Analysis of the Mobility of Healthy Older Adults: Semantic Enrichment of Activity Locations and Their Relationship Between Weekday, Age and Place of Residence

GEO 511 Master's Thesis

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Abstract

The unprecedented shift towards an aging population in western societies poses a challenge for policy and decision makers. By 2050, one in five people will be 60 years or older, totaling in 2 billion people worldwide (WHO, 2015). The goal has to be to provide older adults with a society that is attentive to their needs, and encouraging in their participation in all aspects of society (Nelson, 2016). However to reach this goal, societies are responsible to provide the infrastructure to make healthy aging possible.

Healthy aging is closely linked to the mobility of older adults. Mobility is the key of still having an active and independent live, and is crucial for carrying out commercial, cultural or social activities (Hirsch et al., 2014).

In this thesis we investigate the relationship between healthy older adults activity locations and other variables such as home type, weekday, and age, to get a better understanding of the mobility of older adults and their behaviors.

This thesis is part of the mobility, activity and social interaction study (MOASIS), in which 159 healthy older adults (over 65 years old) were assessed for their physical and mental abilities and tracked for 30 days with a GPS logger to record their position.

We then perform a semantic enrichment on the detected stops of the MOASIS participants to gain more insight in the activity locations of the participants.

We show that the study participants visited different places at weekends than during the week. They recorded a higher number of recreational stops on weekends than during the week. Further we look into the relation between the home type (urban, rural or suburban) and the total number of visited stops of the participants and the unique visited stops. We could not prove a significant difference between the different home types and the mobility levels. Lastly we show a significant difference of more diverse unique place visitations of younger participants (65-72 years old) when comparing them to older participants (73-89 years old).

Acknowledgments

Thanks to Eun-Kyeong Kim and Robert Weibel for being my advisor and supervisor. Additional thanks to Christina Röcke as deputy director and research group leader of the University Research Priority Program (URPP) “Dynamics of Healthy Aging”, which was responsible for the MOASIS study.

Finally I want to thank my girlfriend, family and friends, that supported me in any way during the process of this thesis.

I dedicate this work to my grandmother who passed away past December.

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List of Abbreviations

Abbr.	Description
1:GPS	Global Positioning System
2:MOASIS	Mobility, Activity and Social Interaction Study
3:OSM	Open Street Map
4:POI	Point of Interest

List of Illustrations

1 Introduction

“Mobility is one of the major keywords that characterize the current development of our society. People, goods, and ideas are moving faster and more frequently than ever.” – Parent et al., 2013, p. 2

In today’s time, it is very important to gather information about people’s mobility behavior to get useful insights in daily place visitation. Urban planners and local authorities can use this information to better manage public transport networks or to guide pedestrian flows in high-traffic areas. Therefore it is important to know where the points of interests (POIs) of the people are. This can be their home, their workplace, or the places they visit in their free time, such as a bar or a shopping center. To find out which important places people are visiting, a stay-move analysis can be conducted to derive places where people are spending their time to get valuable insight into their daily activities.

Thanks to modern GPS technologies, we are able to easily record objects moving in space and time (Parent et al., 2013). Therefore a huge amount of high quality and low cost tracking datasets carrying spatiotemporal trajectory information are available. However, those trajectories don’t carry any semantic information and are not readable by a human or semantically meaningful without adding more context (Bermingham and Lee, 2019).

A trajectory of a trace of a human, an animal, or an object like a car, does not carry only geometric spatiotemporal features, but possesses semantic features as well (the meaning of the movement) (Yan and Spacciapetra, 2009).

With a process called semantic enrichment (see section 2.3), where contextual related data is being added to the raw spatiotemporal trajectories, we are able to create so called semantic trajectories. The idea behind this is that already existing and collected trajectory data is being complemented with additional data, which are called annotations (Parent et al., 2013). This process is fundamental for mobility and behavioral analyses that are currently of interest.

Due to the demographic change towards an older population all over the world, it is very important to analyze the mobility of older adults in terms of their physical and mental health. With better insight into their mobility behavior, it is possible to reduce healthcare costs and ensure older people have access to public transportation and the facilities they need. In addition, better infrastructure would promote higher social participation of older adults, which is good for their mental and psychological health, and therefore promotes healthy ageing (Van den Berg et al., 2015).

This thesis is part of the project called MOASIS (Mobility, Activity, and Social Interaction Study), where 159 healthy older adults wore a GPS logger that could measure various variables, including geographic locations and the acceleration of body movements over a span of 30 days. Hence, data about the locations and the accelerometry could be stored. The participants were also surveyed on their physical and mental health. All the participants gave written consent for the usage of their collected data.

The aim of my Master's thesis is to semantically enrich the trajectories collected in the MOASIS study and possibly find meaningful semantic behaviors as well as to analyze the stop variability of the participants. Additional, we will analyze the difference in place visitation in dependence of the age, their place of residence (home type), and see if there is a difference in place visitation during the week or on weekends.

To start this thesis, we will present the discourse of the concept of place as it is important for the further course of this thesis. The following chapter provides an overview of the literature available in this field of research. We will then introduce our research questions and our hypotheses. The chapter with the workflow and our methods is next, followed by the chapter where we present our used data. After this chapter we will show the results of our work and discuss them. To wrap up the thesis, we will point out some limitations of this approach and summarize our findings. We will end this thesis with an outlook on possible further research.

2 Place

The word ‘place’ is being used in everyday life and is known in the research field of geography since many decades. Only since the 1970s, it has been described as a specific location that has a set of meanings and attributes (Cresswell, 2009). It is essential to understand the concept of place to know why semantic enrichment is so important for trajectory data. But what exactly is ‘place’?

2.1 Concepts of Place

The concept of place has been known to geographers since the 1970s (Tuan, 1975), where the author already stated two differentiations of the concept of place. First, place as a location, which is defined as a unit within a hierarchy of units in space. And second, place as a unique artifact, which is defined as center of meaning constructed by experience. Goodchild and Li (2011) refer to the same two perspectives proposed by Tuan (1975) but use the terms space and place.

The first definition of Tuan (1975) can be equated to the definition of space by Goodchild and Li, 2011. Space according to them is referring to the surface and is organized by coordinate systems such as longitude and latitude. Distances and directions in space are therefore measurable or computable. In the last decades, the concept of space and the spatial research have gotten more interest, because of new technologies, such as Global Positioning Systems (GPS), geographic information systems (GIS) or remote sensing (Goodchild and Li, 2011).

The second definition of Tuan (1975) is more congruent with the definition of place in Goodchild and Li’s (2011) paper. Place, they argue, is a social construction. It is a named domain that occurs in human discourse. They also state that a place has no clear boundaries and the perception of the properties of a place may vary from one person to another. A place can exist permanently or can disappear (e.g. a demolition), or can be related to specific events (ibid.).

The definition of the term place in Purves et al. (2019) goes a step further in introducing one base concept named *location*, and four related concepts called *field*, *object*, *network*, and *event*. They based these concepts off of Kuhn's ontology of core concepts of spatial information (2012).

Location, according to them, is the main concept regarding all spatial information, and is the cornerstone of all *where* questions. The term is used two-fold: "location as a spatial relation between 'what is located' and 'what locates it'; and location as a region in the world defined by such relations" (Purves et al., (2019)., p. 1175). So if given a pair of a geographic coordinates for a city center, this will define the city's location. Likewise giving someone the information "the grocery store is near the train station" defines the region "near the train station" as a location as well. Further, location is a term without an identity and is inalterable in time (ibid.).

The concept *field* refers to a function which returns specific values for any given position and time in its domain. This can be precipitation values or any data displayed in a grid, where each grid cell has attribute values (ibid.). As we won't need the concept of *field* in this thesis, a more detailed description is dispensed.

When giving location a set of properties it becomes an *object*. It is "a uniquely identifiable entity existing in space and time and having well defined properties as well as relations with other objects" (ibid., p. 1175). An object may be a building, a park, or a lake. Objects can be derived from fields (e.g. identifying all regions where it has rained more than the average in the last 30 days) or from other objects (e.g. by aggregating or dividing them) (ibid.).

A set of objects in space and time is called a *network*, while the different objects are forming the nodes of the network (ibid.).

Finally an *event* is anything that is happening within a bounded space and time. This may be a rainstorm, or a natural disaster, like a wildfire. Events can change the properties of objects or move or block the nodes of a network (ibid.).

The term place therefore is a derivation of all these mentioned concepts. It is an object resulting from a shared identification of a location. And it thus can become part of a network (as a node), and participate in events as already stated above (Purves et al., 2019).

2.2 Cognitive Dimensions of Place

Cresswell (2009) and Agnew (1987) define place as a meaningful site, that combines location, locale and sense of place.

The term location in Cresswells (2009) definition refers to the ‘where’ of place. It is defined as an absolute point in space with specific coordinates and measurable distances to other locations. Locale on the other hand refers to the way a place looks. This includes all the visible and substantial aspects of a place (building, trees, park). Finally sense of place refers to the more intangible meanings which are connected to a place, which might be emotions and feelings a place induces. Meanings about a place can be shared or be very individual for some people (Cresswell, 2009).

Looking at the coordinates 47.38°, 8.54°, they will tell us a location, which is the Platzspitz in Zurich. That’s all we know with this information. But it is also a locale, there is a park with trees and two rivers are connecting just a bit north of the given coordinates. There is also the historical building of the Landesmuseum. All this information and properties makes it to a place. Finally it has also senses of place, which may vary between individuals. Younger individuals maybe only know the beautiful park where they relax on a sunny day during summer, but older individuals maybe remember the Platzspitz also as being an epicenter of drug addicts and drug trafficking in mid 1980s (www.nzz.ch (20.07.21) (exact access link in literature)).

Places can exist at many scales, taking the example from above, Zurich as a city is a place, but Zurich consists of many places on a smaller level. In the end also a corner in a room can be a place with a specific meaning for an individual (Cresswell, 2009). Places or objects as in Purves definition do not always have clear boundaries like a building, if we for example take an ethnic region as a place, it won’t be clearly bounded but still can be seen as place of this specific ethnicity (Purves et al., 2019).

Finally, people do certain activities in a place, for example going to work, shop groceries or do sports. So the activities people do, are responsible for the meaning a place might have to them (Cresswell, 2009).

To summarize, Roche (2016) describes the concept of place with a function f which we think fits all of the above presented concepts very well. She describes place as: P = f (N, E, L), with P being the place, N the name of it, E the event, and L the location. The place is clearly identifiable with its name and location, while the event refers to a larger spectrum of meanings. It is described as space within humans carry out their daily activities such as work, or shopping. For example the shopping center Sihlcity has a name and a specific set of coordinates. But the event can vary between people, some may visit the mall, some go there to eat, others go to the cinema, and for many people it is their workplace.

2.3. Place and the Importance of Semantic Enrichment of Trajectories

With the recent rise of new technologies such as GPS or GPS equipped mobile devices (Tran et al., 2011), there has been a continuous increase in interest in analyzing motion data. As a result, a huge amount of large trajectory datasets are available. In recent years, interest has shifted from raw motion data analysis to a more informative approach to data analysis. The goal of researchers is to obtain more knowledge about the movement. This is achieved by linking trajectory data with related contextual data. This process is called semantic enrichment and the newly obtained trajectories are called semantic trajectories (Parent et al., 2013). Therefore, the semantic enrichment process is the necessary tool to compute the places where people pursue doing their daily activities, which is key for behavioral and mobility analyses.

In our thesis we need the semantic enrichment to find the different activity locations of the participants of the MOASIS data for a deeper insight in the mobility behavior and place visitations.

3 Background

3.1 General Background

The demographic transition towards older populations in almost every country of the world has profound implications for all of us and for the societies we live in (WHO, 2015). By 2050, one in five people will be 60 years or older, totaling in 2 billion people worldwide. Unfortunately, there is evidence, that many older people today experience much poorer health trajectories that might be possible. Many of those health issues are often associated with chronic conditions that could be prevented or delayed by engaging in healthy behaviors across the life course (WHO, 2017). For the Swiss citizens, the above-mentioned demographic shift will be one of the biggest challenges regarding social security, public finances, and the economy to face in the upcoming decades according to a report of the Swiss federal council (2016). Therefore, one goal of the Swiss federal council is to promote a healthy lifestyle of older adults to prevent more healthcare costs (ibid.).

For the reasons mentioned above, research in the field of gerontology is more important than ever. Physical activity of older adults is seen as one important key of healthy aging (Peel et al., 2005). Mobility as a part of physical activity is fundamental to active aging and is intimately linked to health status and quality of life (Webber et al., 2010). The term mobility in spatial, health and aging sciences typically refers to either spatial mobility and/or physical activity (Fillekes et al., 2019). In this thesis, we will mainly use the term mobility referring to spatial mobility, where individuals move from one place to another.

