


Article

An Empirical Activity Sequence Approach for Travel Behavior Analysis in Vilnius City

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Abstract: The approach defines the process of conducting an empirical research of the travel behavior patterns of residents of Vilnius city. It defines survey methodology and important mobility parameters such as activity sequences and their probabilities of homogeneous urban population segments during the weekday. This empirical research is based on a travel diary survey that was planned and executed in cooperation with Vilnius Municipality during preparation of sustainable mobility plan. The following work describes the research object, the questionnaire design, sampling strategy and the analysis of results based on characteristics of respondents. An innovative activity sequence-focused travel behavior research approach designed to collect data for a tour-based travel demand model.

Keywords: activity sequences; activity-based travel demand; characteristics of respondents; travel survey; sustainable mobility in urban territories

1. Introduction

Travel demand is a demand, arising from the spatial separation of home and basic human social activities such as work, education, shopping, and recreation. Individuals travel from one point to another with trips of different purposes by various modes and durations and at various times of the day.

There is an evidence that the complexity of an activity sequence is highly influenced by land use patterns and increases over time due to the changes in a lifestyle [1]. In addition, there is a potential association between more complex travel behavior and dependence on car use. Ye et al. [2] conjectures that complex activity sequences may lead to an increase in car usage. If one needed to pursue a complex sequence, then the flexibility afforded by the private automobile is desirable. The ability to pursue multiple activities in a single journey is rather limited when constrained by the schedules, routes, and uncertainty associated with public transportation.

Ma et al. [3] finds that complex tours are usually done by people living in a low-density, mono-functional environment located further from the central area. Similar findings have been documented by Krizek [4] who concluded that households living in areas with higher levels of neighborhood access are found to complete more tours but make fewer stops per tour.

Some authors [5–7] have found in their longitudinal studies that activity sequences are becoming increasingly more and more complex over time. Activity sequences have increased in the past decades, in great part due to changes in the location of specific activities, which have moved from in-home to out-home (e.g., stopping for coffee or meals) and to escorting activities (mainly escorting children to school).

Axhausen [8] points out the need for clear definitions to make sense of the scientific observations and outcomes of survey-based research and transport modelling. An activity is defined as an occupation of a person carried out at one location. It is worth differentiating between human needs related

activities such as work, shopping or social communication and travel related activities such as change of mode or a transfer between the vehicles of the same mode, which are referred to as a process. A sequence of activities describes the order of different activities during a person's run of the day, starting and ending at home, for instance, the very frequent sequence undertaken by population members is "Home–Work–Shopping–Home".

A stage is a continuous movement with one mode of transport or one vehicle. A trip is a continuous sequence of stages between two activities. For example, a trip with public transport usually is defined by at least three separate stages: walk, travel by public transport and walk again.

A tour concept is a key term within the scope of this article. According to Krizek [4], tours in literature are defined in terms of the home-to-home loop and analyzed by looking at the number of trips. Simple tours contain two trips; complex tours contain more than two trips. These terms are employed in the further sections and used extensively.

Other authors [9,10] tend to name the same concept as a trip chaining. However, in the context of this article, a similar term (trip chain) is assigned to a slightly different meaning and therefore care should be taken to avoid associating the term trip chaining with the meaning of a tour. These latter three definitions (stage, trip, and tour) align with the ones agreed among the bulk of transport planning professionals and given by Ortuzar et al. [11].

A trip chain is a sequence of two or more trips between two substantial activities (i.e., home and work). An activity is treated as substantial if it takes place longer than some predefined arbitrary time. Further work will be following Wallace et al. [10], who assumed that activity is substantial if it takes place for longer than 90 min. Sometimes a "trip chain" by other authors [12,13] is characterized as travel that almost always begins and ends at home, thus being assigned a meaning of a "tour". To facilitate the apprehension, a schematic representation depicting definitions is given in Figure 1.

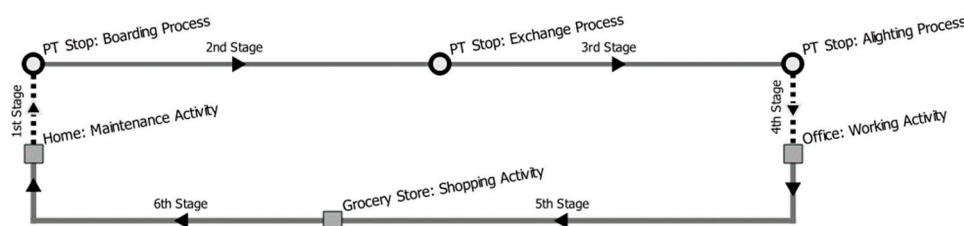


Figure 1. Visualization of the key definitions (created by authors).

In the diagram presented above, there are six stages that comprise three trips. The first trip consists of four stages between two activities maintenance at home and work at the office. The second trip covers only one stage between work and shopping activities. Finally, the third trip is also defined by one (6th) stage and connects shopping and maintenance (at home) activities. If the shopping is not taking place for longer than 90 min, there will be two trip chains: First from home to work and second from work to home. Otherwise there exists only one trip chain—between home and work. All six stages form three trips and two trip chains comprise a single tour that starts and ends at home. An ordered list of activities (Maintenance, Working, Shopping, Maintenance) constitute the activity sequence.

This work embarks on an endeavor to test up-to-date data collection techniques for activity-based travel demand, data analysis, which would be based on the current best practices and state-of-the-research, and which could be accessible by a wide range of transport specialists. In particular, the derivation of activity-based travel demand may lack some potential advantages that can be brought in by a comprehensive approach, data extraction and data analysis. Moreover, the diversity of individual human behavior across geographical locations ensures that traffic behavioral data is not universal. Behavioral characteristics vary widely between different cities (and even different areas within the same city) and while there are some general similarities that can be found in comparisons of cities, there are many different factors that influence human travel behavior, including: The size of the city, its urban density, its layout, the demographic and cultural properties of its population, economic

conditions and the type and quality of the transport networks. All these factors play a vital role in influencing transport demand. Travel demand techniques allow quantification and further analysis of travel demand by taking into account various of the above-mentioned factors and comparison of findings in scientific research.

2. Description of Study Area

Vilnius is the capital of Lithuania and its largest city, with a population of 533,000 residents as per the most recent census data according to The Department of Statistics, 2011 [14]. In this empirical research, the focus is placed on the administrative area of Vilnius City Municipality, for which a detailed definition of its spatial extents is given in Figure 2.

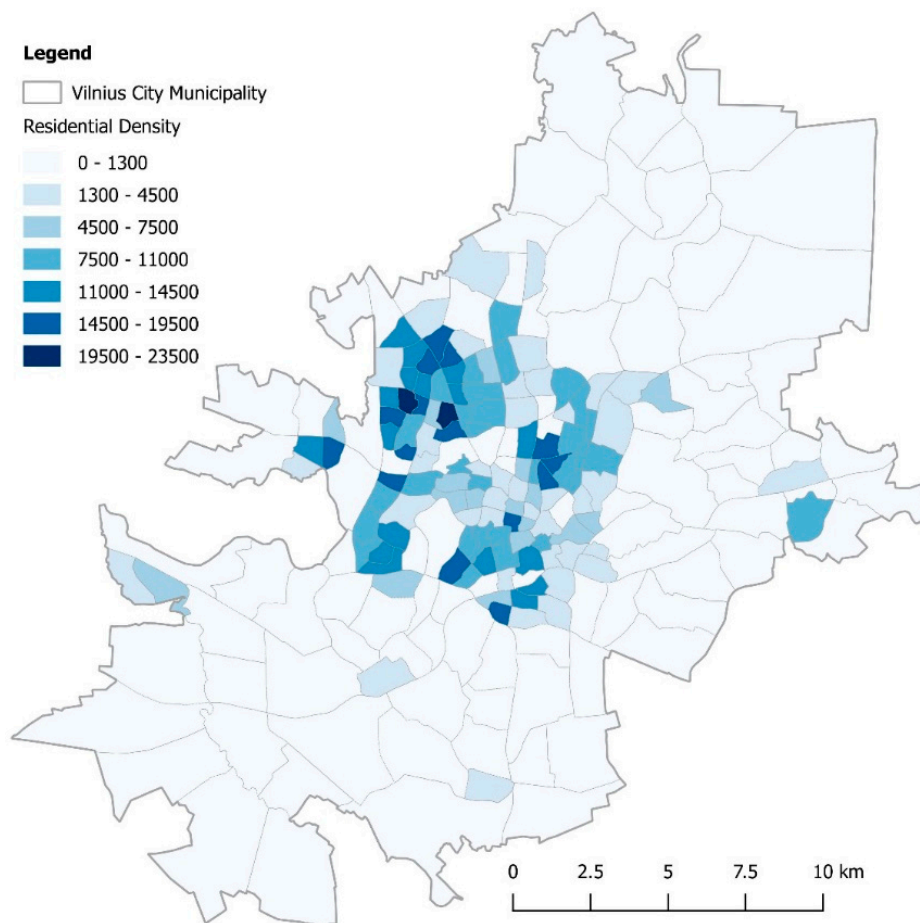


Figure 2. A map of a study area (created by authors using data from the Department of Statistics 2011).

