute of usage, mostly 0.2-0.3$ (Orozco-fontalvo et al., 2023). The rapid proliferation of SDES occurred within a context of urban congestion, climate change concerns, and an ongoing search for effective urban mobility solutions. The simplicity of SDES operation – unlocking available "floating" vehicles and dropping them off near the desired destination at any time – offers users a high degree of flexibility. (Field & Jon, 2021; Smith & Schwieterman, 2018). Moreover, the no-ownership model allows various road users, including non-resident commuters and city visitors, to utilize SDES for addressing first-mile connectivity issues. (Gebhardt et al., 2021; Shaheen et al., 2021). The dockless design enhances the multi-purpose nature of SDES, allowing for high adaptability to demand fluctuations. (Espinoza et al., 2019). The electric-based motorization and compact dimensions of SDES highlight additional benefits, such as low emissions, quiet operation, and space efficiency. (Lazarus et al., 2020; Shaheen et al., 2021). These advantages have positioned SDES as a promising new solution for urban mobility challenges.

SDES characteristics – Users, motivations, and transport modes replacement

Despite the relatively recent introduction of Shared Dockless E-Scooters (SDES) in urban environments, there has been growing interest in investigating their characteristics and integration into city transport systems. Studies examining the sociodemographic profile of SDES users consistently identify typical users as young, healthy men who are city residents, however, other factors such as education level, household income, having children, and car ownership show inconsistent associations or no association across different locations (Christoforou et al., 2021; Dibaj et al., 2021; Mitra & Hess, 2021; Mouratidis, 2022). A review study synthesizing findings from various locations categorized SDES users into four types: "curious one-time users", "casual users", "regular users", and "non-adopters" (Dibaj et al., 2021). Additionally, the primary motivations of users for using SDES are predominantly travel time savings, recreational purposes, and cost savings, though the order of importance may vary depending on local conditions (Christoforou et al., 2021; Kopplin et al., 2021; Mouratidis,

2022). Notably, environmental concerns do not appear to be a significant motivating factor for SDES ridership (Mouratidis, 2022). The similarities and differences in user characteristics, motivations, and composition suggest that while SDES globally attracts a distinct population (young men), for similar reasons, it also exhibits local variations that may reflect the role of SDES in a city's mobility landscape and public perception.

Regarding transport mode replacement, SDES most frequently substitutes walking or public transportation (PT) (Christoforou et al., 2021; Weschke et al., 2022), although some locations show stronger evidence of transitions from private car use to SDES (Wang et al., 2022). The relationship between SDES and PT is bidirectional; while SDES often serves as a substitute for PT trips, it also demonstrates a strong connection with rapid transit stations. (Nawaro, 2021). This dual nature suggests that SDES can both complement and compete with existing public transportation systems, depending on local context and user needs.

SDES spatiotemporal characteristics

Shared Dockless E-Scooter trips are generally short, aligning with their designation as "first/last mile vehicles." The average ride typically covers approximately 2km and lasts about 10-15 minutes. Figure 2.1. illustrates a comparison of trips' distance, duration, and speed made by Badia and Jenelius (2023) Based on the results of different studies. SDES demand exhibits distinct temporal patterns, varying across different locations. Some areas display a clear two-peak demand structure – morning and afternoon-evening, with the latter usually being higher. (Abouelela et al., 2023; Lee et al., 2024). However, other patterns have been observed, including three usage peaks (with an additional lunch peak) or the absence of a morning peak. (Huo et al., 2021; Li et al., 2022). Weekends often demonstrate different temporal demand patterns compared to weekdays, typically featuring a single evening peak. SDES demand is also influenced by other temporal factors, such as weather conditions. Colder and rainier days are associated with lower demand, while warmer and drier conditions correlate with higher usage. Interestingly, even fluctuations in gasoline prices can affect SDES demand. (Mehzabin Tuli et al., 2021).

The spatial factors that impact SDES demand and usage characteristics were examined by Mckenzie (2019) who found that recreational and public land uses are more strongly associated with SDES destination demand compared to commercial and residential areas. Huo et al. (2021) further identified that employment and mixed-land-use areas positively correlate

with SDES demand. Their research also revealed variations in demand between workdays and weekends, with commercial areas experiencing higher demand on workdays and recreational areas seeing increased usage on weekends. Well-maintained road infrastructure, including the availability of cycling infrastructure, street lights, and trees, has been linked to higher SDES demand (Yang et al., 2022). Other spatial factors positively related to SDES demand include roads with less traffic, as well as higher population density, intersection density, and bus stop density (Huo et al., 2021).

SDES challenges and criticism

The rapid emergence and global spread of SDES occurred within just a few years, accompanied by hopes of addressing urban congestion and contributing to more sustainable cities. However, after several years of operation, increasing criticism has emerged, primarily focusing on safety issues such as sidewalk riding endangering pedestrians, public disturbance caused by parked vehicles, and the replacement of other sustainable transport modes (public transit, walking) rather than private car trips. (Gössling, 2020). These challenges have led some cities to ban SDES operations entirely. (France_24, 2023), while others have developed operational policies to regulate usage and vehicle allocation. These policies aim to allow SDES to operate while mitigating the associated challenges. (Ma et al., 2021).

Cycling Infrastructure

One of the primary deterrents to the adoption of micro-mobility as a mode of transportation is the perceived safety concerns, specifically regarding interaction with motorized vehicles (Asadi et al., 2016; Hull & Holleran, 2014). Consequently, the construction of suitable cycling infrastructure is crucial to facilitate increased micro-mobility transport usage. This realization

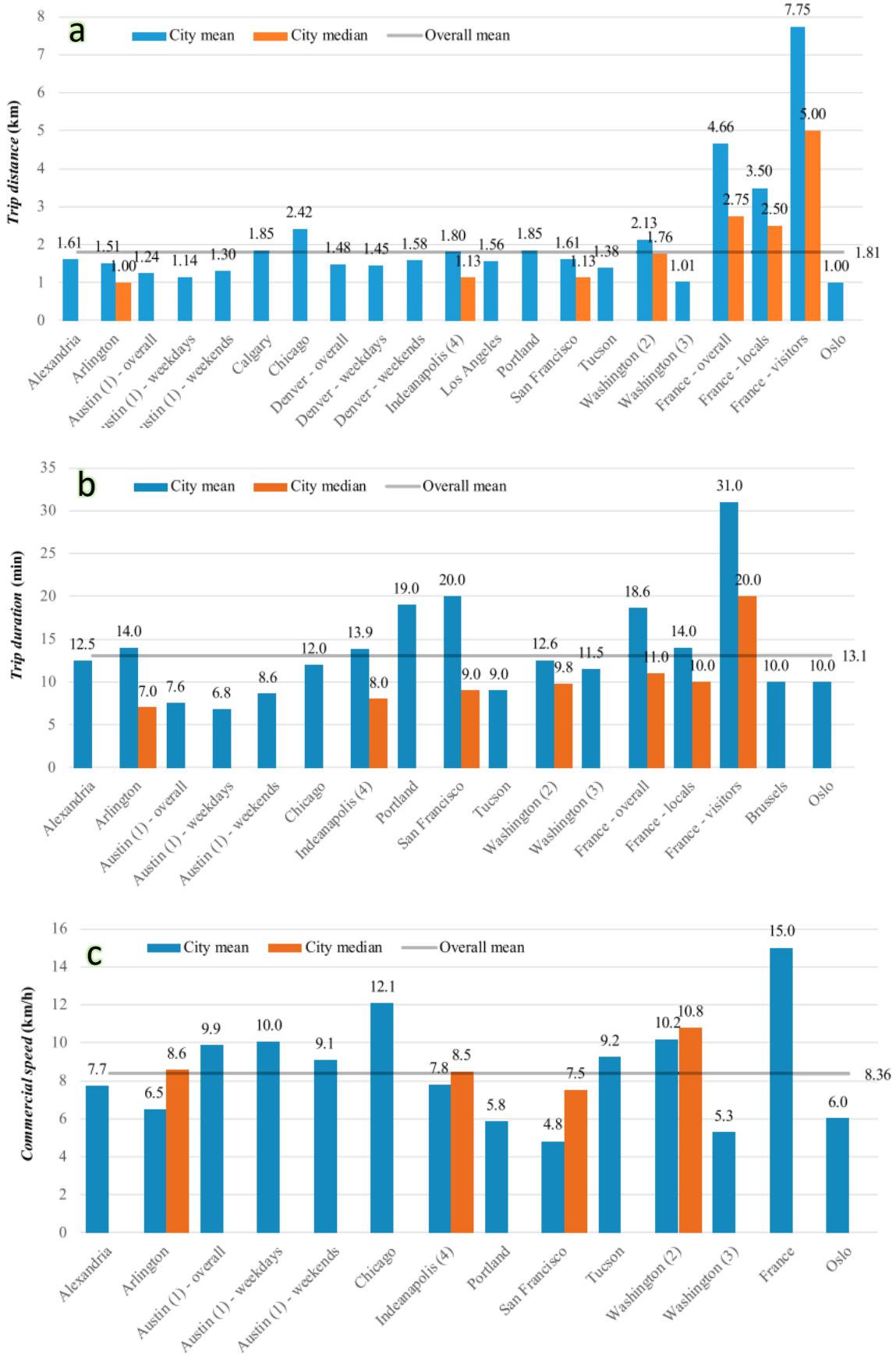


Figure 2.1

Comparison by Badia & Jenelius (2023) of trip characteristics in different cities based on various SDES studies: (a) Average and median trip distance, (b) Average and median trip duration, and (c) Average and median trip speed

has pushed increased investment and planning initiatives over the past three decades to expand cycling infrastructure networks, mostly in cities of the Western world (Buehler & Dill, 2015). The subsequent rise in cycling levels and decline in micro-mobility casualties in these cities suggests a positive correlation between cycling infrastructure, safer riding conditions, and a tendency to cycle (Fraser & Lock, 2010; Marques et al., 2015; Xiao et al., 2023).

Cycle infrastructure network design

Merely constructing cycling infrastructure is insufficient; the design must be adequate and appropriate, or it may generate negative implications for micro-mobility levels and public perception of inefficient resource allocation. (DtF, 2020a). Therefore, various approaches have emerged to pursue optimal cycling infrastructure planning, both from a network perspective concerning where to construct infrastructure within the city streets and from a built environment design standpoint of how to construct the infrastructure. Network-focused approaches typically aim to optimize the cycling network by evaluating variables such as accessibility, demand, land use, travel time, and network characteristics (Doorley et al., 2019; Fonseca et al., 2023; Gehrke et al., 2020; Lowry et al., 2016; Milakis & Athanasopoulos, 2014). Other studies employ qualitative methods to attain a more comprehensive understanding of the human experience when utilizing micro-mobility transport, aiming to elucidate factors influencing riding preferences obscured by quantitative data, thereby informing network planning (Deegan & Parkin, 2011; Zeile et al., 2016).

Cycle infrastructure – the physical design

The second aspect concerns the physical design of infrastructure within the urban environment. The two main infrastructure types are those integrated with motorized traffic via an unseparated or buffered designated lane, commonly termed a "cycle lane", and those segregated from motorized traffic with protected infrastructure typically referred to as "cycle paths" or "cycle tracks" (DtF, 2020b). A more nuanced categorization employs five infrastructure features to accurately classify types: horizontal location, vertical location, dedication to cyclists, segregation from motorized traffic, and segregation from pedestrians (Schröter et al., 2021). Although evidence suggests that increased separation from motorized traffic enhances users' perceived safety (Jarry & Apparicio, 2021), the exclusive implementation of segregated cycle paths is often impractical due to design constraints and budgetary limitations (Hancock & Parkin, 2023).

Cycle Infrastructure and micro-mobility

Since the willingness to encourage micro-mobility transport is rising, the need to understand the riders' route choice has become a key point for infrastructure planning and policy making. Therefore route choice modeling has become essential since it can "appraise travelers' perceptions of route characteristics, to forecast travelers' behavior under hypothetical scenarios, to predict future traffic conditions on transportation networks and to understand travelers' reaction and adaptation to sources of information" (Prato, 2009). Until recently, that task was done almost exclusively by stated preference surveys (Broach et al., 2012; Hood et al., 2016). Stated preference surveys can be appealing to investigate micro-mobility route choice for several reasons, it requires relatively simple design and easy modeling, no need for complex network alternative route computations and they have direct access to the rider's natural behavior (Broach et al., 2012; Fitch & Handy, 2020). However, it has significant limitations such as a relatively small routes sample, difficulty of respondents to take into account all features influencing a ride using a map or pen and paper, and possible strategic bias if respondents believe their answers might influence future policy (Broach et al., 2012; Fitch & Handy, 2020).

GPS data and micro-mobility route choice assessment

The improvement in Global Positioning System (GPS) and the advancement in its availability, provided real routes' trajectory data and hence became very popular among route choice modeling studies and micro-mobility and particular. The route choice modeling studies design is very similar in all cases – trips' GPS data is collected from real rides taken, either by research participants or immunized data provided by authorities or companies owning the data (Buehler et al., 2021; Ghanayim & Bekhor, 2018; Hood et al., 2016). Then the GPS data is assigned to the city's street network (map-matching), so each ride is represented in a flow of links. Then a set choice is generated – a set of alternative routes based on the origin and destination of the ride, and different combinations of the ride's objectives (e.g. shortest path, shortest travel duration, minimization of positive slope, etc). Then each route – the chosen one and the choice set, is estimated with different attributes – based on spatial data, such as land use, cycle infrastructure, traffic volume, and others. Finally, the chosen route and choice set attributes are analyzed with different statistical methods and models to seek riders' preferences, that significantly deviate them from the choice set to their route choice (Broach

et al., 2012; Cubells et al., 2023; Ghanayim & Bekhor, 2018; Hood et al., 2016; Meister et al., 2023; Menghini et al., 2010). A consistent finding of those studies is the ratio between the chosen route length and the choice set average length, which varies between 1.08-1.18, whereas in cities with significant cycling infrastructure that ratio tends to be higher (Ghanayim & Bekhor, 2018).

Cycle infrastructure and micro-mobility route choice

The studies using real GPS trajectories find the role of the built environment as one of the most influential on the micro-mobility riders' route choice. Menghini et al (2010), using a multinomial logic model (MNL) were the first to find, using GPS data, that the share of cycling infrastructure is a major factor in route preferences. Since then, several studies confirmed that highlighting preferences for segregated infrastructure (bike paths/tracks) over unseparated ones (bike lanes) (Broach et al., 2012; Hood et al., 2016; Prato et al.,4 2018). A recent study, using Probabilistic Soft Logic (PSL) and Mixed-Logit models, found that these preferences differ between vehicle types and genders, with regular bike riders and women being more sensitive to cycling infrastructure and more likely to choose it over alternatives (Meister et al., 2023). Importantly, Ghanayim and Bekhor's (2018) study in Tel Aviv-Yafo provided a numeric estimate, demonstrating that the utility of a bike route is equivalent to a route that is 38% longer than the shortest one, with a high preference for a denser cycling network. Other factors that were found to influence cyclists' route sensitivity include: total route length (willingness to minimize), slope, high-volume traffic, and frequency of turns and intersections. (Broach et al., 2012; Prato et al., 2018). Another significant study conducted in Tel Aviv-Yafo by Levy et al. (2019) provided insights into micro-mobility preferences, despite not utilizing trip trajectory data. The research, which focused on bike-sharing, indicated that users not only prefer cycling infrastructure but that this preference becomes more pronounced as the duration of the ride increases.

SDES, route choice, and cycle infrastructure

The route choice research regarding SDES is still in its early stages, as the mode of transport is. The studies not only try to estimate the attributes influencing SDES riders' route choice but also how it is distinct from the micro-mobility users, such as cyclists and private-owned e-scooters. A recent study by Richard et. al (2024), using stated preferences, compared SDES riders' and cyclists' route choices, and found that SDES riders are more sensitive to safety

issues, traffic rules, and road's surface, probably due to the vehicle's small wheels. Additionally, the decision-making of SDES users was found to be more complex than cyclists (Ringhand et al., 2024). In Barcelona, private-owned E-scooters were found with greater detour than shortest-path than non-electric bike-sharing users (Cubells et al., 2023). The reasons offered for that difference are that the private E-scooter riders care less for longer routes (regarding slope and physical activity) and that bike-sharing wants to minimize the rental duration. SDES, in that sense, have both characteristics – electric motor, and time-based pricing which encourage shorter routes. Hsueh and Lin (2023) found, in an SDES route choice study conducted in Taiwan,that users exhibited two main preferences: safety-oriented choices on one hand (avoiding high-volume traffic and remote sites at night), and speed-oriented choices on the other hand (avoiding crowded areas especially during morning peak hours, minimizing intersections, and preferring right turns).

Zhang et al (2021) had the most comprehensive study, as known by the authors, regarding the influence of the built environment and infrastructure on SDES riders' route choice. They used ~2,000 SDES trips in Virginia Tech Blacksburg Campus, map-matched their trajectories to OpenStreetMap (OSM) based graph links, and used the Recursive Logit (RL) route choice set model to assess riders' route choice preferences. Their results reveal that on the one hand SDES riders' route choice shares similar preferences to other micro-mobility users, as they prefer shorter routes, cycle infrastructure, and tertiary routes. But also have some differences, when the willingness to extend their route for cycle infrastructure is a bit higher (59%), and the ride's slope variable doesn't play a significant role (Zhang et al., 2021). Although this study conducted a comprehensive assessment of the influence of the built environment's attribute on SDES riders' route choice, it was limited to the institute campus which is not usually the best representation of a typical urban area. Nevertheless, almost all of the participants were students, which despite probably being composed of different social groups, they do not represent the needs, motivations, capabilities, and schedules of a city's residents and visitors.

Literature review summary

As can be seen in the literature, The SDES has similar patterns all over the world:

- Relatively short trips (1.5-2 km, 10-15 min).
- Users profile – mostly young healthy men

- Users prefer cycling infrastructure
- Users aim to minimize trip duration (pricing model)

But on the other hand, every city shapes characteristics according to the local context:

- Daily usage patterns
- Trips purposes combination
- Vehicles allocation

Therefore, the study's main objective is to investigate the influence of cycling infrastructure on SDES users' behavior, in the context of the city of Tel Aviv-Yafo. The investigation will seek to find the common and different features from other micro-mobility studies in Tel Aviv-Yafo, and SDES studies in other cities. This study not only assesses the influence of cycling infrastructure on SDES users' route choices but also explores previously uninvestigated aspects such as ride speed within the infrastructure and vehicle demand in its vicinity. These elements, which to the author's knowledge have not been examined in prior research, contribute to a broader understanding of the relationship between micro-mobility users and cycling infrastructure. Furthermore, they provide valuable insights for developing locally oriented SDES policies. By addressing these novel aspects, the research enhances both the theoretical understanding of micro-mobility dynamics and the practical application of SDES strategies in urban environments.

3. Tel Aviv-Yafo SDES policy

Tel Aviv-Yafo, the major city in Israel's largest metropolitan area ("Gush Dan"), has a population of approximately 475,000 residents (CBS, 2022) and covers an area of about 51 km². In terms of commuting preferences, micro-mobility ranks as the third most popular mode of transportation (~12%), following private cars (~45%) and public transit (~20%) (The Center for Economic and Social Research, 2024), although that does not count the daily "visitors" (commuters and tourists) – which play a significant role in the city's traffic as it the country's economic and cultural center. A. While a specific assessment of the average micro-mobility trip length in Tel Aviv-Yafo is not available, estimates based on Nadav et al. suggest trips are typically around 2-2.5 km in distance and 20-25 minutes in duration.