Therefore, measuring mobility is crucial for understanding influences on older adult’s health and functioning (Hirsch et al., 2014). In a 6-year study of Unger et al. (1997), they examined the effects of physical activity and social interactions of older adults. When encouraging social interactions and physical activity, they prevent or delay age-related declines in health and mortality. Social interactions are therefore important regarding the mental health of older adults. Ohrnberger et al. (2017) have as well shown in their study, that physical health and mental health are strongly linked and influenced by social interactions.

Yeom et al. (2008) on the other hand stated that impaired mobility is associated with a loss of independence, decreased quality of life and a higher risk for mortality. Further they also state that mobility limitation is part of the normal aging process, because of decreased muscle strength, bone mass, joint erosion and calcification. Not only does mobility decrease with age, but older adults also engage in fewer social activities, have a smaller social network and are therefore at risk of loneliness and social isolation. To reduce these risks, it is crucial to promote the social participation of older people. This can be achieved by creating an environment that supports the social participation of the older population. This is a key challenge for urban and transport planners (Van den Berg et al., 2015).

Finally, the environment is an important factor which influences mobility of older adults. An improved level of mobility is associated with factors such as an easily accessible indoor environment, the availability and access to the services in the local area (e.g. grocery store, pharmacy), and feeling safe. Older adults in rural areas have a lower level of mobility compared to urban older adults (Yeom et al., 2008). Limiting factors of mobility in urban areas may be air pollution, traffic safety, and neighborhood characteristics (e.g. no sidewalk available). Limiting factors of mobility in rural areas on the other hand may be a low level of public transport, or bigger distances between places that hinder mobility of older adults (ibid).

3.2 Measuring Mobility with GPS

Until recently many studies have explored the mobility of older adults relying mainly on reports or observational approaches (Shoval et al., 2010). One of many examples would be the study of Stalvey et al. (1999) in which they developed the so-called Life Space Questionnaire to measure the extent of mobility of older adults. Another example is the 6-year study by Unger (1997), which used questionnaires to examine the relationship between social interactions, physical activity, and physical function in adults aged 70 years and older.

Thanks to today's state of the art in technologies, one can make use of data collected by mobile devices equipped with Global Positioning Systems (GPS) to assess the daily mobility of individuals. This location-sensing technology allows one to gather high-resolution spatiotemporal data at an individual level and thus detect information about individual's mobility patterns (Fillekes et al., 2019). GPS may represent an important opportunity to measure, describe, and compare mobility patterns of older adults (Hirsch et al., 2014).

Studies of health and aging which incorporate measures of GPS-derived mobility are still relatively new (Fillekes et al., 2019). Nonetheless, there exist studies which collected GPS data of older adults to measure the mobility such as Hirsch et al. (2014) or the vast work of Shoval et al. (2007, 2008, 2010, 2015). Hirsch et al. (2014) examined a group of healthy older adults in the Vancouver area and measured their activity space. They found that participants who were younger (65 – 69 of age) had larger activity spaces than the older participants in their study. Just like other studies, they agreed that the use of GPS is of great importance to better understand the geographic mobility patterns of older adults. Shoval et al. (2008) on the other hand mostly studied the out-of-home mobility of older adults with dementia-related disorders. They were the first researchers to do a large scale study with cognitively impaired adults. Li et al., (2017) investigated gender and age differences of physical activity of older adults. They showed, that men had higher levels of physical activity than women of the same age. With advancing age, the level of physical activity decreased for both genders. They used participants that were 65 years and older and recorded their GPS trajectories for 7 days.

A common way to assess the daily mobility of older adults, is by using mobility indicators, which can be used to quantify the individual mobility. Two well-known examples of such indicators in the field of gerontology are time out of home (TOH) and the number of activity locations (#ALs). They are strongly linked with cognitive, physical and emotional functioning of older adults (Fillekes et al., (2019)). According to Fillekes et al. (2019), the indicator TOH describes the time an individual spends outside of their home, whereas the number of activity locations describe the different places that an individual has visited to perform an activity (e.g., going to a bar, grocery shopping). However, in this thesis the main focus lies on the number of activity locations, as this is the main variable we use to answer our research questions (see section 4).

There is a need for additional research on healthy older adults and their number of activity locations in relation to other variables such as age and home type. To our knowledge, our or similar research questions have not yet been investigated together in one study. It is particularly interesting to examine those questions in a dataset as large as MOASIS, which contains a large amount of interesting metadata and additional variables. Additional, the MOASIS dataset consists of healthy older adults, so older adults that had mobility-limiting diseases were excluded of the study. Hence it is particularly interesting to analyze the differences in activity locations of healthy older adults.

3.3 Place Detection and Semantic Enrichment

As stated above, the number of activity locations is an important indicator of the physical and mental wellbeing of older adults. Therefore it is necessary to gain insight into the activity locations of the MOASIS participants. To achieve this, place detection and semantic enrichment is an essential step.

3.3.1 Place Detection

As Thierry et al., (2013) state in their paper: "Activity place detection from GPS data is mainly cluster detection, where a sufficient number of data points are non-randomly distributed and have accumulated." It defines therefore a place where an object has stayed for a specific amount of time. Point cluster detection algorithms work usually with distance and time thresholds. They iteratively test data points if they stay within a given roaming distance and time of the previous ones. If the distance or time threshold is exceeded, a new cluster has been defined and the centroid of it is being defined as the approximation of stay location (Thierry et al., 2013)

One can also use speed thresholds to find point clusters, as Agamennoni et al., (2009) did. If points fall below a certain speed regarding to the previous point, they identify them as activity location, because the object is not moving in these sequences and it is therefore regarded as stop.

There exist many different stop-detection algorithms, for example POSMIT (probability of stops and moves in trajectories), SOC (sequence oriented clustering), Candidate Stops or the MBGP-algorithm (Montoliu, Blum and Gatica-Perez, 2013). Elena Ebert (2020) compared those different stop-detection algorithms in her Master's thesis regarding their performance on the MOASIS dataset. She concluded, that the MGBP algorithm performed best for the MOASIS data.

The MBGP algorithm groups the points of a GPS trajectory using a time-based clustering technique. It uses a parameter 'tmin' that specifies the minimum duration between points for them to be counted as a stop. The second parameter 'dmax' defines the diameter of a found stop cluster between the first and last GPS point of this cluster. It must not be greater than a defined maximum distance. The third parameter ‘tmax’ defines the maximum permitted time distance between two recorded location points that are considered part of the same stop cluster (Montoliu et al., 2013, Ebert, 2020).

3.3.2 Semantic Enrichment

Semantic enrichment is the process of adding contextual data to raw trajectories to gain better insight in trip purposes and activity locations. This process is particularly important for mobility and behavioral analyses (Parent et al., 2013). There is a rising interest in semantic enriched trajectory data to better understand movement behaviors of a particular object (older adults (Hirsch et al., 2014), tourist activity (Shoval et al., 2015), taxi trips (Gong et al., 2016)). With this process, not only the raw GPS points are available, additional information is annotated to the trajectories. The trajectory then contains both the geography on which the trajectory passes and the added geometric properties (when the user stops/moves) (Yan et al., 2013). However, the process of semantic enrichment presents some challenges. In particular, the selection of candidates from the annotation data for each stay point of a trajectory is a difficult task to accomplish. It is therefore needed that the most relevant semantic annotation is selected for each trajectory segment. For example, it does not make sense to annotate a moving object, with the locations it passes by, unless there is a stop (Yan et al., 2013).

As mentioned above, we will mainly focus on the number of activity locations of the MOASIS participants, however there are many other methods that deal with big trajectory datasets to find their underlying hidden information.

3.4 Other Methods to Analyze Big Trajectory Datasets

There exist several methods to analyze big trajectory datasets. Following we will shortly discuss three of them: The Sequence Alignment method, the Stay-Move tree model and the T-pattern analysis.

3.4.1 Stay-Move Tree Model

With the rise of new sensors and communication technologies, there are an increasing number of various trajectory datasets (e.g., MOASIS data). Hence, suitable theories and methodologies to such sequence data with qualitative labels and quantitative variables need to be employed and developed to analyze the data (Kim, 2018). As an example, Kim (2018) proposed to use a methodology called Stay-Move (SM) tree, to categorize spatiotemporal trajectories into a simplified trajectory type, represent the (relative) frequency of trajectories of each trajectory type, and compare trajectories of different groups. This method can deal with big trajectory datasets. However, this method needs pre-processed GPS data and the move(s) and stay(s) must be precisely defined. If those definitions are at a micro scale of space and time, the number of segments of a stay-move tree model may increase to the excessive degree, which would not be desirable to analyze trajectory data concisely (ibid.). Such an example of a stay-move tree is seen in figure 1.

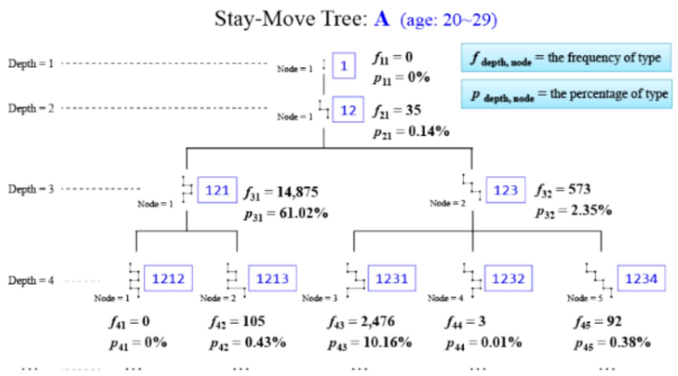


Figure 1: Example of a Stay-Move Tree, whereas 1 symbolizes a stay, 2 is a different stay and so on. f being the frequency of this pattern being detected, and p being the percentage of all detected patterns (Kim, 2018).

3.4.2 Sequence Alignment

Shoval and Isaacson (2007), Stehle and Peuquet (2015), and Shoval et al. (2015) used the methods of sequence alignment as a tool for analyzing the sequential aspects within the temporal and spatial dimensions of human activities (Shoval and Isaacson, 2007). Sequence Alignment was first developed in the 1980s to analyze DNA sequences, but since the 1990s, it is being more and more used in the social sciences (ibid.). The sequence alignment method was also used in an analysis of tourist activity in Hong Kong (Shoval et al., 2015). However, this method has several limitations. For example the lack of concrete ability to assess the reliability of the alignment produced. Another limitation in this study are the pre-defined polygons that define the areas where people will stay, which represent real world geographic locations which differ in size (ibid.). In figure 2, one can see an example of a sequence alignment of tourists in Hong Kong from the study of Shoval et al., (2015).

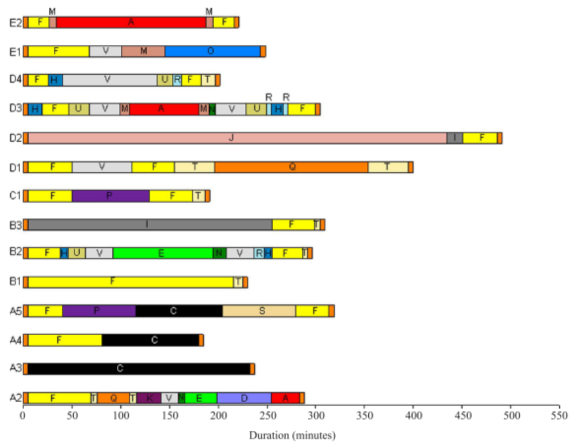


Figure 2: Sequences of movement through Hong Kong including the average duration of stay in each location (Shoval et al., 2015).

3.4.3 T-Pattern Analysis

Peuquet et al. (2015) proposed another method called T-pattern analysis. This T-pattern analysis is being used in the field of psychology for the purpose of finding patterns in social interactions. Peuquet et al. (2015) adapted this method for the use within geography. With their approach, they wanted to discover patterns among many types of spatio-temporal events within real-world data. Their case study was the so-called Arab Spring in Yemen. The main goal was to find patterns of social, economic, political or other types of events that occurred in relation to the Arab Spring in Yemen. They analyzed 12 different RSS newsfeeds to collect their data which finally consisted of over 35’000 news reports. Those were then filtered by their relevance and relation to Yemen. Finally they analyzed the remaining newsfeeds on keywords and geographic location to gain insight into possible patterns and the temporal sequences of events. In figure 3, one can see one arm of their T-pattern analysis (Peuquet et al., 2015).

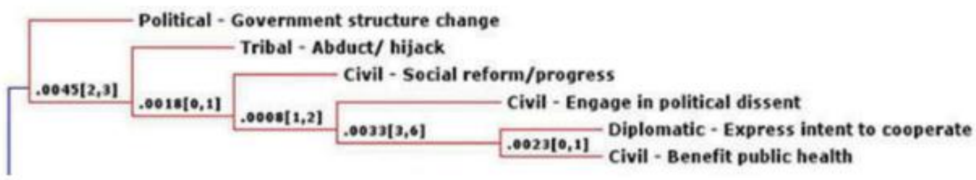


Figure 3: Example of a T-pattern hierarchical cluster showing a set of interrelated events (Peuquet et al., (2015).

