



Mobility on-demand

What about the weekend?

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1 **MOBILITY ON-DEMAND: WHAT ABOUT THE WEEKEND?**

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1 ABSTRACT

2 Mobility on-demand services like ride-hailing, ride-sharing, and car-sharing are changing the way
3 we travel, offering us more options and flexibility. They can be best understood and planned for by
4 using detailed computer simulations. However, these simulations often forget about the weekends.
5 They focus mostly on the average working day when travel is high and fairly predictable.

6 But the way we travel has changed. Unlike the weekdays with rush hours, people tend
7 to travel throughout the day on weekends, especially on Saturdays. In fact, these new types of
8 transport services are used most heavily during the weekends. Even the way we share rides changes
9 - we are more likely to share a ride with others at the weekend than during the week. This difference
10 in our habits could have big impacts on these new travel services and even on the future of transport
11 itself.

12 Our study looks at this overlooked area. We include weekend travel data to get a full
13 picture of how we could use these services. We compare travel patterns during the week and at the
14 weekend for Zurich, Switzerland, as a case study. Our goal is to understand the unique aspects of
15 weekend travel and what they mean for these on-demand services.

16

17 *Keywords:* mobility On-demand, Shared Autonomous Vehicle simulation, ridesharing, weekend
18 modelling, MATSim, agent-based simulation

1 INTRODUCTION

2 There is a growing interest in modelling various Mobility on Demand (MoD) services, including
3 ride-hailing, ride-sharing, car-sharing, and even Shared Autonomous Vehicles (SAV). These ser-
4 vices are viewed as potential strategies to mitigate transport-related externalities. Agent-based sim-
5 ulations have gained popularity as a robust tool for modelling these MoD services. They provide
6 a detailed, microscopic perspective of complex transport scenarios, thus offering valuable insights
7 into the effects of diverse policy decisions and operational interventions on travel behaviour.

8 MoD services, by their nature, offer flexible transport options catering to passenger de-
9 mand with both spatial and temporal flexibility, which can only be properly captured through a
10 microscopic representation of individual travellers and vehicles. Agent-based simulations, thus,
11 can help to understand the impact of such flexible and dynamic behaviour on the transport system,
12 hence their growing popularity.

13 Typically, these MoD simulation models are based on average working day scenarios, and
14 the weekend is rarely considered. The result is that the simulation outcomes, may not fully cap-
15 ture the overall picture of externalities of travel behaviours, and policy impacts (1, 2). While
16 historically, travel demand models have centred around weekdays, rationalised by the higher travel
17 demand on these days, as well as defined commuting patterns that can be modelled, the transporta-
18 tion landscape has changed with the introduction of these flexible modes. For example, unlike
19 weekdays' predictable rush hour periods, weekend travel demand is distributed throughout the day
20 (1, 3, 4).

21 This can be seen in Figure 1 showing the share of trips across the day for the weekday,
22 Saturday and Sunday based on the 2015 Swiss household travel survey. From this figure one can
23 observe that the peak is most pronounced on the average day, indicating a typical rush hour pattern
24 likely due to work and school commutes. On Saturday and Sunday, the morning peak is less
25 intense, which could be due to more flexible schedules or reduced work and school-related travel.
26 Furthermore, many studies have revealed that existing MoD services experience peak demand
27 on weekends, especially on Saturdays. Also, ridesharing patterns differ between weekdays and
28 weekends as travellers may tend to pool more on the weekends (5, 6). Consequently, this deviation
29 in travel patterns between weekdays and weekends can substantially impact the planning for these
30 emerging modes and future mobility solutions such as SAVs.

31 Therefore, including weekend travel data is particularly pertinent for planning and policy
32 decisions related to MoD services. In this context, our study aims to fill this gap in research by
33 examining the role of weekend travel in the operational efficiency of MoD services. By compar-
34 ing weekday and weekend travel patterns, the study hopes to show the unique characteristics of
35 weekend travel and its implications for on-demand service operations.

36 The rest of the paper is structured as follows: Section 3 looks at the relevant background
37 literature. Section 4 outlines the methodology used. Section 5 discusses the results and their
38 implications in detail, and Section 6 concludes the paper, offering directions for future research in
39 this area.

40 BACKGROUND

41 Several studies exist that have examined week-long and weekend travel behaviour, and they pro-
42 vide an analysis of the differences in travel behaviour between weekends and weekdays (7–12).
43 These studies argue that special attention needs to be paid to weekend travel to develop a compre-
44 hensive travel demand model for evaluating transportation policies to reduce congestion, improve

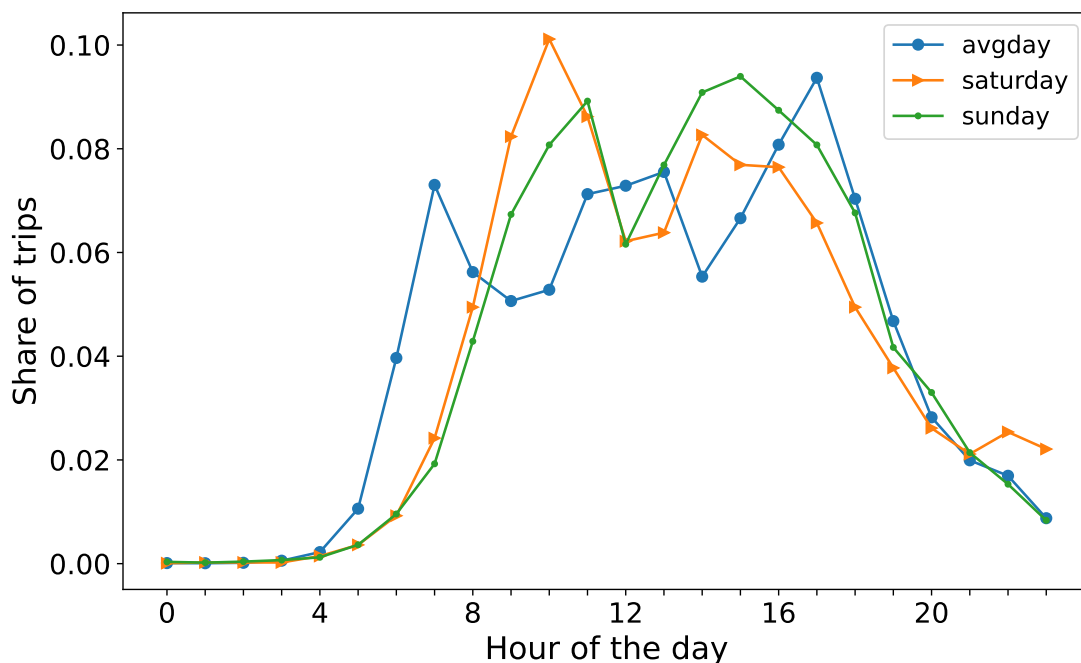


FIGURE 1: "Comparing hourly trip share by day of the Week"

1 air quality, and enhance well-being. For example, Bhat and Misra (8) noted as early as the 1990s
 2 that policies focusing on weekday traffic can exacerbate weekend traffic congestion.

3 The differences in weekend trip patterns are reflected in the activity types, trip length, mode
 4 choice, and even duration of trips. Leisure trips account for a higher percentage of weekend trips,
 5 and vehicle occupancy is higher because there is more time to participate in household and group
 6 activities (12–15). For example, Hunt et al. (13) found that weekend mode choice was related
 7 to travel party size, while Yagi et al. (16) found in Indonesia that the mode share of fully joint
 8 household trips differed between weekdays and weekends. Furthermore, the value of time (VoTs)
 9 between the weekday and weekends differ. While some studies report lower VoTs on the weekends
 10 than on weekdays (13), others suggest higher VoTs on weekends, especially when joint household
 11 activities are considered (15, 17). These differences in VoTs can be linked to the various forms
 12 of activities and trip chaining patterns, and travel behaviour during the weekend compared to the
 13 weekday.

14 These differences in trip patterns also occur between the two weekend days. For example,
 15 while the consensus is that weekend trips are generally longer than weekday trips, some studies
 16 show that Saturday trips are longer than Sunday trips (9), while others find the opposite (12). This
 17 could depend on the region, so it may be necessary to model Saturday and Sunday independently.

18 Transport Network Companies (TNC) data serve as a rich data source for various empirical
 19 studies on ride-hailing and ridesharing. In the Chicago, New York, Boston, Chengdu, Berlin, and
 20 Hamburg regions, these data are available, and studies based on these data show the differences
 21 and similarities between weekday and weekend trip patterns for various travel characteristics (4–
 22 6, 9, 18–20). These studies emphasize the need to model the demand for weekdays and weekends

1 separately. For example, a strong relationship has been found between ride-hailing use and leisure
2 activities (2, 4, 21), which stands to reason that ride-hailing use is more prevalent on weekends
3 than on weekdays, when people engage in more leisure activities. This can be observed in different
4 regions of the world.

5 However, the results do not always agree on some points and reveal that the travel patterns
6 depend on the region. Du et al. (18) and Dean and Kockelman (5) found that ridesharing happened
7 more during the week in Chicago (4.5% higher). However, based on TNC data from the pooling-
8 only service MOIA for two German cities, it was found that there were more ridesharing trips
9 on Saturdays than on any other day of the week (20). Gehrke et al. (6) found that ridesharing in
10 the Boston area was more prevalent on weekends or in the middle of the day during the week.
11 This suggests that a better analysis of weekend ridesharing is needed, especially when examining
12 the potential of future mobility services such as SAVs for ridesharing. In addition, a distinction
13 between Saturday and Sunday is necessary. In Berlin, Bischoff et al. (22) using GPS trajectories,
14 observed a peak in demand for ridehailing and ridesharing trips on Saturdays and lower demand
15 on Sundays. This is similar to other cities such as Madrid, where usage increases on late Friday
16 evenings and on Saturdays (4).

17 Since agent-based simulations are appropriate tools for understanding these MoD services,
18 several MoD simulation studies exist. However, few have addressed the weekend aspect. These
19 few are either toy examples (23), focused on electric vehicles and their energy demand (24, 25),
20 or choose a weekend day, typically Saturday, considered as the day with the highest demand (20,
21 22, 26, 27). In general, these studies do not fully explore the differences between weekends and
22 weekdays, and as far as the authors are aware, no study examines and compares the impact of
23 weekends and weekdays, especially considering the potential for ridesharing. That is why this
24 paper presents a first step towards opening up discussions and research on including richer data,
25 i.e., weekend travel behaviour in MoD simulations.

26 **METHOD**

27 This section describes the methods used in this study to develop an agent-based model for simu-
28 lating an on-demand mobility service in Zurich, Switzerland, for the weekend (see Figure 2).

29 This study uses the multi-agent transport simulation framework MATSim (28) to develop
30 the agent-based model. MATSim is a powerful simulation tool that can model detailed interactions
31 between transport demand and supply. To represent the transportation system within MATSim,
32 the following scenario data is required: a network representation consisting of links and nodes as
33 well as the public transport infrastructure, travel demand data in the form of a synthetic population
34 of agents with their corresponding travel plans, and additional transport elements such as facility
35 locations and transit schedules.

36 The study area consists of the city of Zurich extended by a 5 km buffer covering an area
37 of 383.56 km² and contains a population of roughly 1.2 million. The transport network for the
38 region is extensive, with 61,930 network links represented in MATSim and it facilitates various
39 modes of transport. The 2015 Mikrozensus Household Travel Survey (HTS) by the Bundesamt
40 für Statistik (BFS) provides insights into the travel behaviour in the region. Within Zurich, 57%
41 of the daily distance travelled by citizens of the Canton of Zurich is done by private car, 32% by
42 public transport and 10% by foot, bike or e-bike with little to no presence of on-demand services
43 such as Uber or Lyft. Given Zurich's urban dynamics, MoD simulation is of particular relevance
44 to the city as its transport planners contemplate sustainable transport solutions in the face of rapid

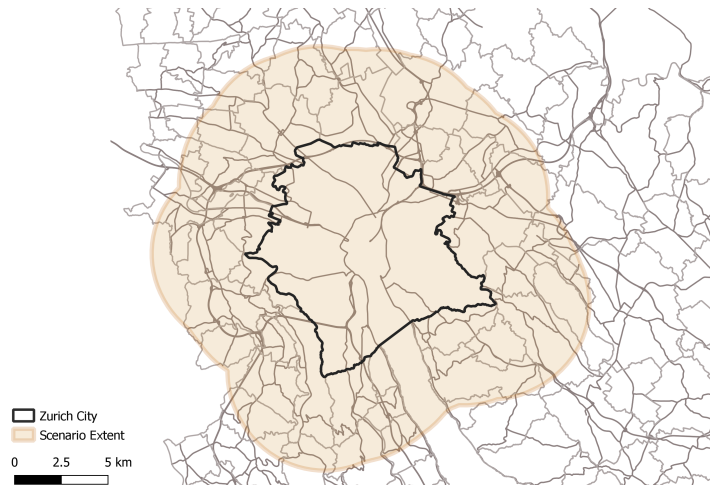


FIGURE 2: Analyzed study area with Zurich’s city limit indicated with black line)

1 urbanisation. As a result studies on the impact of MoD systems have and are currently being
 2 conducted in the city (29, 30).

3 The travel demand model for the Zurich region for this study is extracted from a syn-
 4 thetic travel demand for Switzerland. The demand generation process for an average workday for
 5 Switzerland has been developed by Tchervenkov et al. (31), Hörl (32) and a calibrated simulation
 6 scenario for an average workday for the study region is presented in Hörl et al. (33). Below, the
 7 demand generation process for the weekend is described in detail.

8 **The weekend travel demand model**

9 Several agent-based transport simulation studies conducted for Switzerland use the available Switzer-
 10 land Baseline Scenario, a MATSim scenario created using an established synthetic population
 11 pipeline for Switzerland (31) based on the Eqasim framework (34, 35). The Eqasim pipeline
 12 creates a realistic agent population matching the sociodemographics, mobility patterns, transport
 13 networks and facilities of Switzerland. It draws on raw data, including census records, travel sur-
 14 veys, OpenStreetMap, and GTFS transit data. The resulting output of the pipeline is simulation
 15 files needed by MATSim, which include population, households, facilities, network, and transit
 16 vehicle and schedules files in XML format. The Switzerland Baseline scenario, based on the Swiss
 17 household travel survey (HTS), models an average working day and consists of a synthetic agent
 18 population that reproduces the sociodemographic characteristics and travel behaviour of Switzer-
 19 land. The HTS reports the daily travel behaviour of nearly 60,000 respondents living in Switzer-
 20 land and contains additional information that characterizes weekend travel. Over 22% of the trips
 21 recorded in the HTS are weekend trips, which provides an opportunity to capture weekend travel
 22 behaviour.