The first SDES company began operating in Tel Aviv-Yafo in summer 2018. Since then, SDES have become a popular mode of transport in the city, with four companies operating there as of July 2023. The SDES policy of Tel Aviv-Yafo municipality, up to July 2023 consists of three main elements:

- **Allocation** – Each operator is allowed to distribute up to 1,800 vehicles in the city's area, making it a total of 7,200 vehicles of all operators. The operators are obliged to distribute a fraction of their fleet in the southern quarters of the city (6%) and in the easter quarter (3%).
- **Parking restrictions**– at the center of the city, and other adjacent parts of high demand (North Jaffa, Florentine neighborhood), users are not allowed to park anywhere, just in ~700 designated parking cells (Figure 3.1b). Out of the restricted area – users are allowed to park everywhere, just not in specific locations defined by the municipality (e.g. entries to schools, next to bus stations). Parking restrictions are enforced through geofenced polygons, where ending a ride is not allowed when the vehicle is inside these areas.
- **Riding restrictions** – Speed is limited to 25 km/h and wearing a helmet is mandatory (as for all electric micro-mobility vehicles). Additionally, two restricted areas are defined, "no riding zones" where riding is prohibited, and "speed restricted zone", which automatically limit the speed to 15 km/h (Figure 3.1a).

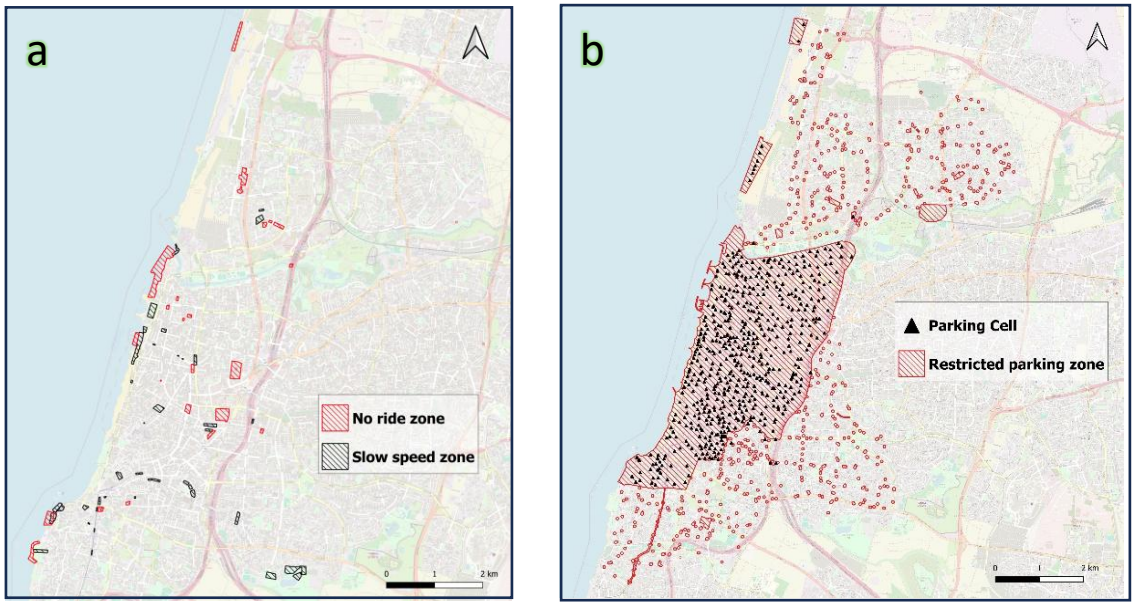


Figure 3.1
(a) Geofenced zones defined by the municipality that restrict riding—no-riding zones and slow-speed zones (up to 15 km/h). (b) Parking restriction zones and the designated parking cells within them

4. Research Objectives and hypothesis

The main objective of this study is to examine how the presence of cycling infrastructure influences the behavior of riders using Shared Dockless E-Scooters within the urban context of Tel Aviv-Yafo. The inquiry concentrates on two key aspects of rider behavior: the route choice and the demand for starting locations of trips. As a result, the main objective can be broken down into three sub-objectives:

- The effect of cycling infrastructure on SDES riders' route choice.
- The effect of cycling infrastructure on SDES trips' speed.
- The effect of cycling infrastructure on the location of trips' beginning.

The hypotheses based on the current knowledge for these objectives are as follows:

- Cycling infrastructure is more appealing for SDES riders and makes them deviate from the shortest path.
- The speed of SDES trips is higher when using cycling infrastructure because it offers better conditions: separation from motorized vehicles creates a greater sense of safety, and the road surface is more appropriate for micro-mobility vehicles, especially SDES.
- Since the cycling infrastructure is more appealing for riders the demand of SDES vehicles will be positively affected in proximity to cycle infrastructure.

5. Methodology

To investigate the research questions, this study utilizes two primary datasets that examine distinct aspects of SDES usage. The "Trips" dataset is employed to analyze user riding behavior, focusing on route choice and speed assessment which is presented in subchapter 5.1. The "Status Changes" dataset is used to evaluate SDES spatial demand, specifically examining where users choose to access vehicles, and further presented in subchapter 5.2. Both datasets were provided by the Tel Aviv-Yafo municipality through the Populus dashboard (Populus, 2024), and all data sources utilized in this study are summarized in Table 5.1.[1]

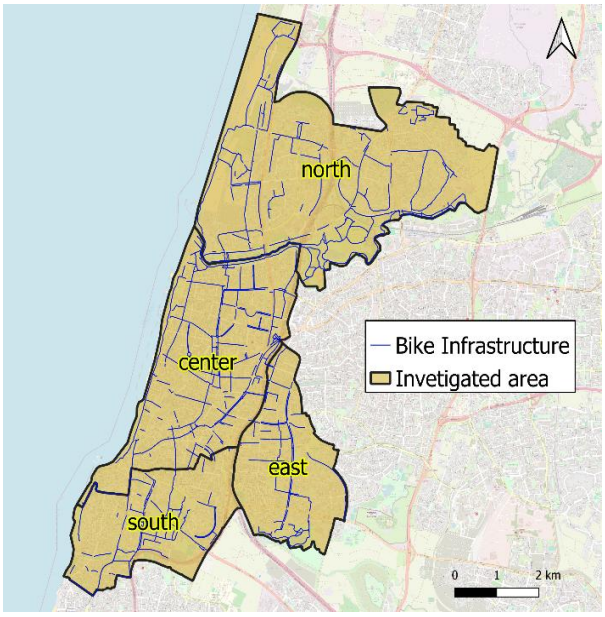


Figure 5.1
The four areas the city was divided in this study. Above it, cycling infrastructure updated to July 2023.

Table 5.1
Data sources used

Data	Source	Format	Description
Trips	Populus	CSV	Dataset contains spatiotemporal data of all trips taken in the city.
Status Changes	Populus	CSV	Dataset of SDES vehicles' operational statuses transitions.
Cycling infrastructure	Tel Aviv-Yafo GIS portal (Tel-Aviv-Yafo, 2023)	Shapefile	lines layer, consisted of ~175 km of bicycle lanes in Tel Aviv-Yafo boundaries, as it was in July 2023 (figure 4.1)
neighbourhoods	Tel Aviv-Yafo GIS portal	Shapefile	71 polygons layer of the city's division for neighbourhoods.
TAZ (Traffic Analysis Zone)	Ministry of Transportation GIS portal	Shapefile	221 TAZ polygons of Tel Aviv-Yafo
Built Area	Tel Aviv-Yafo GIS portal	Shapefile	48,092 polygons of buildings in Tel Aviv-Yafo
Four areas city's division	Made in this study	Shapefile	4 polygons dividing the city – center, north, south and east. The division was based on the SDES parking policy – the main parking restricted area defined as center, and the rest defined accordingly (Figure 5.1)
Open public space	Made in this study	Shapefile	Subtraction of the total city's polygon in the built area polygons. The result is the open public space.

[1] Tables in this study appear either in the main text or in Appendix A. Tables located in the appendix are marked with "(Appendix A)" following the table number, while those without this designation are found within the main text.

5.1. Trips Data Analysis

In this subchapter SDES route choice and speed is analyzed using the “Trips” dataset. Section 5.1.1. describes the “Trips” raw data as provided. Section 5.1.2 presents the route choice analysis, and section 5.1.3 presents the speed analysis.

5.1.1. Trips raw data – description

The trips raw dataset comprises individual rides made by users, containing 1,363,075 documented trips in July 2023, from four operators. The data consists of 13 fields, conforming to the Mobility Data Specification (MDS) format, which was developed to standardize shared micro-mobility data used and transferred between stakeholders, particularly operators and regulators (*MDS, 2023*). Table 5.2 (Appendix A) explains the 13 fields, (See Appendix B for the “Trips” raw data examples). The “Trips” raw data is filtered to 303,710 trip samples in this study, mainly due to insufficient geometry route data. Appendix C presents the trip sample filtration process and logic and illustrates examples of trips retained in the sample and those excluded from it.

5.1.2. Route choice analysis

The primary method for evaluating the influence of cycling infrastructure on route choice involves comparing the share of a trip's trajectory within cycling infrastructure to an alternative shortest path between the trip's origin and destination. This analysis was conducted through four key steps:

I. **Additional removal of trips**: with potential difficulty to compare chosen route and SP trajectories due to long detours or loops. After the removal, 274,168 trips remained in the sample (Appendix C further explains the cleaning procedure)
II. **Map-matching**: the trips' route to OpenStreetMap (OSM) topological links network of Tel Aviv-Yafo.
III. **Shortest path (SP) extraction:** for each trip.
IV. **Cycling infrastructure share assessment**: for the chosen route and SP trajectories.

The OSM data was extracted using the Python package OSMnx, focusing on all walkable street links. The decision to use the "walkable" street network was based on its larger street link representation, which facilitates better map-matching and allows for the inclusion of

pedestrian-only paths. The extracted network comprised 162,718 edges and 141,770 nodes in an undirected graph covering the entire Tel Aviv-Yafo district.

5.1.2.1. Map-matching

Map-matching is the process of projecting GPS coordinates of a given trajectory onto a street network graph, transforming the sequence of coordinates into a sequence of edges. This step is crucial for comparing the chosen route to an SP alternative computed on the same street network, ensuring a like-for-like comparison. The map-matching method employed in this study was straightforward and consisted of two main steps (Figure 5.2. illustrates the map-map-matching process):

I. **Creating a 25m buffer -** around the route linestring and intersecting it with the OSM graph's edges to create a subgraph.
II. **Extracting the SP -** on the subgraph between the nodes closest to the start and end coordinates of the linestring.

The SP computation utilized the "Single shortest path" function from the Python 3 library NetworkX, which implements Dijkstra's shortest path algorithm. The function uses the "length" field of the OSM graph's edges as the weight. The resulting sequence of OSM edges was transformed into a linestring and stored as a new "map-matched route" column in the trips sample dataset. Two additional rules were applied to enhance the accuracy of the map-matching process:

- **Only edges intersecting at least 90%**: of their length were included in the subgraph to prevent the inclusion of edges that only marginally intersect the route's linestring buffer.
- **In cases where an SP could not be computed**: due to a disconnected subgraph, a new edge was assigned between the closest nodes of the disconnected parts. (See Appendix D for an example of a disconnected subgraph and its connection).

The map-matching method employed in this study has inherent limitations that could lead to inaccuracies in the map-matched results. After the steps taken to address those limitations, 200,681 trips remained in the trips sample (See Appendix D for further description of the limitations and resulted in trips removal).

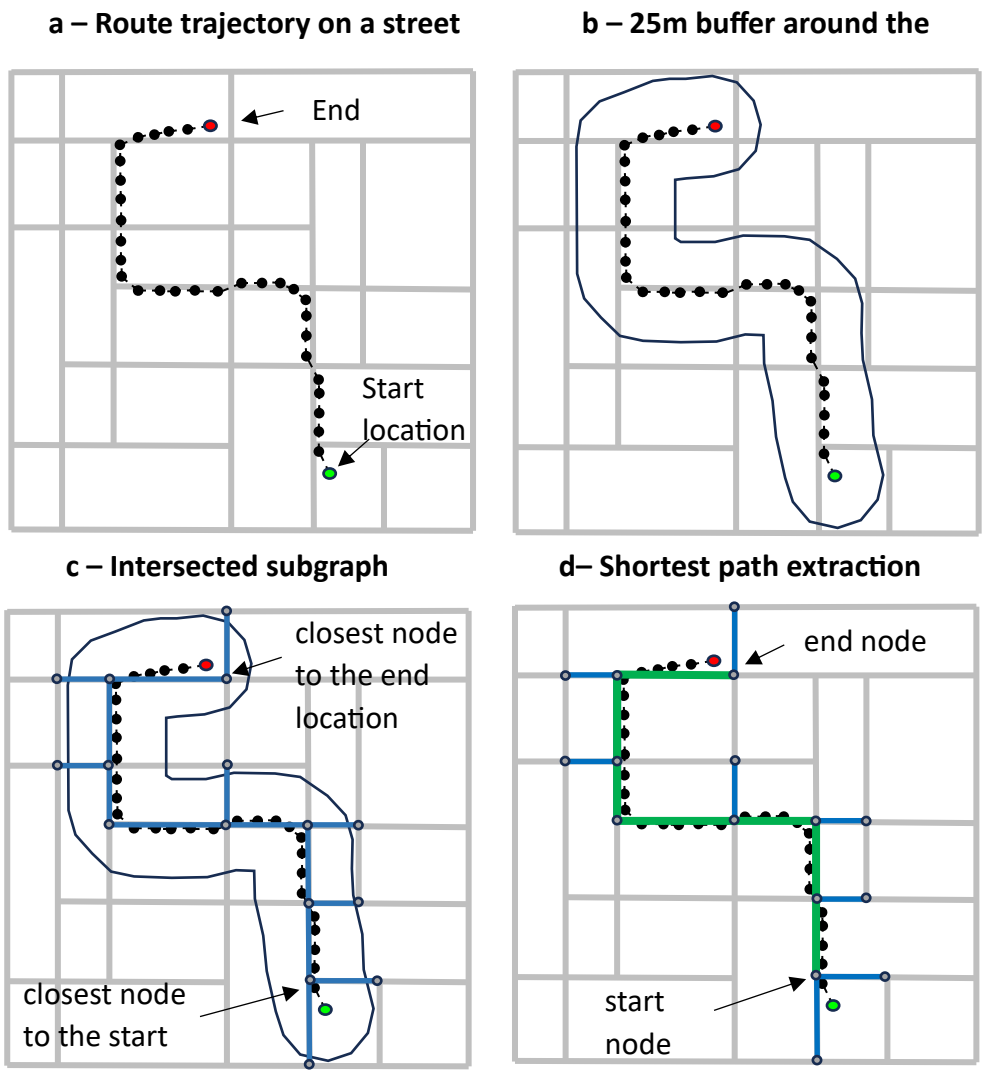


Figure 5.2.
Schematic flow of the map-matching process. (a) The route trajectory extracted from the trip's raw data, with black dots representing the GPS locations collected along the route. (b) A 25 m buffer around the trajectory geometry. (c) All edges with at least 90% intersection with the trajectory buffer, defined as a subgraph. (d) A shortest path computed between the nodes closest to the trajectory's start and end locations. (e) The output map-matched trajectory aligned with the chosen route trajectory

5.1.2.2. Shortest path extraction

For each ride, the shortest path was computed based on the start/end nodes of the OSM walking graph identified during the map-matching process. The decision to use the walking network, which includes not only roads, streets, and bike paths but also pedestrian-only links, is supported by evidence suggesting that SDES users tend to take "shortcuts" through pedestrian paths and often disregard traffic direction rules (Mitropoulos et al., 2023).

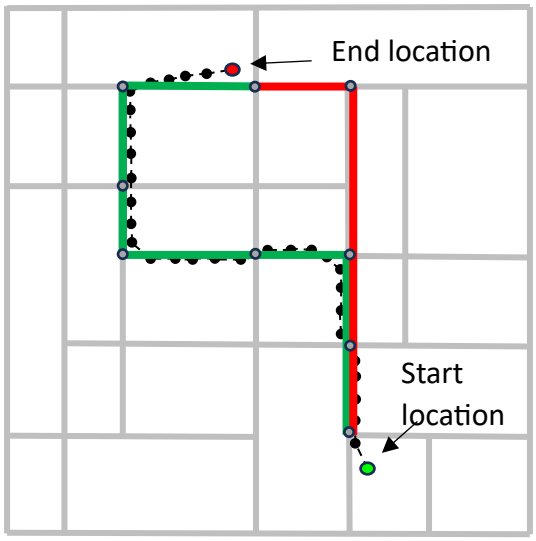


Figure 5.3.
Shortest path trajectory extracted for the start and end nodes of the map-matched route

The shortest path computation method is identical to that used in the map-matching process, with the output stored as a Linestring, and two additional fields were assigned:

I. **"Shortest path length"**: The metric length of the shortest path.
II. **"Chosen route ratio"**: The result of dividing the “matched” length by the SP length.

For rides with a chosen route ratio lower than 1, indicating that the chosen route was shorter than the computed shortest path, the "shortest path" values were replaced with the "matched” values. This situation can occur when the chosen route includes shortcuts or uses links missing from the OSM data. Figure 5.3. illustrates a schematic example of shortest path extraction.

5.1.2.3. Cycling infrastructure assessment

Following the addition of columns for map-matched chosen routes, shortest paths, and their respective metrics, and after refining the sample to a reliable set of trips, an assessment of the share of cycling infrastructure in each trajectory was conducted. This assessment involved:

I. **Intersection with cycling infrastructure:** Both sets of trajectories (chosen routes and SP) were intersected with a 25m buffered layer of the cycling infrastructure.
II. **Intersection measurement**: the intersected parts of the trajectories were measured.
III. **Fields assignment**: length and share of intersected trajectory with cycling infrastructure, both of chosen route and SP trajectories.

5.1.2.4. Route choice assessment variables

The route choice statistical analysis uses the following variables:

- **Dependent Variable**: The share and length of the intersected cycling infrastructure.
- **Independent Variable**: The trajectory's length for both chosen routes and SP.

5.1.3. Speed analysis

The assessment of riding speed within and outside cycling infrastructure is based on the "route" GeoJson field (Appendix B), which contains GPS points collected along the ride, including timestamps. This section presents the analysis undertaken on the trips sample in order to assess speed inside and outside the cycling infrastructure.

5.1.3.1. Segmentation of rides' trajectories

The core concept of the speed analysis involves dividing each route into segments "inside" and "outside" cycling infrastructure, calculating the distance of each segment and the time the rider spent within it. This process is accomplished through the following steps:

I. **Binary Classification:** Each pair of coordinates is compared to a 25m buffered layer of the cycling infrastructure and assigned a binary variable indicating whether it is inside or outside the infrastructure.

II. **Segment Division:** The entire route's sequence of coordinates is divided into sub-sequences of "inside" and "outside" segments (Figure 5.4b).

III. **Transition Point Calculation:** To enhance spatiotemporal accuracy at the transition between segments of different types, a "shift" point is calculated: The exact midpoint between the last pair of coordinates of one segment and the first pair of coordinates of the next segment is determined. The transition timestamp is calculated by the middle time between the two "original" points (Figure 5.4c).

IV. **Start/end location "stay" duration reduction** – The duration the user spent when unlocking the vehicle and finalizing the trip, is reduced from the trip total duration (See Appendix E.1.).