4 Research Questions

My aim in this Master's thesis will be to identify the differences in the mobility behavior of the MOASIS study participants based on their visited activity locations. Below we propose three research questions based off of statements we found in the literature. We would like to investigate whether these statements made in the literature can be verified for the MOASIS dataset. Our research questions were chosen especially because the MOASIS dataset consists of healthy older adults. Therefore, it is really interesting to see if the statements made in the literature apply to a dataset with only healthy older adults, because no literature is known to us with this premise.

RQ1: Gong et al. (2016) found in their study about trip purposes from taxi trajectory data that the activities of people on weekdays differ from the activities on weekends (figure 4). Recreation activities for example are more detected on weekends, whereas work-related or schooling activities took place during the week. However their study is not specifically conducted with only people that are 65 years and older but it would still be interesting to see if there is a difference in detected stops by the MOASIS participants on weekends versus during the week. Is there a difference, and if so, what could be the reasons?

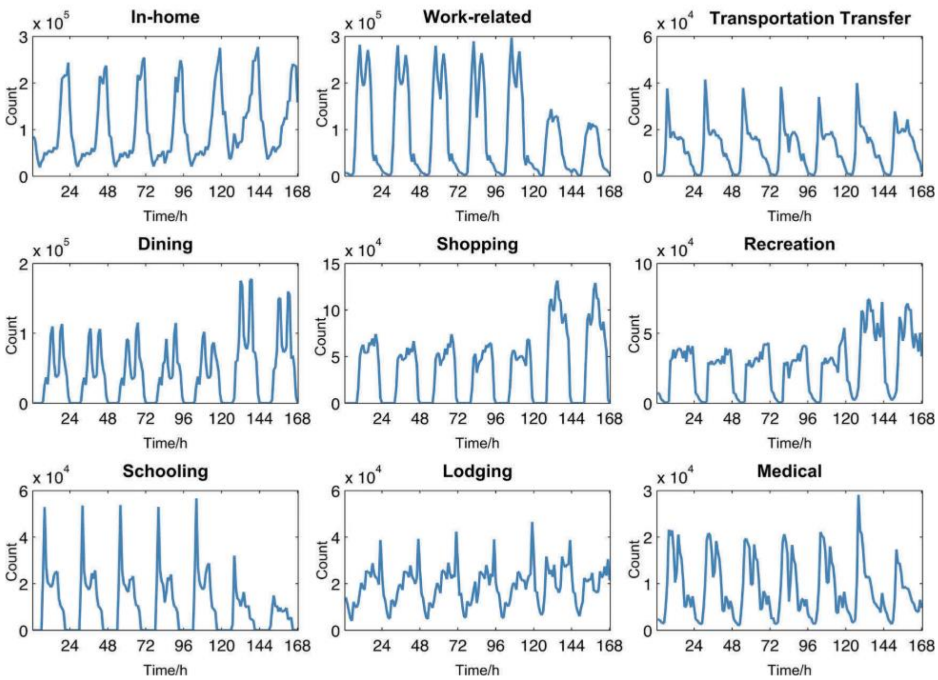


Figure 4: Weekly frequency variations of the nine activities according to Gong et al. (2016).

RQ2: As stated by Yeom et al. (2008) and Melzer & Parahyba (2004), older adults living in urban areas have a higher level of mobility than older adults living in rural areas. It is therefore interesting to see if this is the case within the MOASIS dataset. Especially with the knowledge that the study of Melzer & Parahyba (2004) is located in Brazil and was written almost 20 years ago. The research question we propose is as follows: Is there a significant difference of the place visitations of the MOASIS study participants that live in urban areas to those who live in rural areas?

RQ3: Yeom et al. (2008) also mentioned in their paper, that mobility limitation is part of the normal aging process. And that advanced age has led to increased mobility limitation. These changes in the functionality of older people may result from decreased muscle strength, bone mass, joint erosion and calcification. Hirsch et al. (2014) also found in their study that younger (65 -69 years old) study participants had a greater range of motion than older study participants. Therefore, we would like to investigate whether the activity locations of younger participants are more diverse than those of older participants.

Based on these three research questions we formulate following hypotheses to answer during my MSc thesis:

H1: There are different activity locations on weekends, than on normal weekdays.

H2: The mobility level of urban living participants is higher than of participants that do not live in urban regions.

H3: The older the participants, the place visits are getting less diverse.

5. Workflow and Methods

5.1 Workflow

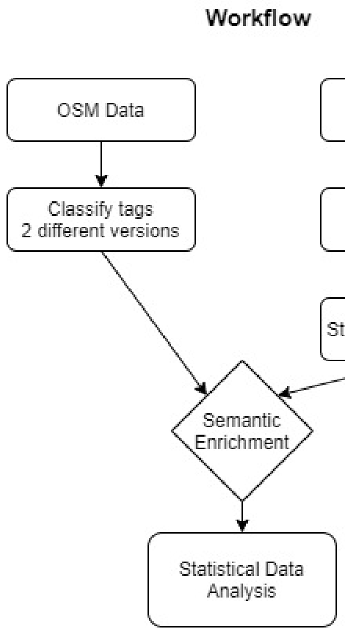


Figure 5: Flowchart of the work process.

As one can see in figure 5, we worked with two sets of data that we had to link together. The MOASIS data was already preprocessed and the stay and moves were already detected. So first we needed to preprocess the OSM data to be able to perform the semantic enrichment. Because of the vast variety of tags in the OSM data, we had to develop a classification (see in appendix) to make the activities comparable (e.g. all different sport tags, we grouped together in the class leisure_sport). Finally we made a second classification similar to Gong et al. (2016) to be able to answer our research question RQ1. For the research questions RQ2 and RQ3 we used the first mentioned classification. The difference between those classifications is the granularity. While Gong et al. (2016) proposed only 9 different classes (for RQ1 we only used 8 different ones), our own classification consists of 43 different classes for the point shapefiles and 29 different classes for the polygon shapefiles. With our approach we can differentiate the activities even more.

With both datasets being ready, we conducted the semantic enrichment to annotate context information to each stop of the MOASIS dataset. Finally we conducted statistical analysis to answer the posed research questions.

5.2 Methods

To get information why this research field is important, we conducted a literature review with state of the art literature to gain insight into the matter.

For the classification of OSM tags, we used ArcGis Pro to edit and summarize the tags as we have considered. Same process we did for the second classification of Tags according to Gong et al. (2016). This was done using the function *'Select Features by Attribute'*. After selecting for example the all different sport tags, we labelled them with the more general term leisure_sport.

For the further processing (semantic enrichment process) of the data and statistical analysis we used RStudio. The pseudo code of the semantic enrichment process can be found in the appendix.

5.3 Semantic Enrichment of the MOASIS Data

To get trajectories with annotated information, we had to perform the semantic enrichment on the MOASIS data. For this process we used RStudio.

As a starting point we had various OSM point and polygon shapefiles (e.g. transportation, traffic, POI) and the dataset from MOASIS. In a first step, we started by finding the nearest feature in each shapefile for each stop. For example for the OSM shapefile transportation, our algorithm found the closest feature among that OSM dataset and for each other dataset as well. The algorithm provided both the feature ID and the stop-feature distance using the geographical features, not the centroids (e.g. the boundaries for polygons/multi-polygons or the point coordinates for points). After having a table for each shapefile (transportation, residential, building), the tables were merged and grouped by stop so we could find the feature that has the minimum distance. This contains the stop and the closest feature among all. The OSM feature with the minimum distance from all OSM shapefiles was then selected as the semantic annotation. In figure 6, the process is illustrated with a flowchart.

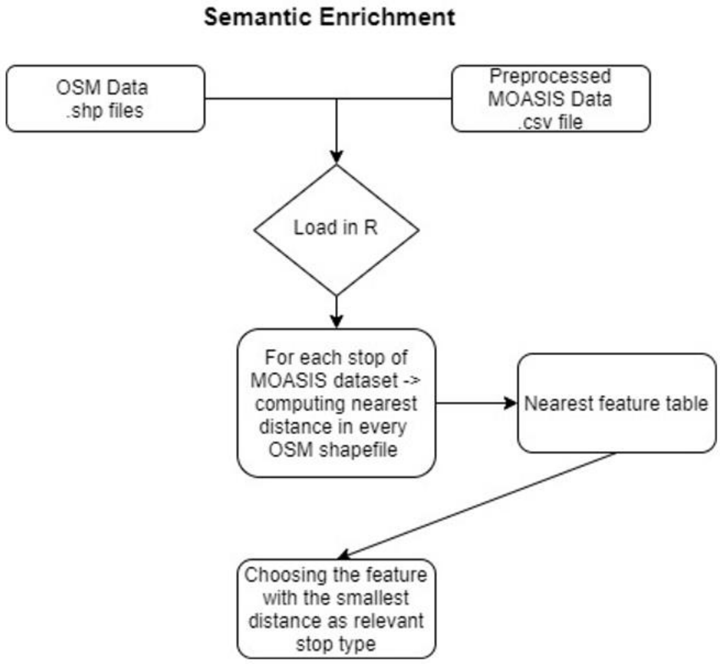


Figure 6: Flowchart of the semantic enrichment process.

6 Data

6.1 Mobility Activity and Social Interaction Study

In this thesis, the data of the mobility, activity and social interaction study (MOASIS) is being used. The study involved healthy older adults who were over 65 years old. Only those participants were taken into account who had reasonable mobility data. The dataset consists of trajectory data of 159 people. All study participants gave written consent that their collected data can be used.

6.2 MOASIS Study Baseline Information

In the MOASIS study, the participants were examined on various factors. First, alongside several questionnaires about their personal details, they participated in a physical and cognitive performance test, to get baseline information about their general health to detect interindividual differences in functioning. Second, the individuals were equipped with different sensors including a GPS logger (uTrail device) which they carried over a span of 4 weeks. For two out of the four weeks, participants also carried a smartphone which prompted them 7 times per day to answer various questions, including those about their current and daily mood, and to perform a cognitive task. Finally, they were again tested in a physical and cognitive performance test and answered some final questionnaires.

For this thesis we will mainly use the collected GPS data. The collected data like longitude, latitude, timestamp, speed, number of satellites, altitude, etc., with a sampling rate of 1Hz form the trajectories used in this thesis. In particular, we used an already preprocessed data sheet of the MOASIS dataset, where the Stop-Move distinction was already done. Ebert (2020) proposed in her MSc thesis that the Stop-Move Algorithm of Montoliu (Montoliu et al., 2013) performed the best on the MOASIS dataset.

6.3 MOASIS Data Preprocessing

As stated above, the preprocessing was not done by me, however it is important to know the most important steps and challenges that come with it, when dealing with GPS trajectory data.

Preprocessing of any trajectory data is essential to solve a number of problems inherent in GPS data and to make data analysis and mining easier. Data preprocessing is therefore crucial to remove potential GPS errors in the data to get meaningful trajectories. To solve those problems, Zheng (2015) described several methods to cope with them.

6.3.1 Noise Filtering

Due to sensor noise and poor positioning signals in urban canyons, spatial trajectories are never completely accurate (Zheng, 2015). This is caused by the limitations of positioning systems (e.g. indoor signal loss, battery outage) (Parent et al., 2013). In some cases the error is acceptable, if it is just a few meters away from the actual point and can be fixed by map-matching algorithms, but in some cases the error is too large to ignore (figure 7). In this case it must be filtered out of the dataset, as it could lead to incorrect results (Zheng, 2015).

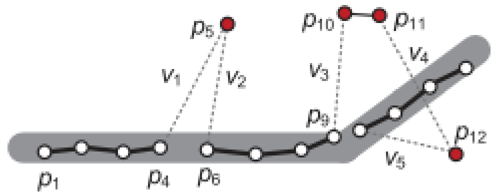


Figure 7: Detecting noise in a trajectory (Zheng et al., 2015).

6.3.2 Trajectory Segmentation

In some scenarios it is useful to divide a trajectory into segments for further processing. Trajectories can be divided based on a time interval, the shape of a trajectory or the semantic meaning of the stay points in a trajectory, depending on the needs of the researchers (Zheng, 2015). A very popular approach is to divide the trajectories into periods when the object is moving and when the object is stationary. The stationary parts are being called *stops*, while the moving parts are being called *moves*. A trajectory is therefore seen as a sequence of alternating stops and moves episodes (Parent et al., 2013).

As seen in figure 8, (a) refers to a time interval based segmentation. (b) and (c) are segmented because of the shape of the trajectory but with two different methods. And finally (d) refers to a segmentation based on the semantic meaning of the stay point (Zheng, 2015). Depending on the application requirements it is suitable to use one or another method of trajectory segmentation. Regarding the research questions of this thesis only the stops are important. Another thesis in the future could focus on the move episodes to gain more insight on the travel modes of the participants. However, identifying stops and moves is a challenge for researchers, because a stop can imply no movement at all, slow speed, movement within a constrained area, or proximity to some POI, among other possible definitions (Parent et al., 2013).