The area of Vilnius City covers 403 km² in total and bearing in mind the number of residents reported above, it has a density of approximately 1320 residents per square kilometer. The following illustration in Figure 2 also contains a more detailed visualization of residential density within the administrative boundaries.

The area of interest was firstly divided into 42 primary transport analysis zones (TAZ) that in terms of spatial coverage agree with the administrative borough areas. Secondly, each primary zone was divided into several secondary TAZs. The spatial extent of the secondary TAZs was governed by the understanding that these zones will be maintained in the later stages of travel demand model development, and by the desire to maintain land use homogeneity and a reasonable model resolution with the size of each zone being close to 3000 residents. This division resulted in 218 transport analysis zones with the average area being equal to 1.85 km² and the average population size being equal to

2830 residents. The technical data management and visualization was undertaken using the open source geographic information system QGIS.

The empirical research concentrates on travel behavior in Vilnius city. The analysis of travel behavior is revealed through activity sequences during weekday. The purpose of this empirical research is to better understand activity sequences and quantify several mobility parameters such as:

(1) Proportion of Travelling Respondents. This represents the share of the sampled respondents who have chosen to travel on the reported day. The proportion of travelling respondents can also be used to approximate a probability of the respondent's choice to travel on any given weekday.

(2) Average Number of Trips. This represents the mean number of trips being undertaken by a random individual.

(3) Mode Split. This represents the relative frequencies of modes that were chosen to make the trips within the area of interest.

(4) Distribution of Trip Purposes. This represents the relative frequencies of activities that were undertaken at the destinations of all the trips made by sampled residents.

(5) Average Trip Length. This represents the average distance of the trips that were undertaken by sampled residents.

(6) Activity Start Times. This represents the relative frequencies of the start times of the observed activities.

(7) Daily Activity Sequences and their probabilities. Activity sequences represent the activities being undertaken over the course of the typical week-day, whereas probabilities represent the likelihoods of those sequences being conducted on the reported day.

All these parameters play a significant role in the development, calibration and quality assessment of a typical tour-based travel demand model. This empirical research is based on a travel diary survey that was planned and executed in cooperation with Vilnius Municipality Enterprise "Vilniaus Planas" in 2017. The company funded the administration of the survey as part of its ongoing development of Vilnius Sustainable Urban Mobility Plan [15]. The following sections describe in more detail the research object, the questionnaire design, sampling strategy, the innovative activity sequence-focused travel behavior research approach and the results of the analysis.

To identify travel behavior patterns and mobility parameters within the depicted area, a travel diary survey has been developed and conducted. The next section describes the principles and processes that were followed in the questionnaire design stage.

3. Materials and Methods

3.1. Questionnaire Design

Germany can be highlighted as a good practice example [16], where it is recognized that up-to-date information about people's travel and mobility behavior is indispensable for transportation policy decisions and planning. Only on the basis of such information the transportation infrastructure can be designed and preserved in order to meet the needs of the population—today and in the future. Since 1994 these German Mobility Panel surveys have been financed by, and carried out on behalf of the German Federal Ministry of Transport and Digital Infrastructure. This survey collects information about the household's travel behavior over a seven-day period within three consecutive years. The Institute for Transport Studies of the Karlsruhe Institute of Technology is responsible for the design and scientific supervision of the survey.

The questionnaire for the residents of Vilnius was comprised of three main sections. The purpose of the first section was to familiarize the respondent with the relevant definitions such as an activity, trip and stage. A clear distinction between stage and trip is essential as people tend to report stages (continuous movement with one mode of transport/one vehicle) as complete trips, even though they connect only one activity with transfer between modes, rather than two activities.

Then, respondents reported the trips carried out during a recent weekday (Monday–Friday). It was specifically chosen to request the information for the most recent working day with a hope that this strategy will decrease cognitive and memory burden on the side of respondent and at the same time potentially increase response rate. For every trip made during the 24-h period, respondents recorded the activity, origin, destination, modes used and the time of day.

Finally, respondents were asked to identify their main sociodemographic characteristics: Gender, age, highest attained education level, occupation etc.

The questionnaire was designed to provide information on travel behaviors for the tour-based travel demand modelling procedure. On a future basis, this kind of survey ideally should be repeated in Vilnius city about every five years to provide data for retrospective analysis and input for demand model update.

3.2. Data Analysis Tools and Methodology

Within the scope of getting valuable results from raw data, four main tools have been utilized:

1. Pandas Library [17].
2. NumPy Library [18].
3. Geocoder Library [19].
4. Microsoft Excel spreadsheets.

Pandas is a Python library written for data manipulation and scientific analysis. It offers data structures and operations for manipulating numerical tables and time series. Moreover, it is free software released under the three-clause BSD (Berkeley Software Distribution) license [20].

NumPy is a Python library adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.

Geocoder is a simple and consistent Python geocoding library allowing to establish a mapping between addresses and spatial location defined in latitude-longitude format.

The analysis has been conducted in two major steps:

1. Raw data cleaning, filling and arrangement into the format ready for analysis have been carried out using Pandas, NumPy, and Geocoder libraries in Python language.
2. Data analysis and visualization were carried out with Microsoft Excel spreadsheets.

The main distinctive feature of this analysis is that it presents most of the travel behavior parameters by classifying the whole population into groups. Most of the parameters were classified by residents' characteristics that were observed during the survey e.g., age, gender, occupation, and education. Statistical analysis starts off with an isolated look at the distributions of these respondents' characteristics and later delves deeper into the investigation of mobility parameters.

3.3. Sampling Strategy

The sampling frame represents the universal but finite set of decision makers to whom the analyst may administer the data collection instrument. The sample frame consists of the population living within the area of interest which is depicted in Figure 2. Due to legal and timeframe constraints, it was decided to reduce the sampling frame by excluding people younger than 16 years.

Generally, surveys may be accomplished in four survey modes: Mail, phone, face-to-face or internet. It has been chosen to conduct this survey in two modes:

1. The first survey step was carried out over June and July months in 2017. Respondents were contacted and asked to fill in the survey form online.
2. The second survey step was conducted in September 2017. The respondents were visited at their household premises and interviewed face-to-face.

The respondents for the sample were chosen using multistage stratified sampling procedure that can be defined by the following stages:

1. First stage—each of 42 primary TAZ has been assigned the fraction of the sample proportional to the size of the population of that primary TAZ.
2. Second stage—the sample of each primary TAZ was distributed to secondary TAZs proportionally to the population of each secondary TAZ.
3. Third stage—respondents were chosen randomly from the population of the secondary TAZ. The sample's proportional distribution of age and gender has been maintained to be as close to the secondary TAZ's distribution as possible.

In practice, the sample size is defined by budgetary considerations most of the time and this has been the case and within the context of this work. Budgetary constraints and time limitations allowed to sample 1773 respondents out of the whole population. All in all, the calculated margin of error of survey is $\pm 2.3\%$ with the confidence level 95% and population of 533,000, assuming that the proportion sampling distribution is nearly normal.

