Sampling Weekly Activity Schedules to Analyze Shopping Behavior under the 15-Minute City Concept

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SHORT SUMMARY

In this research we present a sketch-planning tool for examining how changes in the local environment influence individuals' shopping activity participation and location choice. We consider four scenarios with different built environment configurations and time constraints in a Viennese region, to investigate how travel behavior and activity participation adapt to these setups.

Keywords: activity-based modelling, location choice, time use, travel behaviour, 15-minute city

1. INTRODUCTION

The COVID-19 pandemic, coupled with the ongoing climate crisis, has highlighted the need for inclusive and resilient built environments that enable people to access and fulfill their needs at any external circumstances. The last few years, the 15-minute-city (hereafter FMC) concept has gained popularity among urban planners and stakeholders. The FMC concept aims to shape urban neighborhoods so that all citizens can meet most of their essential needs within a 15-minute walking or cycling distance (Moreno et al., 2021). These basic needs include living, working, shopping, healthcare, education and leisure. The concept promotes polycentric environments while adopting a proximity-centered strategy, where people and amenities are close to each other (Pozoukidou & Chatziyiannaki, 2021). This will lead to an improved quality of urban life by minimizing the carbon footprint of travel and strenghthening economic and social cohesion (Moreno, 2024).

While the concept is widespread, it is not without its critics (Guzman et al., 2024; Mouratidis, 2024). Some of these critics draw attention to the real impact of such design principles on individuals' daily activities and quality of life. Guzman et al., (2024) argue that the popularity of the FMC concept ignores the influence of the built environment on travel behavior and its dependence on the local planning and land use context. To contribute to this research discussion, it is crucial to develop a method that assesses the impact of the FMC concept on travel and activity behavior at a disaggregated level.

The impact of the built environment on destination choice behaviour, and subsequently on the allocation of time to different activity locations, is influenced by numerous factors. People must consider the types of activities they should or want to perform throughout the week, their locations, the travel mode, and the constraints of the environment they live in. Due to this level of complexity, in recent decades activity-based models (hereafter ABMs) have gained popularity among transport planners (Castiglione et al., 2014). A major advantage of ABMs over traditional trip-based models is that they take into account the interrelationship of trips and the influence of personal preferences and spatiotemporal constraints (Pougala et al., 2022; Rezvany et al., 2024).

There are two classifications of activity generation models (Hilgert et al., 2017; Rezvany et al., 2022):

- Utility-based econometric models
- Rule-based computational process models

The utility-based econometric models are based on the utility maximization theorem, which states that people seek to obtain the highest level of satisfaction from their choices. Therefore, individuals will choose an activity schedule that maximizes their utility, subject to a set of time and space constraints. The rule-based computational process models are based on the principle that people use context dependent choice heuristics to make decisions, and they attempt to mimic the way individuals think when building their schedule (Pinjari & Bhat, 2011).

Most existing ABMs generate single-day activity schedules. This can lead to biases in time-use predictions, as time allocation and activity frequency vary from day to day, and especially between weekdays and weekends (Arentze et al., 2011; Calastri et al., 2020). Furthermore, variability in travel and activity behavior can be better explored by modeling longer time periods (Hilgert et al., 2017).

In this research, we investigate the influence of the changes in the local built environment on shopping activity participation and location choice. This will be achieved through a sketch-planning tool that uses a utility-based statistical approach to simulate weekly activity schedules based on specified preferences. Section 2 outlines the method, Section 3 presents the results of four scenarios tested in a Viennese region, and Section 4 provides a discussion of the findings and next steps.

2. METHOD

Sampling process

We adopt a utility-based weekly activity scheduling approach and assume that traveler aims to create a weekly schedule that maximizes utility. A weekly schedule is a sequence of activity type/location tuples annotated with a time structure, plus travel episodes in between.

We index by *i* the different activity types and with t_i^* the target/desired duration of activity type *i* throughout the week. Following Nagel et al., (2016) we define the utility of participating in an activity *i* to be a logarithmic function of the realized duration of this activity. A traveler aims to choose activity participation times $t_1, \dots, t_J$:

$$\max \;\; Q\left(t_1, \dots, t_J\right) = \sum_{i=1}^{J} t_i^* \ln t_i \tag{1}$$

$$s.t. \sum_{i=1}^{J} t_i = T \tag{2}$$

where *J* is the number of different activity types and *T* is the weekly time budget for activity participation.