23 Following an approach similar to that used to develop the average workday travel demand
 24 for Switzerland, an extension of the model has been developed in this study to create a weekend
 25 travel demand model for Switzerland. In Switzerland, Saturday and Sunday have distinctive trip

1 patterns. As a result, the weekend model represents individual Saturday and Sunday synthetic
 2 travel demand. This extended model creates a synthetic population with households and persons
 3 and then defines daily activity patterns for the synthesized persons, using statistical matching ap-
 4 proaches that use the weekend observations of the HTS to attach whole activity chains based on
 5 sociodemographic attributes. A generic pipeline for this synthesis process can be found in (35) and
 6 its application to Switzerland in (31, 32). Below is a brief description of the weekend travel demand
 7 generation process while emphasizing the methodological differences to the weekday model.

8 *The Synthesis Process*

9 This section summarises the synthesis process developed for the weekend travel demand model,
 10 highlighting key differences from the weekday model. The process is detailed sequentially: gener-
 11 ation of synthetic population, statistical matching, assignment of primary and secondary activities,
 12 alongside unique considerations for the weekend model. Refer to Figure 3 for a pipeline diagram
 13 of the process. The synthesis process constitutes a chain of models to transform the data into a
 14 desired synthetic travel demand that can be used in an agent-based transport simulation.

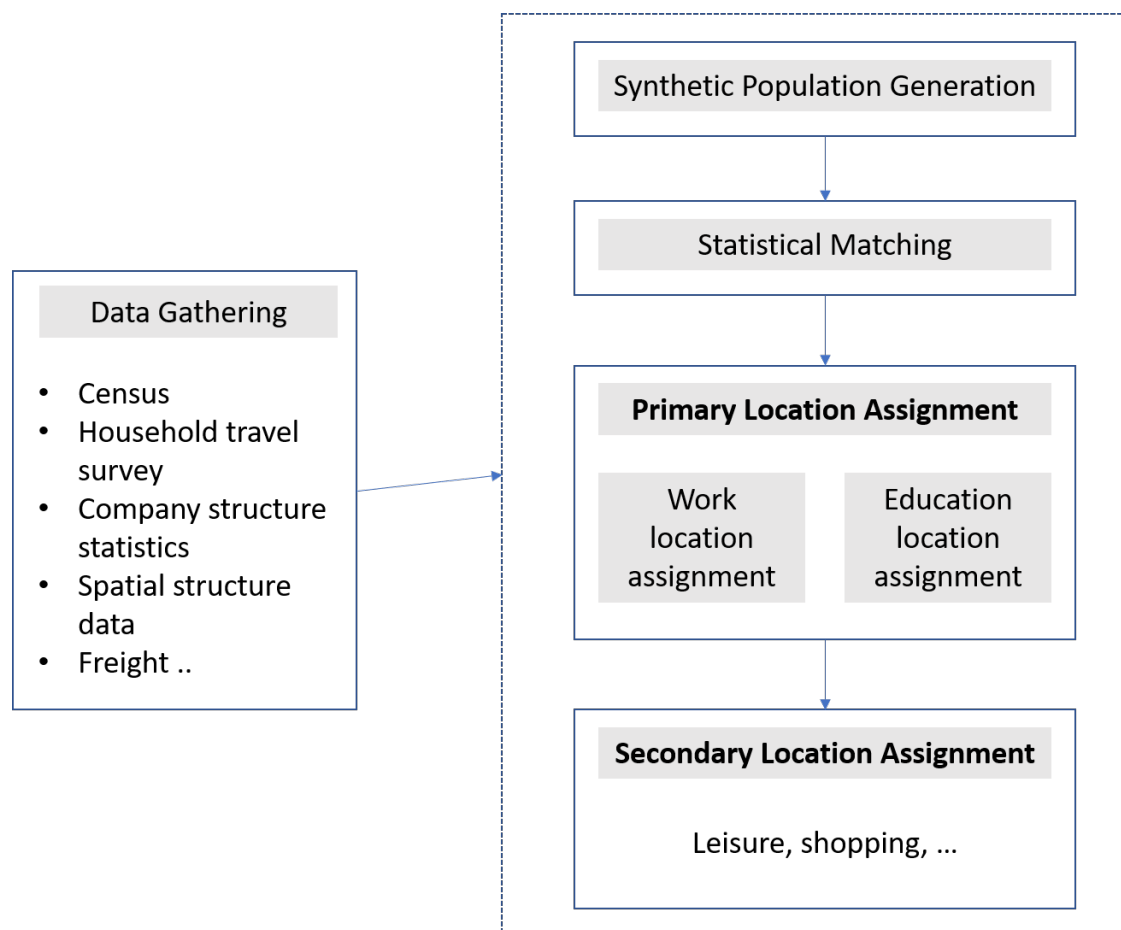


FIGURE 3: The Synthesis process

15 **Synthetic Population Generation:** A synthetic population for Switzerland is generated
 16 from the census data. This involves using household-level and person-level data from the census to
 17 create agents representative of the population. The resulting synthetic population is then enriched

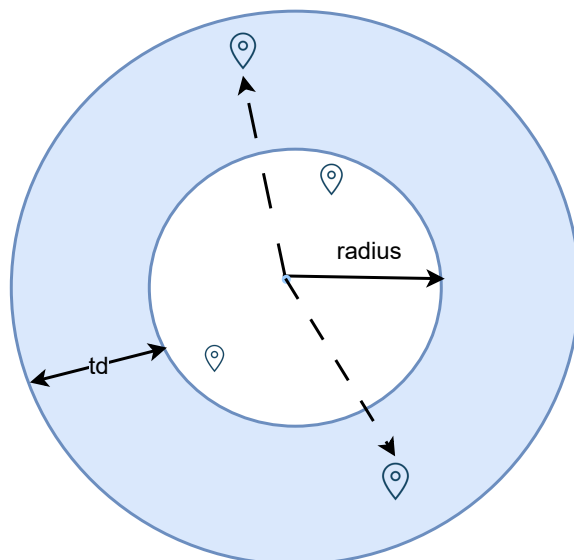


FIGURE 4: Location sampling in doughnut shape region

1 with attributes such as driver's licence and car ownership derived from the Swiss HTS under the
 2 assumption of correlation between these attributes and activity chains. The enrichment process is
 3 detailed in the subsequent section.

4 **Statistical Matching:** This stage involves enriching each agent in the synthetic population
 5 with daily activity chains, which include start and end times, travel distances, and modes. The
 6 enrichment process uses a statistical matching algorithm that matches synthetic agents to observa-
 7 tions in the HTS based on similar attributes (35, 36). For the weekend model, only Saturday and
 8 Sunday activity chains are considered. The matching process is a multi-step process that involves
 9 defining a set of attributes at household and individual levels, noting down attribute vectors for
 10 both target and source observations, and then using a selection set level to sample source obser-
 11 vations based on matching attributes and their weights, with the order of attributes relaxed when
 12 necessary to avoid overfitting. At the household level, five matching attributes, age, sex, type of
 13 residence municipality (urban, suburban or rural), marital status and household size, are used. At
 14 the individual level, additional attributes, household income, number of cars, and number of bikes
 15 are considered. In the matching process, source observations are matched to the target based on
 16 these attributes and use their weights for sampling, while ensuring an adequate number of source
 17 observations to avoid overfitting. After matching, additional attributes are added to the synthetic
 18 persons, and activity chains are attached, detailing the purpose of activities and modes of transport.

19 **Primary Activity Location Assignment:** This stage assigns locations for primary activi-
 20 ties such as home, work, and education. In the weekend model, work and education activity
 21 locations are sampled based on a Swiss-defined facility type and function categorisation (NOGA)
 22 with commute distances that are assigned using a probability distribution derived from House-

1 hold Travel Survey (HTS) data. This approach contrasts with the weekday model, which assigns
2 the nearest facility for commute trips based on Origin-Destination (OD) matrices from the Swiss
3 structural survey data. To reduce selection bias, this stage also involves creating a selection region
4 to choose facilities from, detailed in Figure 4. A unique consideration for the weekend model
5 is the reduced number of education and work trips, which is reflected in the assignment process.
6 Educational facilities active during weekends differ from those during weekdays, leading to addi-
7 tional categorisation of education facilities for the weekend model. Education facilities categories
8 that are considered for the weekend include tertiary schools, driving schools, cultural education,
9 IT training schools, language schools, sports and hobbies schools, adult training and others.

10 **Secondary Activity Location Assignment:** Secondary activities include leisure, shop-
11 ping, and other activities that require multiple places per agent. These activities can be performed
12 in multiple places by each agent. Following a method outlined by Hörl and Axhausen (37), dis-
13 crete locations are assigned to secondary activities whilst maintaining realistic distance distribu-
14 tions given travel times and modes in an activity chain. The output of the synthesis process is a
15 travel demand scenario that can be used as an input to the MATSim simulation.

16 *Validation of the Synthesis Process*

17 It is important for the synthetic population that is generated from the synthesis process to match the
18 overall patterns and capture the variability and distributions observed in real-world data. Figure 15,
19 6a, 15 and 7 and in Appendix 11 show the validation process which demonstrates that the synthetic
20 population generation for the weekend is reasonably successful in replicating the distribution of
21 activity patterns and the travel distances for various purposes, and social demographic groups
22 found in the HTS data.

23 First is an activity chain comparison that shows the distribution of various activity chains
24 for the whole synthetic population and for male, female and age groups above 18 years. This is
25 presented in Figure 15 for Saturday and in Appendix 11. The figures compare the frequency of
26 different activity chains, where each chain represents a sequence of activities, e.g., home-leisure-
27 home (h-l-h) or home-shop-home (h-s-h). The 15 shows that the Saturday trips are mostly leisure
28 trips, as one would expect, with home-leisure-home (h-l-h) and home-shopping-shopping (h-s-h)
29 well represented in the synthetic population. Most activity chains are either under-represented or
30 over-represented, and this is more pronounced when looking at the home activity where people
31 stay at home and also in the sociodemographic grouping for age and gender in Appendix 11.

32 Figure 6a shows the activity counts and Figure 6b shows the activity counts per purpose.
33 The activity counts are done for activities that start from home. For a chain of h-l-h, this chain has
34 only one activity, while a chain of h-s-h-l-h, has three activities.

35 Figure 7 presents a cumulative distance distribution graph for the different activities, com-
36 paring the probability of travel distances between the synthetic population and HTS for different
37 activities. The result shows that the location assignment process performed reasonably well as the
38 synthetic model closely follows the HTS data, although there are a few deviations, particularly for
39 education trips which have very few observations in the travel survey.

40 The validation results suggest that further refinements could be made to improve the fidelity
41 of the weekend synthetic population, particularly in better matching the HTS data for less common
42 activity chains and distribution of activity counts. Still, the results are reasonable for this study and
43 present an opportunity for further calibration to enhance the representativeness of the synthetic
44 population.

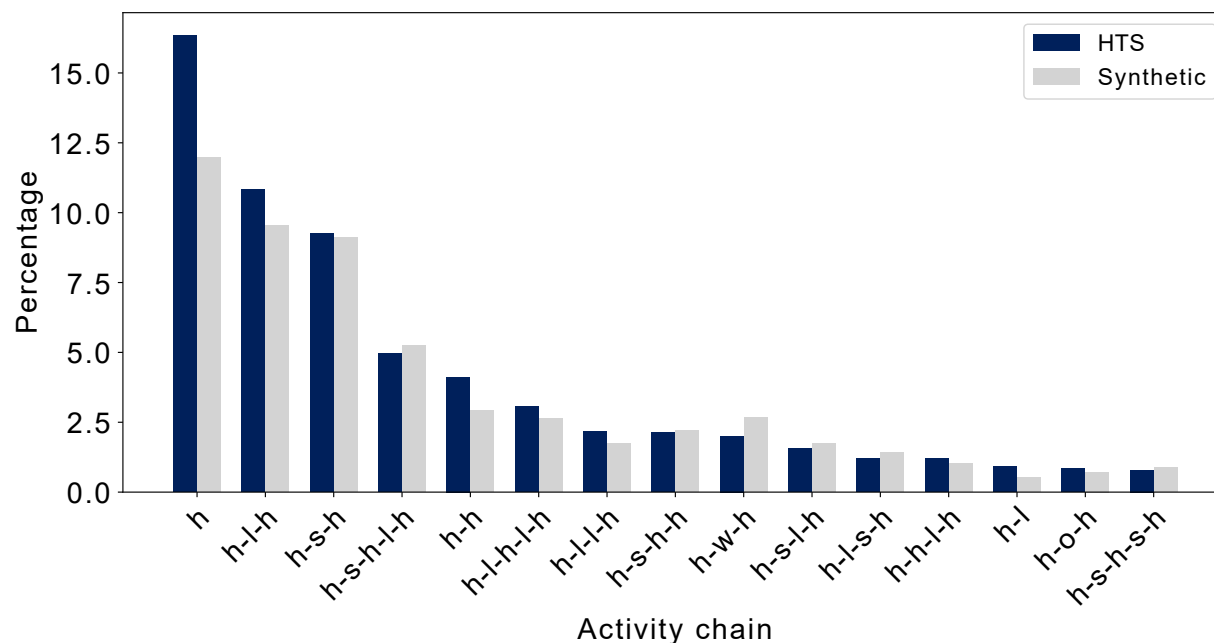


FIGURE 5: Activity chains for Saturday

1 *Weekend mode-choice model*

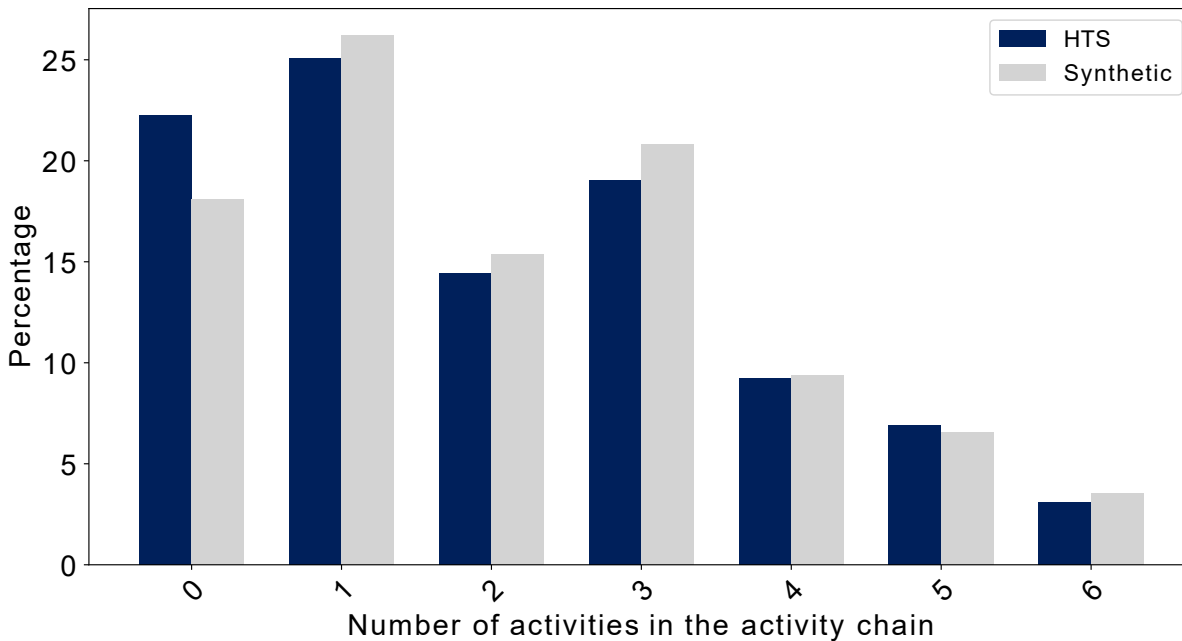
2 To study the transport mode choices that people make, a discrete mode-choice (DMC) extension
3 of MATSim (34, 38) is used, which was already applied to study MoD in Zurich (33).