Survey results has been used to estimate various mobility parameters, such as proportion of travelling respondents, average number of trips, average trip length, mode share etc. Further chapters presenting the results report sample size, sample standard deviation and margin of error (95% confidence interval) for the proportion of travelling respondents and the average number of trips. However, due to space constraints, a confidence assessment has not been provided for the remaining mobility parameters.

4. Travel Survey Data Analysis

4.1. Respondents' Characteristics

The beginning of the analysis started with the distributions of the respondents among the levels of sociodemographic characteristics. Distribution across the age groups is given in Figure 3.

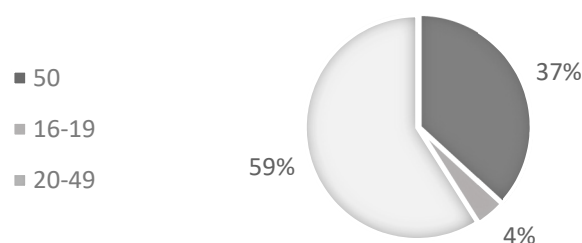


Figure 3. Age distribution of survey respondents (created by authors).

In summary, the total number of respondents surveyed is 1773. People aged between 20 and 49 comprised 59% of the sample and residents that were 50 years or older accounted for 37% of the respondents. It is worth noting that no data has been collected for the youngest population category of between 6 and 16 years old. This is a major dataset drawback, which resulted out of legal constraint as interview requires participation of parents.

The distribution among gender meets a prior expectation and remains compliant with the census data, which identifies slightly higher proportion of females (53%) comparing to males (47%). In terms of occupation, it has been found that the urban population is highly economically active as employed people comprise 72% of the sample and students contribute with another 6%. Unemployed people account for 8% of the sample, whereas retired people account for the remaining 14%.

Distribution across education levels is outlined in Figure 4.

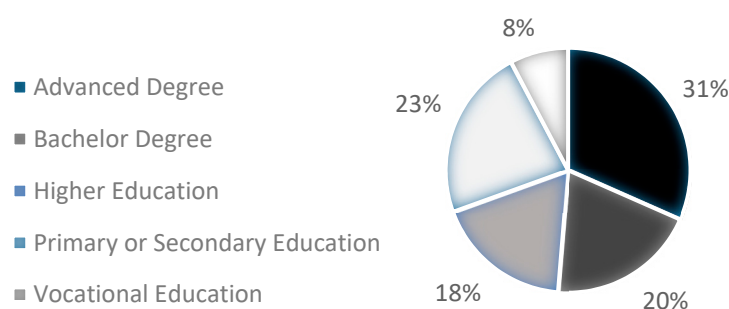


Figure 4. Highest Attained Education Level distribution of survey respondents (created by authors).

It has also been found that the sampled population is quite highly educated. As an example, the total proportion of people possessing Bachelor, Master, or PhD degrees is 51%. At this point there is a natural expectation that urban travel behavior is supposed to be rather intense due to the high education and employability levels. This will be analyzed in more depth in the following sections.

4.2. Identification and Analysis of Probability of Travelling

The analysis of the proportion of respondents who travelled (PT) on the reported day is presented in this section. Other related statistics, such as sample size, sample standard deviation and margin of error for 95% confidence interval are also calculated. The margin of error is calculated assuming that the proportion sampling distribution is nearly normal.

Sample standard deviation was calculated using the following expression:

$$\sigma = \sqrt{\hat{p} \times (1 - \hat{p})} \quad (1)$$

where \hat{p} —sample proportion.

Margin of error formula:

$$m = t \times s \quad (2)$$

where t —critical value; s —standard deviation of sampling distribution/standard error.

Standard error formula:

$$s = \frac{\sqrt{\hat{p} \times (1 - \hat{p})}}{\sqrt{n}} \quad (3)$$

where \hat{p} —Sample proportion; n —sample size.

Critical value expression:

$$t = \Phi^{-1}\left(1 - \frac{\alpha}{2}\right) \quad (4)$$

where Φ^{-1} —inverse cumulative distribution function of the Student distribution with $n - 1$ degrees of freedom; α —significance level (0.05).

A calculated margin of error provides an opportunity to identify the potential range within which a true value of the parameter might be. It has been found that the overall share of travelling urban residents is equal to 0.8, which means that about 80% of the sample people were travelling on the reported days. Table 1 gives some more detailed insight into the proportion of travelling (PT) respondents' classified by several characteristics.

From the table presented above, it can be defined that younger, more economically active and more educated people generally feature higher chances of leaving home on a given weekday. It is also worth noting the small difference in travel behavior between male and female, with the male proportion being slightly higher.

Table 1. Proportion of travelling respondents.

Variable	Level	Proportion	Standard Deviation	Sample Size	Margin of Error
Age	50	0.7	0.48	652	0.04
	20–49	0.8	0.38	1046	0.02
	16–19	0.8	0.43	75	0.10
Gender	Male	0.8	0.41	832	0.03
	Female	0.7	0.44	941	0.03
Education	Primary or Secondary Education	0.6	0.49	404	0.05
	Vocational Education	0.7	0.47	137	0.08
	Bachelor’s Degree	0.9	0.34	350	0.04
	Higher Education	0.7	0.46	322	0.05
	Advanced Degree	0.9	0.35	560	0.03
Occupation	Unemployed	0.6	0.48	151	0.08
	Employed	0.8	0.36	1268	0.02
	Retired	0.4	0.49	253	0.06
	Student	0.7	0.45	99	0.09

4.3. Identification and Analysis of Average Number of Trips

The analysis of average number of trips (ANT) is presented and discussed within the scope of this section. Other related statistics, such as sample size, sample standard deviation and margin of error for 95% confidence interval are also calculated. The margin of error is calculated assuming that the proportion sampling distribution is nearly normal:

$$\hat{\sigma} = \sqrt{\frac{\sum (x_i - \hat{x})^2}{n - 1}} \quad (5)$$

where \hat{x} —sample average; x_i —sample data point; n —sample size.

Margin of error, standard error and critical value computation method remains identical to the one defined in Formulas (2) to (4). A calculated margin of error provides an opportunity to identify the potential range within which a true value of the parameter might be.

The average number of trips in the overall sample is 2.3 per weekday. As it was the case with the proportions of travelling respondents, the average number of trips also varies across the respondents with different characteristics and Table 2 allows a more thorough examination of ANT parameter.

Table 2. Average number of trips by respondents’ characteristics.

Variable	Level	Sample Average Number of Trips	Sample Standard Deviation	Sample Size	Margin of Error
Age	50 and over	1.8	1.7	652	0.13
	20–49	2.6	1.8	1046	0.11
	16–19	2.2	1.7	75	0.37
Gender	Male	2.4	1.8	832	0.12
	Female	2.2	1.7	941	0.11
Education	Primary or secondary education	1.6	1.5	404	0.14
	Vocational education	1.9	1.7	137	0.29
	Higher education	1.8	1.4	322	0.16
	Bachelor’s degree	3.0	1.8	350	0.19
	Advanced degree	2.8	1.8	560	0.15
Occupation	Unemployed	1.8	1.67	151	0.27
	Employed	2.6	1.75	1268	0.10
	Retired	1.0	1.28	253	0.16
	Student	1.9	1.46	99	0.29

From the Table 2, it is obvious that all categorical variables have the power to explain the average number of trips. However, it is worth noting the small difference between males and females with the latter being slightly less active.

In terms of age, the most mobile are middle-aged (20–49) urban citizens with ANT equal to 2.6 whereas elders (50 years and over) make almost one trip less during any given weekday. The estimate for the youngest group is rather uncertain and the only conclusion can be made about the ANT parameter being somewhere between middle aged people and elders.

Further consideration of education, leads to the general trend: more educated people travel more, i.e., people having Bachelor or Advanced (Masters or PhD) degrees make 3.0 and 2.8 trips accordingly.