The objective function *Q* serves as a utility measure for the realized weekly activity schedules, which evaluates the plausibility of the sampled weekly schedule. The closer the time spent for an activity (t_i) to the target activity duration (t_i^*), the higher the utility of the weekly schedule. Without further constraints, the solution to this problem is $t_i \propto t_i^*$.

We assign opening hours and target durations to different activity types and only evaluate activity participation durations that fall within these opening hours in problem (1), (2). For example, workplaces should be visited from Monday to Friday, from 7 a.m. to 7 p.m, and while visiting a workplace outside these hours is still possible, it does not contribute to the working duration evaluated in (1), (2). In this way, plans with activities scheduled outside their opening hours, receive a low utility Q, which makes them less plausible. Additionally, the time spent on an activity may differ from the assigned target duration, affecting the time available for other activities.

Sampling framework and parameters

We deploy a Metropolis-Hastings-based sampling approach to the generation of possible weekly schedules, adopting the method of Flötteröd, (2025). We attach the sampling weight

$$w(t_1, \dots, t_j) = e^{Q(t_1, \dots, t_J)} \quad (3)$$

to a weekly schedule with time structure $t_1, \dots, t_J$, meaning that the Metropolis-Hastings algorithm samples weekly schedules with probabilities that are proportional to these weights.

The considered model includes the following activity types: *home, work, shopping*, and *other*. Walking is the only available travel mode, and distances between locations are calculated based on straight-line distances and a fixed walking speed.

Table 1: Model parameters

Parameter	Value
Weekly working time (Mon. – Sat.)	40 h
Weekly home resting time	84 h
Weekly shopping time	2.5 h
Walking speed (km/h)	1.4 km/h
Number of one-hour time bins	168
Opening hours of work locations	7 a.m. – 7 p.m.
Opening days of work locations	Mon. – Fr.

3. RESULTS

We consider the central area of the Liesing district in the city of Vienna. Figure 1 illustrates the home (HL), work (WL) and shopping locations (SL) – categorized into supermarkets and local grocery shops- encoded in the model. They are included in the model because of their closed proximity to one another, which supports the development of an FMC in the selected area. We call this setup the baseline scenario.

Figure 1: Activity Locations in Liesing (Map Source: OpenStreetMap)

To investigate how shopping behavior adapts to different built environment configurations and constraints, we considered four scenarios. Table 2 presents the scenario parameters.

Table 2: Scenario parameters for shopping locations

Parameter	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Number of locations	11	7	4	11
Opening days	Mon. – Sat.	Mon. – Sat.	Mon. – Sat.	Mon. – Sun.
Opening hours	7 a.m. – 8 p.m.	7 a.m. – 8 p.m.	7 a.m. – 8 p.m.	7 a.m. – 10 p.m.

In Scenario 1, we examine activity participation and timing (hereafter "behavior") based on the baseline neighborhood design which offers a high density of all types of shops. Scenario 2 explores the impact on behavior when all local grocery shops are removed, while Scenario 3 examines the effect of removing all supermarkets. Note that supermarkets and local grocery shops are substitutes for each other. Finally, Scenario 4 focuses on the effect of extended opening hours and days for shopping facilities. All these scenarios aim to provide insight into the impact of density and proximity of shopping facilities on time use and activity behavior, along with the role of time flexibility.

We sample a large number of weekly activity schedules for the residents in each of the three available home locations. Figure 2 illustrates an example of a sampled activity schedule for a random day in a week for an individual living in HL1.