4 A mode choice model for the average workday in Zurich already exists and is based on
5 an empirical study conducted on mode choice patterns from a stated preference survey of the
6 Zurich region that also considered emerging autonomous mobility (33). Hörl et al. (33) formulated
7 a multinomial discrete choice model with utility equations defined for car, PT, walk, bike, and
8 aMoD and the mode choice variables including in-vehicle travel time, out-of-vehicle travel time
9 (plus wait time and access/egress time), and travel cost. The model formulation can be found in
10 Appendix 10.

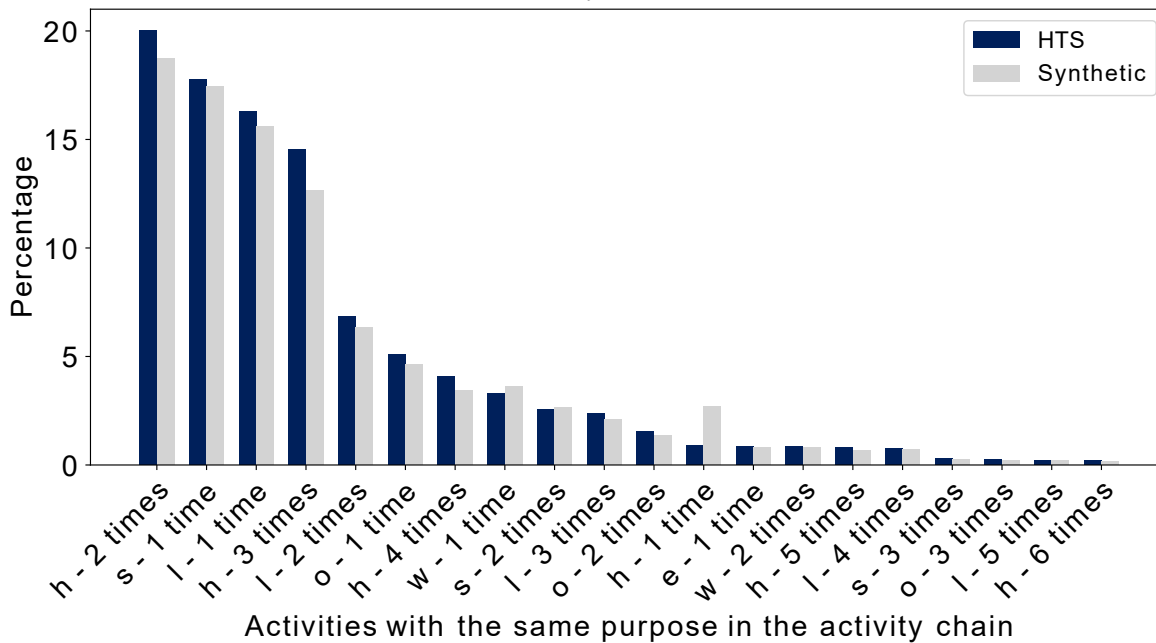
11 For the weekend mode choice model estimation, the estimated average workday model is
12 extended by calibrating the ASCs for each mode of transportation. This process aims to accurately
13 represent the mode shares observed in the HTS during weekends. Applying this method here is
14 based on the assumption that Value of Time (VOTs) and weekend travel dynamics align closely
15 with the average workday. This assumption will be later discussed in this paper.

16 *Calibration*

17 The calibration process for the MATSim simulation was executed without the aMoD service, as
18 aMoD trips are not present in the HTS data and thus cannot be validated. Adjustments were made
19 to the ASCs for car, bike, and walk modes separately for Saturday and Sunday models. The ASC
20 for PT remained at zero, as it served as the reference. These adjustments continued until we
21 achieved a satisfactory alignment of modal shares and mode-specific distances with those recorded
22 in the HTS. This calibration process was implemented to emulate the trip shares that initiate and
23 conclude within our study region.



(a) Activity counts



(b) Activity counts by purpose

FIGURE 6: Number of activities for Saturday

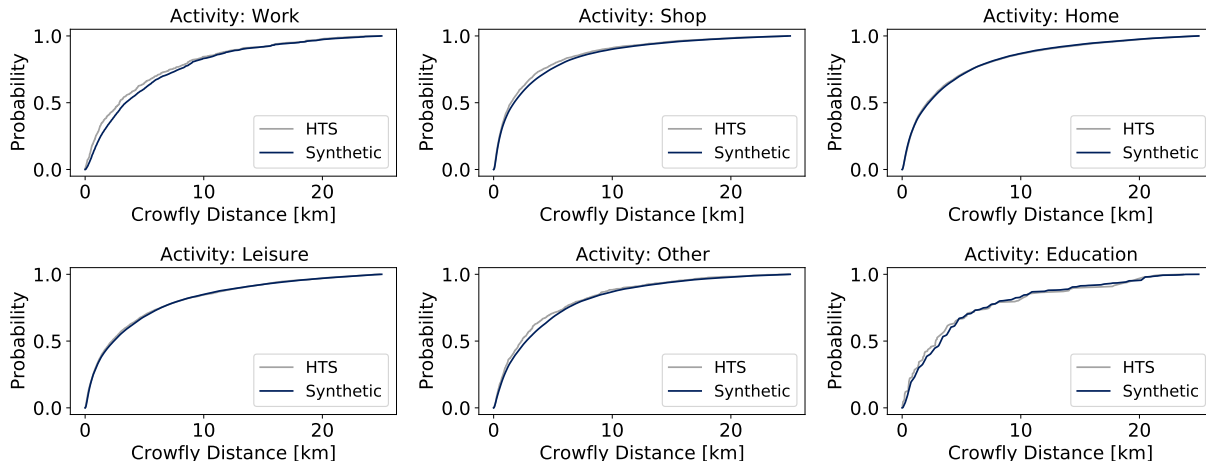


FIGURE 7: Cummulative distance distribution for Saturday

1 The results of this calibration are detailed in Table 1 and Figure 8, which present a compari-
 2 son between the mode shares of the HTS (serving as the reference data) and the calibrated scenario
 3 (Sim). The HTS and simulation data are filtered to include only the trips that occur entirely within
 4 the study region.

5 The primary objective of the initial calibration was to achieve modal shares closely mirror-
 6 ing those of the HTS as shown in Table 1. Simultaneously, the second calibration objective was
 7 to ensure a reasonable distribution of distances per mode. Given the lack of reference data for
 8 trips exceeding 7km—about 40 observations—we constrained our calibration by only comparing
 9 distances up to 7.5km. This ensured that our simulation data adhered closely to the curve shape
 10 of the reference data. Figure 8 illustrates the modal shares of the calibrated modes, with distances
 11 segmented into 1km bins.

	Avgday	Saturday	Sunday
$\beta_{ASC,car}$	-0.8	-1.6108	-1.6632
$\beta_{ASC,bicycle}$	0.1522	-0.640	-1.575
$\beta_{ASC,walk}$	0.5903	-0.305	-0.6875

TABLE 1: Updated parameters from average workday model

12 Weekend Simulation of MoD

13 In this study, the representation of a MoD service utilizes the MATSim Demand-Responsive Tran-
 14 sit (DRT) extension (39). The DRT extension was specifically developed to enable MATSim to
 15 simulate dynamic ridesharing services, where vehicles can pick up and drop off passengers upon
 16 request. A central dispatching system manages the fleet of vehicles and is responsible for schedul-
 17 ing and accepting incoming requests.

18 When a request is made, the dispatcher is presented with a list of available vehicles. The
 19 dispatcher algorithm traverses the list and assigns each request to the closest vehicle while ensur-
 20 ing that predefined constraints on wait and detour times for passengers are not violated. These

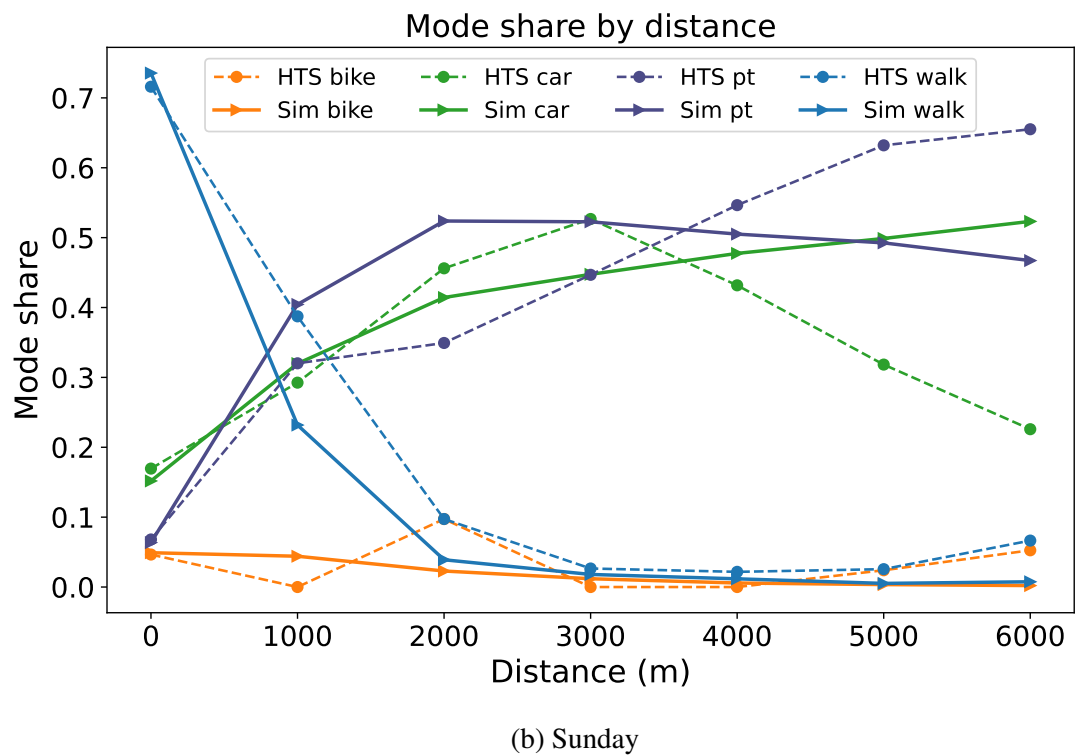
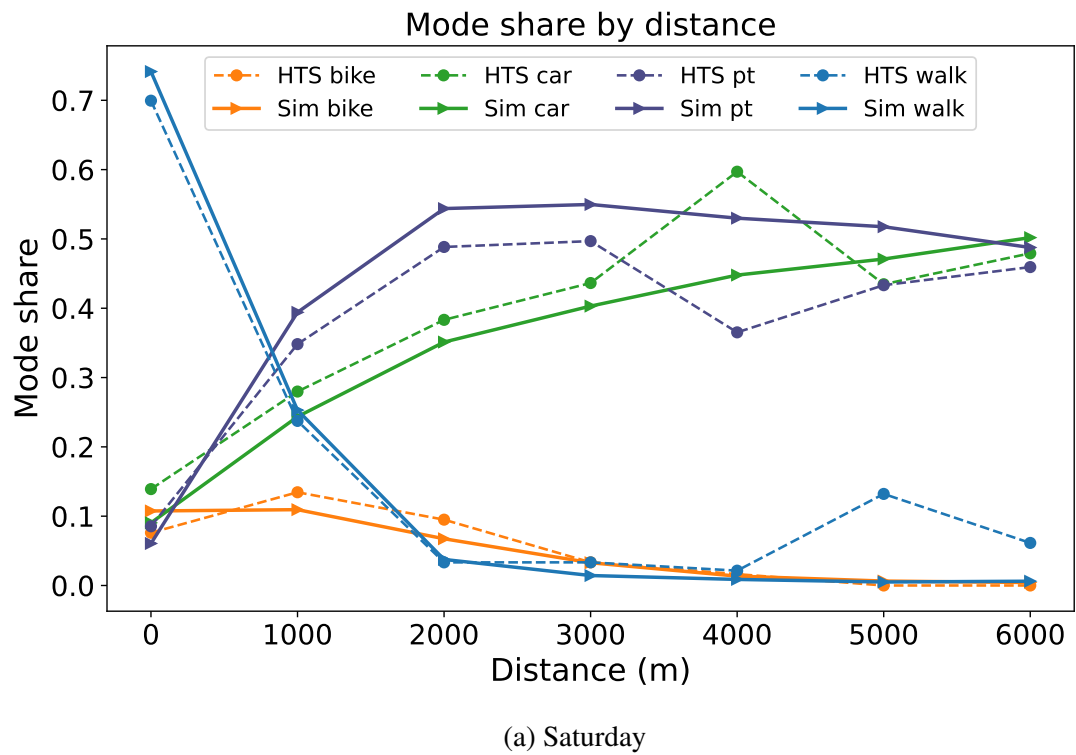


FIGURE 8: Mode share by distance from the calibration process

1 constraints include: (1) ensuring that the overall travel time for passengers, including those cur-
 2 rently in the vehicle or waiting for the vehicle, and the new customer, does not exceed predefined
 3 thresholds, and (2) ensuring that the expected boarding times for awaiting customers and the new
 4 customer fall within a requested time frame. If no suitable vehicle is available, the request is
 5 rejected. For further details on the DRT extension, refer to Bischoff et al. (39).