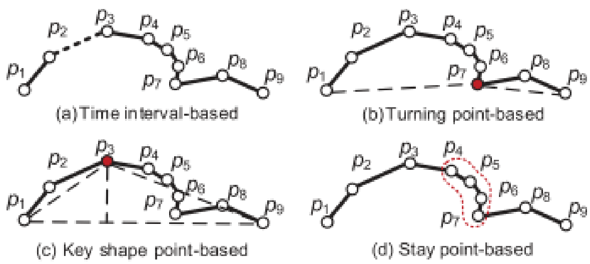


Figure 8: Different methods of trajectory segmentation (Zheng et al., 2015).

6.3.3 Map Matching

Map matching is the process that fits a sequence of raw coordinates on to a sequence of road segments. This is important for assessing traffic flows, traffic predictions, detecting main travel routes and so on. However this process is not an easy task to do since there are many roads, overpasses and different lanes (Zheng, 2015).

In many applications moving objects are restricted to move within a given network (trains can only use the railroad network, and cars are restricted to the road network). These are examples of a spatial constraint. Other constraints on trajectories may be spatiotemporal constraints (a train is not allowed to go more than a specific velocity, a pedestrian is not able to move above a certain speed limit). Temporal constraints are possible as well, but are more popular in animal trajectory datasets (nocturnal animals are most likely not on the move during the day) (Parent et al., 2013).

Map matching methods may be used on such network-constrained trajectories to clean the trajectories by replacing each point of the trajectory with a point on the network, which is most likely the position of the moving object (Quddus et al., 2007).

6.3.4 Trajectory Compression

If using a device that records the position of a moving object every second, it can be costly on battery power and data storage (Zheng, 2015). The goal of trajectory compression are: reduce the size of the dataset, computations should not be cost intensive, and have a low deviation from the original dataset (Parent et al., 2013). Trajectory compression can be performed either offline or online. Online compression is performed immediately while the object is moving, while offline compression is performed after the trajectory is fully created (Zheng, 2015). A popular example for a trajectory compression method is the Douglas-Peucker algorithm. It merges GPS points together until some halting conditions are met (Parent et al., 2013).

6.3.5 Stay Point Detection

Not all recorded spatial points on a trajectory are equally important. Depending on the research question it may be interesting to identify the stay points, where objects have stayed for a while, like a shopping mall or a restaurant. It is thus possible to generate a sequence of meaningful places from a trajectory with time-stamped spatial points (Zheng, 2015). These sequences can be meaningful for numerous applications such as popular travel destinations (Zheng et al., 2011) or taxi recommendations (Yuan et al. 2013). However, in other applications, it is necessary to omit the stay points, for example when calculating travel time of a path (Wang et al., 2014). In this thesis, the stay points will get semantically enriched to gain more insight on the activities and meaningful locations of the MOASIS participants.

6.4 MOASIS Data Overview

As described in section 6.2, the MOASIS data consists of trajectory data of 159 participants who took part in the study. In order to get an overview of the data, it is essential to record and briefly discuss the most important characteristics with a statistical analysis. In figure 9, one can see the detected stop points of the participants. It is clearly visible that we have more detected stop points in the region of Zurich and the agglomeration. It is also visible that we have more detected stops in urban areas, and we see more data collected in German-speaking Switzerland than in other language-speaking parts of Switzerland.

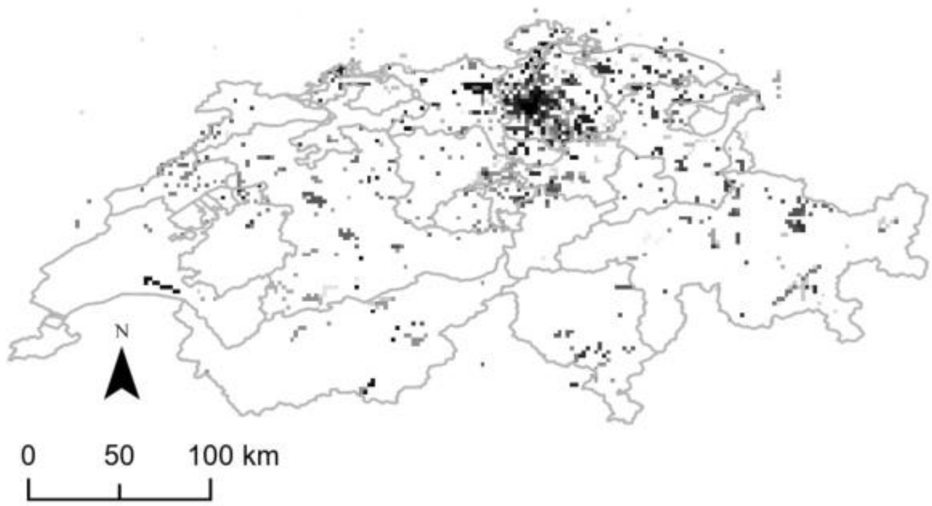


Figure 9: Detected stops of the MOASIS dataset.

Looking at the stop count per participant, we have two participants with 233 detected stops and 57 participants in total with 100 detected stops and more. The twenty most active participants according to their stop count are shown in figure 10.

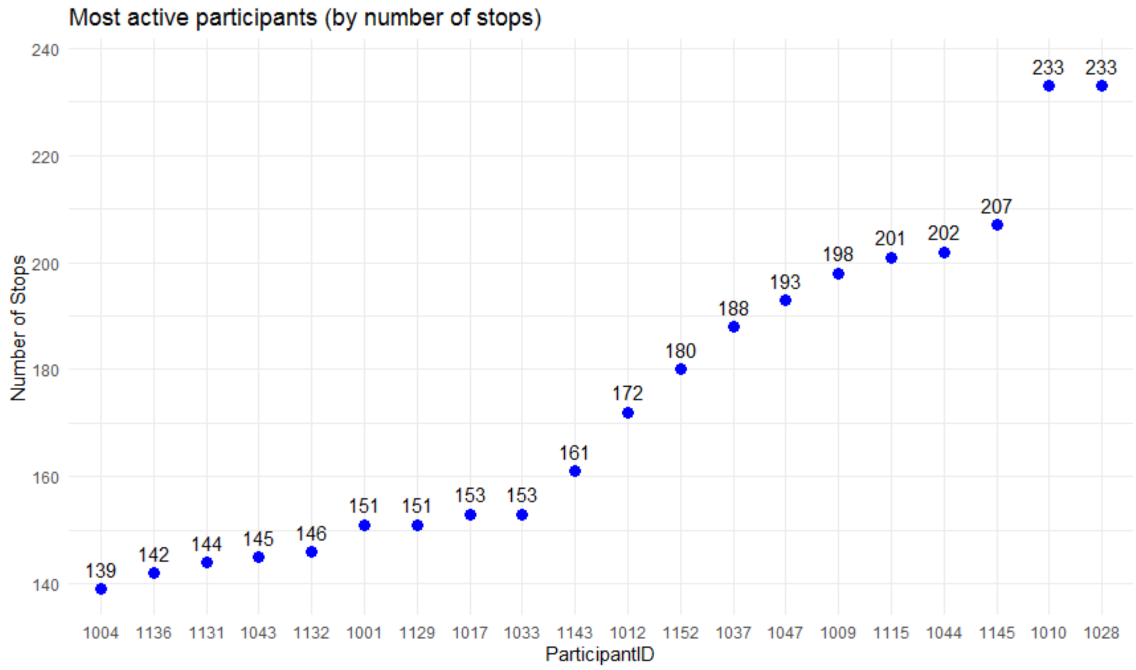


Figure 10: Count of detected stops per MOASIS study participant (most active).

On the other hand we have three participants with two detected stops and less. In total there are 45 participants that recorded 50 stops and less. In figure 11, one can see the participants with the fewest stops recorded during the study.

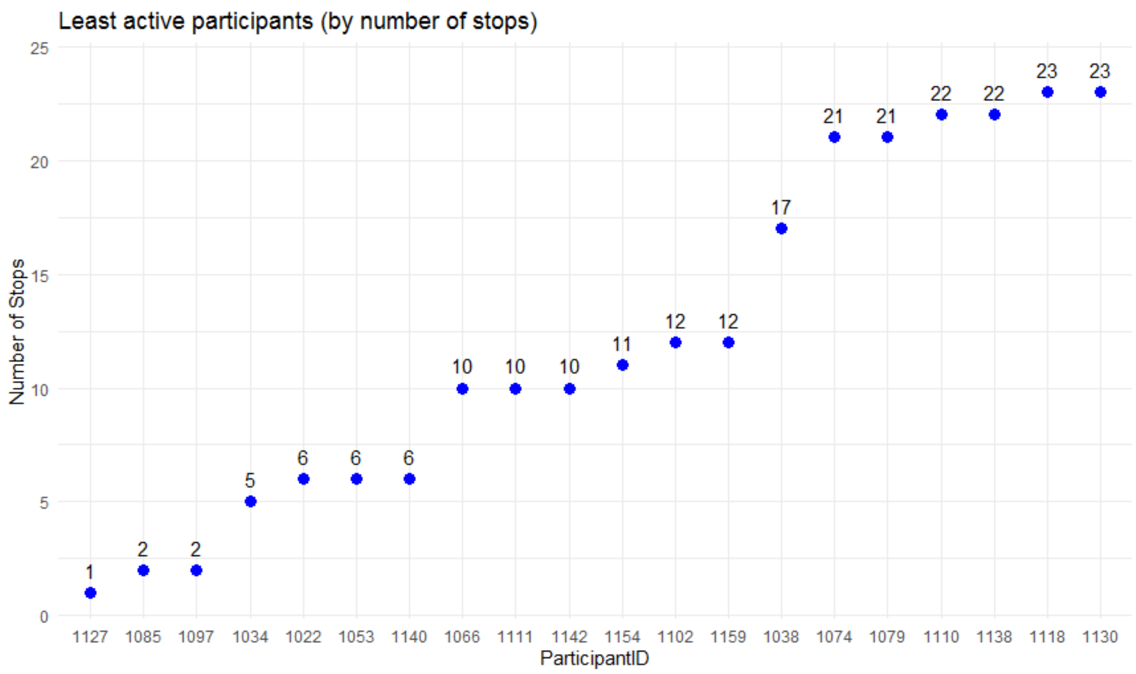


Figure 11: Count of detected stops per MOASIS study participant (least active).

Only healthy participants over 65 years old were included in the study. The age distribution within the MOASIS dataset is seen in figure 12. The youngest participants at the time of the study were 65 years old, and the oldest participant was 89 years old. Most participants were 72 years old (14 participants in total). There is a light skewness visible towards the younger participants.

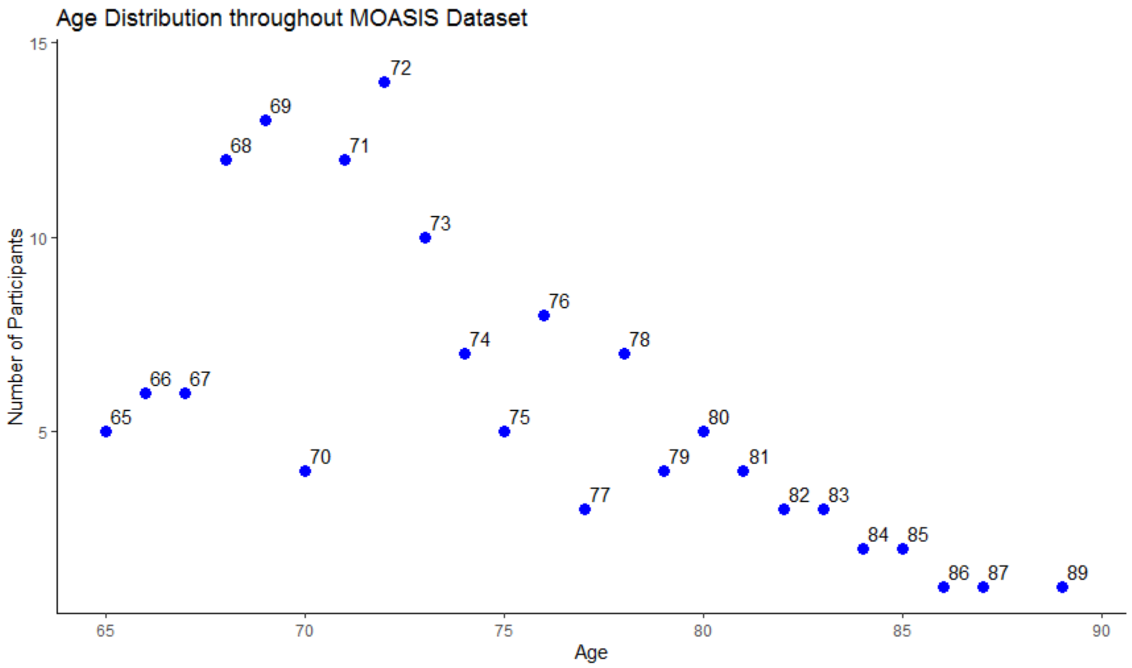


Figure 12: Age distribution in the MOASIS dataset.