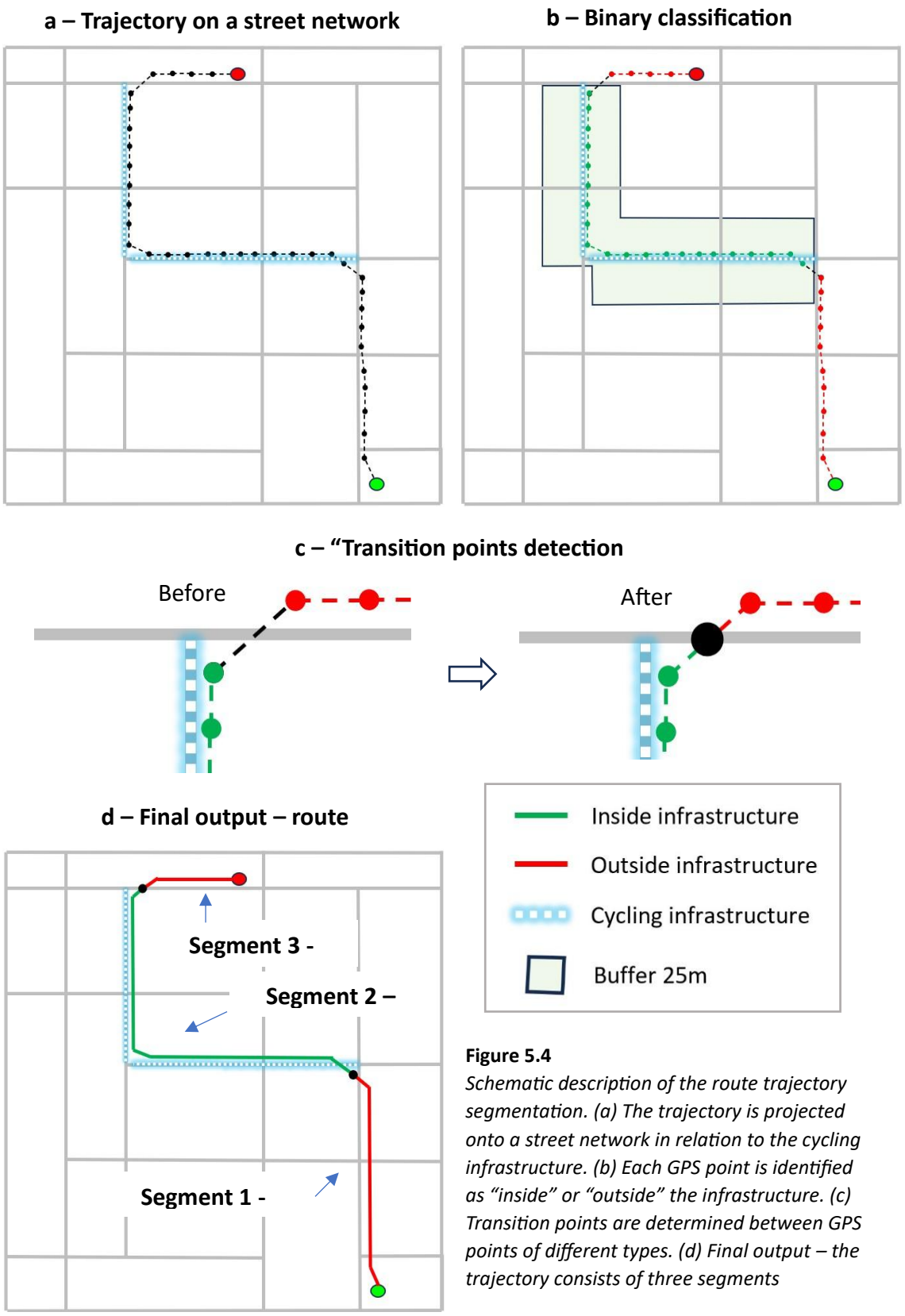


Figure 5.4
Schematic description of the route trajectory segmentation. (a) The trajectory is projected onto a street network in relation to the cycling infrastructure. (b) Each GPS point is identified as "inside" or "outside" the infrastructure. (c) Transition points are determined between GPS points of different types. (d) Final output – the trajectory consists of three segments

The segmentation method allows us to assess the speed inside/outside the cycling infrastructure for each trip, using the distance and duration assigned to each segment. The segments crossing the slow speed zones (Figure 2.1) were excluded from the analysis for each trip. See Appendix E.2. for a description of the method limitations and the procedure taken to address them and assure the reliability of the routes' segmentation.

5.1.3.2. Speed analysis variables

The variables used to analyze the influence of cycling infrastructure on SDES speed:

- **Dependent Variables**: "Inside Speed" and "Outside speed" (to cycling infrastructure).
- **Independent Variable**: "Trip length" and "Share of cycling infrastructure"

5.2. SDES vehicles' demand analysis

This subchapter presents the analysis conducted to assess SDES vehicle demand. Section 5.2.1. describes the "Status Changes" raw dataset which is the basis for the demand analysis. Section 5.2.2. explains the structure of the parking events dataset, built in this study, and based on the "Status Changes" raw data. Lastly, section 5.2.3. explains how this dataset is used to assess SDES vehicle demand.

5.2.1. Status Changes raw data – description

The "Status Changes" dataset provides a comprehensive view of SDES vehicle dynamics, developed as part of the MDS format (*MDS*, 2023). Unlike the "Trips" data, which focuses on vehicle movements, the status changes data captures information about where and when vehicles are stationary, their current status, and what prompted a change in it. The status of a vehicle changes according to activities or events, and each change is recorded as a new row in the "Status Changes" raw data. The MDS format defines specific rules for status transitions. Table 5.3 describes the seven statuses; Table 5.4 describes the "Status Changes" data's fields

Table 5.3
All seven statuses used in the MDS format and their description

Status	Description
Available	Deployed in the city, and can be used by users
On trip	On a ride
Reserved	Was reserved by a user, and can be activated only by them
Non-operational	Deployed in the city, and cannot be used (mostly due to technical issues)
Removed	Was taken by the operator and no longer deployed in the city
Elsewhere	The vehicle left the city's boundaries during a ride (no longer at the city)
Unknown	There is no information for the vehicle's state

and Figure 5.5 illustrates all possible transitions between them (see Appendix B for an example of a sequence of status changes for a single vehicle).

Table 5.4
Trips raw data attributes – formats and descriptions

Field Name	Format	Description
Provider_id	String	Unique string id for each operator
Provider_name	String	The name of the operator as it's known
Vehicle_state	String	The status the vehicle changes to
Event_types	String	The activity led to the transition
Event_time	Timestamp	The exact timestamp the status changed (yyyy-mm-dd hh:mm:ss)
Device_id	String	A long unique id of each vehicle
Vehicle_id	String	The vehicle short unique number presented on its plate
Vehicle_type	String	The type of the vehicle that the ride had done with, for SDES there is no difference
Propulsion_types	String	Distinction between different types of vehicles. In SDES, there is no difference
Lat	Float	Latitude of the location the status changed
Lon	Float	Longitude the location the status changed
MDS_version	Float	The version of MDS format that the data was provided

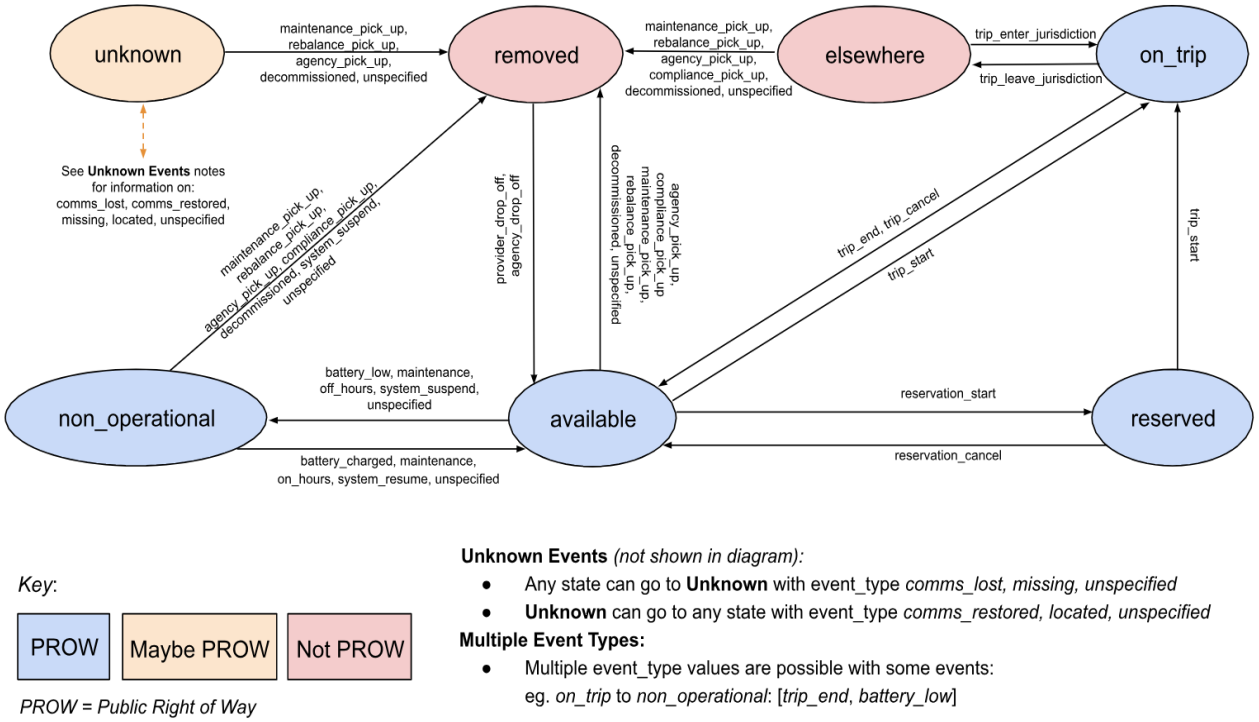


Figure 5.5.
All MDS statuses (versions 1, 1.2) and the possible transitions between them (MDS, 2023). For example, a vehicle in "on_trip" status cannot directly change to "non_operational"; it must first transition to "available" (indicating the end of a ride) before changing to "non_operational"

5.2.2. Parking events dataset

The parking events dataset is transformed from the "Status Changes" raw data, in order to create one coherent dataset that can be utilized to assess SDES demand. The basic concept of the dataset construction is to go over each vehicle's sequence of statuses, sorted in ascending time order, and detect for each time the vehicle stayed available for use in a given location – when and why it was no longer available at that location (See Appendix X for a detailed explanation of that process). Eventually, the parking events dataset consists of 899,501 records, of three of the four operators (Table 5.5 describes its fields).

Table 5.5
Parking events dataset fields – formats and description

Field Name	Format	Description
Vehicle id	String	Unique string id for each vehicle
Vehicle status	String	Status based on the MDS format; all records have "available" value
Start time	Timestamp	The exact timestamp the parking event has started in YYYY-MM-DD hh:mm:ss
End Time	Timestamp	The exact timestamp the parking event has ended in YYYY-MM-DD hh:mm:ss
Parking duration	Integer	Number of seconds the parking event last (End time – Start time)
End reason	String	The reason the parking event ended
Area	String	The area (from the four areas of the city) the event occurred in
Neighbourhood	String	The neighbourhood the event occurred in
Distance to cycling infrastructure	integer	Distance in meters to the nearest cycling infrastructure
Associated Trip	String	For events ended in a trip, the associated trip id in the "Trips" raw data

5.2.3. SDES demand & cycling infrastructure – assessment methods

Using the parking events dataset, an assessment of the SDES demand with respect to the cycling infrastructure can be performed. To focus on the area most likely influenced by the infrastructure, the analysis is limited to parking events within 100m aerial distance of any cycling infrastructure. That threshold was divided into four groups in 25m intervals (Figure 5.6). The dependent variable used is the parking duration and the independent variable is the distance to the nearest cycling infrastructure (the distance groups.

The assessment is divided into two parts:

I. **General Overview**

The average parking duration of the distance groups, in two spatial resolutions: city-wide and the four main areas. Additionally, the ratio between the average parking duration in the nearest group (0-25m) to the furthest group (75-100m) is assessed on a larger scale – the neighborhood level.

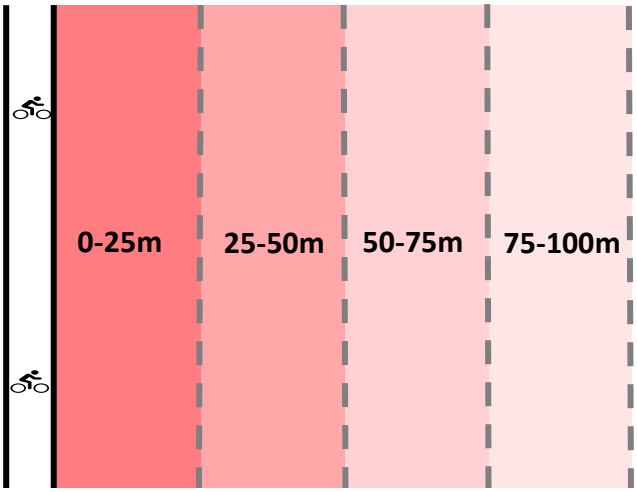


Figure 5.6
Four distance groups based on proximity to cycling infrastructure (left-hand side of the figure)

II. **Cycling Infrastructure location and SDES demand - commercial centers study case**

Two commercial centers in northern Tel Aviv-Yafo are investigated: “Brodetzky Center” and “Shuster Center”. The lack of municipal parking restrictions in that area allows for a more direct representation of user preferences in parking patterns. Both centers offer similar amenities but differ in their cycling infrastructure layout. At “Brodetzky Center”, the cycling infrastructure runs adjacent to the center, providing high accessibility. In contrast, the infrastructure near “Shuster Center” is on the opposite side of the street, requiring users to cross a two-way street and two crossroads, potentially reducing accessibility (Figure 5.7). Around each center, an "investigated area" polygon is defined encompassing the center and relevant cycling infrastructure sections. Within these defined areas, the parking events duration is examined and compared in each distance group relative to the cycling infrastructure. This approach aims to reveal how the location of cycling infrastructure with respect to a point of interest may influence SDES demand patterns. Important to mention, that on the north side of “Brodetzky” center stands “Ramat Aviv” shopping mall. One of its side entries is in front of the commercial center, and therefore, some of the SDES demand

might be directed to the shopping mall. However, since the mall's entry is positioned the same way as the cycling infrastructure, it should not bias the demand patterns with respect to it.

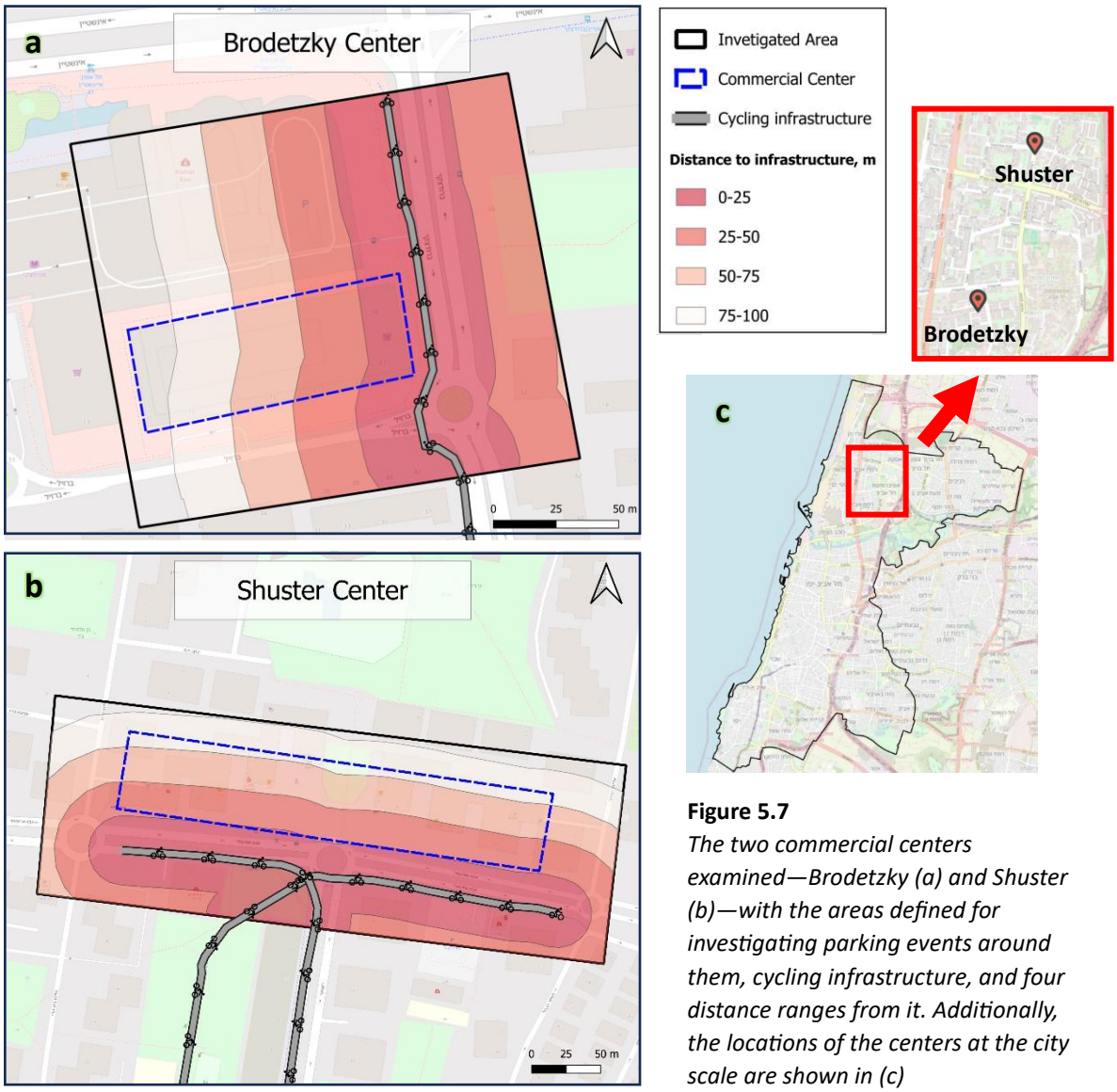


Figure 5.7
The two commercial centers examined—Brodetzky (a) and Shuster (b)—with the areas defined for investigating parking events around them, cycling infrastructure, and four distance ranges from it. Additionally, the locations of the centers at the city scale are shown in (c)

6. Results

This chapter presents the results of the SDES data analysis according to the research questions. Subchapter 6.1. shows the results regarding the Trips analysis, section 6.1.1. general overview of trips spatiotemporal patterns in Tel Aviv-Yafo. Sections 6.1.2. and 6.1.3. presents the results regarding the influence of cycling infrastructure on SDES user's route choice, and speed, respectively. Subchapter 6.2. shows the results of the parking events dataset analysis, where 6.2.1. is a general overview of the demand in Tel Aviv-Yafo, section 6.2.2. the demand with proximity to cycling infrastructure, and 6.2.3. shows the results of the study case of two commercial centers and the location of cycling infrastructure around them.

6.1. Trips Analysis Results

This subchapter contains three sections – first general SDES trips' characteristics in Tel Aviv-Yafo, second the chosen routes versus the shortest path analysis, and third the speed analysis results.

6.1.1. Trips General Characteristics

The final trip sample, based on three operators and after the removal of insufficient data, consists of 303,710 records (before additional removals for route choice and speed analysis). The general trips' characteristics observed:

- **Basic trip metrics:** The trip distance and duration exhibit right-tailed distributions, with average and median distances of ~2km and ~1.6km respectively, and average and median durations of 10.1 and 8.2 minutes respectively (Figure 6.1). However, these metrics may be biased downward due to the geometry correction removal method, longer trips are more likely to contain geometry deficiencies and therefore may have a higher probability of elimination.