6 The MoD service offers a convenient door-to-door experience and allows for pooling, with
 7 a maximum seating capacity of four people. The service has a defined coverage area for only trips
 8 originating and ending within the study region. The service is not available for trips shorter than
 9 250 meters in Euclidean distance.

10 *MoD mode choice:* For the MoD service, the utility is calculated based on Equation 1. The
 11 equation includes x variables, which represent estimated trip level attributes such as travel time
 12 and wait time. The β represents behavioural parameters that are estimated from empirical studies
 13 and quantify the share of the mode in the overall generalized costs for the trip. The ξ represents
 14 the elasticities of Euclidean distance on travel time (ξ_{TD}), cost (ξ_{CD}), and household income (ξ_{CI}).
 15 The variables used to define trip purposes or location are represented with x_{work} and x_{city} . The
 16 model parameters in Equation 1 are listed in Table 4 in Appendix 10.

$$\begin{aligned}
 \tilde{v}_{AMoD}(\mathbf{x}) = & \beta_{ASC,AMoD} \\
 & + \beta_{inVehicleTime,AMoD} \cdot \xi_{TD} \cdot x_{inVehicleTime,AMoD} \\
 & + \beta_{accessEgressTime,AMoD} \cdot x_{accessEgressTime,AMoD} \\
 & + \beta_{waitingTime,AMoD} \cdot x_{waitingTime,AMoD} \\
 & + \beta_{work,AMoD} \cdot x_{work} \\
 & + \beta_{highAge,AMoD} \cdot [a_{age} \geq 60] \\
 & + \beta_{cost} \cdot \xi_{CD} \cdot \xi_{CI} \cdot x_{cost,AMoD}
 \end{aligned} \tag{1}$$

18 Travel times and costs are provided by the MATSim network router, which is estimated dy-
 19 namically during the simulation's evolution depending on traffic, the number of vehicles, pricing,
 20 departure time, etc. Wait times and additional delays for the MoD service observed throughout
 21 the day are fed back into the choice model based on the estimation of the average wait times per
 22 defined zones and time intervals. This is to add additional behavioural realism as travellers make
 23 decisions; they should be informed by the operator of the expected wait time or delays in their
 24 area and during the time of day that they would make the trip so as to decide to use the service.
 25 Therefore during every iteration of the mobility simulation, wait times and travel time information
 26 of agents who use the MoD service are tracked for each time interval and zone. Then the mean is
 27 calculated over all waiting times and delays experienced in the zone. When no waiting is observed
 28 in a zone and time interval in a particular iteration, the existing value is maintained, and in the case
 29 when none exists, a default wait time of 10 minutes is applied. After different sensitivity analyses,
 30 a square grid size of 1km is used with a time interval of 15 minutes.

31 Additionally, since a door-to-door DRT scheme is applied in this study, there is no access
 32 or egress time, and the parameter is set to zero. The cost is taken from the study by (33) where 0.6
 33 CHF/person km is determined to cover the cost of operating a 4000 fleet for Zurich city. This is
 34 reasonable to use across the different fleet sizes as the study by Bösch et al. (40) estimated that the
 35 cost of taxi services would be about 0.41 CHF/person km for the canton of Zurich.

1 **Simulation Scenarios**

2 This study focuses on the potential impact of considering weekend travel demand when modelling
3 MoD services. Focusing on the weekend demand aims to address a gap in the current research
4 landscape and explore an important aspect of operational planning for on-demand services.

5 A baseline scenario which represents the current travel demand state without the MoD
6 service is defined for each of the modelled days: an average workday, Saturday and Sunday. The
7 transport network encompasses a comprehensive representation of the study area, including its road
8 infrastructure and transit lines. Different transit schedules have been generated for the weekend,
9 using the 18th and 19th of January 2020 for Saturday and Sunday, respectively, and the 15th of
10 January 2020 (a Wednesday) to represent a typical workday.

11 Eight MoD service scenarios are defined for each of the simulation days. Each MoD sce-
12 nario is differentiated by simulating different fleet sizes ranging from 3,000 to 10,000 in 1,000
13 intervals. See Table 2

TABLE 2: Simulation scenarios

Scenario	Simulation Day	MoD Fleet Size Range
Baseline	Average workday, Saturday, Sunday	N/A (No MoD)
MoD Scenario 1-8	Average workday, Saturday, Sunday	3,000 - 10,000

14 The study focuses on the following areas:

- 15 • Operational planning policies: The impact of various fleet sizes on the MoD level of
16 service and vehicle utilization is examined.
- 17 • Service reliability and availability: How the demand varies temporarily and spatially
18 between the days, which can affect service reliability.
- 19 • Policy and planning implications: The implications for transport policies on modal shifts
20 are drawn out by examining how the shifts occur for the different days modelled and
21 potentially revealing why.

22 **RESULTS**

23 The following section presents the results for the scenarios simulated, providing insights into the
24 impact of weekend travel demand on service reliability, operational planning policies, and policy
25 implications.

26 **Operational Planning Policies**

27 The operational planning policies of MoD services, particularly fleet sizing, are examined here
28 in regards to the weekend travel demand. Figure 9 shows the influence of varying fleet sizes on
29 the level of service metrics, which reveals potential impacts on MoD's operational efficiency and
30 effectiveness during weekends.

31 Since the fare structure is fixed at a rate of 0.6 CHF/km, regardless of the fleet size, one
32 can examine how the fleet size is influenced by demand patterns across different days, allowing
33 for insights into how potential users may weigh service wait times and delays against the utility of
34 alternative modes of transport. It can be observed that the demand patterns are different depending
35 on the day. Thus, the number of vehicles required to provide reliable service varies with the
36 fluctuating demand. By considering these different demand patterns, we can better address the
37 crucial question of the optimal fleet size. For example, Saturday and Sunday, which have a higher

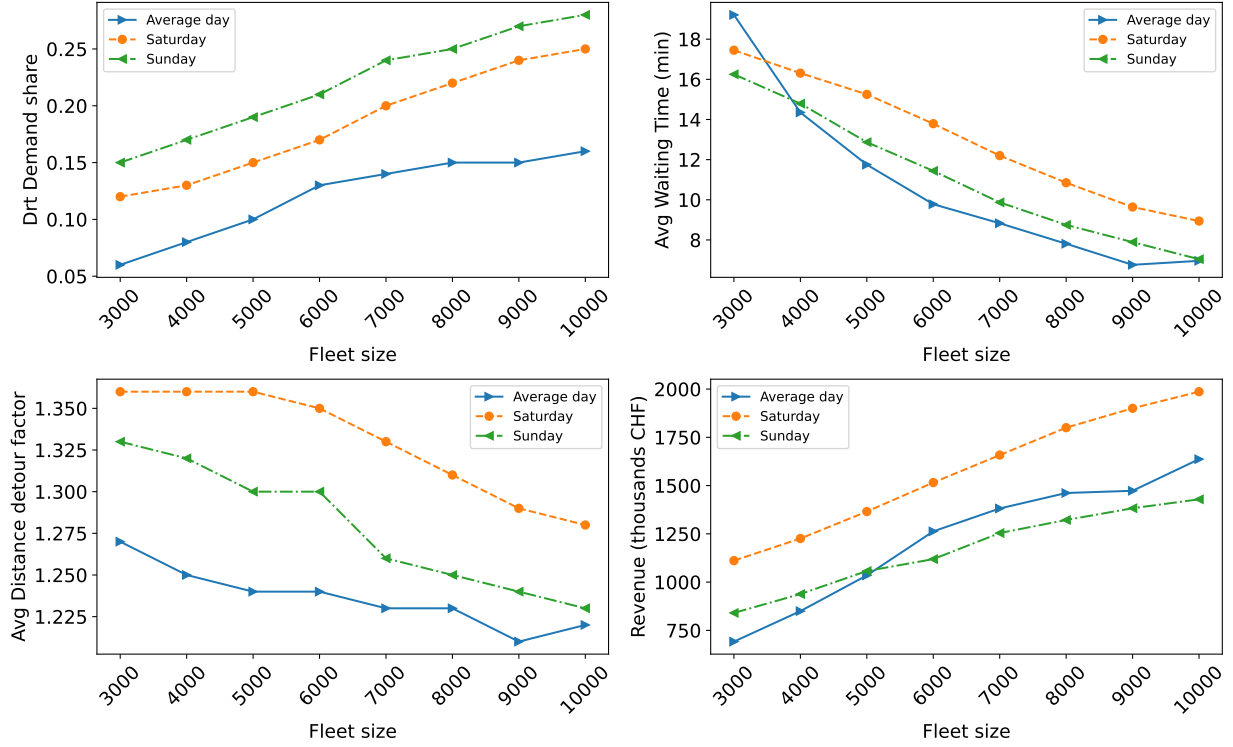


FIGURE 9: Service level metrics by fleet size

1 demand for the MoD service, do not necessarily have a larger difference in wait times than the
 2 average day; however, the travellers may experience longer delays during the weekends, possibly
 3 due to the spatial distribution of the demand and is reflected in the longer detours for the average
 4 work day. Furthermore, distances travelled on Saturday are longer, bringing in more revenue that
 5 could cover operational costs.

6 Similarly, Figure 10 highlights how various fleet sizes perform in key areas, travel distance,
 7 operational cost, empty distance travelled and vehicle occupancy and operational performance
 8 metrics that contribute to decision-making concerning fleet sizing and operational cost. The cost
 9 of maintaining a fleet of vehicles is calculated using the cost calculator suggested by Bösch et al.
 10 (40) and adapted in Hörl et al. (33) where the authors feed the Bösch et al. (40)'s cost model
 11 with measured values from an agent-based transport simulation, as opposed to using "best-guess"
 12 predictions for fleet utilization and empty distances.

$$13 \quad C_{fleet} = c_{perDistance} \cdot d_{fleetDistance} + c_{perTrip} \cdot n_{numberOfTrips} + c_{perVehicle} \cdot n_{fleetSize} \quad (2)$$

14 where $d_{perDistance}$ describes the total fleet distance, $n_{numberOfTrips}$ describes the total num-
 15 ber of rides given, and $n_{fleetSize}$ describes the number of vehicles in the fleet. The following cost
 16 units are used:

$$17 \quad c_{perDistance} = 0.098 \text{ CHF/km}$$

$$18 \quad c_{perTrip} = 0.375 \text{ CHF}$$

$$19 \quad c_{perVehicle} = 33.30 \text{ CHF (per day)}$$

20 From an operator's standpoint, tracking distances, costs, and vehicle occupancy are essen-
 21 tial to ensure optimal fleet performance at a minimal cost. For instance, although the average day

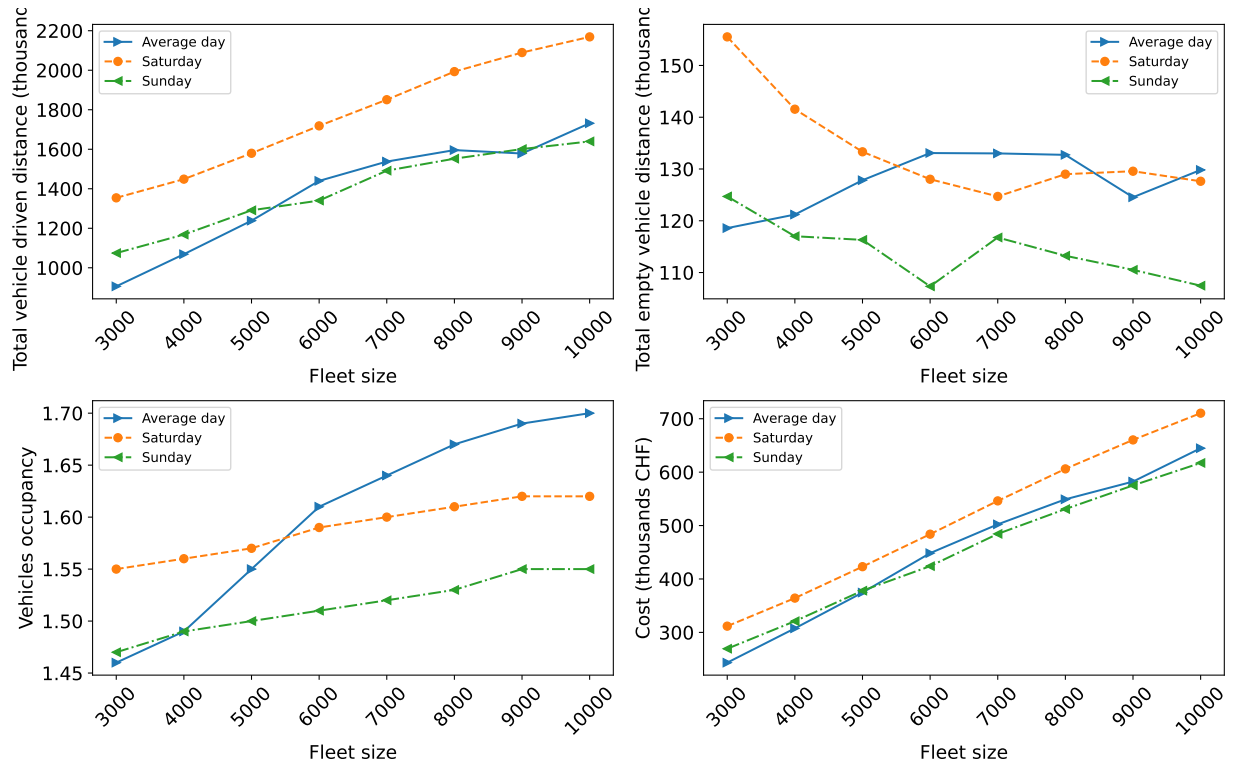


FIGURE 10: Vehicle operational performance by fleet size

1 and Sunday demonstrate similar trip distances compared to Saturday, the 'empty' distances vary,
 2 likely owing to differing demand densities. This observation is supported by the vehicle occupancy
 3 results, which hint at increased ride pooling for Saturday and very low pooling for Sunday. No-
 4 tably, this study does not account for group travel, implying that for weekend trips, which have a
 5 higher potential for group travel, the vehicle occupancy could be underestimated.