The distribution of the home type (are the participants living in urban, sub-urban or rural regions) is shown in figure 13. The home types are pretty even distributed. However three participants did not make a statement about their home type. 49 participants live in rural areas, 50 participants in sub-urban areas, and 39 participants stated that they live in urban areas. The left bar in the figure stands for the participants without any statement about their home type.

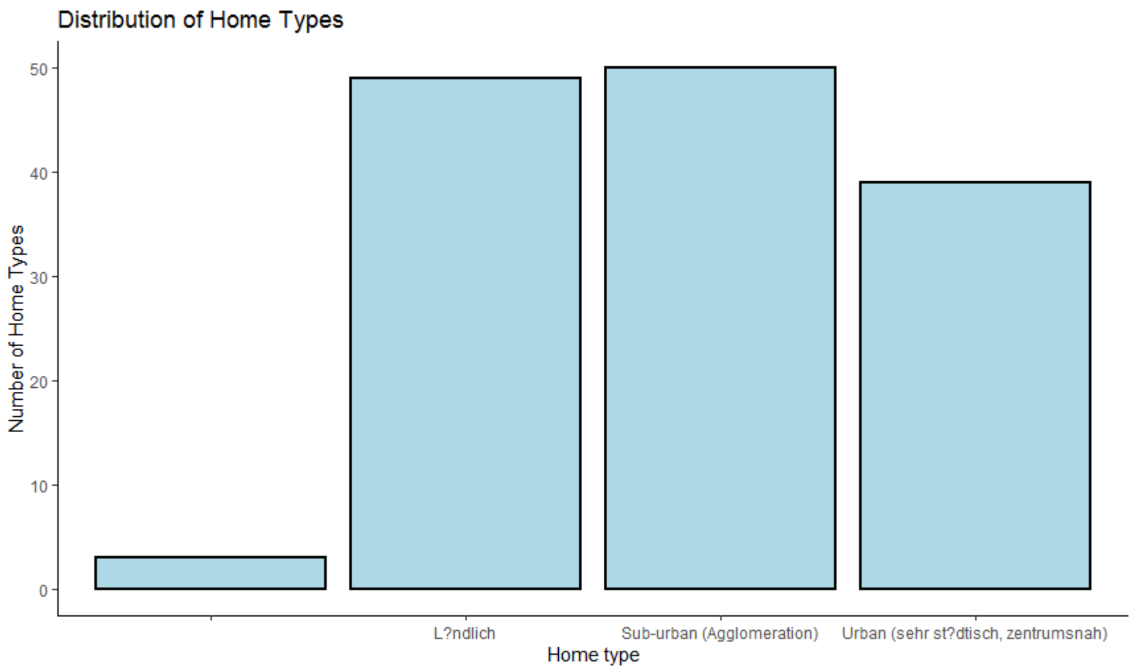


Figure 13: Distribution of the different home types in the MOASIS dataset.

For the next step we needed to compute the unique visited stops. For this we filtered the total detected stops of each participant and counted every unique visited tag occurence, to get information about the diversity of place visitation.

In the next figure 14, one can see the relation between the unique visited stops in relation to the total amount of stops visited by the participants. As it is shown with the trend line in red, there is clearly a positive correlation between the amount of stops visited and the amount of unique stops visited. So the more stops were visited by the participants in general, the more unique stops were visited as well. There were 6 participants who visited 17 different unique stops. And as already stated above there were 2 participants with 233 stops in total. It is interesting to look at the ratio of these two variables as it does say much about which participant visited the most unique stops with fewest total stops. This can be seen in figure 15. We only considered participants with more than 10 unique stops visited in this figure because it is relatively easy to have many unique stops visited with very few total stops. Therefore we can see that participant 1150 was the most active regarding the visitation of unique places. He visited 14 unique stops within his 70 total stops.

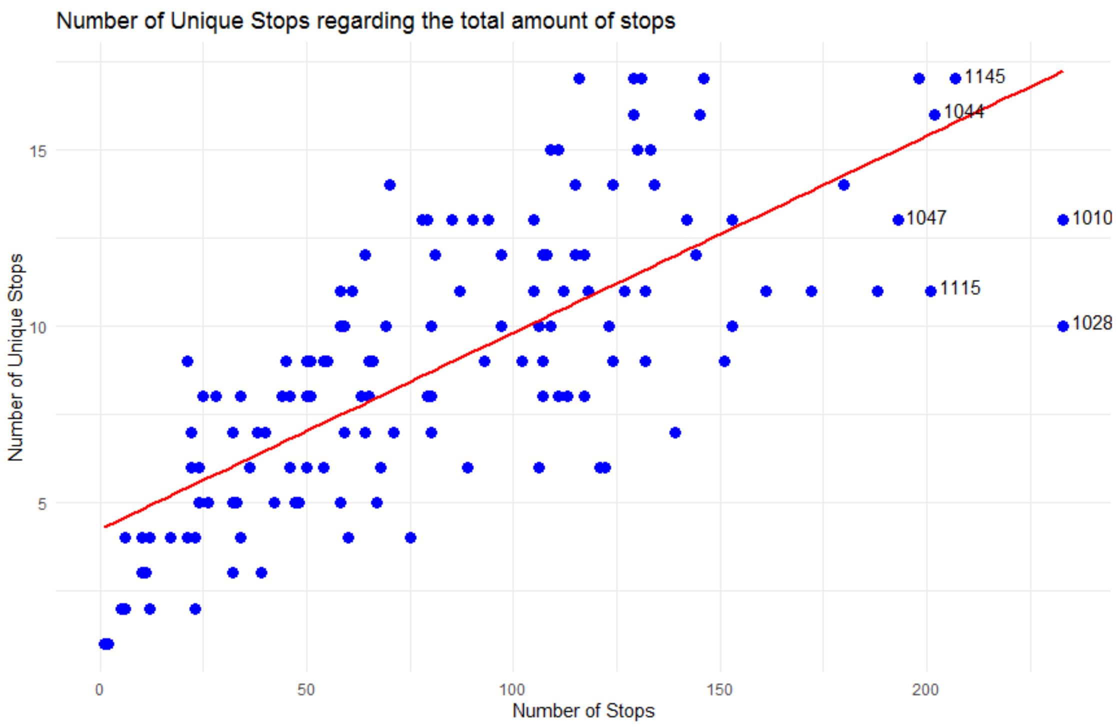


Figure 14: Unique stops of the MOASIS participants regarding their total counted stops.

	participantID	unique_stops	n_stops	ratio_stops_unique
	<int>	<int>	<int>	<dbl>
1	1150	14	70	5
2	1071	11	58	5.27
3	1141	12	64	5.33
4	1054	11	61	5.55
5	1128	13	78	6
6	1048	13	79	6.08
7	1091	13	85	6.54
8	1041	12	81	6.75
9	1062	17	116	6.82
10	1125	13	90	6.92

Figure 15: Ratio of unique stops and total stops. Only considering participants with more than 10 unique stops.

6.5 Open Street Map (OSM) Data

To link the ‘stays’ of the participants with semantic meaning, we downloaded data from Open Street Map.

Open Street Map is a cooperative project where volunteers are working together on a free usable and editable map of the world. The data is freely available and downloadable for everyone and it is being used for spatial analysis and data mining due to its data format (Bermingham and Lee, 2019).

In OSM, places have a unique ID, some kind of geometry (point, line, polygon), and a series of key-value description tags. In figure 16 one can see an example of a point, polygon and line feature of OSM data in the quarter of Wiedikon in Zurich. For example the point feature has a set of coordinates with the key ‘natural’ and the description tag ‘tree’. The polygon feature is the area of a graveyard and the line feature describes a tramway.

Point feature	Polygon feature	Line feature

Figure 16: Different types of Open Street Map data.

For this project, the OSM data were downloaded from Geofabrik’s download server (https://download.geofabrik.de/europe/switzerland.html). All the data we downloaded and used in this project lies within the boundaries of Switzerland. The data were in the format of point, polygon and line shapefiles. For our purposes of this project we only used the data of the point and polygon shapefiles, as the line shapefiles do refer more to movement of an object rather than to a stop. Because there is such a huge variety of tags, we have summarized them into more broader categories. E.g. all tags with a religious background were collected in the broader tag ‘place_of_worship’, seen in figure 17. In the appendix one can see how all the tags were combined.

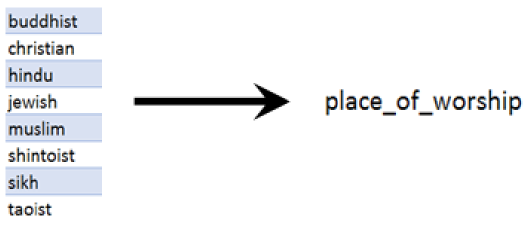


Figure 17: Classification example of the tag 'place_of_worship'.

Finally the classification process led us to 2 classifications. One of them being for research question 1 and was similar to Gong et al. (2016), the other being our own approach and was used to answer research question 2 and 3.

7 Results

7.1 Open Street Map Tags

In a first step, we analyzed the count of the OSM tags after our own classification to get an overview of their distribution. In figures 18 and 19, one can see the total count of the tags. If we look at the feature tags of the polygon data, the tag ‘building’ is by far the most frequent, while the tag ‘dock’ and ‘heath’ are not that common. In the point data, tag distribution is a bit more even. The tags ‘parking’ and ‘bench’ are the most common and the tag ‘prison’ is the least common. Be aware that both figures are being displayed with a logarithmic scale, which can distort the real ratio between the most and least frequent tags.

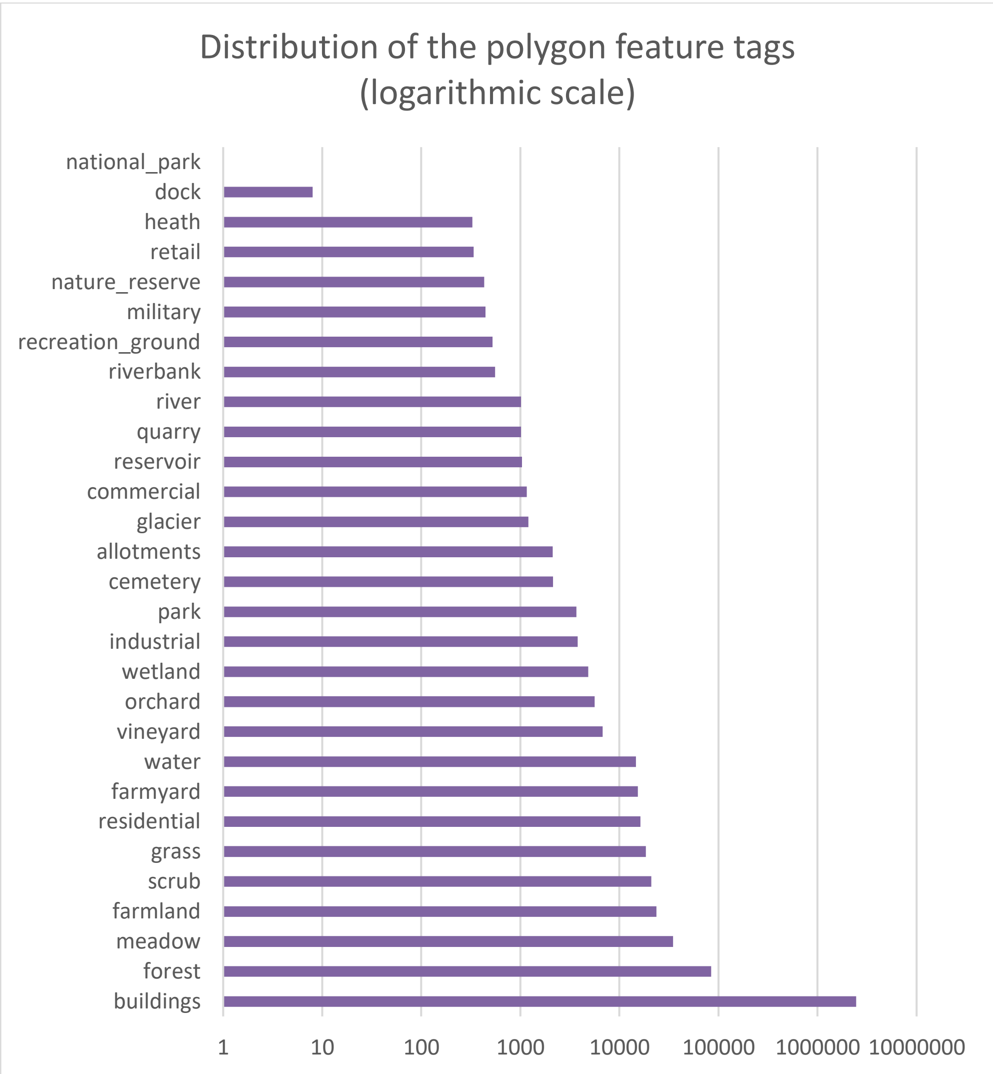


Figure 18: Total count of the downloaded OSM polygon tags.