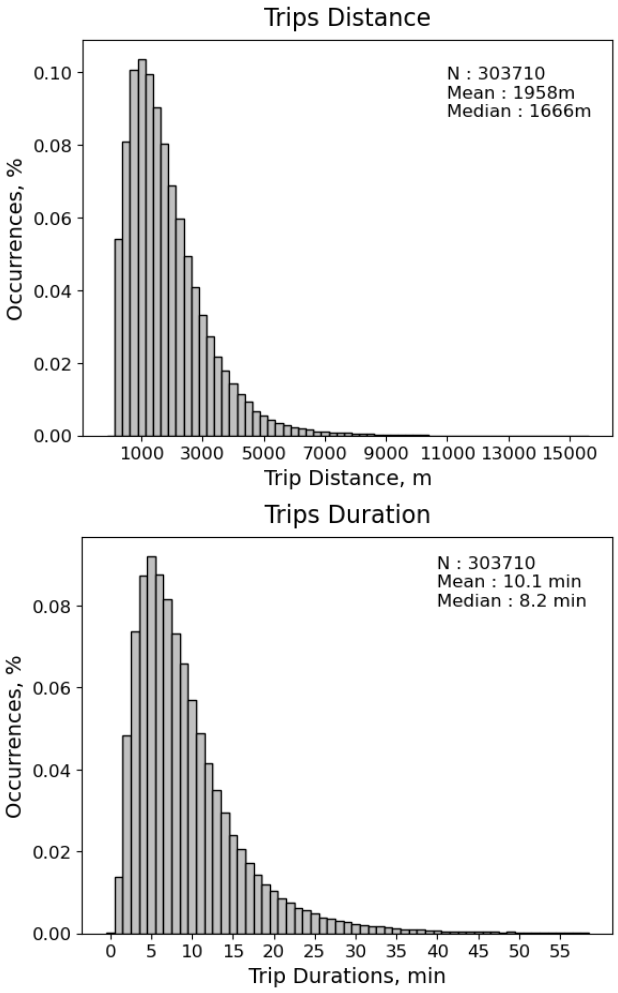


Figure 6.1.
Trip distance (a) and duration (b) distributions

- **Hourly trips' demand pattern:** The trips' distribution throughout the day differs among three types of days: working days (Sunday to Thursday), Friday, and Saturday (Figure 6.2). Working days show two usage peaks that correlate with business hours – a morning peak around 8 am, a decrease during late morning and noon, and a higher usage peak around 6 pm. Friday exhibits different characteristics, with the morning peak disappearing and instead showing high peaks around midday and midnight. Saturday also presents a distinct hourly pattern, with one usage peak in the evening around 7 pm.

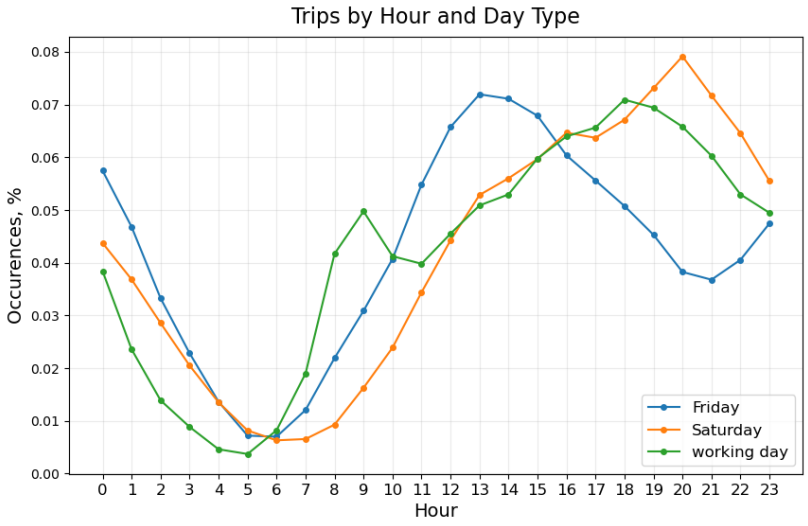


Figure 6.2.
Trip distributions by hour of the day and day type: working day (n = 214,709), Friday (n = 40,304), and Saturday (n = 48,697)

- **Origin-destination matrix spatio-temporal patterns:** The origin-destination matrix by TAZ for working days reveals spatio-temporal patterns of SDES trips (Figure 6.3). Trips demand concentrates in the city center and generally in a few locations, including employment areas (Downtown, Begin area), recreational zones (Beach, Old Jaffa, Dizengof-Allenby area, Downtown), and train stations (HaShalom & Savidor). In the morning, demand concentrates more on transportation and employment areas, while in the evening, it tends towards recreational locations. It is important to note that since the investigated data is from summer, the high demand around the beach might be more significant. Finally, as the origin-destination analysis is not the primary objective of this study, it was not developed beyond the working days' two peak usages. Nevertheless,

this initial analysis indicates the preferences of SDES users and how they vary throughout the day. Table 6.1 (Appendix A) presents the number of trips by hour.

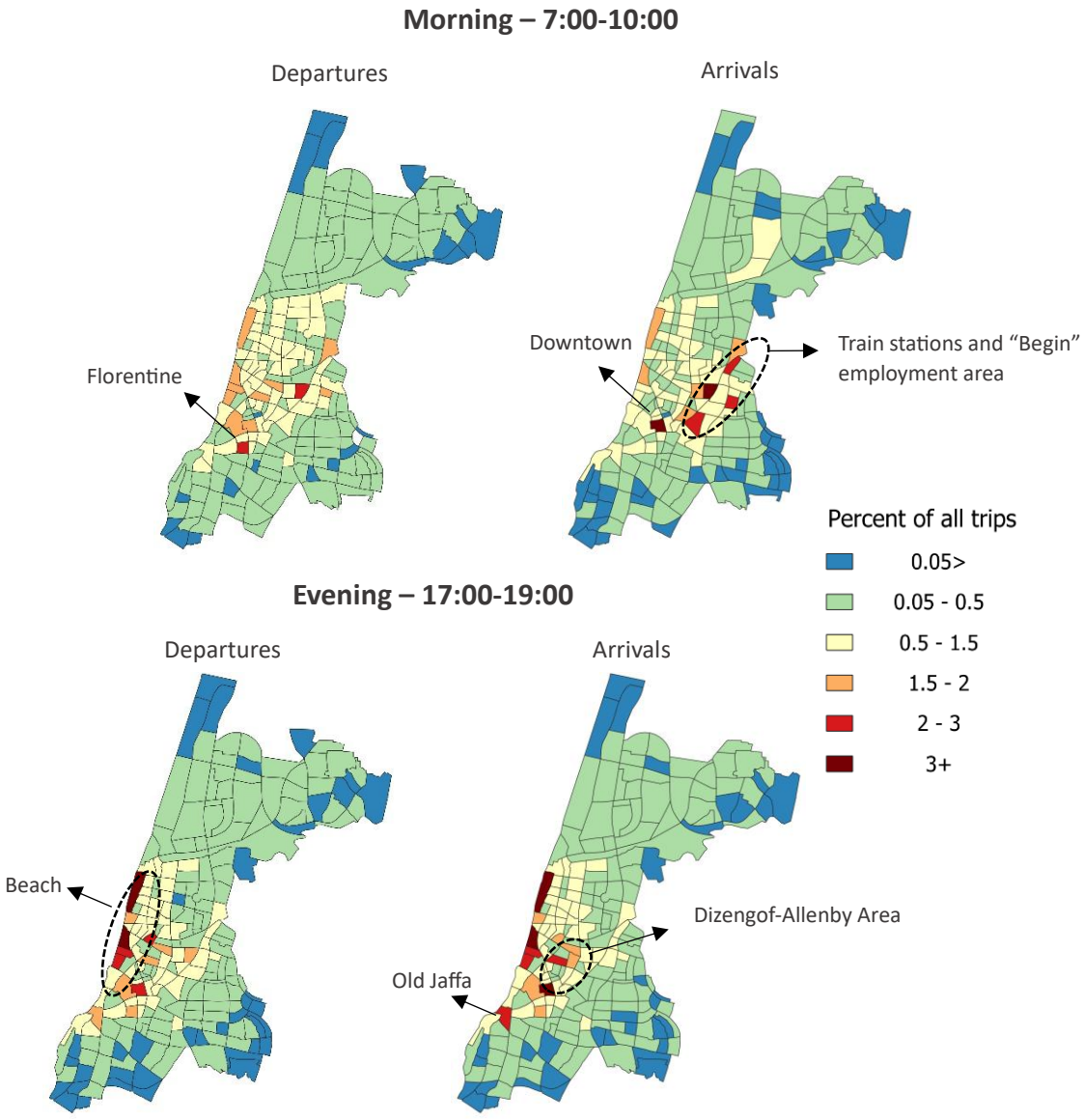


Figure 6.3.
Origins and destinations of trips on working days, by morning (7:00-10:00, n = 23,703) and evening (17:00-20:00, n = 44,211), aggregated by TAZ. Areas with high values are marked on the maps

6.1.2. SDES route choice & cycling infrastructure

The comparison between chosen routes and alternative SP reveals:

- **Higher share of cycling infrastructure in chosen routes**: Analysis of the proportion of cycling infrastructure on chosen routes versus alternative shortest paths indicates that SDES riders utilize a higher fraction of cycling infrastructure in their chosen routes – ~58% versus ~44% on average (Figure 6.4a). Moreover, the longer the ride, the higher the fraction of infrastructure in the chosen route and the greater the difference from the

fraction of infrastructure in the shortest path. For rides longer than 4 km, the share of cycling infrastructure is ~40% higher than the shortest path. Table 5.2 (Appendix A) presents a number of trips in each route length interval.

- **The greater the detour from the SP – the higher the share of cycling infrastructure:** Comparison of the difference in cycling infrastructure share between the chosen route and SP trajectories, shows that as the rider extends the deviation from the SP – the share of cycling infrastructure increases and reaches almost 30% difference at 55-70% detour from SP (Figure 6.4b). Table 6.3 (Appendix A) presents a number of trips in each ratio range interval.
- **The longer the route the higher the detour:** that, on average, riders extend their route by ~9% from the shortest path (Figure 6.5a). This ratio changes with route length – the longer the route, the higher the deviation from the shortest path. For trips over 5km, the average detour is ~17% (Figure 6.5b).

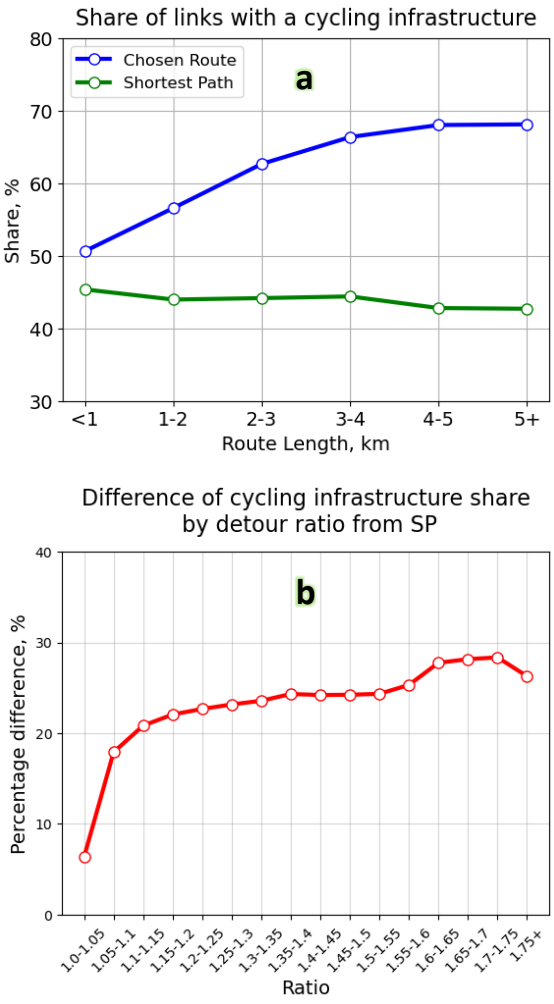


Figure 6.4.
(a) The share of cycling infrastructure in the chosen routes and SP's trajectories by route length. (b) The difference in the share of cycling infrastructure between the chosen routes and SP's trajectories, based on the ratio of detour from the SP (chosen route length divided by the SP length)

- **Typology of cycling infrastructure detour:** Visual assessment of routes with high share of cycling infrastructure and high difference from the share in the SP, hint for different types of "ways" to detour in order to use cycling infrastructure:
  I. **"Force of inertia"** - the rider begins on the cycling infrastructure naturally and continues along it, despite deviating from the shortest path (Figure 6.6a).
  II. **Deviating from SP to join cycling infrastructure -** the rider starts off the infrastructure, then deviates from the shortest path to join a cycling infrastructure, continuing along it for a significant portion of the route (Figure 6.6b).

III. **Pre-ride decision –** similar to the second, but the rider chooses to deviate from the beginning of the trip, even briefly traveling in the opposite direction of the destination, to access an "axis" of cycling infrastructure (Figure 6.6c).

The latter two examples suggest riders familiar with the city's cycling infrastructure and possessing some prior riding experience. However, the first example could correspond to two main rider types: a “regular” rider familiar with the city's street network, or an “occasional” rider - for whom the "force of inertia" on the cycling infrastructure played a significant role.

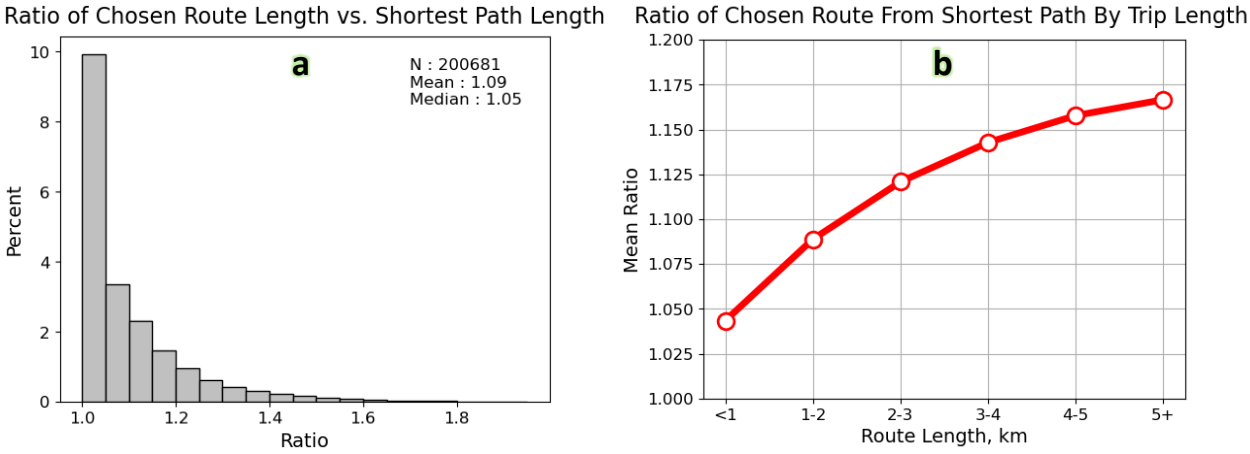


Figure 6.5.
Percentages of the ratios between the chosen route length and the SP (a), and the ratio by trip length (b)

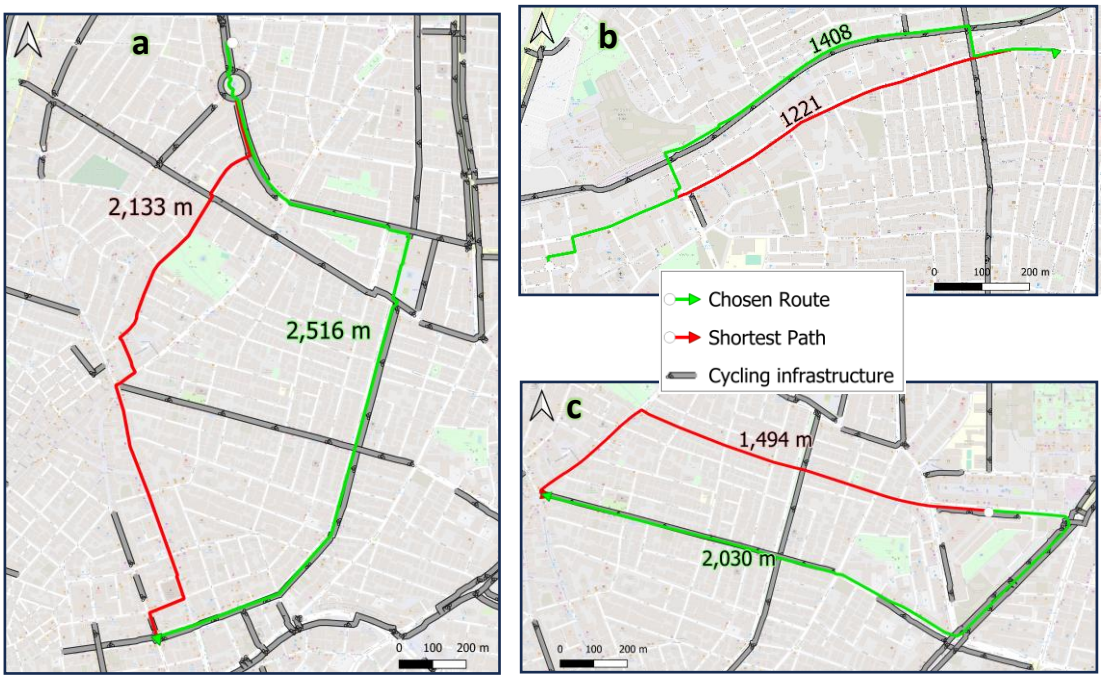


Figure 6.6.
Examples of chosen routes versus the shortest path, where it appears the rider preferred to extend the route in order to use the cycling infrastructure, based on the suggested three “types.” Labels indicate the length

6.1.3. Speed Analysis

Analysis of the SDES speed shows several findings:

- **Speed inside cycling infrastructure is higher:** An assessment of the speed inside versus outside cycling infrastructure reveals two main observations. The speed inside the cycling infrastructure is slightly higher than outside (13.05 and 12.54 km\h respectively). For short rides (lower than 1 km) the speed is almost identical, however as the ride is longer, the average speed inside the infrastructure is higher than the speed outside (Figure 6.7). The difference between them, for rides longer than 3 km, is 1-1.5 km/h, which is 8.5-11% faster than the speed outside the infrastructure.

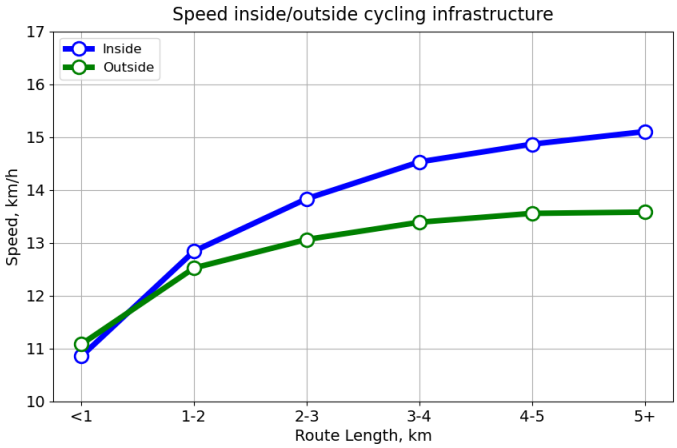


Figure 6.7.
Average speed inside/outside cycling infrastructure by route length. Table 6.2 (Appendix A) presents the number of trips in each route length interval.