The ANT estimates for different occupations also varies considerably with the numbers meeting a priori expectation. The most mobile employed group makes 2.6 trips per day whereas retired people are the least mobile with ANT being equal to 1.0. Unemployed people and students have somewhat similar ANT values with their estimates being rather uncertain.

4.4. Identification and Analysis of Modal Split

Mode split (MS) has an interesting role of revealing how well developed and attractive various transport systems within the analysis area are. Within this section the overall as well as homogeneous group specific mode split statistics are presented and discussed.

The survey captured all used travel modes (stages) for each trip, however the duration or lengths of each mode within one trip has not been identified and, therefore, the analysis is based on the main modes. The main trip mode was assumed considering the following order of modal priority: Car, public transport, motorbike, taxi, bike, and walk. For example, if the car, public transport and walk modes are observed within a trip, the car receives a main mode label due to it being earlier in the modal priority list.

The total number of observed urban residents' trips were 4049, therefore, the statistical reliability of mode shares is considered as very high. It is clear from Figure 5 that the sampled persons rely on three main modes i.e., public transport, car and walk for daily mobility needs with the car mode being dominant.

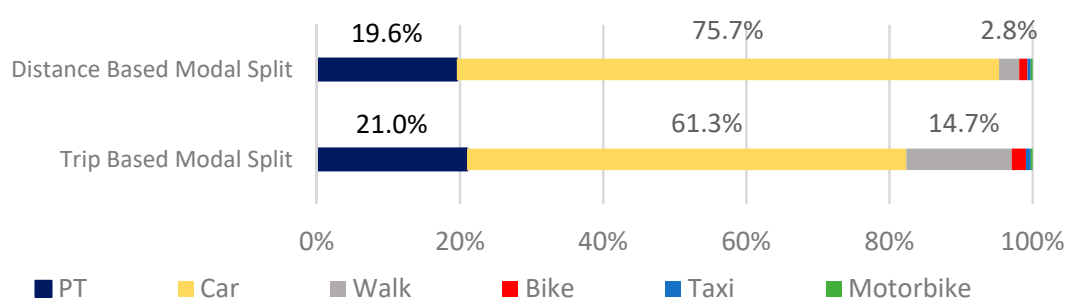


Figure 5. Sample modal shares (created by authors).

The trip-based assessment reveals that car share is equal to 61% whereas public transport with walk modes take up 21.0% and 14.7% respectively. Due to walking being used only for short nature related travel, the walk mode accounts for only 2.8% when the distance-based modal split is considered. Consequently, the car mode receives a higher proportion (75.7%) as the car trips are on average longer. It is interesting to have a look at the modal share's conditional on the trip distance. Modal shares categorized by six mutually exclusive distance bands are presented in Figure 6. The most significant difference between distributions can be noticed with-in the first trip length band (0–5 km) where the distance-based assessment assigns lower modal share to walk trips and consequently a higher share to car and public transport trips.

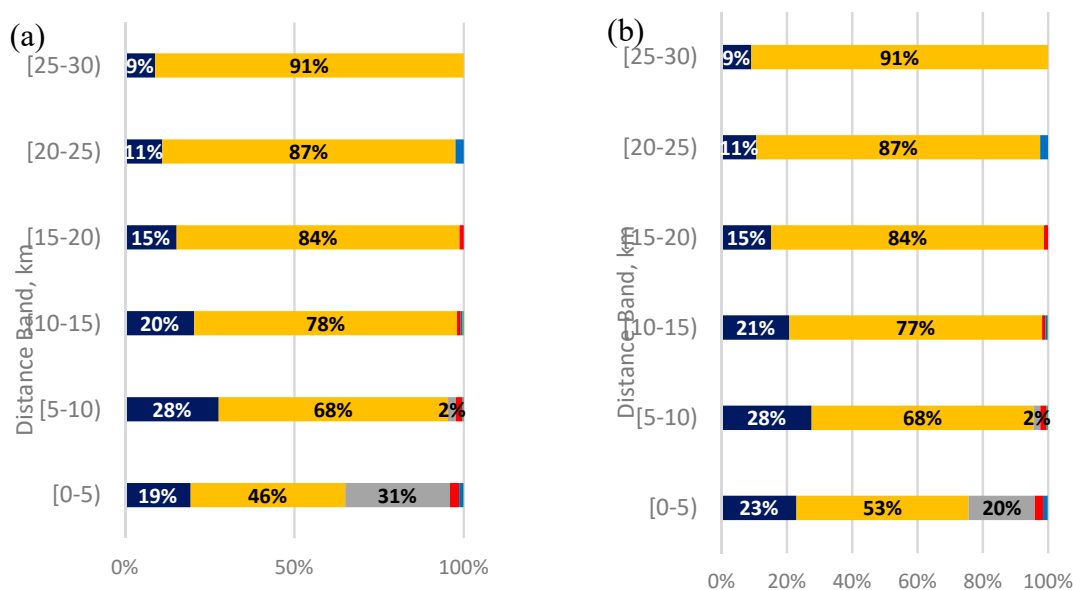


Figure 6. Trip-based modal split (a) and distance-based modal split (b) by distance bands (created by authors).

Further, an investigation of MS conditional on the levels of the residents’ characteristics is presented in Table 3 and discussed. It is important to note that the estimated modal shares given in Table 3 are based on two different measures: the number of trips and the estimated distance. Modal split based on first estimation method is more common among practitioners, because the distance is rarely obtained during the surveys. The second method considers each trip’s distance and reveals the actual modal usage within the sample.

There are several trends to note:

- (a) Young and elderly people tend to use public transport and walk more often than middle aged residents;
- (b) females choose public transport and walk more often than males; and
- (c) the more educated the urban resident is, the more likely that a car is chosen for the trip making.

Table 3. Modal split (%) categorized by resident’s characteristics.

Variable	Level	PT		Car		Walk		Bike		Taxi		Motorbike	
		T	D	T	D	T	D	T	D	T	D	T	D
Age	50 and over	29	30	53	66	17	3	1	1	0	0	0	0
	20–49	17	15	67	81	13	3	2	1	1	1	0	0
	16–19	31	37	37	48	23	7	5	3	1	2	3	3
Gender	Male	16	15	67	80	13	2	3	2	1	1	0	0
	Female	26	24	56	72	17	3	1	1	1	0	0	0
Education	Primary or secondary education	29	29	51	65	16	3	2	1	1	1	1	1
	Vocational education	27	31	58	66	14	2	1	0	0	0	0	0
	Bachelor’s degree	14	11	69	84	13	3	3	2	1	1	0	0
	Higher education	23	22	64	76	13	2	0	0	0	0	0	0
	Advanced degree	21	18	60	77	16	3	2	2	1	0	0	0
Occupation	Unemployed	12	14	69	83	18	3	1	0	0	0	0	0
	employed	18	17	65	79	14	3	2	1	1	0	0	0
	Retired	43	43	28	48	24	4	5	5	0	0	0	0
	Student	50	52	31	39	13	4	3	2	2	3	1	1

Abbreviations: T—Trip-based Modal Split, D—Distance-based Modal Split, PT—Public Transport.

4.5. Identification and Analysis of the Empirical Distribution of Trip Purposes

An analysis of activities undertaken throughout the course of the day allows for a better understanding of the needs of contemporary urban residents. During the survey residents were asked to identify the purpose of their trips or in other words, activities to be undertaken at the end of the trip. Throughout data cleaning and transformation, all the activities were assigned to one of the predefined categories identified in Table 4.

Table 4. Classification of trip purposes/activities and their abbreviations.