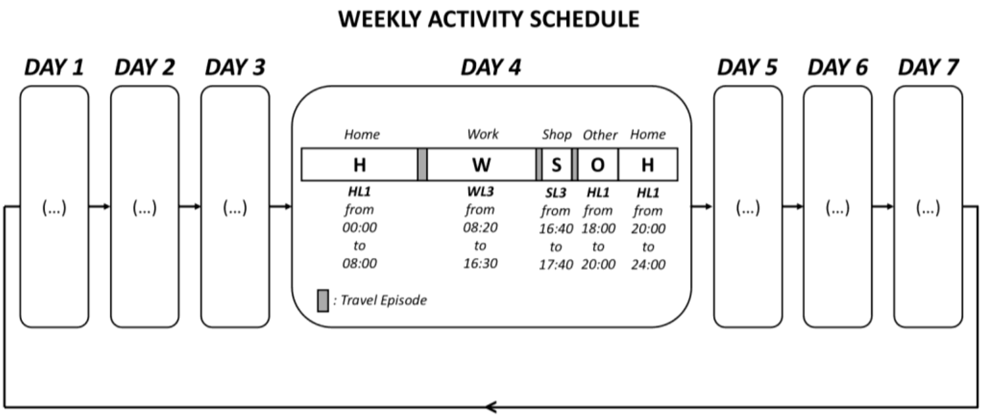

Figure 2: Example of a sampled weekly activity schedule of a HL1 resident

Table 2 shows the sampled statistics and Table 3 shows the proportion of visits to each shopping location for each scenario and home location. In the baseline scenario, residents of HL1 spend on average more time traveling to shop, while the average duration of shopping episodes for all residents is approximately 3 hours. The setup of scenario 2 increases the travel time to shop for the residents of HL2, while it decreases it for the residents of HL1 and HL3. However, due to the high variance, the slight decrease in the duration of shopping episodes observed in this scenario is not meaningful. Furthermore, the lack of local grocery shops leads to an increase in the number of visits to the supermarkets that are either close to the place of work or residence. From the results of Scenario 3, it is evident that a further decrease in density of shopping facilities doesn't have a strong effect on the duration of shopping episodes and the number of locations visited compared to Scenario 2. However, in Scenario 2, residents of HL2 and 3 must travel more to reach a shopping facility. In Scenario 4, the extension of opening days and hours does not have a strong effect on the average shopping time compared to the baseline scenario, but it does influence the number of locations visited. The extended opening schedule of shopping facilities encourages travelers to visit different shopping locations, either near or far from their residential location. The most visited shopping locations are the same as in the baseline scenario, however there is an increase in visits to other shopping locations that weren't as popular in the baseline scenario due to time flexibility.

Table 2: Sampled statistics related to weekly shopping episodes for each scenario and home location

		Variables Related to Shopping Episodes					
Home Location	Scenario	Travel Time for Shopping (min)		Duration of Shopping Episodes (h)		Number of Shopping Locations Visited	
		Average	Std. Dev.	Average	Std. Dev.	Average	Std. Dev.
HL1	1	29.08	0.49	3.04	1.09	1.37	0.58
	2	24.58	0.36	2.94	1.08	1.56	0.69
	3	17.99	0.25	2.95	1.06	1.52	0.66
	4	22.01	0.32	3.08	1.14	1.69	0.75
HL2	1	19.95	0.38	2.92	1.03	1.28	0.50
	2	30.52	0.45	2.76	0.99	1.50	0.68
	3	35.59	0.41	2.69	0.99	1.33	0.56
	4	32.25	0.45	2.9	1.06	1.52	0.69
HL3	1	18.9	0.42	3.06	1.11	1.35	0.56
	2	17.44	0.41	2.97	1.07	1.49	0.66
	3	18.44	0.28	2.94	1.06	1.48	0.64
	4	19.25	0.36	3.23	1.16	1.63	0.72

Table 3: Proportion of weekly visits to each shopping location for each scenario and home location

Distribution of Shopping Trips Across Locations by Home Location and Scenario

Home Location	Scenario	Shopping Locations										
		1	2	3	4	5	6	7	8	9	10	11
HL1	1	1%	8%	27%	11%	7%	0%	0%	31%	15%	0%	0%
	2	2%	13%	52%	21%	12%	1%	0%				
	3								65%	34%	0%	0%
	4	1%	10%	26%	12%	6%	0%	0%	28%	16%	0%	0%
HL2	1	7%	38%	9%	14%	5%	0%	1%	13%	10%	1%	2%
	2	11%	50%	12%	17%	7%	1%	2%				
	3								54%	42%	1%	3%
	4	7%	35%	8%	14%	5%	0%	2%	16%	11%	1%	1%
HL3	1	12%	1%	0%	0%	0%	6%	37%	1%	0%	6%	37%
	2	19%	3%	0%	0%	0%	10%	67%				
	3								0%	0%	13%	86%
	4	12%	2%	1%	0%	0%	8%	36%	0%	0%	7%	35%

Figure 3 shows the distribution of shopping episodes throughout the day for each home location and scenario, considering all days of the week. Shopping episodes in the baseline scenario are almost evenly distributed between the morning and evening hours. In Scenario 2 and 3 there is an increase of shopping episodes during the morning hours. The low density of shopping opportunities, combined with the opening hours implemented in these scenarios, results in travelers satisfying their shopping needs before participating in other activities of the day by visiting shopping locations close to their home or workplace. The extension of opening hours in Scenario 4 leads to a noticeable increase of shopping episodes in the evening hours. However, there has not been much of an increase in the number of shopping episodes after 20:00.