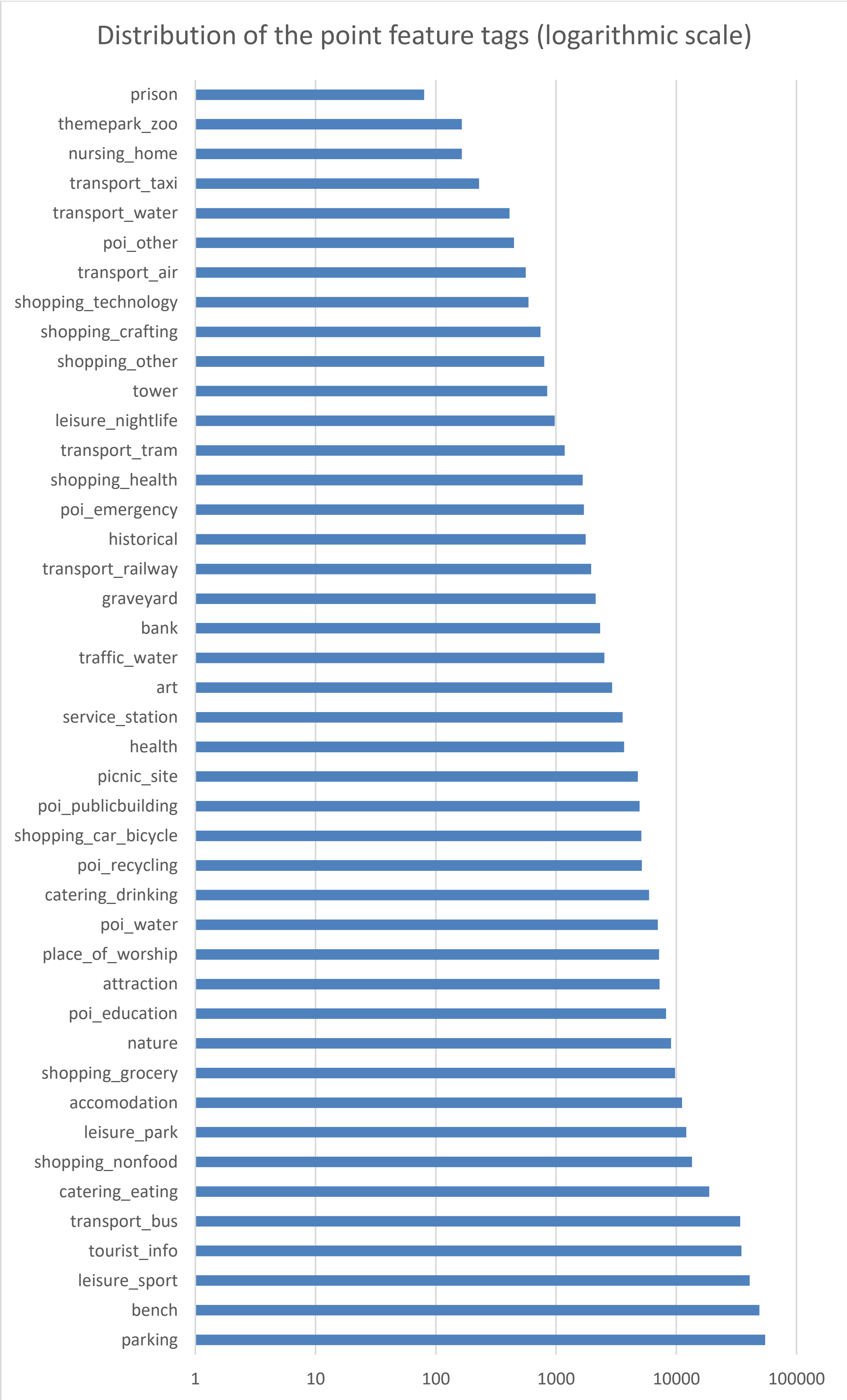


Figure 19: Total count of the downloaded OSM point tags.

7.2 Research Question 1

Can we find similar activity patterns in the MOASIS study data like Gong et al. (2016) did in their study, when looking at the activities done day by day?

To answer the RQ1, we classified the OSM tags according to Gong et al. (2016). Like this we can compare our results with the results of their study. In figure 20 one can see the count of tags of all the semantic enriched stops when classified according to Gong et al. (2016). The tag 'building' is clearly the most found tag in the MOASIS dataset, followed by the tag 'recreation'. The tags 'transportation' and 'shopping' are also found a considerable amount. The last 4 tags 'lodging', 'schooling', 'medical' and 'dining', we left them out of the analysis, because they were not found enough times to be significant.

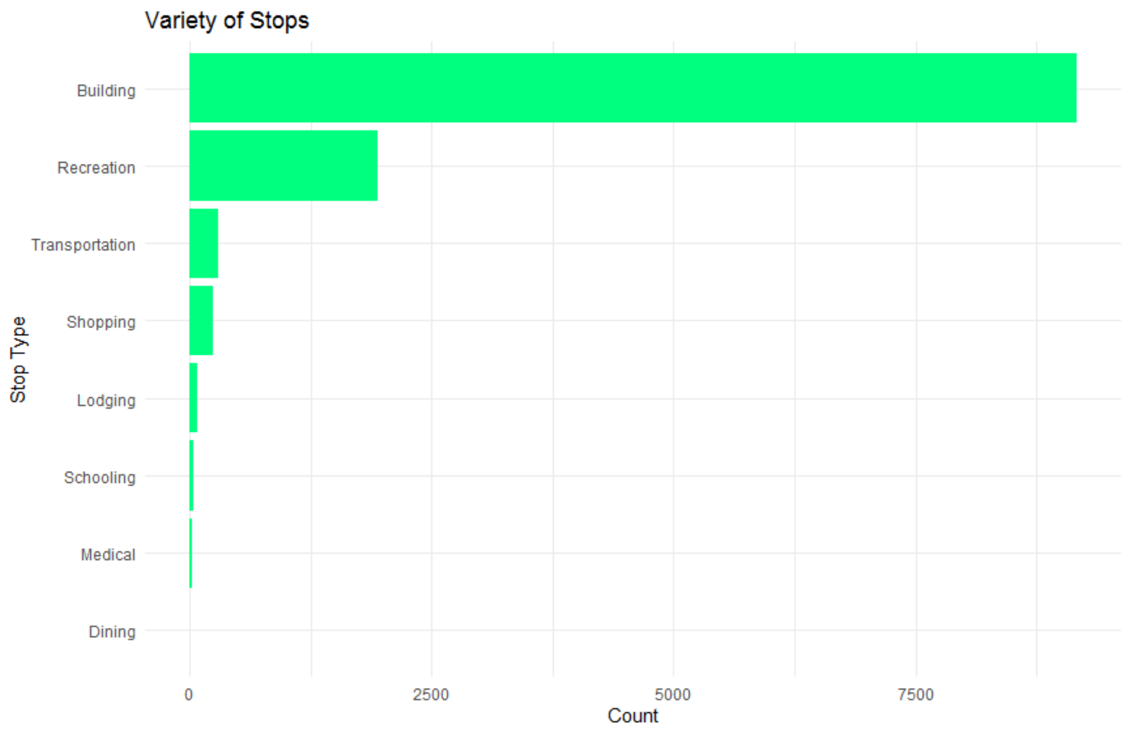


Figure 20: Total count of the tags using the methodology of Gong et al. (2016).

As a next step we computed the distribution of the top four tags, but filtered by weekday (figure 21). We only show the top four tags 'Building', 'Recreation', 'Transportation' and 'Shopping', due to the reasons mentioned above.

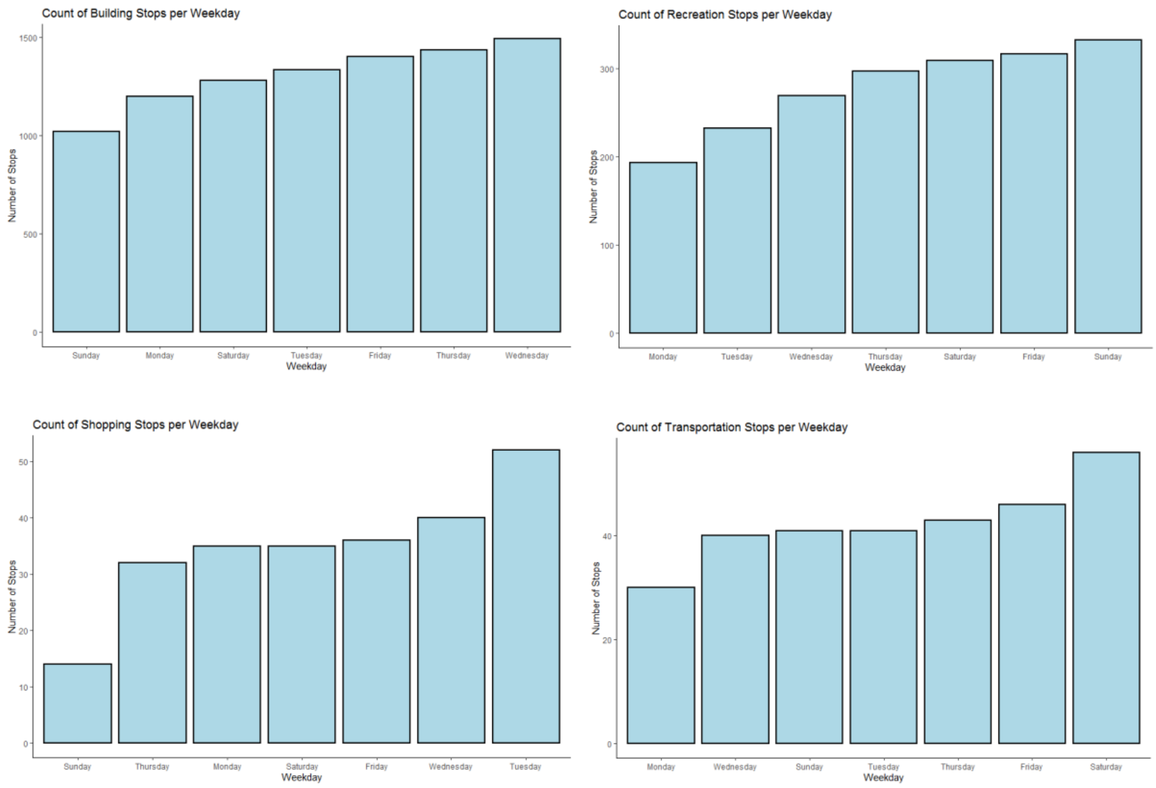


Figure 21: Count of different tags per weekday. Top right: ‘Building’ / Top left: ‘Recreation’ / Bottom left: ‘Shopping’ / Bottom right: ‘Transportation’

As one can clearly see, the tag ‘Building’ is least often found on Sunday and most often found on Wednesday. The tag ‘Recreation’ is most often found on Sunday and least often found on a Monday. ‘Shopping’ is least often done on Sunday and most often done on a Tuesday. And lastly the tag ‘Transportation’ which is found most often on Saturday and least often found on Monday.

Those results do partially correlate with the results of the study of Gong et al. (2016). They too found that recreational activities occur more on and towards the weekend, as we detected within the MOASIS data. Gong et al. (2016) did not have a tag ‘Building’, because they distinguished between in-home and work-related activities. As we had a study set of participants who were 65 years and older, we decided to combine those tags as the majority of people that are 65 years and older do not work anymore. In our data one can see that activities with the tag ‘Building’ are less likely to be done on the weekends than during the weeks. The tag ‘Shopping’ and ‘Transportation’ do not really correlate with the study of Gong et al. (2016). We will discuss this issue in section 8.

7.3 Research Question 2

Is the mobility level of older adults living in rural areas lower than the mobility level of older adults living in urban areas?

In the MOASIS study participated 49 older adults, who stated that they live in rural areas. They recorded a total of 4466 stops. 50 older adults lived in sub-urban regions and collected a total of 3775 stops. Finally 39 participants stated that they live in urban areas and collected a total of 3358 stops. This is seen below in the figures 22, 23 and 24, where we show the distribution of stops per participant when filtered by the different home types. Some participants did not indicate a home type, we left those out of the analysis of this research question.