No.	Activity Code	Activity	Activity Type
1	W	Work	Subsistence
2	C	Communication/social	Discretionary
3	E	Educational	Subsistence
4	B	Business	Subsistence
5	S	Shopping	Maintenance
6	L	Leisure	Discretionary
7	H	Healthcare	Maintenance
8	A	Athletics	Maintenance
9	O	Outdoors	Discretionary
10	M	Maintenance activity/staying at home	Maintenance
11	D	Drop off (at school)	Subsistence
12	K	Drop off (general)	Maintenance
13	P	Pick up (school)	Subsistence
14	Z	Pick up (general).	Maintenance
15	F	Car maintenance (refuelling etc.)	Maintenance
16	X	Not identified	-

In total, there are fifteen activities reflecting the most common endeavors undertaken by sampled respondents. The first ten categories identify temporary longer activities, which usually take place from between half an hour to several hours, with the next five activities being of a short-term nature and taking place for up to just half an hour. There was a need to allow unknown activities (X) as some respondents have provided no information on the trip purpose. Other authors are using a significantly more aggregated classification. For example, Reichman [21]) and Krizek [4] classify the activities into three main categories:

- Subsistence activities that includes work, school or college related activities;
- maintenance activities that includes personal, appointment, and shopping related activities;
- discretionary activities that includes social visits and free-time.

Unfortunately, when considering only these three types of activities, lots of useful information is lost and the analysis suffers from less precise and sometimes even slightly obscure insights. Therefore, the full set of 16 activities will be maintained. It is worth noting that only up to 4 trip purposes are usually considered in conventional trip-based models, which consequently are inferior to the tour-based models taking into account daily trip sequences.

By looking at the overall distribution of activity frequencies, it is seen that the most likely purposes are related to Home (M), Work (W), and Shopping (S). These three purposes alone account for 69% of all the trips. However, it is worth noting at this point that this distribution applies to the population older than 16 years and therefore there is a rather low percentage of Education (E) trips, which would have been significantly higher had the whole population been considered. Table 5 provides more detailed information on the distribution of activities categorized by residents' characteristics.

Table 5. Empirical activity frequencies categorized by residents characteristics.

Variable	Level	Empirical Activity Frequencies, %															
		W	C	E	B	S	L	H	A	O	M	D	K	P	Z	F	X
Gender	M	26	3	2	5	10	2	2	2	1	38	2	2	1	1	0	3
	F	22	5	1	3	11	3	3	2	2	39	3	1	3	1	0	3
Education	AD	24	4	1	3	11	2	2	3	2	37	3	1	2	1	0	3
	BD	24	4	0	4	12	3	1	2	2	35	3	2	3	1	0	2
	HE	27	2	0	3	9	1	4	2	1	41	2	1	2	1	0	3
	PSE	19	4	7	3	10	2	4	2	1	42	1	1	1	0	0	2
	VE	26	2	1	3	8	3	3	0	1	41	4	2	2	2	0	2
Age	20–49	25	3	1	4	10	3	2	2	2	38	4	1	3	1	0	2
	>50	22	4	0	3	13	2	4	2	1	40	1	1	1	1	0	4
	16–19	10	8	18	1	8	7	1	4	1	39	0	2	0	0	0	2
Occupation	U	4	4	2	1	12	3	5	1	6	42	9	1	6	0	0	2
	E	28	3	0	4	10	2	2	2	1	37	2	1	2	1	0	2
	R	1	6	0	0	21	2	10	4	2	44	1	1	1	1	0	7
	S	6	7	22	1	9	5	2	3	1	41	0	2	0	0	0	2

There are no very clear distribution differences in terms of gender. In general, females are slightly less likely to undertake work activities, more likely to undertake social communication and pick up (school related) activities and less likely to do business related trips.

The age characteristic allows us to distinguish different travel behaviors in terms of undertaken activities/trip purposes. Young people undertake a relatively higher proportion of social communication and education related trips and a lower proportion of work and shopping trips, which is a rather expected outcome. Furthermore, people aged 50 and over tend to do more healthcare related trips, more shopping trips, and less work trips.

The occupation categorical variable also seems to influence the observed activity frequencies. Unemployed people show a relatively high proportion of shopping, outdoors, drop off and pick up activities. Retired individuals can be characterized by frequent shopping, healthcare, and social communication activities. Employed individuals feature a high frequency of work related and shopping trips whilst students conduct education, shopping and social communication related trips most of the time.

4.6. Identification and Analysis of Trip Lengths

Unfortunately, trip lengths have not been surveyed directly from respondents and that posed a significant issue during the analysis of trip distances. However, practical experience shows that even if distances had been observed, the reported estimates would have been significantly biased due to the respondents' inability to evaluate the travelled distance accurately.

The respondents were asked to identify the approximate addresses of their undertaken activities and this piece of information was used to estimate the distance between a properly defined origin and destination locations. Origin and destination locations were fed into the computational procedure that allowed the estimation of the shortest distance and travel time in the congested transport network between defined origins and destinations via Google Maps Distance Matrix Application Programming Interface [22].

The procedure consists of the two main steps:

1. Geocoding of the addresses using Geocoder library [19] written in Python language. This library allowed the conversion of the addresses into a set of geographical coordinates: latitude and longitude in WGS84 coordinate system. It is worth noting that significant checking and correction efforts have been made to ensure that the geocoded locations were sensible.

2. Trip distance estimation. As soon as the locations have been identified properly the search of the shortest path was carried out with the help of Google Maps Distance Matrix Application Programming Interface following the procedure set out by Dumbliauskas et al. [23] and Wang et al. [24]. Within this step, an explicit assumption that travelers have chosen the shortest route was made, which is not necessarily true in all the observations. However, bearing in mind that this is the only way to estimate travelled distances, the procedure is deemed to be fit for purpose.

Figure 7 provides average trip length (ATL) estimates for various transport modes. The data reveals that the ATL of all the trips (4049) in the sample is 7.5 km. From a comparison of separate modes, car trips are about 30% longer than public transport trips and cycling trips are approximately two times shorter than car trips. It is worth noting that walking trips are comparatively long with an average distance of 2.0 km.

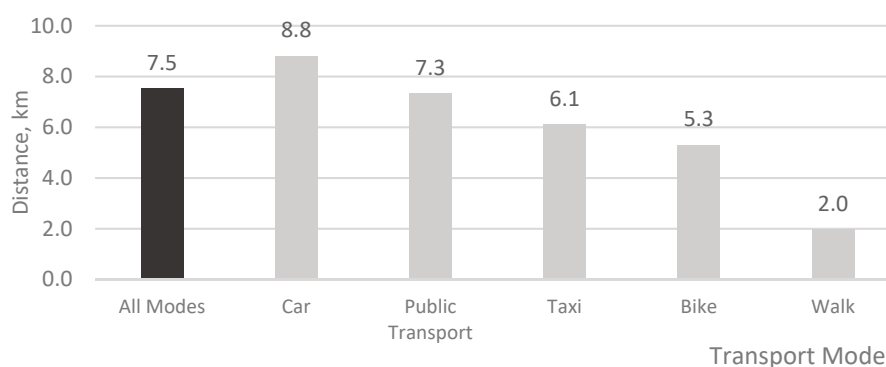


Figure 7. Estimation of average trip lengths by mode, km (created by authors).

Table 6 provides a more detailed analysis of the ATL parameter categorized by respondents' characteristics and mode.

Table 6. Average trip lengths (km) categorized by residents' characteristics and mode.

Variable	Level	All Modes	Public Transport	Car	Walk	Bike	Taxi
Age	50 and over	7.0	7.0	8.4	1.6	7.2	-
	20–49	7.8	7.5	8.9	2.1	4.9	5.4
	16–19	7.5	8.2	10.0	2.5	4.3	23.6
Gender	Male	7.9	7.3	9.2	1.9	4.8	7.0
	Female	7.2	7.4	8.4	2.1	7.3	5.1
Education	Primary or secondary education	8.4	8.1	10.3	2.0	5.4	-
	Vocational education	8.4	8.7	9.9	1.7	-	-
	Higher education	8.3	9.1	9.0	1.9	-	-
	Bachelor's degree	7.1	6.8	8.1	2.2	5.0	4.9
	Advanced degree	7.1	6.1	8.6	1.9	5.7	4.0
Occupation	Unemployed	8.2	8.6	9.4	1.6	-	-
	Employed	7.6	7.2	8.8	2.1	4.9	5
	Retired	6.2	7.5	7.9	1.3	7.7	-
	Student	7.8	7.6	10	2.5	4.8	-

By looking at the age levels it is obvious that across all modes the longest trips are being made by middle aged (20–49) individuals. Furthermore, it is seen that males (7.9 km) tend to take longer trips than females (7.2 km); however, the difference is rather small. Consideration of ATL across education levels brings a conclusion that more educated people make shorter trips. It has been noted previously that more educated people make more trips, so it seems that generally this group tries to maximize their number of activities while minimizing the time spent for travelling. Finally, it should be noted that the unemployed people make the longest trips whereas retired individuals make the shortest ones. The derived trip lengths allowed the identification of trip length distributions, which is the critical

piece of information within the calibration of the trip distribution sub model. Modelled trip distances will be compared to the observed ones and trip distribution model parameters will be optimized to achieve a reasonable representation. The following graph in Figure 8 illustrates trip length distribution by time intervals within the whole sample, irrespective of the trip purpose.