- **Solid characteristics**: The speed is normally distributed around ~13 km\h (mean and median are 12.8 and 13.1 km/h respectively, see Figure 6.8). Trips

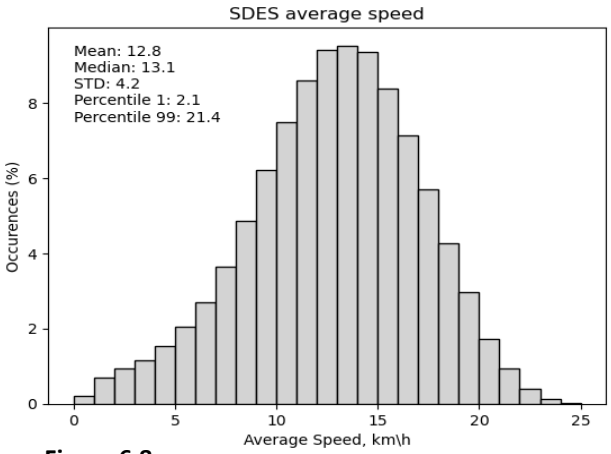


Figure 6.8.
SDES average speed distribution

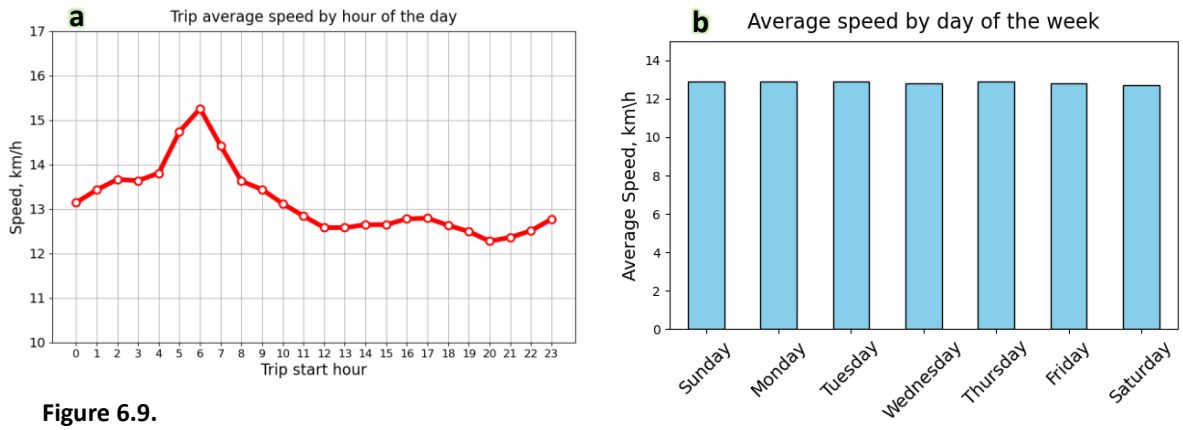


Figure 6.9.
(a) Average speed by trip start hour. Table 6.1 (Appendix A) presents the number of trips by hour. (b) Average speed by day of the week

below quantile 1 and above 99 are removed from further analysis. Most of the day the average trip speed is below 13, at night there is a significant increase in the speed, probably due to less traffic (Figure 6.9a). The speed average is constant over the week, and there is no significant change between working days and weekends (Figure 6.9b).

6.2. Parking events analysis results

This subchapter presents the findings of the SDES demand analysis, which was conducted using the parking events dataset derived from the Status Changed raw dataset. Section 6.2.1 provides an initial evaluation of the parking events dataset, resulting in further sample refinement. Section 6.2.2 offers a general overview of SDES vehicle demand and its associated spatio-temporal patterns. Section 6.2.3 examines the impact of cycling infrastructure proximity on SDES vehicle demand, while section 6.3.3 sheds light on some aspects of the relationship between cycling infrastructure location relative to points of interest and the surrounding SDES vehicle demand.

6.2.1. Parking events dataset – initial evaluation

The initial assessment of the parking events dataset led to additional records cleaning prior to further analysis (See Appendix G). The final parking events dataset comprised 794,170 events, of these, 93.1% concluded with a ride, 3.8% were terminated by the operator (classified "non-operational" or "removed"), and 3.1% had undetectable parking end reasons (Table 6.4). In order to assess the SDES demand, the dataset was further analyzed only on the events that ended in a ride (739,330 events).

Table 6.4.
Summary of the parking events' end reasons and their share of the total dataset

Parking end reason	Count	%
On Trip	739,330	93.1%
Non-Operational	16,434	2.1%
Removed	13,494	1.7%
Unknown	24,912	3.1%
Total	794,170	100%

6.2.2. General SDES demand overview

General overview of the SDES demand:

- **Parking events' duration distribution**: The distribution of parking duration exhibits a decay pattern, with approximately 39% of events concluding within 30 minutes, followed by a gradual decline as duration increases (Figure 6.10a). Notably, long-duration events (12 hours and longer) account for approximately 6% of all events, indicating a subset of

the SDES fleet that remains unused throughout the day. The majority of SDES activity is concentrated in the city center, accounting for ~84% of all events, with the remainder distributed relatively evenly across peripheral areas (Figure 6.10b). It is important to note that the areas defined in this study vary in size and population, with the central area being significantly larger.

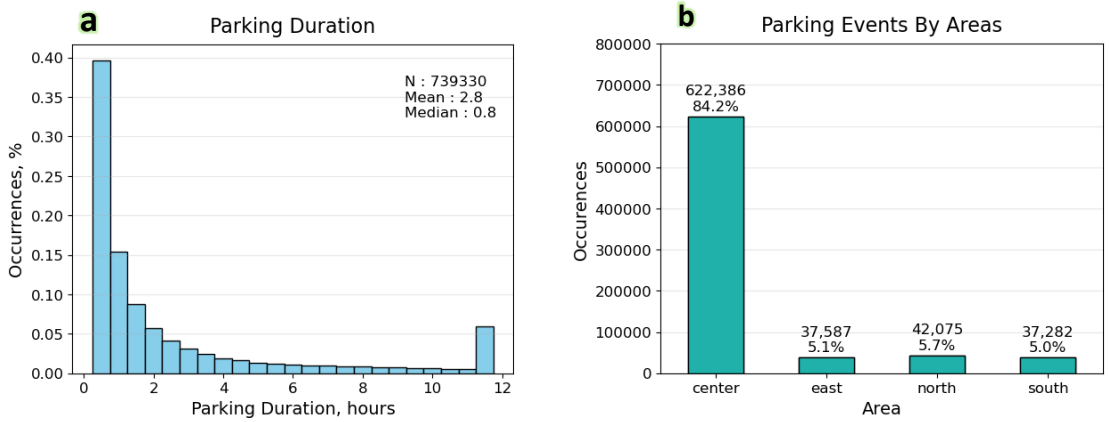


Figure 6.10.
(a) Parking duration histogram of parking events in the city that ended in a ride. (b) Distribution of parking events by area

- **Spatio-temporal patterns:** Analysis of average parking duration by event start time reveals longer parking durations during nighttime hours, peaking around 4 AM. This is followed by a decrease in duration during daylight hours and a slight increase in the evening, a pattern consistent across all city areas (Figure 6.11a). A brief, minor increase in parking duration is observed following the "morning drop," with slight variations between areas while maintaining the overall pattern. Spatially, SDES demand is markedly higher in the city

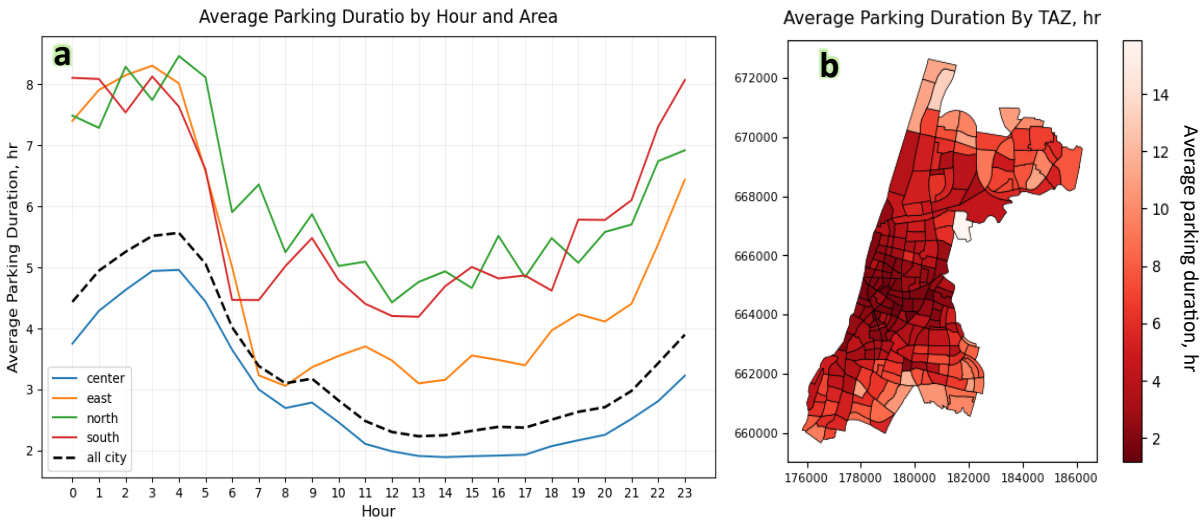


Figure 6.11.
(a) Average parking duration by area and the start hour of the parking event. It presents the number of trips by hour and area. (b) Average parking duration by TAZ

center, characterized by a high concentration of mixed land uses including residential, employment, recreational (nightlife, beach), and transport facilities (Figure 6.11b).

6.2.3. SDES supply, demand, and cycling infrastructure

The analysis of the parking events spatial distribution and parking duration, with respect to the cycling infrastructure, led to a few key findings:

- **Higher SDES supply with proximity to cycling infrastructure:** The cycling infrastructure in Tel Aviv has expanded significantly in recent years, encompassing approximately 175 km of cycling infrastructure as of July 2023, as measured by the data provided by the municipality at that time (Tel-Aviv-Yafo, 2023). While the infrastructure varies in type and quality, nearly all public open space across the city's areas is within 500m of some form of cycling infrastructure (Table 6.5.). It is important to note that this analysis does not account for the specific features or connectivity of cycling infrastructure, factors which influence the quality of service provided. However, when comparing the distribution of SDES parking events to the coverage of open public space by distance to infrastructure, it becomes evident that SDES supply tends to concentrate around cycling infrastructure at more than double the rate expected from a random distribution across public open space (Table 6.5.). This observation, however, should not be interpreted as direct causation between cycling infrastructure and SDES supply. Other factors likely contribute to this pattern, such as the strategic placement of infrastructure in high-demand areas or the unsuitability of certain public open spaces for SDES parking. Nevertheless, the key finding remains significant:

Table 6.5.
The coverage of the cycling infrastructure at ascending distances from the open space area in the city (~46 km²), versus the number and percentage of parking events (total = 794,170 events) at the same distances

Distance to cycling infrastructure, m	Open Space		Parking events	
	Area, km²	Coverage, %	Events	Percent
25	7.8	16.8%	388,080	48.9%
50	14.2	30.4%	450,766	56.8%
75	19.6	42.2%	511,413	64.4%
100	24.1	51.8%	575,255	72.4%
250	39.6	85.1%	758,588	95.5%
500	44.6	95.7%	792,846	99.8%

SDES supply is more prevalent around cycling infrastructure.

- **Higher demand for SDES vehicles adjacent to cycling infrastructure:** To assess the influence of infrastructure on SDES parking duration, the sample was limited to events within 100m of cycling infrastructure, as detailed in the methodology section. Analysis of average parking duration across distance thresholds reveals an inverse relationship: the closer a vehicle is to the infrastructure, the shorter its parking duration, indicating higher demand (Figure 6.12). This pattern is most pronounced in the central and eastern areas of the city, slightly less so in the north and the south areas, although the main pattern the

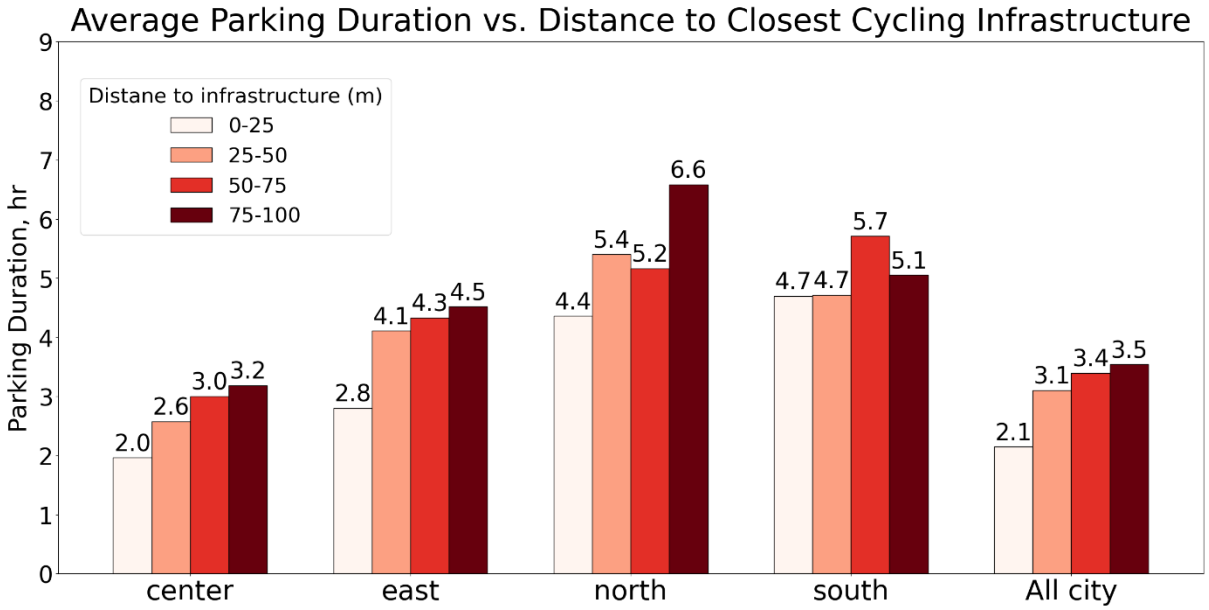


Figure 6.12.
Average parking duration of events that ended in a ride, by distance to cycling infrastructure (up to 100m) and area in the city.

general trend persists: further thresholds (50-100m) consistently exhibit higher parking durations than closer thresholds (0-50m). Table 6.6 (Appendix A) presents the number of parking events in each distance group by area.

- **Consistent along all the city – with some exceptions:** A more granular investigation at the neighborhood level yields similar results with some exceptions. The ratio of average parking duration between the events closest to the infrastructure (25m and less) and the furthest events (75-100m) reveal that in most of the city, this ratio is below 1, indicating shorter average parking durations immediately adjacent to infrastructure compared to 75-

100m away (Figure 5.13). However, some neighborhoods exhibit ratios greater than 1, a phenomenon that requires further investigation to explain fully.

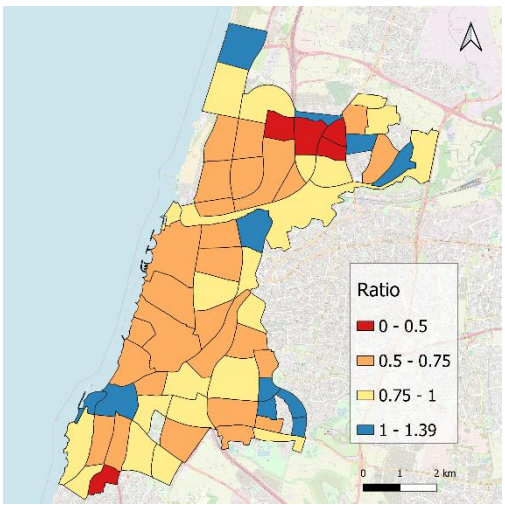


Figure 5.13.
Ratio by neighborhood of the average parking duration for the closest parking events (less than 25m) to the furthest parking events (75-100m). Only neighborhoods with at least 10 observations in each distance group are presented

6.2.4. Cycling infrastructure location and SDES supply and demand

To evaluate the spatial influence of cycling infrastructure on SDES supply and demand, a high-resolution analysis was conducted on two case studies: "Brodetzky Center" and "Shuster Center". As outlined in the methodology section, these centers share similar characteristics but differ in their cycling infrastructure accessibility. Brodetzky Center is better connected, while at Shuster Center, the infrastructure is on the opposite side of the street, reducing its spatial accessibility (Figure 5.7.).

The comparable number of parking events around each center suggests similar SDES demand (Table 6.7.); however, the distribution of vehicles relative to the bike lane differs significantly. At Brodetzky, the majority (65%) of vehicles are parked within 25m of the cycling infrastructure, whereas at Shuster, only 27% fall within this threshold, with the majority (55%) in the 25-50m range (Table

Table 6.7.
Average parking duration by distance group to cycling infrastructure for the two investigated commercial centers – Brodetzky and Shuster. Only parking events that ended in a ride are included in the sample

Distance group, m	Value	Brodetzky Center	Shuster center
0-25	Count	280	106
	%	65%	27%
	Average parking duration, hr	2.8	4.1
25-50	Count	30	217
	%	7%	55.5%
	Average parking duration, hr	3.0	3.2
50-75	Count	71	24
	%	17%	6%
	Average parking duration, hr	3.1	3.9
75-100	Count	48	45
	%	11%	11.5%
	Average parking duration, hr	3.9	2.7
Total	Count	429	392
	%	100%	100%
	Average parking duration, hr	3.0	3.4

6.7.). At Brodetzky, the distance group with higher demand correlates with a longer average parking duration. Interestingly, at Shuster, the 75-100m distance group exhibits the shortest average parking duration (2.7 hours).

A closer examination of both centers' investigated areas (Figure 6.14.) reveals that Brodetzky Center has three main event densities: the primary concentration along the bike lane in front of the center, and two smaller clusters "deeper" within the center, on the southern and northern sides of the building. Additionally, only a few parking events are scattered across the street along the sidewalk. At Shuster Center, although parking events appear more dispersed, several hotspots are discernible along the sidewalk in front of the center. These hotspots fall within the 25-50m group, explaining the high numbers in this threshold (Table 6.7.). On the opposite side of the street, adjacent to the cycling infrastructure, there are fewer parking events, but still a significant number (Figure 6.14.).

In summary, when cycling infrastructure is well-connected to the riders' point of interest, it generates parking event hotspots in its vicinity. Conversely, where connectivity is lower, a

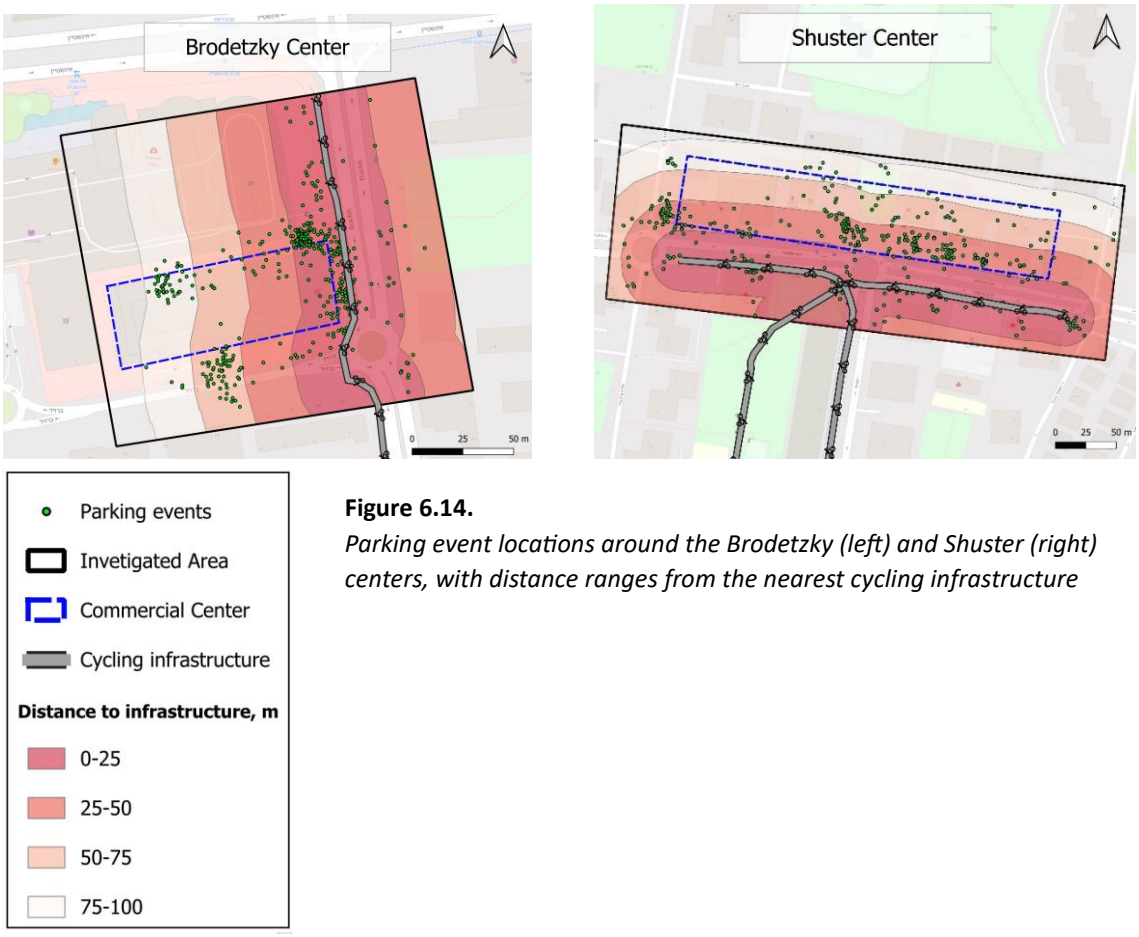


Figure 6.14.
Parking event locations around the Brodetzky (left) and Shuster (right) centers, with distance ranges from the nearest cycling infrastructure

substantial proportion of riders opt to start or end their journeys not at the bike lane, but closer to their destination.