6 Operational costs play a critical role in determining fleet size. While having enough ve-
 7 hicles to minimise wait times and delays is essential, maintaining the fleet's costs is equally im-
 8 portant. The results show the costs between the average day and weekend are not very different.
 9 Saturday only incurs on average about a 10% increase in cost compared to Sunday and an aver-
 10 age day. However, this higher expenditure is offset by the increased revenue generated over the
 11 weekend.

12 If using empty vehicle distance and vehicle occupancy as a determinant of a reasonable
 13 fleet size that can serve the different days, one can see that if only the average day is considered,
 14 the size of the fleet that would be selected would be different than when the weekend is considered.
 15 Furthermore, Table 3 illustrates the operational performance across different days for a fleet size
 16 of 5000. By examining the empty distance ratio and net income, the cost of operating this fleet
 17 can be covered by the revenue generated on all the days, with an average wait time of 15 minutes
 18 across all days. Consequently, this fleet size is utilised in the subsequent analysis.

19 **Service Reliability and Availability**

20 This section presents the findings related to the service reliability and availability of the MoD
 21 service, specifically focusing on the impact of weekend travel demand. The analysis looks at

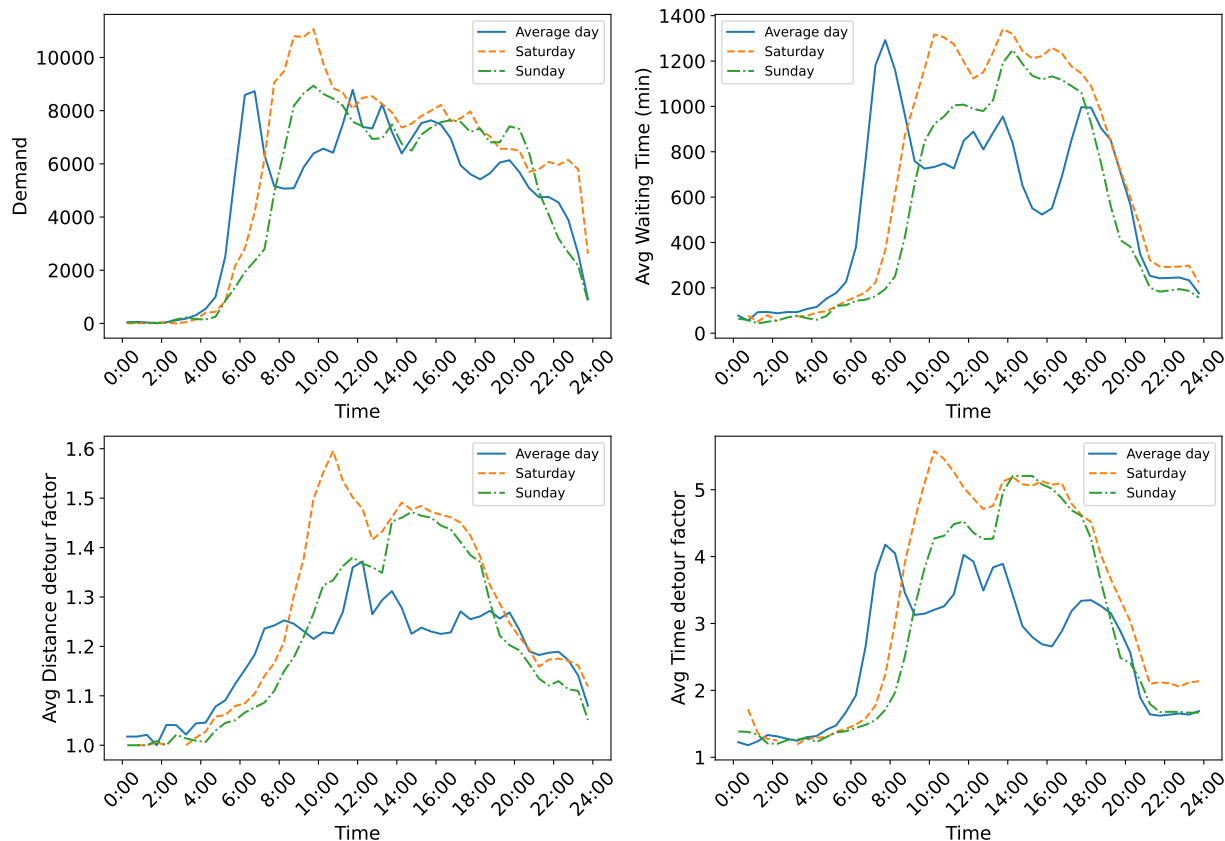


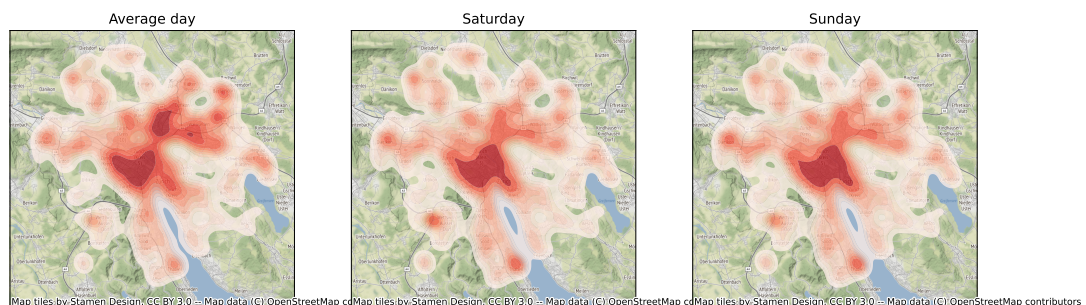
FIGURE 11: Temporal distribution of travel patterns

1 how reliable the service is over the different days of the week, both temporally and spatially, by
 2 identifying demand peaks. This helps to examine how the fluctuating demand during the weekends
 3 might affect service reliability in comparison to the weekday and then be able to identify the
 4 specific time slots or regions that experience higher demand and may require additional attention.
 5 As expected, from Figure 11, the average day has distinct peaks following the typical morning and
 6 afternoon commute patterns in Switzerland, compared to the weekend, although the evening peak
 7 is missing. However, for the weekend, one can observe that trips start a bit later, and the demand
 8 is almost flat most of the day, especially for Sunday. What is also noticeable is that wait times and
 9 delays are higher towards the evening period, and this could be in effect due to overall congestion
 10 of the roads from car users.

11 Similarly, the spatial distribution of demand differs between the weekday and weekends, as
 12 can be seen from Figure 12. One can observe two clusters of originating MoD trips for the average
 13 day (Zurich city centre and Oerlikon) compared to weekends where trips are concentrated in the
 14 centre. This makes sense as Oerlikon is a commercial centre which would attract commuting trips
 15 that use MoD. Considering these differences in temporal and spatial patterns, attention needs to
 16 be paid to the outcomes of dispatching and rebalancing methods to account for these differences,
 17 among other factors.

TABLE 3: Operational performance for the scenario with a fleet size of 5000

Metric	Average day	Saturday	Sunday
Demand	231166	271291	226842
Avg Waiting Time (min)	11.75	15.25	12.87
Avg Distance detour factor	1.24	1.36	1.3
Avg Time detour factor	2.98	4.04	3.69
Passenger Distance (thousands pkm)	1724.59	2275.68	1762.4
Total vehicle driven distance (thousands km)	1238.5	1579.7	1291.04
Total vehicle occupied distance (thousands km)	1110.67	1446.39	1174.73
Total empty vehicle distance (thousands km)	127.83	133.32	116.31
Empty ratio	0.1	0.08	0.09
Rejections	0	0	0
Rejections rate	0	0	0
Avg Travel time (min)	20.57	17.1	15.56
Cost (thousands CHF)	374.56	423.05	378.09
Revenue (thousands CHF)	1034.75	1365.41	1057.44
Net income (thousands CHF)	660.19	942.36	679.35

**FIGURE 12:** Spatial distribution of on-demand mobility trips

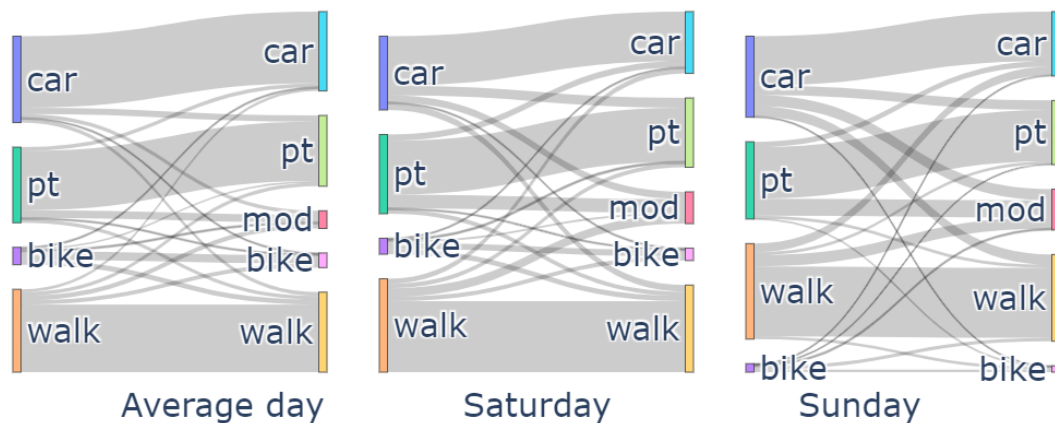


FIGURE 13: Modal shift dynamics between the baseline scenario and MoD scenario

1 Policy and Planning Implications

2 This section discusses the policy and planning implications of the study's findings with a focus on
 3 modal shift analysis. The analysis examined how weekend travel demand affected modal shifts,
 4 considering whether individuals were more inclined to switch from private vehicles or other travel
 5 modes to MoD services during weekends. To do this, MoD trips in a selected MoD scenario for
 6 each day of the week are identified in the baseline scenarios where there was no MoD service. The
 7 set of trips is compared, and the results of this analysis are shown in Figures 13 and 14. First, from
 8 the Sankey diagram presented in Figure 13 one can see how much private car mode is shifting to
 9 the MoD service compared to PT and active modes. While one can observe that more PT trips are
 10 being replaced during the weekend. The reason for this can be observed in Figure 14, which shows
 11 that travellers shift from PT to the MoD service mostly for long-distance trips during the weekend
 12 compared to the shift from private cars.

13 These findings contribute to a deeper understanding of the challenges and opportunities
 14 associated with incorporating weekend travel demand in the modelling and planning of MoD ser-
 15 vices, ultimately informing policy and decision-making processes in the field of urban mobility.

16 DISCUSSION AND CONCLUSION

17 The study's hypothesis centred around the relevance of including weekend travel data for effective
 18 MoD operational planning and policy decisions, is supported by the evidence produced in the study.
 19 The role of weekend travel demand in MoD service efficiency was examined through various key
 20 areas: operational planning policies, service reliability and availability, and policy and planning
 21 implications.

22 The results presented the nuances of weekend travel demand and its impact on MoD simu-
 23 lations. Variations in demand patterns across the days of the week were shown to affect the choice
 24 of the optimal fleet size required to deliver reliable service. Unsurprisingly, the weekend, particu-
 25 larly Saturday, showed higher demand levels for MoD services. It was observed that the increase in
 26 demand during weekends did not dramatically alter wait times compared to weekdays. However,
 27 there were longer delays, potentially attributed to the differing spatial distribution of demand. The

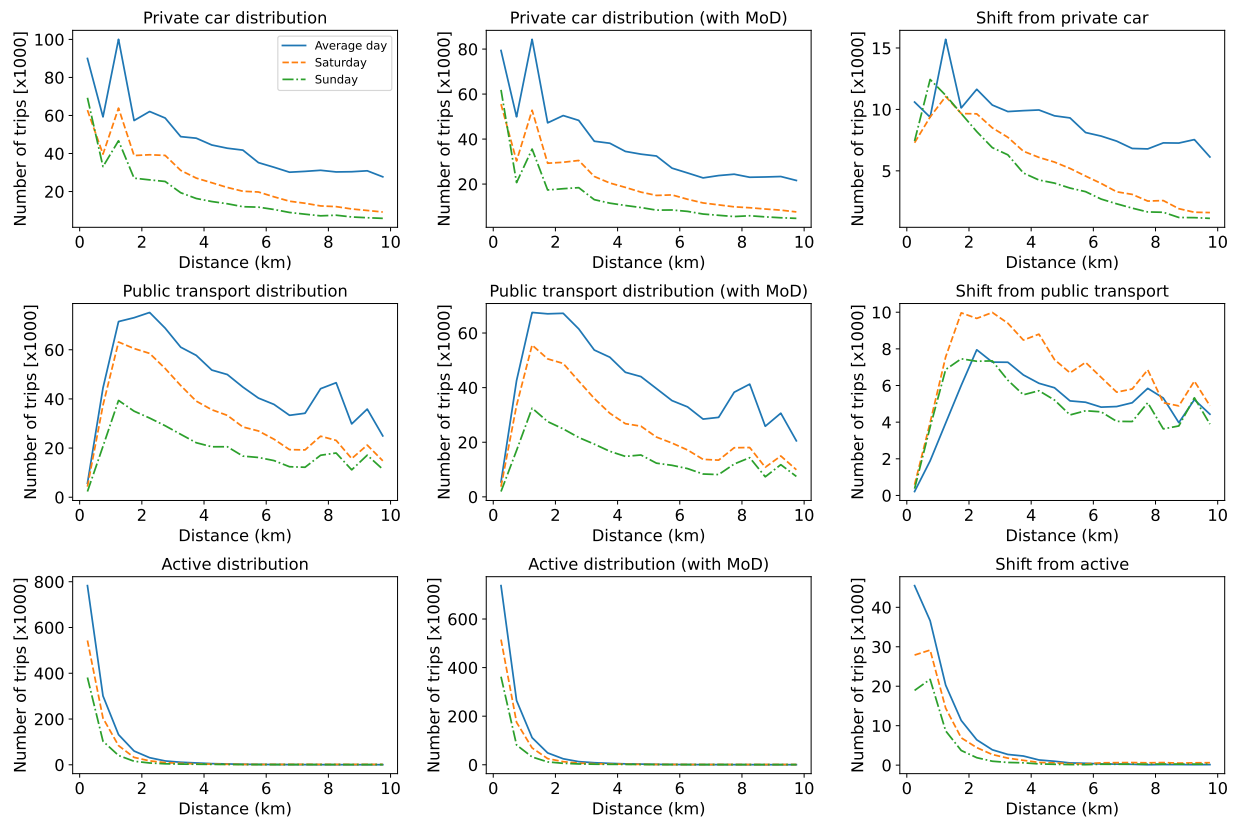


FIGURE 14: Distance distribution of trips by modal shifts

1 importance of considering such variations when deciding on fleet size becomes apparent, as the
2 optimal fleet size would be different if only weekdays were considered.