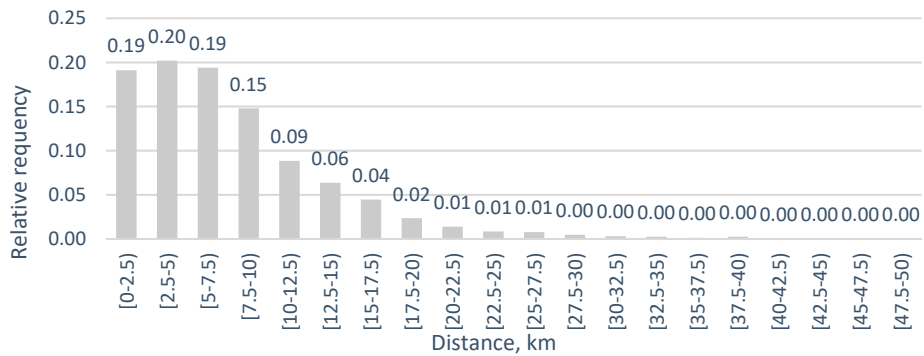


Figure 8. Trip length distribution by distance intervals for all activities/trip purposes (created by authors).

The distribution reveals that about 60% of trips are not longer than 7.5 km, about 80% of trips are not longer than 12.5 km and the average trip length is 7.7 km. This is rather typical shape of the trip length distribution that is also found across many towns and cities. It has an exponential shape significantly skewed to the right and its range usually depends on the size of the city or town. The three figures that follow (Figures 9–11) define trip distributions for work, shopping, and home maintenance activities.

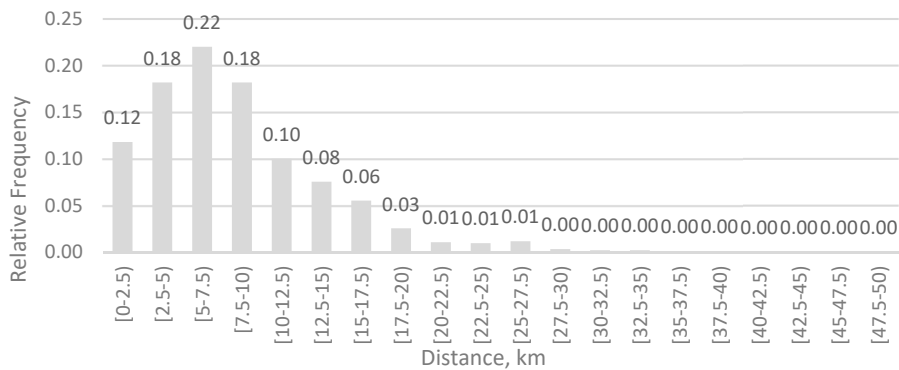


Figure 9. Trip length distribution by distance intervals for work activity (created by authors).

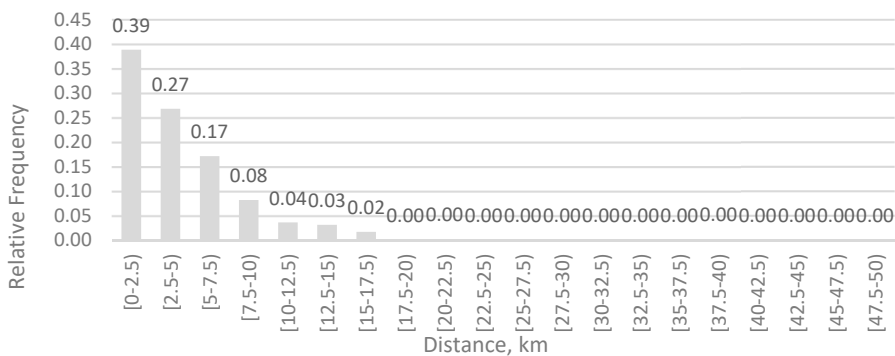


Figure 10. Trip length distribution by distance intervals for shopping activity (created by authors).

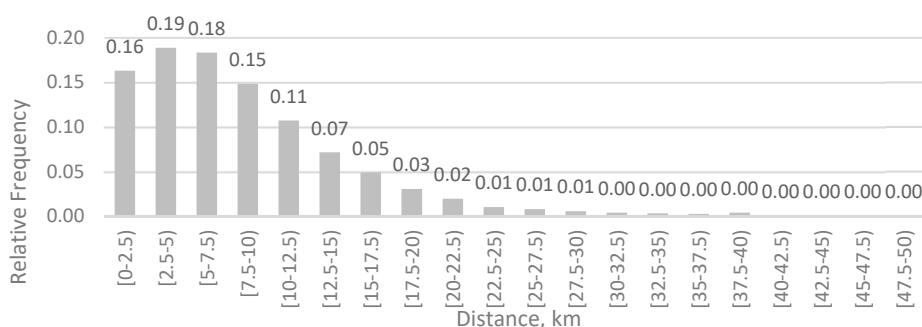


Figure 11. Trip length distribution by distance intervals (km) for home maintenance activity (created by authors).

Researchers [25] have found work related trips to be less sensitive to separation/distance compared to other trips. And this statement is backed up by the outputs of our survey. The average trip length is 8.4 km and it is far above the overall average (7.7 km). Compared to overall distribution it has more mass to the right. The distribution reveals that about 52% of trips are not longer than 7.5 km and about 80% of trips are not longer than 12.5 km.

Distribution related to shopping activity features a significantly different shape and resembles exponential distribution. The average shopping trip length is 4.4 km, which is far below the overall average of trips. This difference is mainly due to the shopping activity being rather flexible and not fixed to a particular location over time (short term decision) as well as due to the availability of shopping centers spread all over the place.

The average home related trip length is 8.4 km, which is slightly above the overall average and equal to the average associated to work related trips. About 54% of trips are not longer than 7.5 km and about 79% of trips are not longer than 12.5 km.

Trip length distributions can be approximated by Gamma probability density function, expression of which is given below:

$$f(x) = \frac{x^{\alpha-1} \times e^{-x/\beta}}{\beta^{\alpha} \times \Gamma(\alpha)} \tag{6}$$

where α, β —distribution parameters; x —trip length; $\Gamma(\alpha)$ —Gamma function.

The gamma function $\Gamma(\alpha)$ is an extension of the factorial function to real numbers and is calculated as follows:

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} \times e^{-x} dx. \tag{7}$$

The graphs given in Figure 12 presents gamma distributions fitted using least squares methodology for work, shopping, home and all trips in combination.

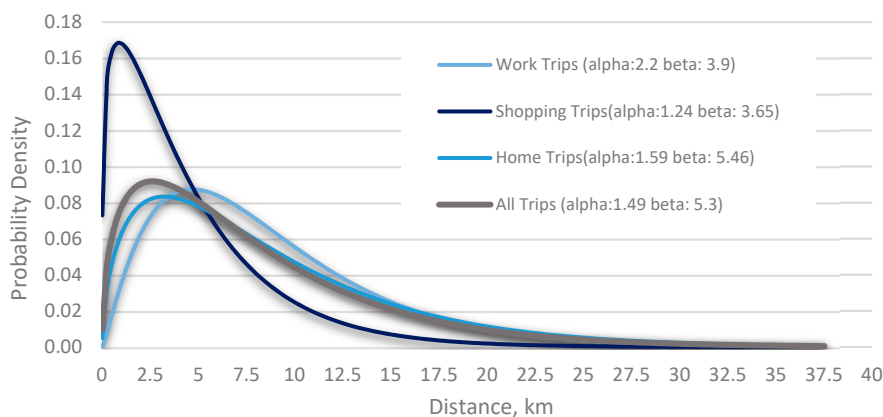


Figure 12. Gamma distributions fitted to trip length distributions (created by authors).