7. Summary

This study illuminates the SDES usage patterns in Tel Aviv-Yafo, with particular emphasis on how cycling infrastructure influences users' route choices and vehicle demand. This chapter discusses the main findings in relation to the research questions and existing micro-mobility and SDES studies, offering interpretations and explanations. It then outlines the study's limitations, suggests directions for future research, and presents the main conclusions.

Discussion

SDES Trip Characteristics & Cycling Infrastructure

The results validate the first two research questions regarding cycling infrastructure's influence on SDES users' route choice and travel speed:

- **SDES Users Prefer Cycling Infrastructure**

The high proportion of cycling infrastructure use in SDES trajectories, compared to alternative SP routes, indicates its significant influence on riders' route choices, confirming the first research question. This finding aligns with existing SDES route choice literature (Cubells et al., 2023; Huber et al., 2023; Zhang et al., 2021). The preference becomes more pronounced as route length increases, with long trips (5 km and above) showing an average cycling infrastructure usage of approximately 65%—roughly 40% higher than the SP alternative.

- **Higher Speeds on Cycling Infrastructure**

The speed analysis confirms the second research question: average speeds are higher within cycling infrastructure than outside it. This pattern emerges only in trips exceeding 1 km and becomes more pronounced with increasing distance. For trips over 5 km, speeds within cycling infrastructure are approximately 11.5% higher on average. While no other known studies specifically examine speed differences within cycling infrastructure, these results align with general micro-mobility research (Jarry & Apparicio, 2021; Ringhand et al., 2024), suggesting that cycling infrastructure enables safer, less interrupted travel with reduced interference from other road users.

Additional significant observations include:

- **Tel Aviv's SDES trips' characteristics align mirror global SDES trends**

The general trip characteristics in Tel Aviv-Yafo align with most SDES studies: approximately 1.5-2 km average distance, 10-15 minutes duration, and 12-14 km/h speed (Badia & Jenelius, 2023). This consistency suggests that SDES demand exhibits universal features, that do not change significantly between cities.

- **Route length deviation from SP Increases with trip distance**

The average ratio between chosen routes and shortest paths (~9%) corresponds with previous research (Cubells et al., 2023; Ghanayim & Bekhor, 2018). However, it differs from Ghanayim & Bekhor's findings for cities with denser cycling networks like Tel Aviv-Yafo, where ratios typically reach 15-18%. This discrepancy might be attributed to the prevalence of short SDES trips, which are less common among private micro-mobility users—a hypothesis supported by the higher ratios observed in longer SDES trips in this study.

- **Cycling infrastructure route choice: "Regular" versus "Occasional" users**

Visual analysis of trips deviating from SP with high cycling infrastructure usage suggests three distinct deviation patterns. Two patterns likely correspond to users familiar with the city's cycling infrastructure ("regular" users), while the third requires no prior knowledge and may be employed by both regular and "occasional" users.

SDES Vehicle Demand & Cycling Infrastructure

Analysis reveals consistently shorter average parking durations for SDES vehicles parked in close proximity to cycling infrastructure across all investigated scales throughout the city. While this initially confirms the third research question, additional observations provide important context regarding SDES demand patterns:

- **High SDES vehicle supply correlates with high demand**

Areas of high demand consistently demonstrate high vehicle supply. This indicates that demand is influenced not only by users' preferred starting locations but also by operator vehicle placement and, more significantly, by where users complete their journeys. This pattern manifests across multiple scales: while the city center shows the highest overall

demand and supply, at the micro level, locations adjacent to studied commercial centers with high vehicle supply similarly exhibit peak demand within their respective areas.

- **Users parking next to cycling infrastructure – might create a higher demand**

Building on the previous observation, the elevated demand near cycling infrastructure might be attributed not solely to users' preference for initiating rides near these facilities, but to the tendency of users to conclude their journeys in these locations. This distinction is not merely semantic—it suggests that the underlying phenomenon might actually reverse the study's initial hypothesis.

- **Higher Demand Near Cycling Infrastructure: Effect Rather Than Cause**

When cycling infrastructure is well-designed and effectively connects micro-mobility routes with surrounding points of interest, riders naturally terminate their journeys nearby. This creates a concentration of available vehicles, which in turn attracts new users to initiate rides from these locations, thereby generating increased demand. This suggests that high demand adjacent to cycling infrastructure isn't inherent, but rather serves as an indicator of how well the infrastructure integrates with and provides accessibility to surrounding destinations.

Limitations

This study encompasses several key limitations:

- **Cycling infrastructure usage assessment method**

The study employs an assumption that riders traveling within a 25-meter buffer zone of cycling infrastructure are utilizing that infrastructure—specifically, that travel on a street with cycling infrastructure indicates the use of the infrastructure itself. This may not reflect reality, as some riders might opt for streets or sidewalks adjacent to, but separate from, the designated cycling infrastructure. While a narrower buffer zone (e.g., 5 meters) could theoretically distinguish between different paths within the same street segment, GPS inaccuracies precluded the use of such precise measurements. Consequently, the current methodology does not fully address this limitation.

- **Route Choice Set**

Standard practice in route choice analysis involves comparing chosen trajectories against multiple alternative routes (a choice set), acknowledging that riders typically have various

path options. This approach yields more robust comparisons, as it considers different route choice priorities and multiple shortest-path alternatives, reducing the potential bias introduced by comparing against a single computed shortest path. However, due to computational constraints, this study was limited to calculating just one SP per trajectory.

- **Parking Policy Restrictions**

Tel Aviv-Yafo's SDES parking policy, as outlined in Chapter 2, imposes restrictions in high-demand areas and mandates trip completion within designated parking cells. These constraints potentially influence vehicle supply and demand patterns, as users' parking choices—and consequently, their trip starting points—are not entirely discretionary. To address this potential bias in assessing demand relative to cycling infrastructure, the study designated the city center as the primary restricted zone and evaluated "free-parking" areas separately. Furthermore, the selected commercial centers for investigation were deliberately chosen outside the city center to eliminate any parking policy influence on user behavior.

Future research directions

This study's findings and emerging questions suggest several promising avenues for future research:

- **Impact of different cycling infrastructure types**

The current study treated cycling infrastructure as a uniform entity, without distinguishing between its various forms. However, as discussed in the literature review, different infrastructure types have distinct characteristics and varying levels of user preference among micro-mobility riders. Further investigation into how specific infrastructure types influence SDES users' route choices could yield valuable insights applicable to broader micro-mobility usage patterns. Such research could provide crucial operational guidance for urban and transportation planners in designing appropriate cycling infrastructure.

- **Spatial analysis of route choice between infrastructure segments**

While cycling infrastructure's importance for micro-mobility enhancement is established, optimal infrastructure placement remains crucial for effectiveness and successful planning. The current methodology and extensive trajectory data present an opportunity to expand analysis by evaluating individual infrastructure segments' attractiveness—specifically,

measuring the extent to which SDES users will deviate from direct routes to utilize particular segments.

- **Comprehensive speed analysis**

This study revealed that SDES users both extend their routes to use cycling infrastructure and achieve higher speeds within it. However, it remains unclear whether this speed advantage effectively "compensates" for route deviation, potentially neutralizing the time cost, or whether it represents a beneficial but insufficient offset to longer travel distances. To resolve this question, future research should simulate speeds along shortest-path routes based on spatial characteristics of the street network.

- **SDES parking cell utilization assessment**

The parking events dataset developed for this study enables multiple spatiotemporal analyses of SDES supply and demand at both local and global scales. One particularly valuable research direction involves evaluating SDES parking cell effectiveness. This analysis could serve two key purposes: first, assessing the current distribution of parking cells to identify opportunities for expansion or removal; and second, developing a pre-planning tool for future parking cell placement.

Conclusions

This study's primary objective was to evaluate how cycling infrastructure influences SDES usage patterns in Tel Aviv-Yafo. The impact on trip characteristics proved particularly significant—SDES users, like other micro-mobility riders, demonstrate a strong preference for cycling infrastructure even when it requires route extension while benefiting from higher travel speeds within these dedicated paths. Well-connected cycling infrastructure also serves as a preferred destination for trip completion, naturally creating vehicle hubs characterized by heightened demand.

The study makes several key contributions. First, it not only expands existing knowledge about the relationship between SDES route choice and cycling infrastructure compared to other micro-mobility vehicles but also introduces a novel dimension through analysis of travel speeds within infrastructure segments. The substantial sample size of analyzed trips reinforces the reliability of these findings. Second, the identification of supply as a crucial determinant

of demand offers valuable insights into SDES vehicle spatiotemporal dynamics, providing important implications for policymakers. Furthermore, the developed parking events dataset presents a flexible and relatively straightforward tool for evaluating SDES supply and demand. This analytical framework can serve multiple purposes in advancing understanding of the SDES phenomenon, enabling policymakers to enhance its benefits, meet user demand more effectively, and mitigate potential challenges.

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11. Appendices

Appendix A: Tables

The following appendix contains tables referred to which are not presented in the body of text.

Table 5.2
Trips raw data fields formats and description

Field Name	Value format	Description
Provider_id	String	Unique string id for each operator
Provider_name	String	The name of the operator as it's known
Vehicle_type	String	The type of the vehicle that the ride had done with, for SDES there is no difference
Propulsion type	String	Distinction between different types of vehicles. In SDES, there is no difference
Device_id	String	A long unique id of each vehicle
Vehicle_id	String	The vehicle short unique number presented on its plate
Trip_id	String	A long unique id of each trip
Trip_duration	Integer	Trip duration in seconds
Trip_distance	Integer	Trip Duration in meters
Start_time	Timestamp	The exact timestamp the vehicle was activated for a trip in YYYY-MM-DD hh:mm:ss format
End_time	Timestamp	The exact timestamp the trip finished its ride, in YYYY-MM-DD hh:mm:ss format
Route	GeoJson	A GeoJson consists trips route data, including coordinates and timestamp of each GPS ping during the ride
MDS_version	Float	The version of MDS format that the data was provided

Table 6.1

Counts and percentages of SDES trip start hours (beginning) in the trip sample, and the two analysis samples – route choice and speed samples

Start hour	All trips sample		Route choice sample		Speed sample	
	Count	%	Count	%	Count	%
0	12,686	4.2%	7,904	3.9%	12,316	4.1%
1	8,740	2.9%	5,213	2.6%	8,403	2.8%
2	5,711	1.9%	3,448	1.7%	5,425	1.8%
3	3,819	1.3%	2,202	1.1%	3,599	1.2%
4	2,196	0.7%	1,262	0.6%	2,078	0.7%
5	1,485	0.5%	942	0.5%	1,377	0.5%
6	2,351	0.8%	1,749	0.9%	2,223	0.7%
7	4,880	1.6%	3,675	1.8%	4,750	1.6%
8	10,285	3.4%	7,596	3.8%	10,101	3.4%
9	12,714	4.2%	9,382	4.7%	12,510	4.2%
10	11,655	3.8%	8,046	4.0%	11,468	3.9%
11	12,427	4.1%	8,203	4.1%	12,208	4.1%
12	14,570	4.8%	9,517	4.7%	14,313	4.8%
13	16,391	5.4%	10,657	5.3%	16,123	5.4%
14	16,960	5.6%	11,143	5.6%	16,680	5.6%
15	18,471	6.1%	12,076	6.0%	18,156	6.1%
16	19,311	6.4%	12,899	6.4%	18,999	6.4%
17	19,429	6.4%	12,969	6.5%	19,108	6.4%
18	20,536	6.8%	13,819	6.9%	20,258	6.8%
19	20,284	6.7%	13,653	6.8%	19,978	6.7%
20	19,518	6.4%	12,898	6.4%	19,184	6.4%
21	17,915	5.9%	11,690	5.8%	17,627	5.9%
22	16,145	5.3%	10,202	5.1%	15,851	5.3%
23	15,231	5.0%	9,536	4.8%	14,847	5.0%

Table 6.2

Counts and percentages of the three trip samples – the entire trip sample included in the data process, and the two analysis samples: Route choice (trips removal described in Appendix C) and the Speed sample (trips with extreme total speed values removed, based on the 1st and 99th percentiles)

Route length, km	All Trips sample		Route choice sample		Speed sample	
	Count	%	Count	%	Count	%
<1	71,769	23.6%	56,382	28.1%	68,980	23.2%
1-2	113,491	37.4%	66,235	33.0%	112,411	37.8%
2-3	66,352	21.8%	43,828	21.8%	65,412	22.0%
3-4	30,446	10.0%	20,843	10.4%	29,794	10.0%
4-5	12,611	4.2%	8,298	4.1%	12,281	4.1%
5+	9,041	3.0%	5,095	2.5%	8,755	2.9%
Total	303,710	100%	200,681	100%	297,638	100%

Table 6.3.

Counts and percentages of trips by the ratio between the chosen route and shortest path (SP) length in the route choice sample

Ratio	Count	%
1 - 1.05	99,640	49.7%
1.05 - 1.1	33,504	16.7%
1.1 - 1.15	23,150	11.5%
1.15 - 1.2	14,665	7.3%
1.2 - 1.25	9,590	4.8%
1.25 - 1.3	6,282	3.1%
1.3 - 1.35	4,206	2.1%
1.35 - 1.4	2,957	1.5%
1.4 - 1.45	2,093	1.0%
1.45 - 1.5	1,532	0.8%
1.5 - 1.55	1,068	0.5%
1.55 - 1.6	790	0.4%
1.6 - 1.65	526	0.3%
1.65 - 1.7	329	0.2%
1.7 - 1.75	174	0.1%
1.75+	175	0.1%
Total	200,681	100%

Table 6.6.
Counts and percentages of parking events (ended in a ride) by area and distance to cycling infrastructure. Only events within 100m are included

Area \ Dist, m	0-25		25-50		50-75		75-100	
	Count	%	Count	%	Count	%	Count	%
Center	331,882	70.6%	44,022	9.4%	45,147	9.6%	49,009	10.4%
East	13,886	58.8%	3,571	15.1%	2,902	12.3%	3,250	13.8%
North	13,251	50.4%	5,507	20.9%	4,576	17.4%	2,960	11.3%
South	8,765	45.1%	4,302	22.1%	2,978	15.3%	3,404	17.5%
All City	367,784	68.2%	57,402	10.6%	55,603	10.3%	58,623	10.9%

Appendix B: Raw data

The following appendix presents examples of the raw data as it was provided by Tel Aviv-Yafo municipality via the Populus dashboard. Section 1 illustrates the “Trips” raw data, and section 2 the “Status Changes” raw data.

1. “Trips” raw data

1.1. Sample of the raw data

	provider_name	vehicle_type	vehicle_id	trip_id	trip_duration	trip_distance	start_time	end_time	route	mds_version
0		scooter		530f987f-290d-4789-b1bb-b0eab9d030c4	320	1095	2023-06-30 23:55:10	2023-07-01 00:00:30	{"type": "FeatureCollection", "features": [{"t...	1.0
1		scooter		3cefb813-e908-4016-9c5d-13ad864eb58d	615	3002	2023-06-30 23:50:20	2023-07-01 00:00:36	{"type": "FeatureCollection", "features": [{"t...	1.0
2		scooter		2a5bbad9-fc73-4366-9d18-c0c46ed7d64c	938	2479	2023-06-30 23:45:03	2023-07-01 00:00:42	{"type": "FeatureCollection", "features": [{"t...	1.0
3		scooter		26b0d75f-b514-48d1-b6b4-a44c4e12df85	1382	4032	2023-06-30 23:37:41	2023-07-01 00:00:44	{"type": "FeatureCollection", "features": [{"t...	1.0
4		scooter		6a7249be-393a-4465-b29a-b1c57878b922	856	2739	2023-06-30 23:46:33	2023-07-01 00:00:49	{"type": "FeatureCollection", "features": [{"t...	1.0

Figure B.1.
Screenshot of 5 rides in the trip's raw data. Provider name and vehicle ID values were redacted, and 3 columns were removed to include all the columns in one table example ('device_id', 'provider_id', 'propulsion_types')

1.2. Example of the “Route” field GeoJson structure

```
{'type': 'FeatureCollection',
 'features': [{'type': 'Feature',
   'geometry': {'type': 'Point', 'coordinates': [34.76666, 32.07832]},
   'properties': {'timestamp': 1688910122000}},
  {'type': 'Feature',
   'geometry': {'type': 'Point', 'coordinates': [34.76665, 32.0783]},
   'properties': {'timestamp': 1688910187875}},
  {'type': 'Feature',
   'geometry': {'type': 'Point', 'coordinates': [34.76666, 32.07829]},
   'properties': {'timestamp': 1688910253750}},
  {'type': 'Feature',
   'geometry': {'type': 'Point', 'coordinates': [34.76579, 32.07581]},
   'properties': {'timestamp': 1688910319625}},
  {'type': 'Feature',
   'geometry': {'type': 'Point', 'coordinates': [34.76479, 32.07331]},
   'properties': {'timestamp': 1688910385500}},
  {'type': 'Feature',
   'geometry': {'type': 'Point', 'coordinates': [34.76729, 32.07244]},
   'properties': {'timestamp': 1688910451375}},
  {'type': 'Feature',
   'geometry': {'type': 'Point', 'coordinates': [34.76942, 32.07151]},
   'properties': {'timestamp': 1688910517250}},
  {'type': 'Feature',
   'geometry': {'type': 'Point', 'coordinates': [34.77027, 32.07018]},
   'properties': {'timestamp': 1688910583125}},
  {'type': 'Feature',
   'geometry': {'type': 'Point', 'coordinates': [34.77062, 32.06995]},
   'properties': {'timestamp': 1688910649000}}]}
```

Figure B.2.
Example of the route field in GeoJSON format, with the route's GPS ping coordinates and timestamps

2. *"Status Changes" raw data*

2.1. Sample of the raw data of one vehicle id

	provider_id	provider_name	vehicle_state	event_types	event_time	device_id	vehicle_id	vehicle_type	propulsion_types	lat	lon	mds_version
0	2411d395-04f2-47c9-ab66-d09e9e3c3251		available	trip_end	2023-07-01 19:12:57	088a3f85-9d3d-4468-9d47-61feae7856b3		scooter	electric	32.072338	34.778679	1.0
1	2411d395-04f2-47c9-ab66-d09e9e3c3251		on_trip	trip_start	2023-07-01 23:05:23	088a3f85-9d3d-4468-9d47-61feae7856b3		scooter	electric	32.072357	34.778717	1.0
2	2411d395-04f2-47c9-ab66-d09e9e3c3251		available	trip_end	2023-07-01 23:20:56	088a3f85-9d3d-4468-9d47-61feae7856b3		scooter	electric	32.082195	34.791714	1.0
3	2411d395-04f2-47c9-ab66-d09e9e3c3251		on_trip	trip_start	2023-07-02 14:30:18	088a3f85-9d3d-4468-9d47-61feae7856b3		scooter	electric	32.082176	34.791725	1.0
4	2411d395-04f2-47c9-ab66-d09e9e3c3251		available	trip_end	2023-07-02 15:04:59	088a3f85-9d3d-4468-9d47-61feae7856b3		scooter	electric	32.082172	34.791775	1.0
5	2411d395-04f2-47c9-ab66-d09e9e3c3251		non_operational	battery_low	2023-07-02 15:07:03	088a3f85-9d3d-4468-9d47-61feae7856b3		scooter	electric	32.082172	34.791775	1.0

Figure B.3.
Screenshot of a sequence of status changes for one vehicle (vehicle ID and operator name were redacted), sorted by time in ascending order

Appendix C: Trips sample filtering

This appendix presents the procedure conducted to consolidate the trip sample in this study. Section one presents the whole study's trip sample, which means the procedure made from the raw data provided, and prior to any further analysis. Section 2 presents an additional removal of trips made to the route choice analysis.