3 The cost analysis showed that the operational cost of the fleet doesn't vary much between
4 the average day and the weekend. Although Saturday showed a slight increase in cost, the corre-
5 sponding increase in revenue more than compensated for this, choosing a larger fleet expenditure
6 to accommodate weekend demand to be potentially worthwhile.

7 Analysing the service reliability and availability revealed distinct patterns in the tempo-
8 ral and spatial distribution of the demand between weekdays and weekends. While weekdays
9 saw peak demand times aligning with typical commute hours, weekend demand started later and
10 remained consistent throughout the day. Also, two major clusters were identified for weekdays
11 (Zurich city centre and Oerlikon), while weekend trips were more centralised. These patterns
12 provide valuable input for refining dispatching and rebalancing methods in the MoD operational
13 strategy. In looking at modal shift to MoD service, particularly over the weekends. Modal shifts
14 from private car, PT and active modes were observed, especially for long-distance PT trips.

15 In conclusion, including weekend travel demand in MoD simulations is essential for trans-
16 port planning. By considering weekend travel demand, MoD services can be optimised to meet
17 varying patterns of demand effectively, resulting in enhanced operational efficiency and service re-
18 liability. Furthermore, weekend travel demand data can inform policy decisions about encouraging
19 a shift away from private vehicle use towards more sustainable modes.

20 While informative, the results of this study should be interpreted with a degree of caution.
21 Certain limitations are worth noting. A major limitation of the study is estimating the weekend
22 mode choice model, whereby an existing average workday model has been extended by calibrating
23 the ASCs of the different modes to represent mode shares observed in the HTS for the weekends.
24 Using the same VOTs for the weekday and weekends supposes that the behavioural preferences
25 that determine the mode of transport on weekdays remain constant and extend to the weekends.
26 However, it is important to note that this assumption may oversimplify the complexities of travel
27 behaviour (41, 42). As a result, using weekday VOTs to calibrate weekend models could introduce
28 bias and potential inaccuracies into the model. However, using average weekday VOTs is practical
29 without specific weekend survey data. Therefore, future research in this area should address this
30 limitation identified in this study. Collecting specific weekend travel data to calibrate weekend
31 models more accurately would be beneficial. Alternatively, a mixed-mode choice model could be
32 explored, which allows for heterogeneity in VOT across individuals and potentially captures the
33 variances between weekday and weekend travel behaviours as well as accounting for trip purposes.

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37 **AUTHOR CONTRIBUTION STATEMENT**

38 The authors confirm their contribution to the paper as follows: Study conception and design:
39 G.O Kagho, M. Balac, K.W. Axhausen; analysis and interpretation of results: G.O Kagho; draft
40 manuscript preparation: G.O. Kagho, M. Balac, K.W. Axhausen. All authors reviewed the results
41 and approved the final version of the manuscript.

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27 APPENDIX

28 MODE CHOICE MODEL FORMULATION FOR ZURICH REGION

29 The mode choice model estimation for the weekend is based on the average workday model devel-
 30 oped from an empirical study conducted on mode choice patterns from a stated preference survey
 31 of the Zurich region that also considered emerging autonomous mobility Hörl et al. (33). Hörl
 32 et al. (33) formulated a multinomial discrete choice model with utility equations defined for car,
 33 PT, walk, bike, and aMoD.

34 The model equations are presented in Equations 3, 6, 7, and 8 and the corresponding pa-
 35 rameter values are presented in Table 4. Within the model, the utility U_i is computed for each mode
 36 (i), while choice variables are represented as x . The marginal utility parameters are denoted as β ,
 37 and the alternative specific constants (ASCs) are denoted as $\beta_{ASC,i}$. The mode choice variables
 38 encompass factors such as in-vehicle travel time, out-of-vehicle travel time (including wait time
 39 and access/egress time), and travel cost. The $\beta_{ASC,car}$ had to be adjusted from 0.223 shown in Table
 40 4 to -0.8 to achieve a good model fit. This is explained in detail in Hörl et al. (33).

41 The utility for *car* is defined by the equation

$$\begin{aligned}
u_{car} = & \beta_{ASC,car} \\
& + \beta_{inVehicleTime,car} \cdot \xi_{TD} \cdot x_{inVehicleTime,car} \\
& + \beta_{work,car} \cdot x_{work} + \beta_{city,car} \cdot x_{city} \\
& + \beta_{cost} \cdot \xi_{CD} \cdot \xi_{CI} \cdot x_{cost,car}
\end{aligned} \tag{3}$$

2 The attribute x_{work} defines whether the trip originates or ends at a *work* activity, and the
3 attribute x_{city} describes whether the trip starts or ends inside of the city area of Zurich. ξ_{TD} , ξ_{CD}
4 and ξ_{CI} are elasticities of Euclidean distance on travel time and on cost and elasticity of household
5 income on cost and they are defined in the utility equations where λ describes additional model
6 parameters that need to be estimated.

$$\xi_{TD} = \left(\frac{x_{euclideanDistance}}{\theta_{referenceDistance}} \right)^{\lambda_{TD}} \quad \text{and} \quad \xi_{CD} = \left(\frac{x_{euclideanDistance}}{\theta_{referenceDistance}} \right)^{\lambda_{CD}} \tag{4}$$

$$\xi_{CI} = \left(\frac{a_{householdIncome}}{\theta_{referenceIncome}} \right)^{\lambda_{CI}} \tag{5}$$

9 The utility for *PT*:

$$\begin{aligned}
u_{pt} = & \beta_{ASC,pt} \\
& + \beta_{inVehicleTime,train} \cdot \xi_{TD} \cdot x_{inVehicleTime,train} \\
& + \beta_{inVehicleTime,other} \cdot \xi_{TD} \cdot x_{inVehicleTime,other} \\
& + \beta_{inVehicleTime,feeder} \cdot x_{inVehicleTime,feeder} \\
& + \beta_{waitingTime,pt} \cdot x_{waitingTime,pt} \\
& + \beta_{accessEgressTime,pt} \cdot x_{accessEgressTime,pt} \\
& + \beta_{headway,pt} \cdot x_{headway,pt} \\
& + \sum_G \beta_{pt\ quality,G} \cdot x_{pt\ quality,G} \\
& + \beta_{cost} \cdot \xi_{CD} \cdot \xi_{CI} \cdot x_{cost,pt}
\end{aligned} \tag{6}$$

11 $x_{inVehicleTime,train}$ is the time a traveler spends in a train. Whereby there are additional feeder
12 modes such as buses or trams to a train, $x_{inVehicleTime,feeder}$ is considered as the travel time in these
13 feeder modes, while $x_{inVehicleTime,other}$ is zero. In the absence of a rail leg on the chosen route, travel
14 time in busses, trams or ferries is considered as $x_{inVehicleTime,other}$ while $x_{inVehicleTime,feeder}$ is set to
15 zero.

16 The attribute $x_{ptQuality}$ quantifies the accessibility to public transport at any place in Switzer-
17 land as defined by the Federal Office of Land Use in Switzerland, based on proximity to PT
18 stops and stations and the frequency of the respective lines. It is defined on five levels $G \in$
19 $\{A, B, C, D, \text{None}\}$ with A as the highest.

1 The utility for cycling:

$$\begin{aligned}
 u_{bicycle} = & \beta_{ASC,bicycle} \\
 & + \beta_{travelTime,bicycle} \cdot \xi_{TD} \cdot x_{travelTime,bicycle} \\
 & + \beta_{highAge,bicycle} \cdot [a_{age} \geq 60]
 \end{aligned} \tag{7}$$

3 where a represents agent-level attributes, in this case, the age of each agent.

4 The utility for walking is defined as:

$$\begin{aligned}
 u_{walk} = & \beta_{ASC,walk} \\
 & + \beta_{travelTime,walk} \cdot \xi_{TD} \cdot x_{travelTime,walk}
 \end{aligned} \tag{8}$$

6 There was a need to correct for an increased attractiveness of the walk mode, therefore
 7 Equation 8 was adjusted by including an additional penalty term. For shorter travel time, the
 8 penalty tends to zero while for travel time equal to the threshold of 120 minutes, there is a large
 9 offset of -100 as shown in Equation 9

$$u_{walk_i} = u_{walk} - \exp\left(\log 10 \cdot \frac{x_{travelTime, walk}}{\theta_{walkThreshold}}\right) + 1 \tag{9}$$

11 VALIDATION OF THE SYNTHESIS PROCESS FOR WEEKEND SYNTHETIC POPU- 12 LATION

13 The validation of the synthetic population generation process for Sunday is shown in the following
 14 figures below, which consist of the activity chains, activity counts and distance distribution com-
 15 parisons between the household travel survey data and the generated synthetic travel demand for
 16 Saturday and Sunday. The process outline in the Methodology appears to capture the overall trends
 17 in activity patterns and travel distances but reveals discrepancies in the representation of certain
 18 activity chains and counts, especially when looking at specific demographic groups. Considering
 19 the age and gender aspect, it is clear that the synthetic model may need more nuanced behavioural
 20 patterns specific to different demographic groups.