The fitted distributions closely follow observed ones and here again a major difference between shopping and other trips can be identified.

4.7. Identification and Analysis of Trip Start Times

Within this section, the temporal distribution of trip starting times will be examined. First the distribution of the overall sample of trips is presented and then a more detailed analysis of the distributions by activity follows. The chart shown in Figure 13 describes the relative frequencies of trip starting times for each hour during the day.

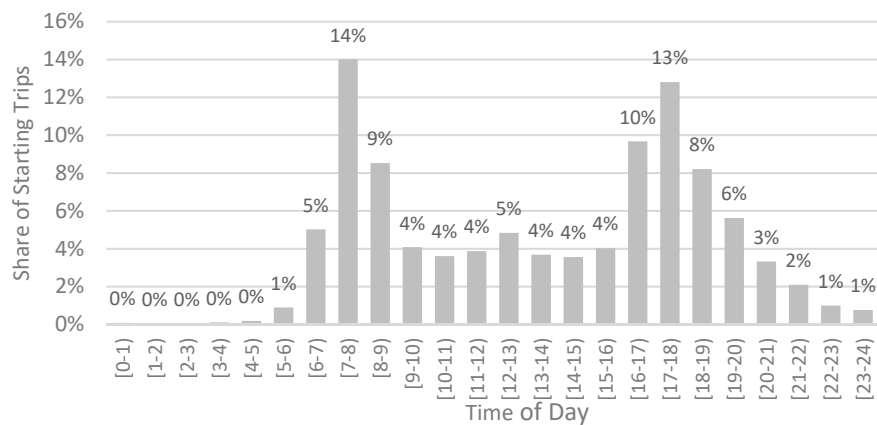


Figure 13. Distribution of trips by start time (created by authors).

There are two clear global a.m. and p.m. peak periods and a rather flat profile of trips between them. The most intensive hour, during which about 14% of trips are made, belongs to the a.m. peak and is between 7:00 and 8:00 o'clock. The next most intensive hour containing about 13% of trips lies within p.m. peak and is between 17:00 and 18:00 o'clock. It is worth noting that out of the five most intensive hours two belong to a.m. peak and three belong to p.m. peak. This suggests that even though a.m. peak has higher short-term intensity, p.m. peak takes place longer.

Further, the distribution of trips by start times and purposes were analyzed. The analysis reveals, that about 79% of work (W) related trips start between 6:00 and 9:00 with an a.m. peak hour containing 42%. Shopping (S) trips are made mainly during lunch time and immediately after work. The period between 11:00 and 13:00 contains about 19% and the period between 16:00 and 19:00 holds about 40% shopping (S) trips. About 60% of home related trips take place during the four hours (16:00–20:00) located within the p.m. peak period. School related drop-off (D) trips mainly (82%) are undertaken during two a.m. peak hours between 7:00 and 9:00, whereas pick-up (P) trips are slightly more dispersed within p.m. peak period with 82% of trips being located between 16:00 and 19:00. It is important to recognize that car maintenance related trips (F) and trips without any defined purpose (X) have had very low samples, therefore their frequency estimates are unreliable.

Temporal distributions of the trips are a key survey output as they will be directly used to model temporal distribution of activity sequences.

4.8. Identification and Analysis of Activity Sequences

This section describes the final piece of the analysis conducted within the scope of this empirical survey. Here, the observed activity sequences and their various statistics are presented. Observed activity sequences and, their relative frequencies with associated probabilities for the overall sample are presented in Table 7.

Table 7. Observed activity sequences.

Observed Activity Sequences	Number of Observations	Relative Frequency	Probability
Staying at home	424	21.4%	0.239
MWM	525	26.5%	0.296
MSM	122	6.2%	0.069
MWSM	86	4.3%	0.049
MHM	48	2.4%	0.027
MCM	46	2.3%	0.026
MEM	42	2.1%	0.024
MLM	38	1.9%	0.021
MXM	37	1.9%	0.021
MOM	29	1.5%	0.016
MBM	26	1.3%	0.015
MWBM	26	1.3%	0.015
MAM	25	1.3%	0.014
MDM	25	1.3%	0.014
MDWPM	22	1.1%	0.012
MWCM	18	0.9%	0.010
MDWM	16	0.8%	0.009
MPM	12	0.6%	0.007
MWAM	11	0.6%	0.006
MWLM	10	0.5%	0.006
MWXM	10	0.5%	0.006
MKM	8	0.4%	0.005
MBSM	7	0.4%	0.004
MCSM	7	0.4%	0.004
MHSM	7	0.4%	0.004
MSSM	7	0.4%	0.004
MWASM	6	0.3%	0.003
MWBSM	6	0.3%	0.003
MWPM	6	0.3%	0.003
MWSCM	6	0.3%	0.003
All other sequences	321	16.2%	0.181
Total:	1979	100.0%	1.116

It is worth noting that the high number of different sequences were identified during the analysis and listing all of them in the following table was just not feasible. Therefore, the list presents only the 30 most likely different sequences. Together these form the basis of all the resident-related mobility taking place in Vilnius City, as all other sequences contribute towards mobility to a significantly smaller extent (321 observed sequences out of 1979 cases).

Probabilities were estimated by following a rather simple procedure: a number of observations of a specific activity sequence made by members of the sample is divided by the total sample size ($n = 1773$ residents). The probability represents the likelihood of a typical member of the population conducting the given activity sequence throughout the course of a typical weekday.

Table 7 contains one dummy activity sequence entitled “Staying at Home”, which is not an actual sequence but just a placeholder for a probability of not travelling, and is given just for clarity and convenience. As one individual can undertake more than one activity sequence during any given day, the probabilities sum to more than one. For example, a person can choose to travel to work, get back home and then do another tour by travelling to the local supermarket. Probabilities are a key to tour-based travel demand modelling as the multiplication of probabilities with the total population size allows the estimation of the total number of conducted sequences.

5. Discussion of the Results

It is seen from the Table 7 that most of the sequences are single purpose and only few of them are complex combining multiple activities. There is no surprise that the two most frequent simple sequences relate to work and shopping activities as these are undertaken daily most of the time.

The eight most likely complex sequences (MWSM, MDWPM, MWBM, MWCM, MDWM, MWXM, MWLM, and MWAM) involves work as one of the activities, which highlights that people tend to supplement their work-related travel with additional activities en route. De Abreu e Silva [1] argues that chaining trips and having a smaller number of more complex tours during a day is considered as an individual strategy to reduce the total amount of travel, particularly total distances travelled.

Considering Table 8 given below, which identifies by diagonal sum that about 69.2% of typical residents in Vilnius city do not undertake complex tours, it can be concluded that low travel complexity is not the main reason for poor public transport usage. However, it should be noted that complexity has the potential to increase over time and the public transport system may face additional challenges in the future as activity sequences become more complex [5–7] and lead to an increase in car usage [2]. Such a strong reliance on the car mode in Vilnius (distance based 75.7%) results in frequent congestion and consequently environmental and social costs such as air and noise pollution, high energy consumption, road accidents, and delays. To move towards more sustainable mobility, some proactive measures are necessary. In general, sustainable mobility is a broad definition and according to Banister [26] it encourages not only modal shift, but also the reduction of travel, and greater efficiency in the transport system.

Table 8. Distribution of sampled residents across sequences and activities.