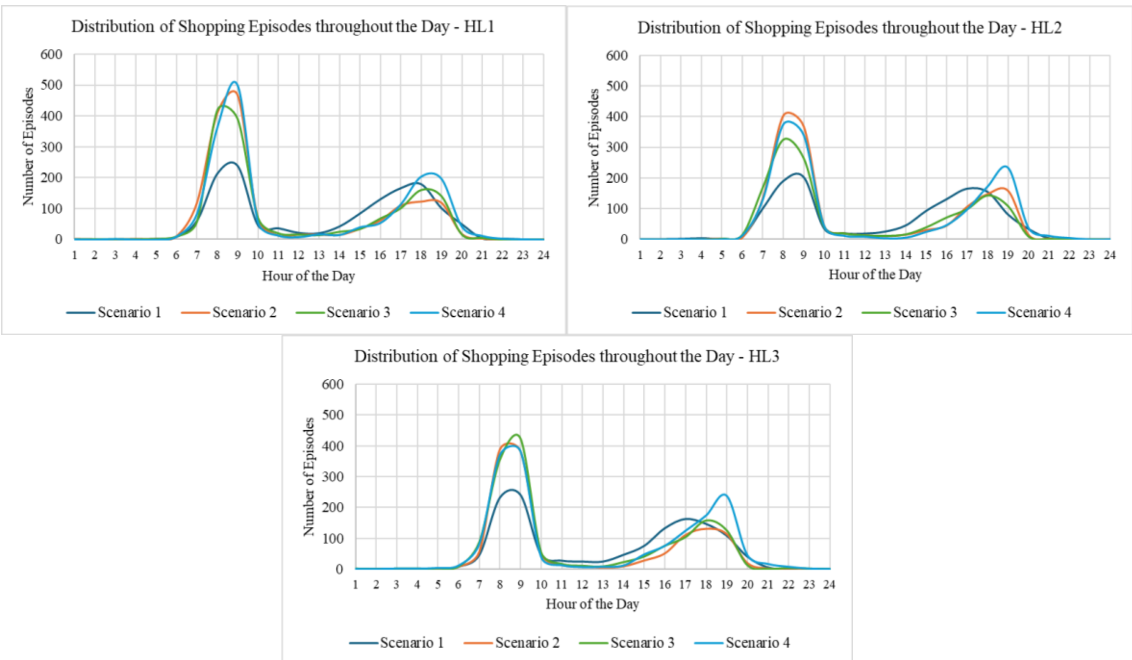

Figure 3: Distribution of shopping episodes throughout the day for each scenario and home location, considering all days of the week

4. DISCUSSION

In this study we presented a sketch-planning tool for examining how changes in the local environment influence individuals' shopping activity participation and location choice. The deployed time use model adjusts weekly schedules plausibility in response to spatiotemporal constraints. The results suggest that reducing the density of shopping locations can affect both location choice and shopping frequency. This finding highlights the influence of proximity on shopping behavior, as travelers may adapt their activity schedules in different circumstances by either combining trips to save time or traveling longer distances because they have no better alternative. Nevertheless, the results vary depending on where individuals live and work, although the sequence of trips has not been examined extensively in this research. Conversely, the extension of opening days and hours of these locations does not influence significantly shopping behavior. In this scenario setup, individuals experience flexible work schedules that allow them enough time to meet their shopping needs during the normal opening hours. Results may differ if stricter time schedules are followed, such as working at least 8 hours per day. This could have a noticeable impact on time allocation, especially if shops and workplaces share the same opening schedule, as travelers would have to accommodate their shopping needs when they have free time and shops are open. However, the lack of socioeconomic characteristics and the absence of travel modes other than walking, limit the scope of the present analysis.

These results underscore the potential of FMC-related policies in shaping location choice and weekly activity participation. The developed sampling tool for weekly activity schedules, even in its current preliminary version, demonstrates its potential to explore activity behavior under new planning policies. Future steps include the model enrichment with socioeconomic characteristics, additional travel modes and activity types. These adjustments will enhance the model's applicability in sampling weekly schedules for more complex and real-world scenarios.

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