1. Study's Trips sample

Due to insufficient data for the required "Trips" analysis (subchapter 4.1), particularly regarding geometry accuracy, a crucial sample consolidation process was undertaken for the initial Trips raw data. The outcome of this sample consolidation is prior to both later trips' analyses – route choice and speed. The sample consolidation is taken in four steps:

I. **Removal of faulty data**: 359,573 trips from one of the four operators were removed due to completely faulty geometry data (basically missing trajectory data).
II. **Clearing low-resolution route geometry**: GPS trajectory data was examined to detect instances where the distance between sequential points exceeded 70m (based on a maximum 10-second interval between GPS pings and a 25 km/h speed limit). 632,454 trips were cleared in this step.
III. **Short trip removal**: 41,010 trips shorter than 250m were removed as they were too short to demonstrate route preferences or speed patterns.
IV. **Geographical constraint**: 19,299 trips not entirely within Tel Aviv-Yafo's city boundaries were removed to prevent bias in the analysis of cycling infrastructure usage since only Tel Aviv-Yafo's infrastructure data is used.

2. ***Route choice trips sample removal***

The study's trip sample consolidation was mainly based on the geometry correctness of the trips' trajectories. However, the route choice analysis demands another removal in order to eliminate trips where the distance or duration minimization was not part of the rider objectives. That is not because those riders' route choice is not affected by cycling infrastructure, but because the ability to compare them to alternative shortest paths is useless. The main method to detect those was by a new attribute added – "aerial distance" – measuring the distance between the start and end coordinates, then two rules were applied:

I. **Route rationality check:** The ratio of the trip length to aerial distance was calculated, and all the trips with a ratio higher than 2 were removed (30,288 trips). Figure C.1. exhibits an example of such a route.

II. **Full circular trips:** 26 trips with identical start and end locations (0 aerial distance) were also removed.

The final trips sample dataset consisted of 303,710 trips. Figure C.2. illustrates examples of trips that remained in the sample, and trip trajectories that were removed.

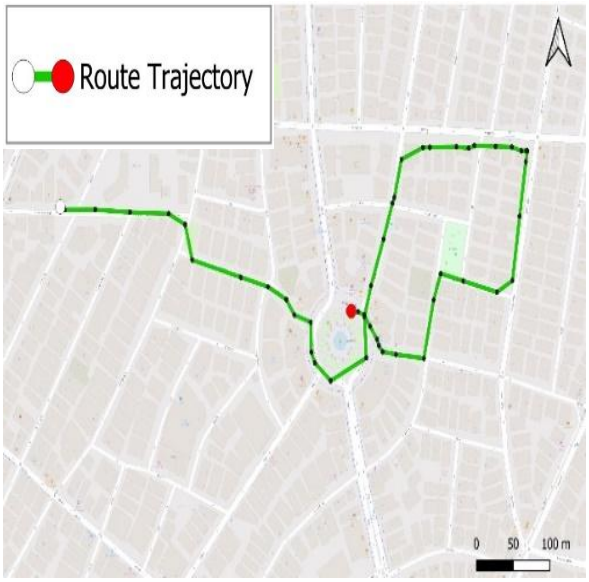


Figure C.1.
An example of a trip removed from the route choice analysis sample due to the trajectory rationality check—the ratio between the trajectory's length and the aerial distance between its start and end nodes is greater than 2



Figure C.2.
Examples of trip trajectories – black dots represent GPS locations collected along the route. (a) Example of a trip with correct geometry (70m or less between each pair of sequential coordinates), which remained in the trip sample. (b) Poor GPS resolution route, and hence eliminated from the sample. (c) Very short trip (~150 m), where route choice is irrelevant.

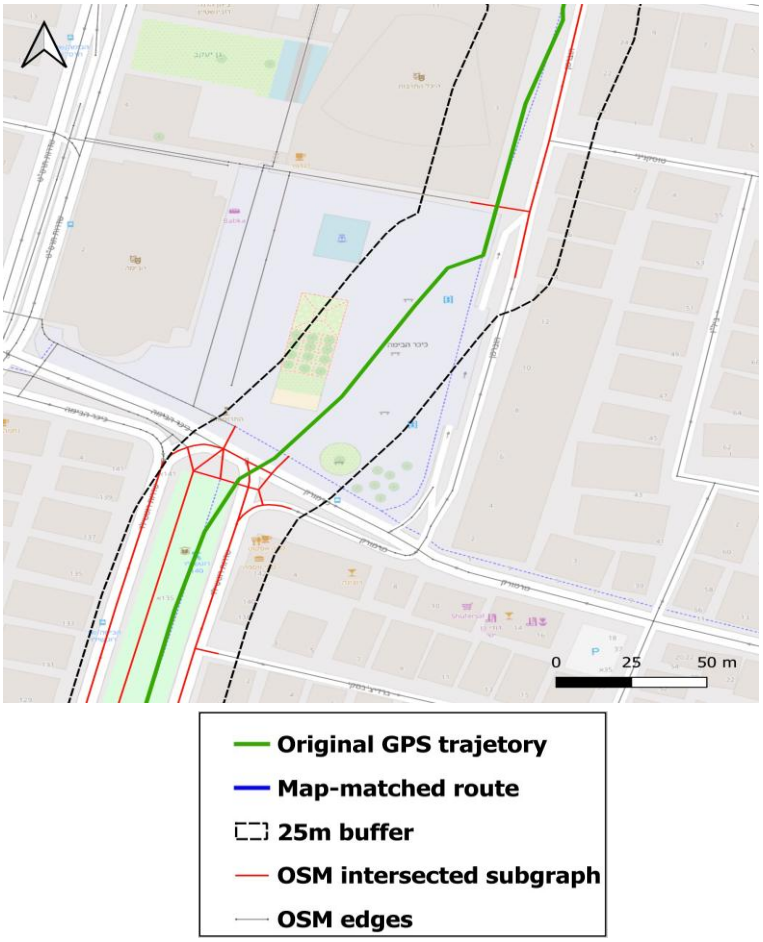
Appendix D: Map-matching

This appendix is complementary to the description of the map-matching method used in this study and explained in section 4.1.2.1. The first section presents the method used to correct disconnected subgraphs, section 2 describes the method limitations, and section 3 how those limitations are addressed.

1. Disconnected subgraph correction

The main concept of the map-matching method in this study is extracting OSM subgraph that intersects the trip trajectory's 25m buffer, and computing SP between the start/end location upon this subgraph. In some cases, the subgraph extracted is a multisubgraph – the network is "disconnected" from more than one network. That can occur when the rider uses a path that does not exist in the OSM links data, and therefore no links are assigned to the subgraph at that part of the trajectory. Then, an SP could not be computed - there is no connection in the subgraph between the start/end nodes.

In order to address this case, a new edge is assigned between the closest nodes of the two parts of the subgraph. Figure D.1. presents an example of that case from the real trip sample.



Before Correction:
Subgraph (red links) is disconnected

After Correction:
An edge is assigned, and SP can be computed

Figure D.1.
An example of a disconnected subgraph that required correction. (Top) – As seen in the middle of the route, it did not intersect OSM links because the rider took a shortcut through the square. Therefore, an additional link was assigned to the subgraph, connecting the nearest two points of each part, and the shortest path (SP) could be computed (Bottom)

2. *Map-matching limitations*

The map-matching method (section 5.1.2.1.) employed in this study has two primary inherent limitations that could lead to inaccuracies in the map-matched results:

I. **Discrepancies between start/end trip coordinates and OSM graph nodes distribution**: These differences can result in minor deviations from the original route, usually when the closest node is slightly before or after the route's start/end coordinate. While these deviations are typically insignificant (Figure D.2a), more substantial discrepancies can occur, especially when the extracted OSM subgraph does not fully represent all possible movements of two-wheel vehicles in space (Figure D.2b).

II. **Back-and-forth movements:** When a user rides back and forth along the same links (e.g., traveling down a street and then turning back), all the links appear in the subgraph. However, the shortest path (SP) algorithm will not include these repeated links, as it finds a shorter route between the start and end nodes (Figure D.2c).

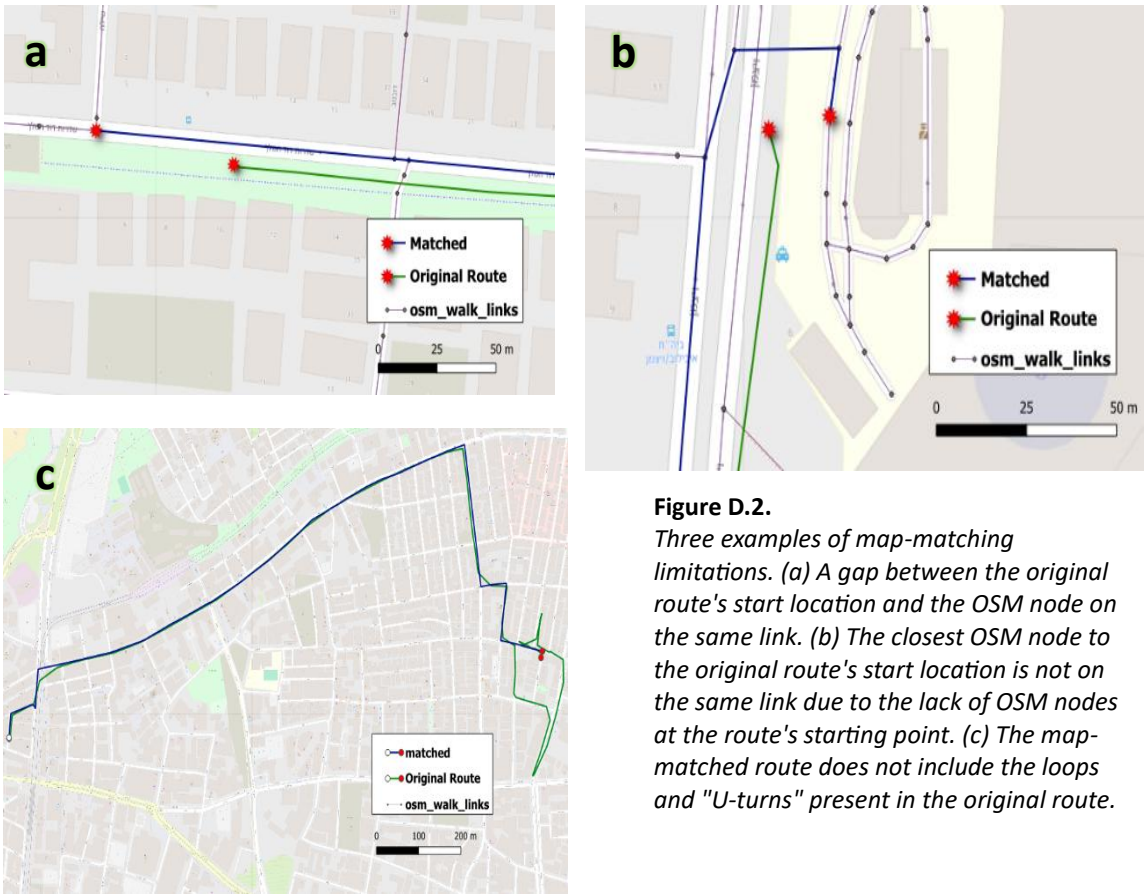


Figure D.2.
Three examples of map-matching limitations. (a) A gap between the original route's start location and the OSM node on the same link. (b) The closest OSM node to the original route's start location is not on the same link due to the lack of OSM nodes at the route's starting point. (c) The map-matched route does not include the loops and "U-turns" present in the original route.

3. Faulty map-matched results removal

To address the map-matching method limitations and clean routes with suspected deviations between map-matched results and original routes, the following steps were taken:

I. **Two columns were added to the dataset:**

- Absolute difference between the original route length and the map-matched route length.
- The percentage of the absolute difference from the original route length.

II. **Filtering criteria:**

- For short rides (1 km and less): trips with an absolute difference value lower than 100 m were filtered out (7,915 trips removed).
- For long routes (1 km+): trips with a 5% or greater deviation between map-matched and original routes were removed (65,564 trips removed).

This refinement process resulted in the removal of 73,479 rides from the total sample, leaving 200,681 rides in the final sample for route choice analysis.

Appendix E: Speed assessment methodology- addition of information and limitations

This appendix contributes and completes the description of the SDES speed assessment methodology. The first section describes why and how the duration users spend at the beginning and end of rides is detected and reduced from the total duration. Section 2 presents the limitations of the segmentation method and how they are addressed.

1. Reduction of duration at the start/end location

Part of the operation of SDES vehicles includes unlocking/locking procedures, which can take a substantial amount of time, which might bias the total duration and consequently the speed. The procedure at the beginning of the ride includes unlocking the vehicle, wearing a helmet, and preparing for a ride. At the end of the ride that can be assuring the vehicle is in a parking cell and eligible to lock, taking a photo of the vehicle (required by the operators), and returning the helmet. The amount these procedures take is not consistent and might change between the user, vehicle, and operator.

In order to detect this time, and reduce it from the total trip duration, the sequence of coordinates in the "route" GeoJson (Appendix B) is investigated for each trip, and the following steps are taken:

- If there are two or more sequential identical coordinates at the beginning of the GeoJson, the last pair of coordinates them counts as the beginning of the ride.
- If there are two or more sequential identical coordinates at the end of the GeoJson, the first pair of coordinates of them counts as the end of the ride.
- The total duration is recalculated according to the new start/end timestamps.

Id	coordinates	timestamp
1	X,Y	1,000
2	X,Y	2,000
3	X,Y	3,000
4	X1,Y1	4,000
5	X2,Y2	5,000
6	X3,Y3	6,000
7	X4,Y4	7,000
8	X5,Y5	8,000
9	X5,Y5	9,000
10	X5,Y5	10,000

Id	coordinates	timestamp
1	X,Y	1,000
2	X,Y	2,000
3	X,Y	3,000
4	X1,Y1	4,000
5	X2,Y2	5,000
6	X3,Y3	6,000
7	X4,Y4	7,000
8	X5,Y5	8,000
9	X5,Y5	9,000
10	X5,Y5	10,000

Figure E.1.
Schematic example of how the duration a vehicle is idle at the beginning and end of a ride is detected. On the left is an example of the route sequence of coordinates and timestamps along the route. On the right is the route's data after reduction – records with identical coordinates at the beginning and end are removed, and only the last/first of these identical sequences are preserved. As a result, the trip's duration becomes shorter

2. Segmentation method limitations

The segmentation method (section 4.1.3.1.) while effective in dividing routes based on their spatial relation to cycling infrastructure, has an inherent limitation that can create non-real segments. This occurs due to the following:

I. **False "Inside" Segments**: When a ride passes through a street without infrastructure but intersects a street with infrastructure, a GPS point collected at that intersection may be falsely classified as "inside" the cycling infrastructure. This can create short, inaccurate "inside" segments that do not reflect actual infrastructure usage.

II. **Short "Breaks" in Infrastructure**: Brief interruptions in cycling infrastructure can create short "outside" segments during a long ride that is predominantly within the infrastructure. These short breaks may not genuinely indicate a rider's decision to leave the infrastructure.

To address these limitations and improve the accuracy of the segmentation, the following rule “short segment modification” was implemented. All segments shorter than 80m are modified to the opposite type (i.e., "inside" to "outside" or vice versa). These modified segments are then dissolved into adjacent segments of the same type, creating a unified segment (Figure E.2.). This rule effectively addresses both false "inside" segments at intersections and short "outside" segments due to infrastructure breaks.

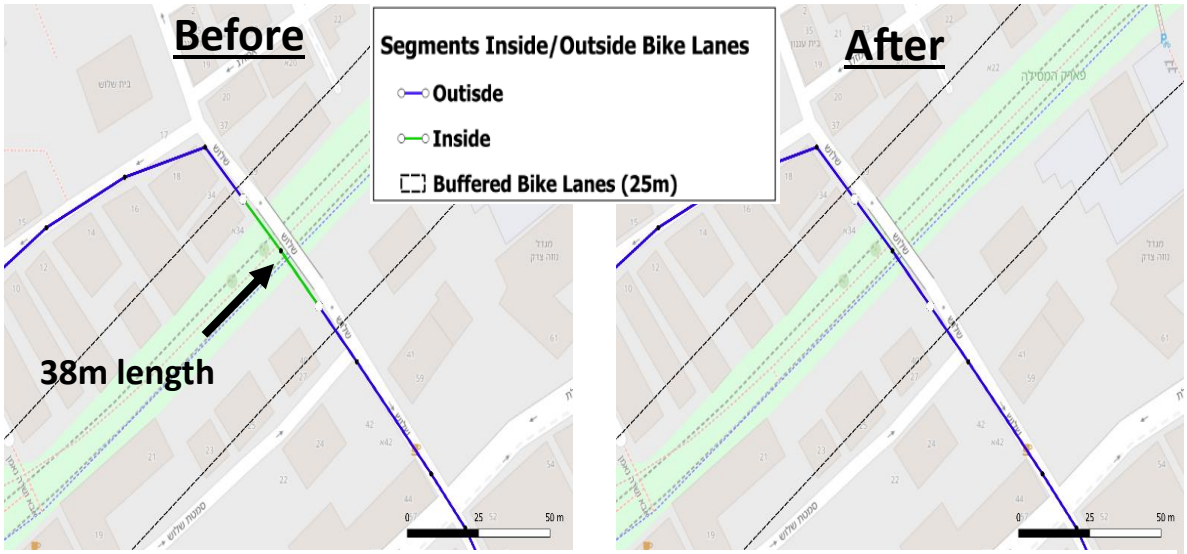


Figure E.2.
Example of a false "inside" cycling infrastructure segment, which was created because the GPS location was collected while the rider crossed the cycling infrastructure (left). Since its length is less than 80m, it changed its type to "outside" cycling infrastructure

Appendix F: Parking events data set construction

The “Status Changes” raw dataset was the base for the construction of the parking events dataset (section 4.2.2.). In order to construct the parking events dataset that will be adequate for the SDES demand analysis, a five-stage data process was conducted. Figure F.1. describes schematically the process, and each stage will be further explained.