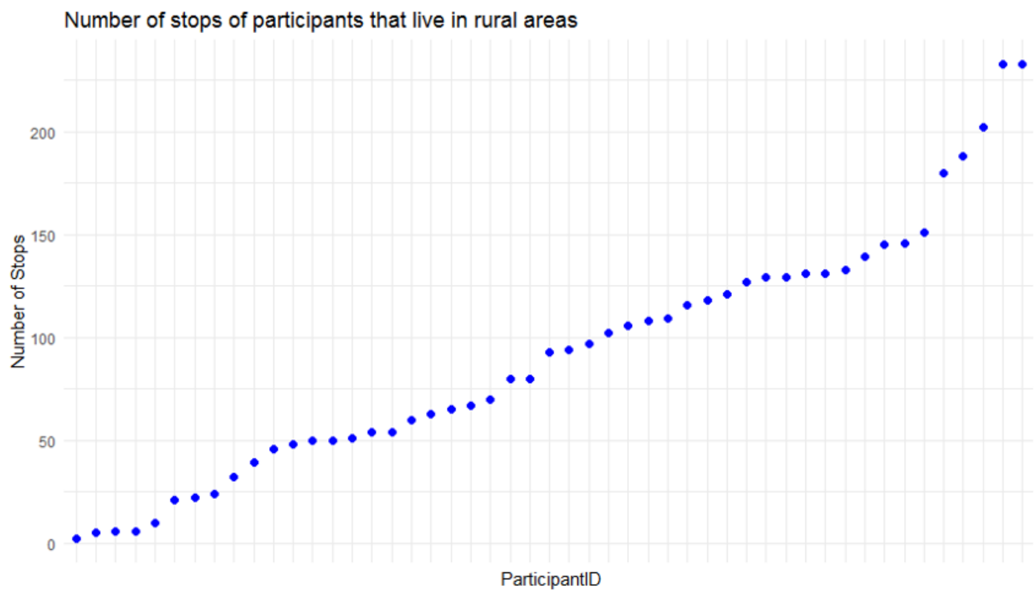


Figure 22: Stop count of participants living in rural areas.

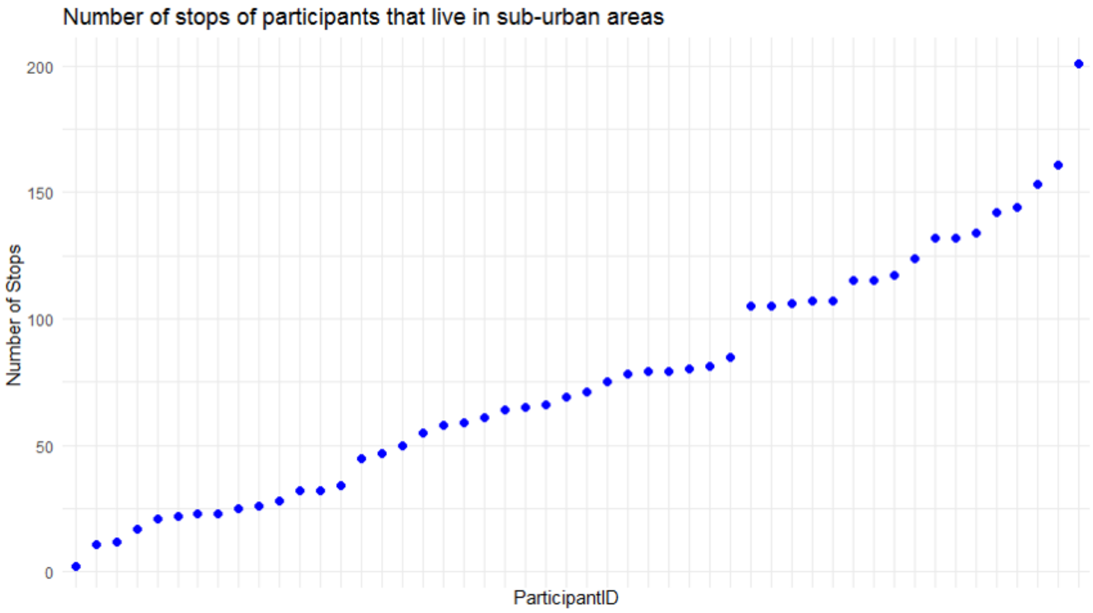


Figure 23: Stop count of participants living in sub-urban areas.

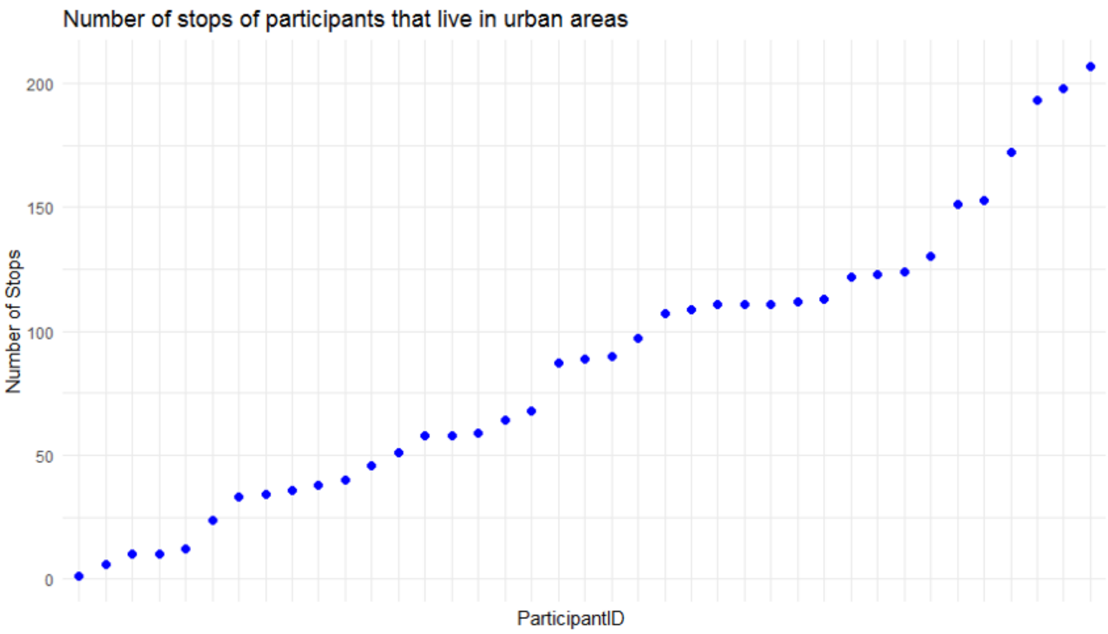


Figure 24: Stop count of participants living in urban areas.

To further analyze the relationship of the home types regarding the stop count, we conducted the relevant statistical tests. First we computed the descriptive statistics, seen in figure 25. To make the analysis easier we replaced the string characters of the home type and set up the value 1 for rural, 2 for sub-urban and 3 for urban living participants.

```
 Descriptive statistics by group
group: 1
   vars  n  mean    sd median trimmed  mad min max range skew kurtosis  se
X1    1 49 91.14 58.83     93   87.59 59.3   2 233   231 0.47    -0.38 8.4
---------------------------------------------------------------------------
group: 2
   vars  n mean    sd median trimmed  mad min max range skew kurtosis   se
X1    1 50 75.5 46.32     70   72.78 55.6   2 201   199 0.46    -0.54 6.55
---------------------------------------------------------------------------
group: 3
   vars  n mean    sd median trimmed   mad min max range skew kurtosis   se
X1    1 39 86.1 55.74     89   83.12 56.34   1 207   206 0.36    -0.75 8.92
```

Figure 25: Descriptive statistics regarding the relationship of home type and the total counted stops per participant. Group 1 represents the participants living in rural areas, group 2 is sub-urban, and group 3 is referring to the participants living in urban areas.

As one can see the average values of the stops are the highest for the rural living participants and lowest for the sub-urban participants. Further noticeable is the rather big difference in the standard deviation, respective variance when doubling the standard deviation. Further conspicuous is the highest maximum value, which can be found again in the rural group. The median value is 70 for the sub-urban participants and 93 for the rural participants, while the median of the urban group (89) lies a lot closer to the rural group than to the sub-urban group.

In a next step, we show the unique stops per total recorded stops of the participants, shown separately by home type, seen in figures 26, 27 and 28.

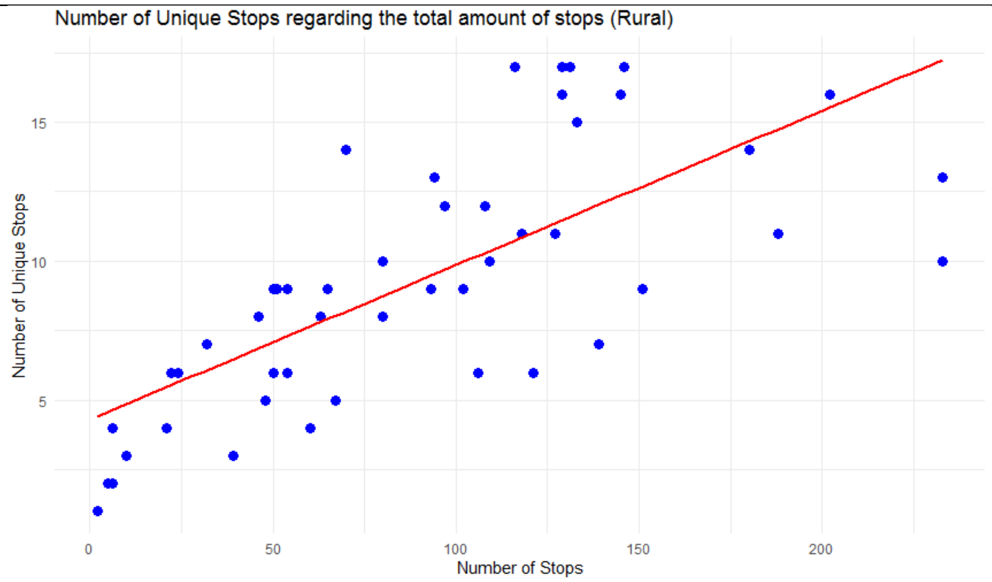


Figure 26: Number of unique stops regarding the total amount of stops of the rural living participants.

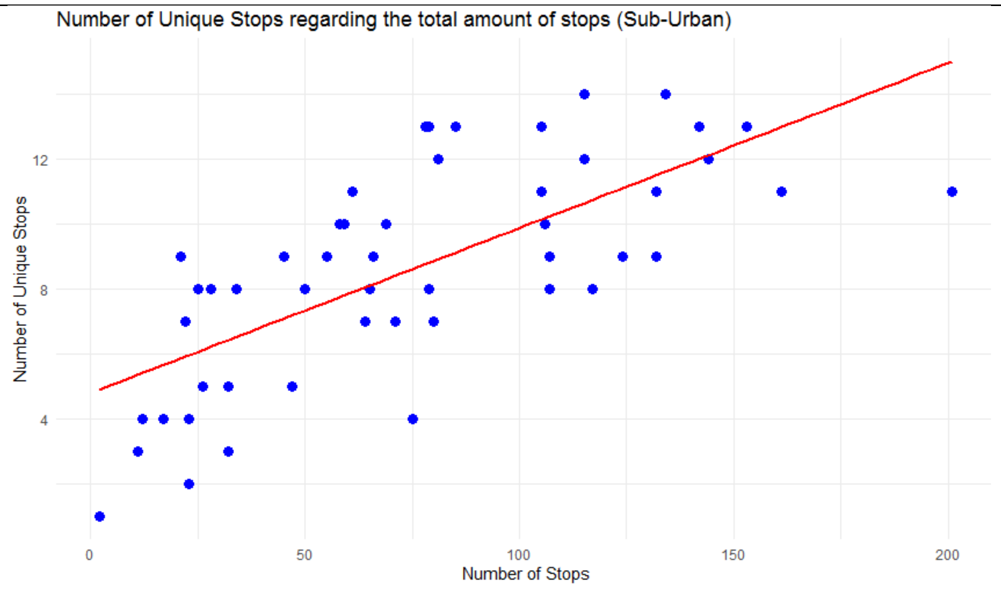


Figure 27: Number of unique stops regarding the total amount of stops of the sub-urban living participants.