21 Activity Chains

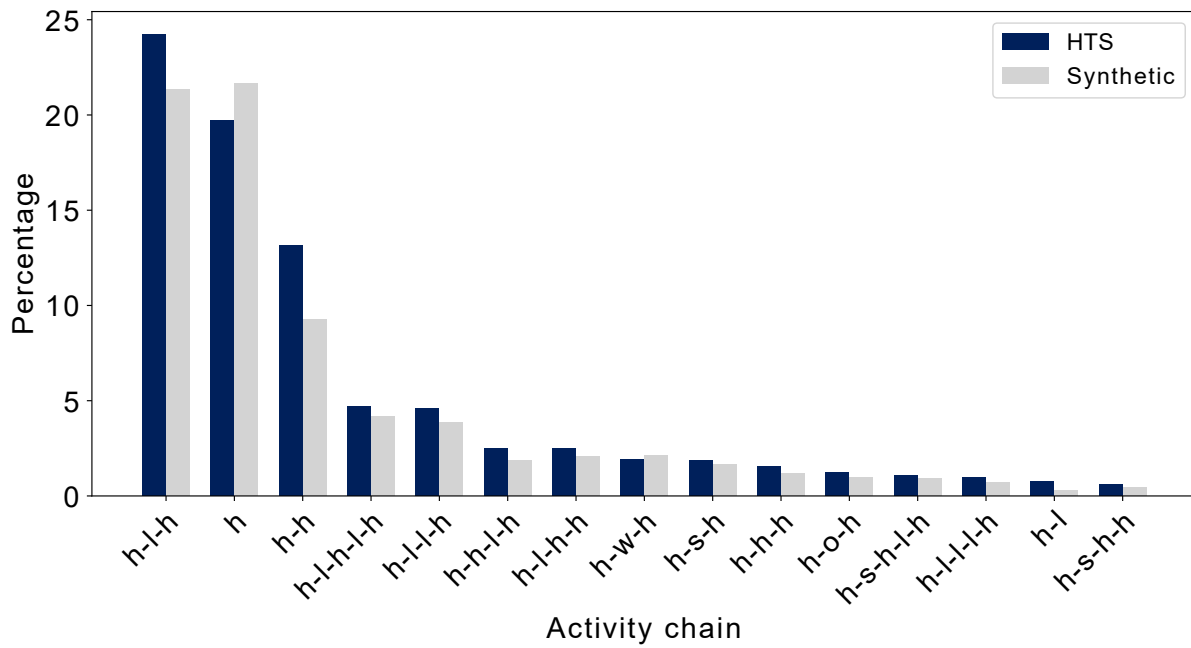


FIGURE 15: Activity chains for Sunday

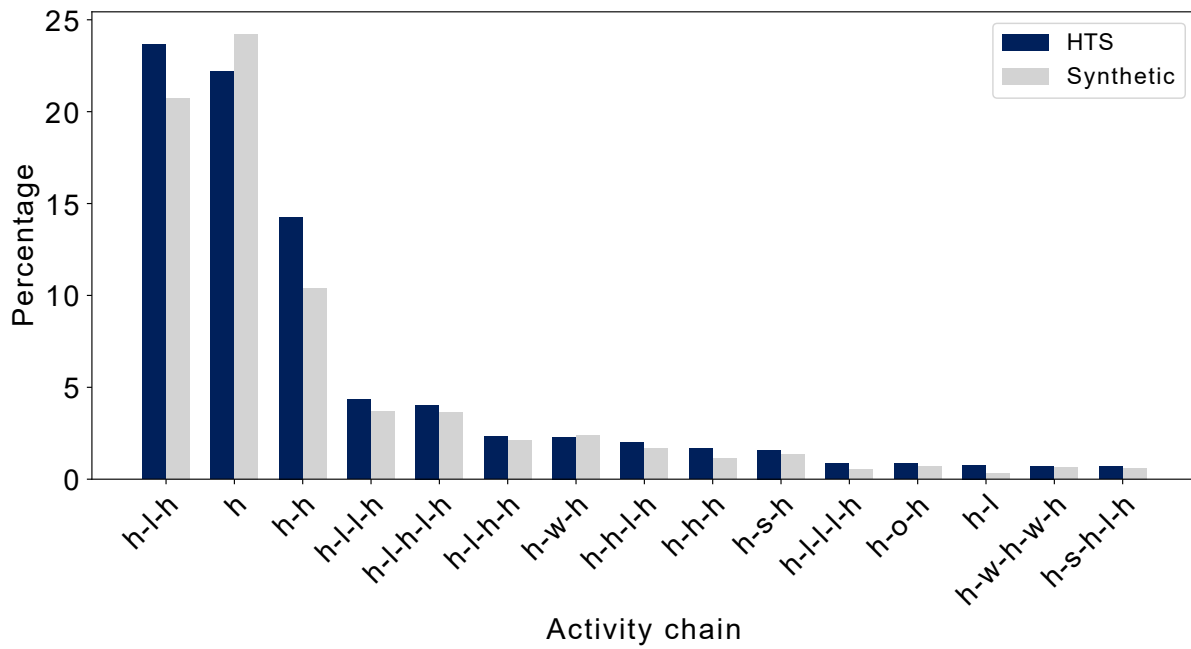


FIGURE 16: Activity chains for Women for Sunday

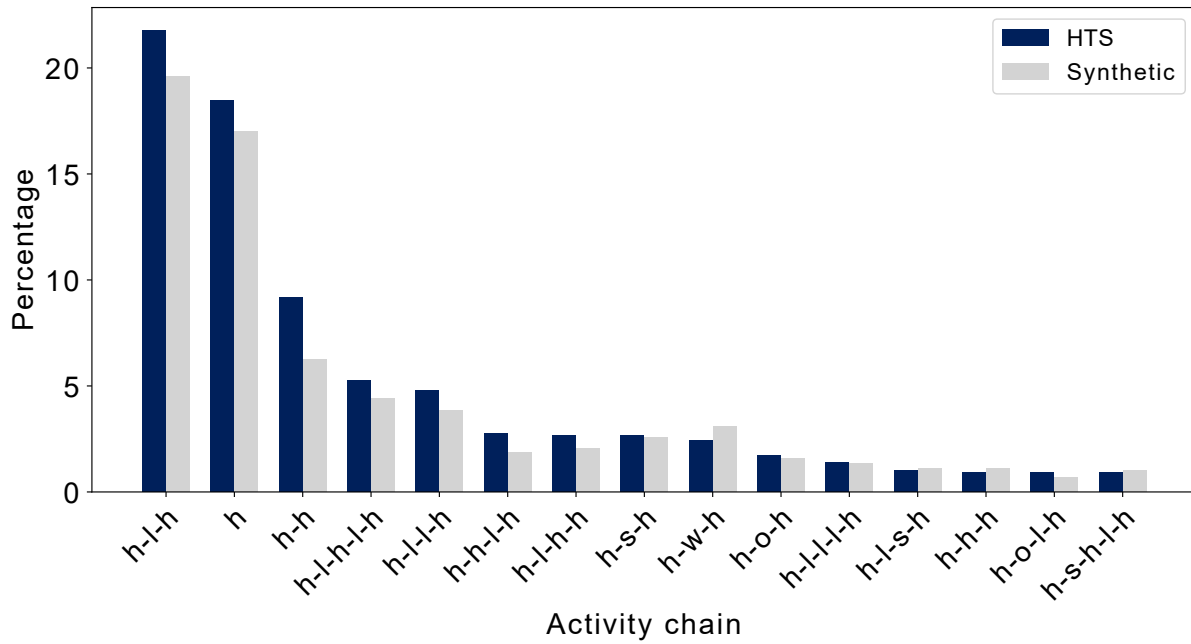


FIGURE 17: Activity chains by Men aged 18 - 40 for Sunday

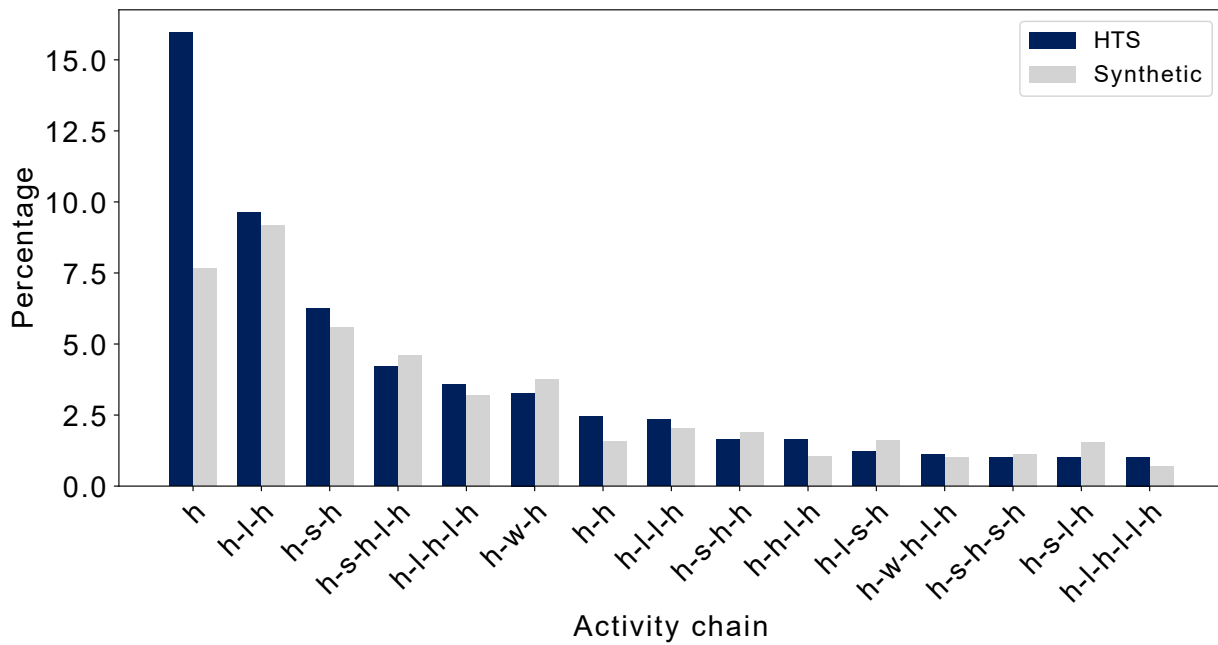


FIGURE 18: Activity chains by Men aged 18 - 40 for Saturday

	Parameter	Estimate	
Car	$\beta_{ASC,car}$	0.224*	
	$\beta_{inVehicleTime,car}$	-0.019	[min ⁻¹]
	$\beta_{work,car}$	-1.161	
	$\beta_{city,car}$	-0.459	
Public Transport	$\beta_{ASC,pt}$	0.0	
	$\beta_{inVehicleTime, feeder}$	-0.045	[min ⁻¹]
	$\beta_{inVehicleTime, other}$	-0.012	[min ⁻¹]
	$\beta_{inVehicleTime, train}$	-0.007	[min ⁻¹]
	$\beta_{transferTime, pt}$	-0.012	[min ⁻¹]
	$\beta_{accessEgressTime, pt}$	-0.014	[min ⁻¹]
	$\beta_{headway, pt}$	-0.030	[min ⁻¹]
	$\beta_{pt\ quality, B}$	-1.744	[min ⁻¹]
	$\beta_{pt\ quality, C}$	-1.641	[min ⁻¹]
	$\beta_{pt\ quality, D}$	-0.965	[min ⁻¹]
$\beta_{pt\ quality, None}$	-1.089	[min ⁻¹]	
Bike	$\beta_{ASC,bicycle}$	0.152	
	$\beta_{travelTime,bicycle}$	-0.126	[min ⁻¹]
	$\beta_{highAge,bicycle}$	-2.659	[a]
Walking	$\beta_{ASC,walk}$	0.590	
	$\beta_{travelTime,walk}$	-0.046	[min ⁻¹]
AMOD	$\beta_{ASC,AMoD}$	-0.061	
	$\beta_{inVehicleTime,AMoD}$	-0.015	
	$\beta_{waitingTime,AMoD}$	-0.093	
	$\beta_{work,AMoD}$	-1.938	
	$\beta_{highAge,AMoD}$	-2.6588	
Other Parameters	β_{cost}	-0.089	[CHF ⁻¹]
	λ_{CI}	-0.817	
	λ_{CD}	-0.221	
	λ_{TD}	0.115	
	$\theta_{referenceDistance}$	39	[km]
	$\theta_{referenceIncome}$	12.260	[CHF]

TABLE 4: Parameters of the discrete mode choice model

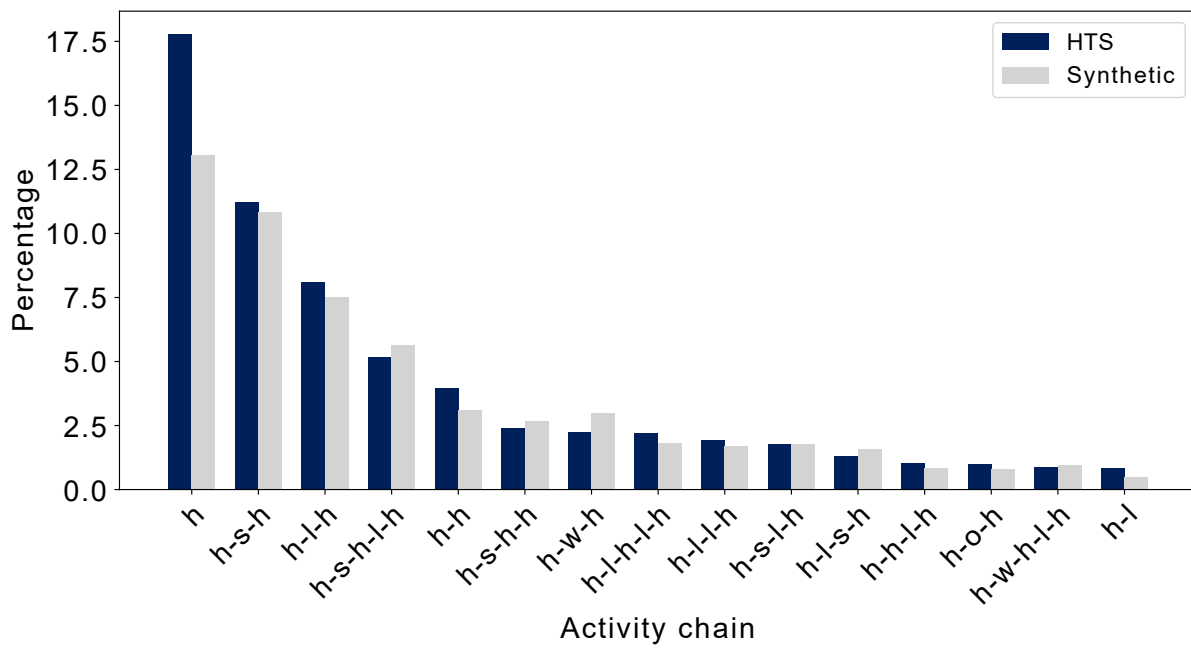
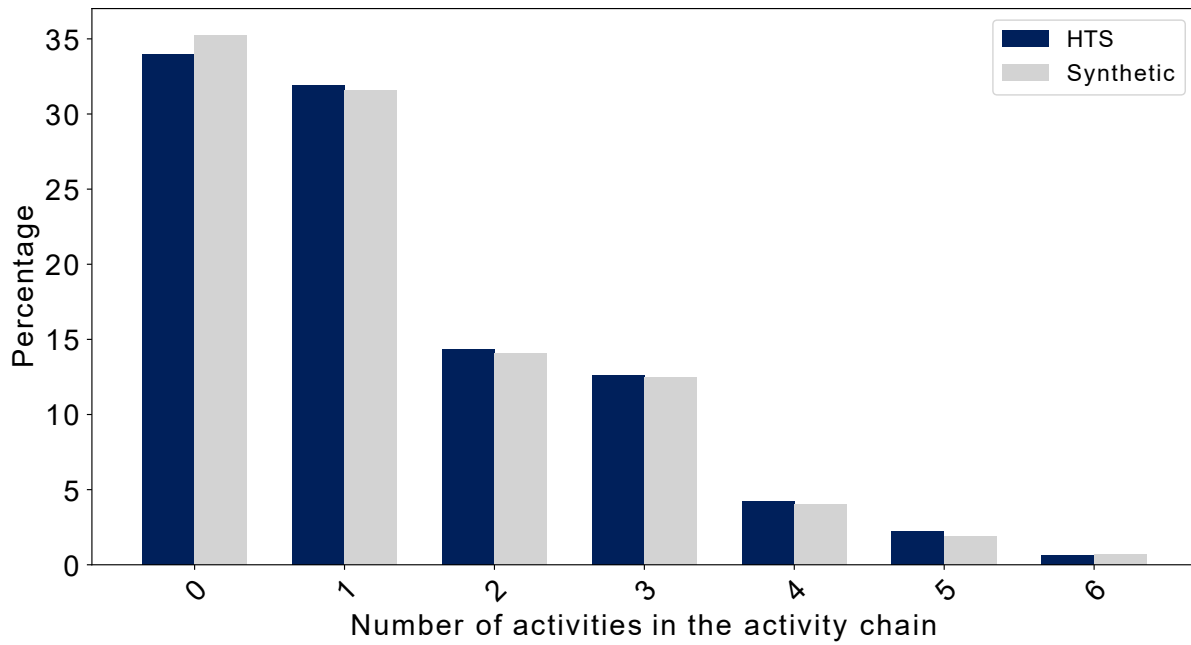
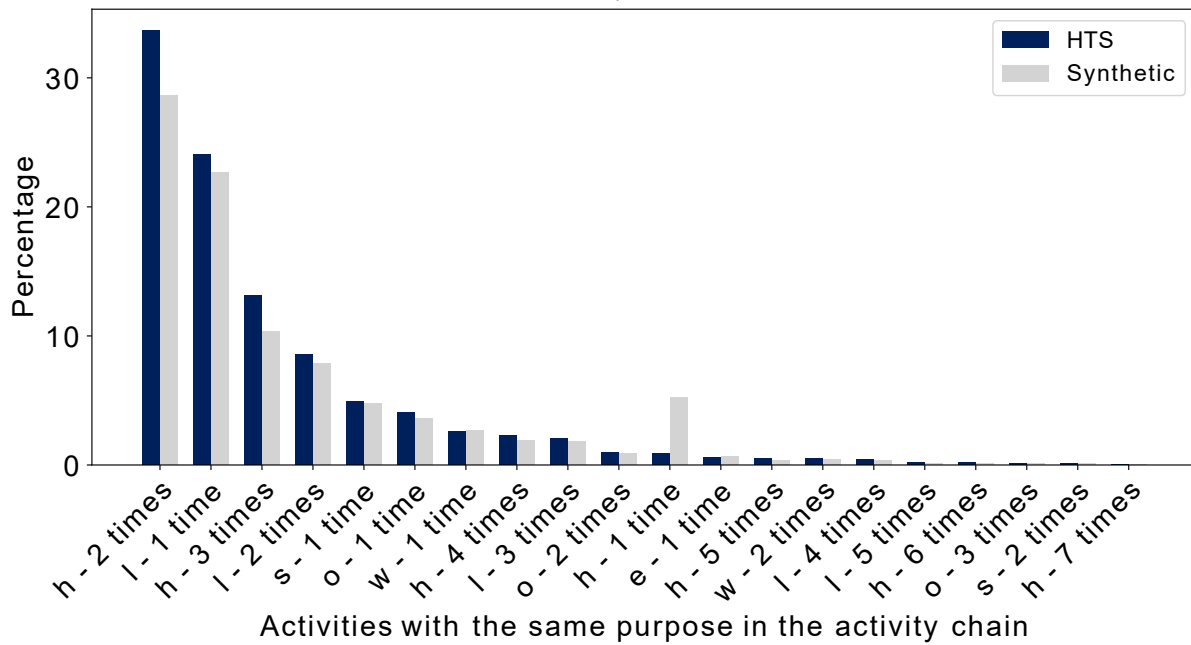