Number of Daily Sequences	Number of Daily Activities, %									Total
	0	1	2	3	4	5	6	7	8	
0	23.9	–	–	–	–	–	–	–	–	24
1	–	40.3	14.2	7.2	2.5	0.7	0.2	0.2	0.1	65
2	–	–	4.6	2.2	1.7	0.8	0.3	0.3	0	10
3	–	–	–	0.3	0.2	0.2	0.1	0	0	1
4	–	–	–	–	0.1	0	0	0	0	0
Total	24	40	19	10	4	2	1	0	0	100

According to Table 8 above, the highest share of sampled residents pursues simple activity sequences (45.3%), e.g., people tend to conduct an activity and travel directly back home. The complex travel and activity sequences are featured by 30.8% of the sampled residents. The rest of the sample (23.9%) did not travel at all.

The identification of key behavioral differences was analyzed between defined population segments. For example, the five most likely activity sequences associated with the retired person aged over 50 are: MSM (0.17), MHM (0.08), MCM (0.04), MXM (0.03), and MOM (0.01). In contrast, the employed person aged over 50 will most likely undertake the following sequences: MWM (0.42), MWSM (0.08), MSM (0.05), MXM (0.03), and MHM (0.02). The differences are apparent: retired persons have no incentive to undertake complex travel and their activities are concentrated on shopping, healthcare and social communication, whereas working individuals still do working and shopping activities most of the time and try to tie in compatible activities into one sequence.

An empirical travel behavior data collection, processing, and analysis approach allowing the identification of activity sequences and their probabilities by homogeneous population segments has a great potential. An innovative activity sequence-focused survey of travel behavior and associated data analysis methodology proposed within the scope of this thesis allows identification of daily activity sequences and their probabilities for the homogeneous population segments. With this approach for urban territories, insights about travel distance and travel time estimates is gained through secondary datasets coming from Google travel time database and associated route choice algorithms. As a

result, the errors of travel time and distance estimates are eliminated, data collection procedures are accelerated. A comprehensive data collection framework is universal and transferable to the context of any other urban territory without restrictions to the national context. However, additional data collection, manipulation, analysis, and modelling efforts will be necessary.

The main approach that helps in seeking the sustainability of transportation systems is Travel Demand Management (also known as Mobility Management), which aims at promoting sustainable transportation by changing traveler behavior [27–29].

It is a common knowledge, that no single measure can make a difference and a set of push and pull measures should be used to relieve the situation. Habibian et al. [30] identifies that pull policies encourage the use of non-car modes by making them attractive to car users; these policies include transit-oriented development, street reclaiming and the development of bus rapid transit. Inversely, push policies are those that discourage car usage by making it less attractive; these policies include road tolls, parking fees, and cordon pricing.

A very well-developed review of the full range of measures is compiled by Litman [31] and is made available for transportation professionals, politicians and the general public via the online Travel Demand Management Encyclopedia [32]. This information has been reviewed by experts and is regularly expanded and updated.

Having in mind the geographical, social and political situation, Vilnius would benefit from further finetuning of the bus rapid transit coupled with transit-oriented development and restrictions on downtown parking. At this stage, restrictions on the use of polluting vehicles would also improve the situation. Even though the travel behavior data analysis had a focus on activities and their sequences rather than individual trips, the administration of the survey was carried out through the traditional web-based self-report and face-to-face interview. It is worth noting that traditional methods (face-to-face interviews, telephone interviews, pencil-and-paper, or web-based self-reporting) have considerable drawbacks, such as [33]:

- (a) Low accuracy due to dependence on memory and under-reporting and
- (b) low sample sizes due to high administration cost.

As it is difficult to remember minute details with certainty, accuracy of the collected data (departure and arrival moments, geographic locations, purposes) falls. Moreover, due to the same memory issue, small trips remain unreported most of the time. According to Hossain et al. [34], all short trips (less than 15 min trip duration) were subject to being misreported and this phenomenon was statistically significant at 0.05 level. For longer trip lengths, no significant trip misreporting was observed.

Recently, an alternative data collection method [35–38] employing smartphones has emerged. Since most smartphones are equipped with various sensors (GPS and accelerometer), and since smartphones are integrated in the daily life of most people, they provide an unprecedented opportunity for large-scale travel data collection. The method has numerous advantages:

- (a) Very convenient for participants;
- (b) longer time span surveys;
- (c) high accuracy;
- (d) extensive datasets;
- (e) unbiased data; and
- (f) less-costly due to high smartphone penetration.

This method is a viable alternative that can be applied in the national practice as smartphone penetration in Lithuania is over 70%. However, there are some potential challenges that requires a special consideration, such as recruitment of participants, and more importantly data privacy issues.

Recruitment of participants, for example, can be improved by suggesting small financial incentives (discounts on public transport trips, parking charges etc.) to members of the public that keep data collection applications running in the background on their smartphones. In addition, the proper data

anonymization algorithms need to be employed in order to ensure positive public perception and compliance with General Data Protection Regulation. Such datasets are rather sensitive and should be collected, anonymized, and used with exceptional care.

6. Conclusions and Recommendations

- (1) The empirical travel behavior studies, using an activity-based approach, coupled with advanced data collection technologies such as Google Maps Distance Matrix Application Programming Interface and data analysis tools, provide a basis for retrospection and ensure a detailed identification of travel behavior patterns across homogeneous population segments, guarantee the capability of representing daily demand within travel demand models. The application of prepared datasets within the travel supply model development ensures detailed transport demand representation and potential in financial cost reduction. This novel approach can be harnessed in scientific and applied travel behavior studies.
- (2) An empirical travel behavior survey and secondary travel distance data collection by Google Distance Matrix API were employed in gathering information about respondents' mobility patterns. Python programming language and its standard libraries such as Pandas, NumPy, etc. were used to undertake data mining, cleaning, and statistical analysis of data further utilized for the representation of demand within travel demand model. The proposed elements could serve as the best practice guide to ensure statistical reliability, transparency, and methodological consistency.
- (3) An innovative activity sequence-focused travel behavior research approach designed to collect data for tour-based travel demand model for Vilnius city takes into account a set of 16 trip purposes, which is a significant improvement over conventional travel behavior research approaches designed to cater trip-based models and typically considering 2–4 trip purposes. With this approach, insights about travel distance and travel time estimates is gained through secondary datasets coming from the Google travel time database and associated route choice algorithms. As a result, the errors of travel time and distance estimates are diminished. Data collected under activity sequence-focused approach allows quantification of essential mobility parameters such as the proportion of travelling residents, the average number of trips, average trip lengths, mode splits as well as daily activity sequences and their probabilities.
- (4) After application of activity sequence-focused survey with a sample size of 1773, it was found that the Vilnius city resident conducts on average 2.3 trips on a weekday with the average length of 7.5 km per trip. The chances of each trip being made by public transport, car or by foot on average are 21%, 61%, and 15% respectively. The trips are related to work, shopping or home most of the time, as these three activities have 24%, 11%, and 38% average probabilities of being undertaken, respectively.
- (5) The highest share of sampled residents pursues only simple activity sequences (45.3%), i.e., people conduct only sequences (one or several) that involve one activity and two trips: first from home to the activity's location and second from activity's location to home. In addition, 30.8% of the sampled residents conducted at least one complex sequence, whilst the rest of the sample (23.9%) did not travel at all. The most likely simple sequence is the "Home–Work–Home" being made with a 29.6% average probability, whereas the most likely complex sequence is the "Home–Work–Shopping–Home" being done with a probability of 4.9%.
- (6) Transportation is an element in pursuance of sustainable urban development. Travel patterns are a component of sustainable urban transportation. Providing sufficient access by private car in Vilnius is unsustainable on account of the limited capacity of the street's network, the environmental and social problems caused by the consequent congestion. This situation is an opportunity for the city's authorities to provide the required level of public transport in Vilnius.
- (7) Empirical estimates of the above variables and especially activity sequences and their probabilities will feed the tour-based travel demand model, which is to be developed by employing macro modelling application.

- (8) Even though the travel behavior data analysis had a focus on activities and their sequences rather than individual trips, the administration of the survey was carried out through the traditional web-based self-report and face-to-face interview. This method has several disadvantages and more innovative approaches employing smartphone devices with built-in location and acceleration sensors will become more prominent and should be tested in further studies.

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