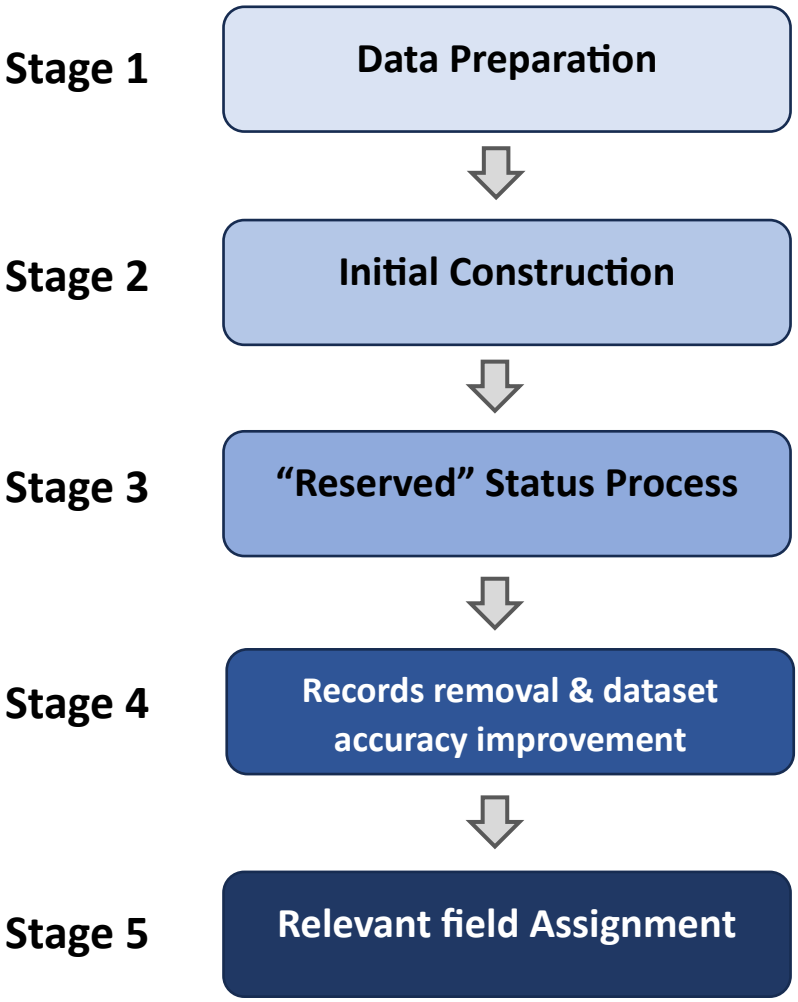


Figure F.1.
The flow of the "Status Changes" process from the raw data to the final parking events dataset

1. ***Stage 1: data preparation***

The data preparation phase constitutes an essential initial step to ensure the data's suitability for subsequent processing. This phase primarily involves converting and formatting time and geometry columns appropriately and storing the data as a GeoPandas dataframe (Python). Subsequently, the coordinate system was transformed from geographic (WGS84) to a projected coordinate system (ITM – Israel Transverse Mercator).

2. *Stage 2: Initial construction*

This stage represents the core of the parking events dataset construction, generating a new dataset based on the initial raw data. The fundamental principle involves extracting records from the “Status Changes” dataset that indicate a vehicle in a “ready-to-ride” status and investigating when and why they ended. In this study, "ready-to-ride" statuses are defined as those representing vehicles available for user rides, according to the MDS format – specifically, "Available" and "Reserved".

To achieve this, the initial “Status Changes” raw data was grouped by "vehicle_id" and sorted by ascending time, then all the “ready-to-ride” statuses were extracted and inserted in a new data frame – the parking events dataset. The new record retains the same fields, and four new fields are assigned, based on the next row in the “Status Changes” raw data:

- “End time” – takes the next row “start time” value
- “End coords” – takes the next row coordinates value
- “End reason” – takes the next row “vehicle_state” value
- “Parking duration” – Subtraction of “End time” and “Start time”, value is in seconds.

Initial “Status Changes” raw data

Record_Id	Vehicle_id	Status	Timestamp	coords
1	HKJFC	‘Available’	2023-07-01 10:00:00	X, Y
2	HKJFC	‘On_trip’	2023-07-01 12:30:00	X, Y
3	HKJFC	‘Available’	2023-07-01 12:45:00	X2, Y2
4	HKJFC	‘Non_operational’	2023-07-01 19:00:00	X2, Y2
5	HKJFC	‘Removed’	2023-07-01 20:00:00	X2, Y2
6	HKJFC	‘Available’	2023-07-02 06:00:00	X3, Y3
7	HKJFC	‘Reserved’	2023-07-02 07:30:00	X3, Y3
8	HKJFC	‘On_trip’	2023-07-02 07:32:00	X3, Y3
9	HKJFC	‘Elsewhere’	2023-07-02 07:40:00	X4, Y4

New parking events dataset

Record Id	Vehicle id	Status	Start time	coords	End time	End coords	End reason	Duration (sec)
1	HKJFC	‘Available’	2023-07-01 10:00:00	X, Y	2023-07-01 12:30:00	X, Y	‘On_trip’	9,000
3	HKJFC	‘Available’	2023-07-01 12:45:00	X1, Y1	2023-07-01 19:00:00	X1, Y1	‘Non_operational’	13,500
6	HKJFC	‘Available’	2023-07-02 06:00:00	X2, Y2	2023-07-02 07:30:00	X2, Y2	‘Reserved’	5,400
7	HKJFC	‘Reserved’	2023-07-02 07:30:00	X2, Y2	2023-07-02 07:32:00	X2, Y2	‘On_trip’	120

Figure F.2.
Schematic example of the extraction of "ready-to-ride" statuses from the initial "Status Changes" raw data (marked in red) to the new parking events DataFrame, with four new fields based on the next status in the raw data (stage 2)

3. Stage 3 – "Reserved" Status Process

The goal of this stage is to determine for each "Reserved" event in the new parking events dataset – whether the user fulfilled the reservation and took the vehicle for a ride (thus ending the parking event), or abandoned the reservation, resulting in the vehicle remaining in place. In order to do it, two sub-stages are executed:

I. Sub-stage 1: "Merging" sequences of "Reserved" statuses

The first sub-stage involves detecting sequences of "Reserved" records for the same vehicle and eliminating redundancies. The exact reason for these sequences, which are not possible according to the MDS format, is not entirely clear and may be related to technical misreporting or similar issues. To address this, in every sequence (more than two "Reserved" records in succession), only the first record remains, and the four new attributes are assigned based on the last "Reserved" record (Figure F.3. illustrates schematically this sub-stage operation). At the conclusion of this sub-stage, no more than one "Reserved" record

Before merge

Record Id	Vehicle id	Status	Start time	Start coords	End time	End coords	End reason	Duration (sec)
1	HKJFC	'Available'	2023-07-01 10:00:00	X1, Y1	2023-07-01 12:00:00	X1, Y1	'Reserved'	7,200
2	HKJFC	'Reserved'	2023-07-01 12:00:00	X1, Y1	2023-07-01 12:10:00	X1, Y1	'Reserved'	600
3	HKJFC	'Reserved'	2023-07-01 12:10:00	X1, Y1	2023-07-01 12:20:00	X1, Y1	'Reserved'	600
4	HKJFC	'Reserved'	2023-07-01 12:20:00	X1, Y1	2023-07-01 12:22:00	X1, Y1	'On_trip'	120
5	HKJFC	'Available'	2023-07-01 12:50:00	X2, Y2	2023-07-01 13:50:00	X2, Y2	'On_trip'	3,600

After merge

Record Id	Vehicle id	Status	Start time	Start coords	End time	End coords	End reason	Duration (sec)
1	HKJFC	'Available'	2023-07-01 10:00:00	X1, Y1	2023-07-01 12:00:00	X1, Y1	'Reserved'	7,200
2	HKJFC	'Reserved'	2023-07-01 12:00:00	X1, Y1	2023-07-01 12:22:00	X1, Y1	'On_trip'	1,320
5	HKJFC	'Available'	2023-07-01 12:50:00	X2, Y2	2023-07-01 13:50:00	X2, Y2	'On_trip'	3,600

Figure F.3.
Schematic example of the "Reserved" sequences merging (sub-stage 1). The "Reserved" events are marked in red. Before the merge, there are three sequential "Reserved" events, which merge into one after the sub-stage execution

II. Sub-stage 2: Identifying "Reserved" outcome

The second sub-stage focuses on identifying the outcome of the "Reserved" event and updating it accordingly. In case a "Reserved" ended in a ride (has "On trip" value in "end reason" field), it is merged to the previously "Available" parking event. In case the "Reserved" vehicle was not fulfilled by the user (has "Available" value in "end reason" field), it merged to

the previous and next “Available” statuses as one parking event (Figure F.4.). The implementation of this sub-stage resulted in the removal of 300,681 records from the dataset.

Case 1 – “Reserved” ended in a ride

Before merge

Record Id	Vehicle id	Status	Start time	coords	End time	End coords	End reason	Duration (sec)
1	HKJFC	‘Available’	2023-07-01 10:00:00	X1, Y1	2023-07-01 12:00:00	X1, Y1	‘Reserved’	7,200
2	HKJFC	‘Reserved’	2023-07-01 12:00:00	X1, Y1	2023-07-01 12:10:00	X1, Y1	‘On_trip’	600
3	HKJFC	‘Available’	2023-07-01 12:50:00	X2, Y2	2023-07-01 13:50:00	X2, Y2	‘On_trip’	3600

After merge

Record Id	Vehicle id	Status	Start time	coords	End time	End coords	End reason	Duration (sec)
1	HKJFC	‘Available’	2023-07-01 10:00:00	X1, Y1	2023-07-01 12:10:00	X1, Y1	‘On_trip’	7,800
3	HKJFC	‘Available’	2023-07-01 12:50:00	X2, Y2	2023-07-01 12:10:00	X2, Y2	‘On_trip’	3600

Case 2 – “Reserved” returned to

Before merge

Record Id	Vehicle id	Status	Start_time	coords	End time	End coords	End reason	Duration (sec)
1	HKJFC	‘Available’	2023-07-01 10:00:00	X1, Y1	2023-07-01 12:00:00	X1, Y1	‘Reserved’	7,200
2	HKJFC	‘Reserved’	2023-07-01 12:00:00	X1, Y1	2023-07-01 12:10:00	X1, Y1	‘Available’	600
3	HKJFC	‘Available’	2023-07-01 12:10:00	X1, Y1	2023-07-01 13:10:00	X1, Y1	‘On_trip’	3600

After merge

Record Id	Vehicle id	Status	Start time	coords	End time	End coords	End reason	Duration (sec)
1	HKJFC	‘Available’	2023-07-01 10:00:00	X1, Y1	2023-07-01 13:10:00	X1, Y1	‘On_trip’	11,400

Figure E.4.
Schematic examples of the two cases of the "Reserved" status outcome and how they are processed differently. Case 1 – The "Reserved" event ends in a ride; therefore, it is merged with the previously "Available" status into one event. Case 2 – The "Reserved" event returns to "Available" and is therefore merged with both the previous and the next "Available" statuses

4. Stage 4: Records removal & dataset accuracy improvement

At this stage, the parking events dataset is supposed to contain exclusively records with "Available" status. In order to accurate the sample and eliminate unreliable events, six additional removals/modifications were executed:

I. **Remaining “Reserved” events**: 1,073 records removed.

II. **Remaining “Available” statuses with “Reserved” end reason**: all records remain with “reserved” change to “unknown” (314 records).

III. **Gap between start and end coordinates**: Theoretically the distance should be 0m. Therefore, all records with a distance larger than 25m (due to GPS deviation) the value in the field “end reason” is changed to “unknown” (99,775 records removed).

IV. **False short events:**

Such false events can arise in scenarios where a user activates a vehicle but terminates the ride after minimal movement or without moving the vehicle at all. Another instance is when an operator briefly switches a vehicle to "non-operational" status before reverting it to "available" at the same location. In both cases, it is crucial to determine whether a new parking event has genuinely commenced or if it should be treated as a continuation of the previous event. Therefore, two thresholds are defined:

- **Time threshold**: 5 minutes
- **Distance threshold:** 25 meters

For each pair of consecutive events (of the same vehicle id), if the duration between the end of the first event and the start of the second event was less than the time threshold, and the distance between their locations was less than the distance threshold, the two events were merged into a single parking event. This process resulted in the removal of 56,792 records from the dataset.

I. **Events outside Tel Aviv-Yafo’s boundaries**: 3,161 events occurring outside the city's boundary were removed since only the infrastructure in Tel Aviv-Yafo was investigated.

II. **Events not within the public open space area**: The public open space area was derived by subtracting the built area layer from the city's boundary polygon. The resulting polygon was buffered by 2.5m to account for the interface between sidewalks and buildings, where SDES vehicles typically park. Events outside this polygon likely experienced significant GPS deviation, reducing the reliability of their reported locations, and were thus excluded from the dataset (18,229 records).

5. Stage 5: Relevant attributes assignment

The final stage involved the addition and recalculation of relevant spatio-temporal attributes to enhance the dataset's analytical value:

I. Spatial Attributes:

- Area (derived from a division into four distinct areas)
- Neighbourhood
- Distance to the nearest cycling infrastructure

II. **Temporal attributes:**

- Start hour
- End hour

I. **Trip Association**: For all records with "on_trip" value in the "parking end reason" attribute, an additional attribute was introduced to indicate whether an associated trip was found in the "Trips" dataset. The association criteria were:

- Matching vehicle ID
- Temporal proximity (no more than 1 second difference)
- Spatial proximity (at most 25 meters distance difference)

If a corresponding trip was identified, its ID was assigned to the record; otherwise, the field remained null. Eventually, 899,501 records remained in the parking events dataset.

Appendix G: Parking events dataset – records removal after initial evaluation

After the construction of the parking events dataset, initial evaluation led to the identification of events that were likely to be false, which led to two record removals in order to assure the reliability of the dataset:

I. **Unassociated trip event**: Of the 819,874 parking events that concluded with a ride ("parking end reason" is "on trip"), 7.6% (62,670) could not be associated with a corresponding trip. Although some of these events may be valid and accurately reported in the parking events dataset, it was deemed prudent to exclude them from further analysis.

II. **Extremely short events**: Notably a high proportion of extremely short events lasting only a few seconds was identified. Investigation into these events yielded two key findings:

- **Trip ends with Insufficient battery level:** Vehicles concluding a ride with insufficient battery to meet the "operational" threshold immediately transitioned to "non-operational" status upon ride completion. This resulted in 31,880 events with a "parking duration" of 0 seconds. These are not real events and are consequently removed from the parking events dataset. The removal criteria were extended to encompass all events that transitioned to "non-operational" status within 10 minutes, based on the assumption that some vehicles completed rides with minimal battery charge, which subsequently dropped below 20% in the minutes following the ride (42,470 events removed in total).
- **5 second rule**: All events with a parking duration of less than 5 seconds were eliminated. A detailed examination of the parking duration distribution for events shorter than one minute, differentiated by the three operators under investigation, revealed that one operator exhibited a high frequency of events shorter than 5 seconds. This frequency declined between 0 and 5 seconds before increasing in line with the other two operators (Figure G.1.). This observation prompted the removal of all ride-ending events lasting less than 5 seconds, as they deviated from the standard distribution of event parking durations (457 records removed).

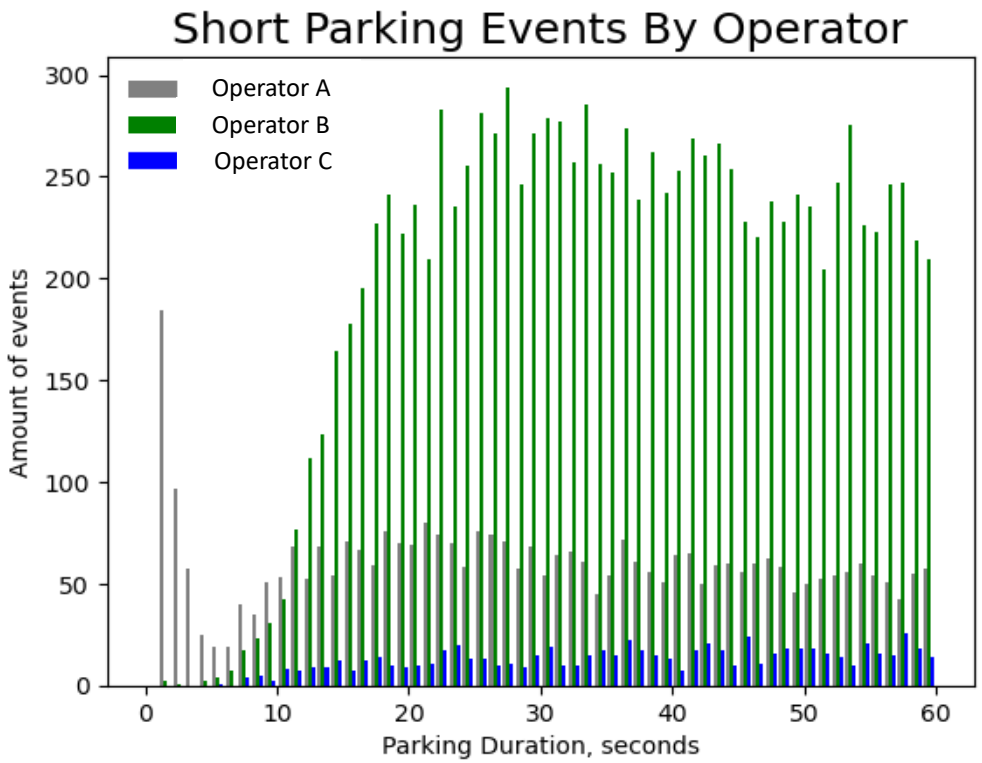


Figure G.1.

Parking duration histogram of events lasting less than one minute, by the three operators (their names are anonymized). The different pattern between operator A and the two others for events between 0-5 seconds led to the application of the "5-second rule"

אוניברסיטת תל אביב

בית הספר לסביבה ולמעדי כדור הארץ ע"ש פורטר

החוג לגיאוגרפיה וסביבת האדם



עבודת תזה לתואר מוסמך אוניברסיטה

עופר שחל, 203167291

ההשפעה של תשתית רכיבת אופניים על מגמות שימוש והתנהגות רכיבה של משתמשי קורקינטים שיתופיים חשמליים בלתי מעוגנים

מנחים:

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נובמבר 2024

תקציר

קורקינטים שיתופיים חשמליים בלתי מעוגנים התבססו כגורם משמעותי במערכות התחבורה העירוניות מאז הופעתם לפני כמה שנים. היכולתם שלהם לספק מענה לנסיעות קצרות-בינונית באמצעות פלטפורמה גמישה וידידותית למשתמש, הובילו לתפוצה רחבה שלהם ואימוץ על-ידי ערים בכל רחבי העולם. המחקר זה בוחן את הקשר שבין תשתית רכיבה לכלים דו-גלגליים ודפוסי השימוש של רוכבי הקורקינטים השיתופיים בתל אביב-יפו, על-ידי ניתוח מידע של כמיליון רכיבות וכשני מיליון שינויי סטטוסים של כלים, שתועדו ביולי 2023. הממצאים מצביעים שרוכבי הקורקינטים השיתופיים נוטים לחרוג מהמסלול הקצר ביותר על-מנת להשתמש בתשתית הרכיבה, והיצע וביקוש גבוהים בסמוך לשבילי האופניים בעיר. בנוסף, המחקר מספק תובנות מעשיות לגיבוש מדיניות עירונית של חניית קורקינטים שיתופיים בעיר, ועיצוב תשתית רכיבה דו-גלגלית אופטימלית.