FIGURE 19: Activity chains by Women for Saturday



(a) Activity counts



(b) Activity counts by purpose

FIGURE 20: Number of activities for Sunday

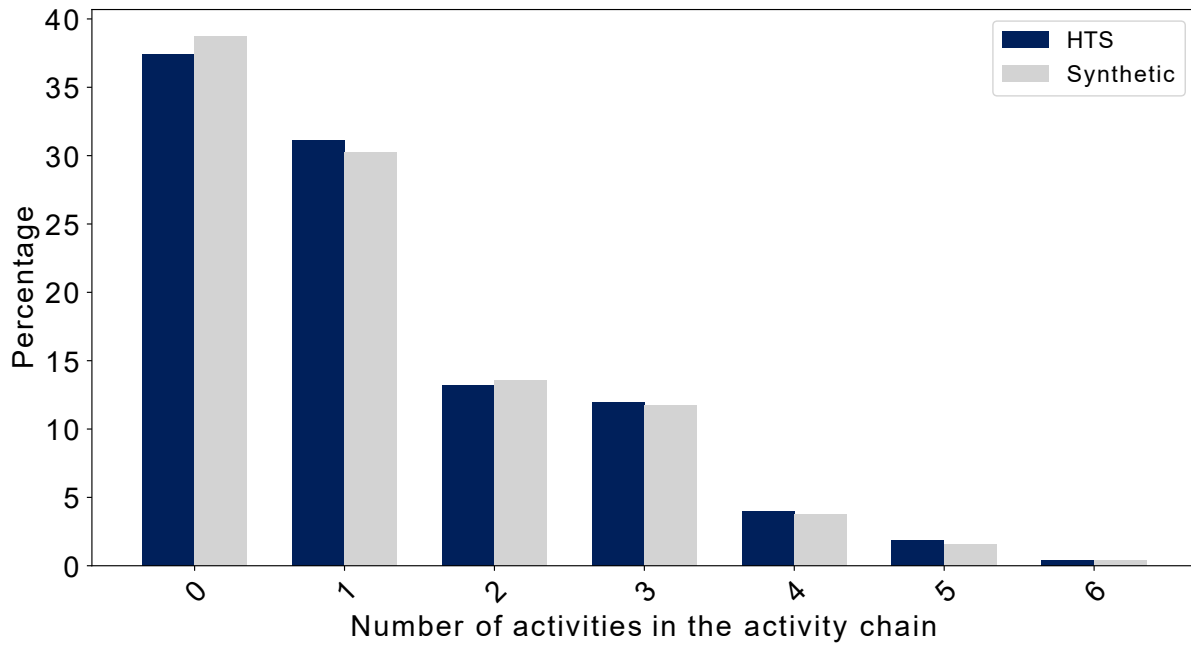


FIGURE 21: Activity counts women for Sunday

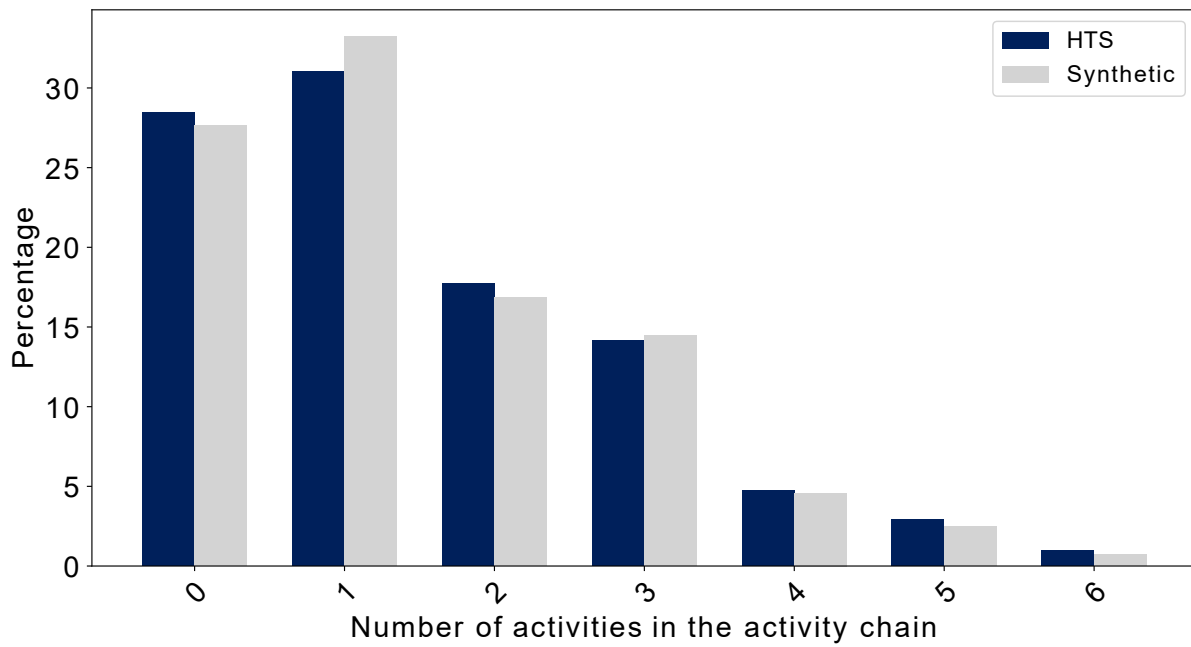


FIGURE 22: Activity counts men for Sunday

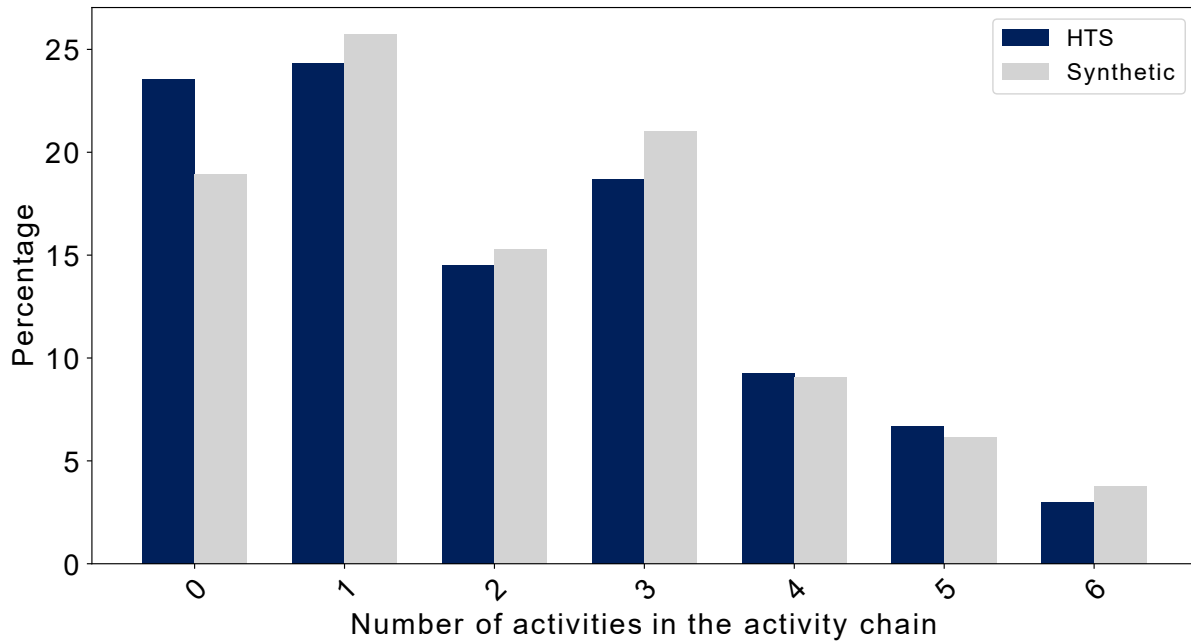


FIGURE 23: Activity counts women for Saturday

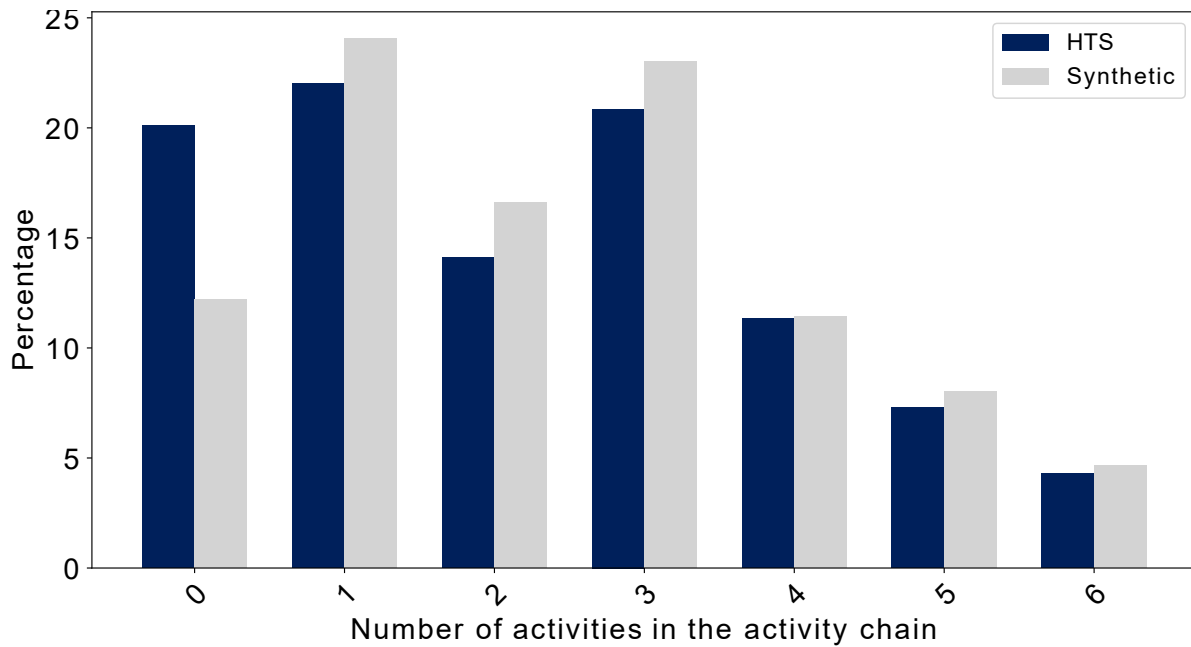


FIGURE 24: Activity counts men for Saturday

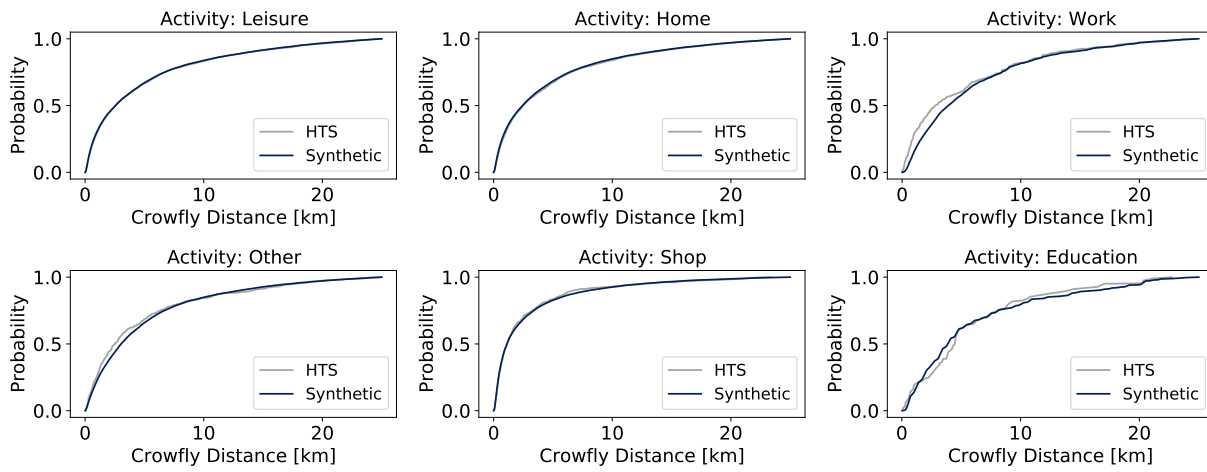


FIGURE 25: Cummulative distance distribution for Sunday