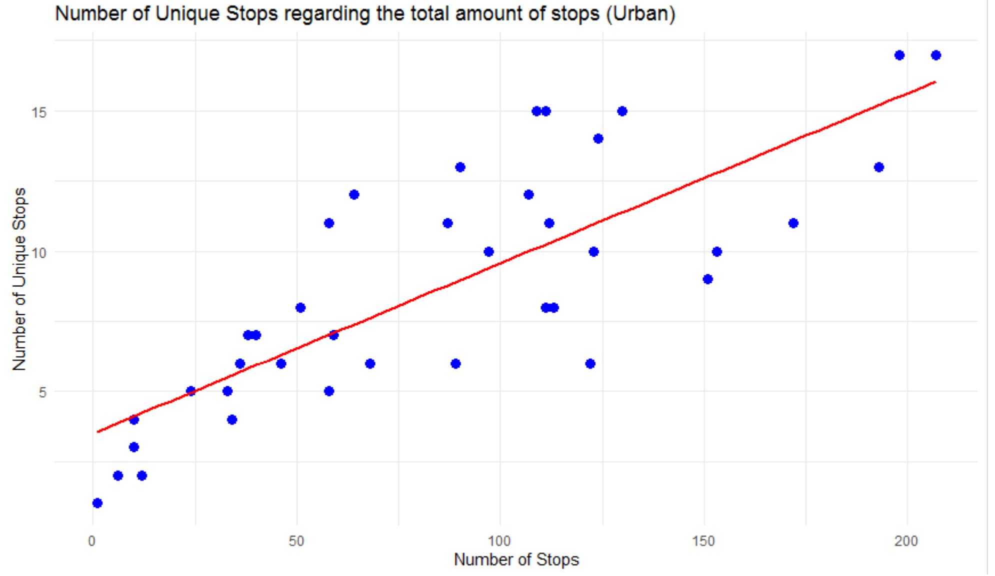


Figure 28: Number of unique stops regarding the total amount of stops of the urban living participants.

We also computed descriptive statistics for the unique visited stops. Here the differences between the three different home types, are not so clearly visible anymore. The average of all three groups lies between 8.64 (sub-urban) and 9.37 (rural) visited unique stops. The standard deviation and therefore the variance is very similar in all three groups. Also the maximum values moved closer together, and the median value is almost the same for the three groups.

```
 Descriptive statistics by group
group: 1
   vars  n mean  sd median trimmed  mad min max range skew kurtosis   se
X1    1 49 9.37 4.6      9    9.34 4.45   1  17    16 0.17    -1.03 0.66
------------------------------------------------------------------------------
group: 2
   vars  n mean   sd median trimmed  mad min max range  skew kurtosis   se
X1    1 50 8.64 3.34      9     8.8 2.97   1  14    13 -0.36    -0.73 0.47
------------------------------------------------------------------------------
group: 3
   vars  n mean   sd median trimmed  mad min max range skew kurtosis   se
X1    1 39 8.72 4.24      8    8.67 4.45   1  17    16 0.19    -0.91 0.68
```

Figure 29: Descriptive statistics regarding the relationship of home type and the total counted unique stops per participant.

In each of the three groups, there are some participants with very few recorded stops, which is not very meaningful and can lead to a distortion of the result. So we left all participants out of the further statistical analysis with fewer than 30 recorded stops. This step changes the descriptive statistics towards higher numbers as seen in figures 30 and 31.

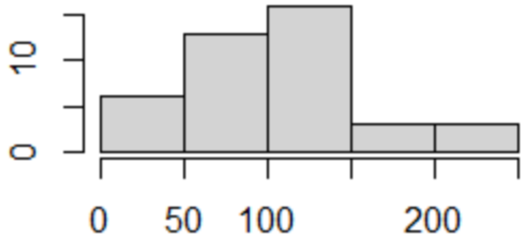
```
 Descriptive statistics by group
group: 1
   vars  n   mean    sd median trimmed   mad min max range skew kurtosis   se
X1    1 41 106.59 51.41    106  101.48 57.82  32 233   201 0.68    -0.15 8.03
----------------------------------------------------------------
group: 2
   vars  n  mean    sd median trimmed   mad min max range skew kurtosis   se
X1    1 39 91.41 39.62     80   89.45 40.03  32 201   169 0.56    -0.28 6.34
----------------------------------------------------------------
group: 3
   vars  n  mean    sd median trimmed   mad min max range skew kurtosis   se
X1    1 33 99.85 49.12    107   96.07 63.75  33 207   174 0.47    -0.65 8.55
```

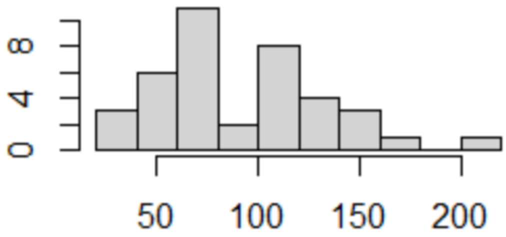
Figure 30: Descriptive statistics regarding the relationship of home type and the total counted stops per participant with a minimum number of total 30 stops.

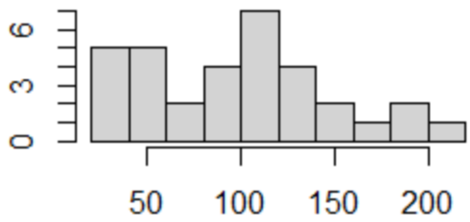
```
 Descriptive statistics by group
group: 1
   vars  n  mean   sd median trimmed  mad min max range skew kurtosis   se
X1    1 41 10.51 4.08     10   10.48 4.45   3  17    14 0.18    -1.11 0.64
----------------------------------------------------------------
group: 2
   vars  n mean   sd median trimmed  mad min max range skew kurtosis   se
X1    1 39 9.67 2.77     10    9.82 2.97   3  14    11 -0.4     -0.5 0.44
----------------------------------------------------------------
group: 3
   vars  n mean   sd median trimmed  mad min max range skew kurtosis   se
X1    1 33 9.79 3.66     10    9.63 4.45   4  17    13 0.35    -1.02 0.64
```

Figure 31: Descriptive statistics regarding the relationship of home type and the total counted unique stops per participant with a minimum number of total 30 stops.

Next we checked if the data of the unique stops and the data of the total counted stops is normally distributed with the Shapiro-Wilk test. We found that the group of the rural participants is not normally distributed, with a p-value of 0.022 which is below the level of significance. This tells us that the data in this group is not normally distributed. The data of the urban and sub-urban participants however, were normally distributed, with a p-value of 0.06 and 0.147 respectively. This issue can be seen as well in the histograms in figure 32. The histogram of the rural participants is heavily skewed towards the left side. Many participants performed up to 100 stops and more, but then a strong break can be seen, whereas the data of the sub-urban participants and urban participants looks more like a curve and therefore are normally distributed.

<table>
<tr>
<td>

Rural living participants</td>
<td>

Sub-urban living participants</td>
</tr>
<tr>
<td>The histograms are shown for all the three groups. The x-axis shows the count of total stops. The Y-Axis displays the frequency of participants.</td>
<td>

Urban living participants</td>
</tr>
</table>

Figure 32: Histograms of the distribution of the home types and the total number of stops.

We proceeded to compute a Kruskal-Wallis test, to check whether our three different home types are significantly different from one another when looking at the total count of stops or the visited unique stops. We chose this test because of the non-parametric distribution in our data (rural participants), and the inequality of the variances.

```
        Kruskal-Wallis rank sum test

data:  hometype_numbers_filtered$n_stops by hometype_numbers_filtered$bl_home_type
Kruskal-Wallis chi-squared = 1.3553, df = 2, p-value = 0.5078
```

Figure 33: Kruskal-Wallis test for the relationship of total visited stops vs. the three home type groups.

```
        Kruskal-Wallis rank sum test

data:  hometype_numbers_filtered$unique_stops by hometype_numbers_filtered$bl_home_type
Kruskal-Wallis chi-squared = 0.73854, df = 2, p-value = 0.6912
```

Figure 34: Kruskal-Wallis test for the relationship of total visited unique stops vs. the three home type groups.

For both tested groups the results of the p-value are clearly higher than the level of significance of 0.05 seen in figures 33 and 34. This means that there are no significant differences between the three home type groups regarding the total number of stops and the unique visited stops. We also conducted a pairwise Wilcoxon-Mann-Whitney test to see the interindividual differences between the 3 groups (1 = urban, 2 = sub-urban, 3 = rural).

	1	2
2	0.78	-
3	1.00	1.00

Total number of stops vs. home type

	1	2
2	1	-
3	1	1

Unique stops vs. home type

Figure 35: Result matrices of the Wilcoxon-Mann-Whitney test. Level of significance = 0.05.

In figure 35 one can see the result matrices of the Wilcoxon test. It is clearly visible that no value is below 0.05 which is the level of significance. Therefore participants living in urban, sub-urban and rural areas did not differ significantly within all the three groups from one another, regarding the total number of stops and the unique visited stops. The only thing one can maybe say, is that the rural group is a little bit different than the sub-urban group, because the value between those groups is slightly lower than 1, but clearly not enough to be a significant difference.

7.4 Research Question 3

Do younger participants in the MOASIS study have more diverse stops than older participants? Are younger participants therefore more active than older participants?

First we have to decide, which participants belong to the younger group and which participants belong in the older group. As seen in the section 6.4, the MOASIS study examined older adults in the range of 65 – 89, the distribution is lightly skewed towards the younger participants. We decided to make the cut at 73 years old, to make both groups similarly big and easier to compare. Three participants did not make a statement about their age, therefore we left them out of the analysis for this research question.

This leaves us with a group of younger participants, 72 years and younger, containing 72 participants. And a group of older participants, 73 years and older, containing 66 participants. Like in the previous research question, we left out all participants with less than 30 total counted stops as those are not representative. This leaves the group of the younger participants with 56 participants and the group containing older participants with 57 participants. First we again computed the descriptive statistics with the younger group and the older group regarding the total detected stops and the total visited unique stops seen in figures 36, 37, 38 and 39.

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	57	96.25	41.47	97	94.47	47.44	32	233	201	0.59	0.31	5.49

Figure 36: Descriptive statistics of the older participants regarding the total number of stops.

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	56	102.57	52.18	105.5	98.46	60.79	32	233	201	0.63	-0.47	6.97

Figure 37: Descriptive statistics of the younger participants regarding the total number of stops.

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	57	9.39	3.28	9	9.28	2.97	3	17	14	0.25	-0.47	0.43

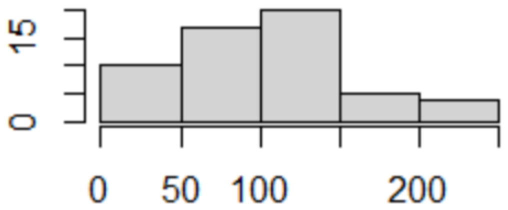
Figure 38: Descriptive statistics of the older participants regarding the total number of unique stops.

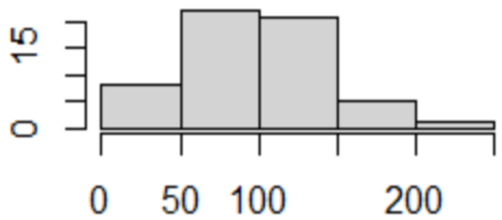
	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
X1	1	56	10.64	3.69	10.5	10.59	3.71	3	17	14	0.13	-0.95	0.49

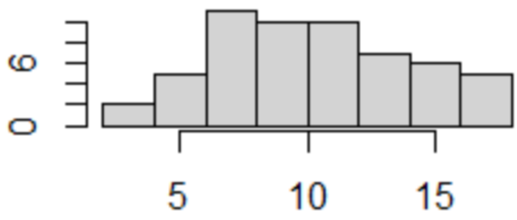
Figure 39: Descriptive statistics of the younger participants regarding the total number of unique stops.

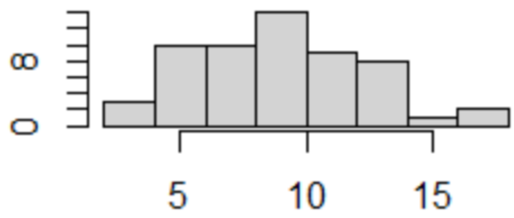
It can be seen that the younger participants recorded slightly more total stops on average than the older participants. Also they recorded more unique stops on average than the older group, despite having the same minimum and maximum values. The median value of the total number of recorded stops is noticeably higher in the group of the younger participants and slightly higher for the unique stops.

First we checked again if the data is normally distributed. The data regarding the total number of stops of the younger and the older group are both not normally distributed. The Shapiro-Wilks test resulted in a p-value of 0.003 for the young group and 0.04 for the older group. Both values lie below the significance level of 0.05, which means that the data is not normally distributed. We also tested the unique stops per group and found out that the unique stops for both groups are normally distributed with a value of 0.09 for the young group and a value of 0.29 for the older group. We computed the histograms (figure 40) for the distributions of the younger and older group regarding the total count of stops and the unique stops. We can clearly see that the histograms regarding the total count of stops are skewed to the left side.

<table>
<tr>
<td>

Younger participants (total number of stops)</td>
<td>

Older participants (total number of stops)</td>
</tr>
<tr>
<td>

Younger participants (total number of unique stops)</td>
<td>

Older participants (total number of unique stops)</td>
</tr>
</table>

Figure 40: Distribution of the young and old group in relation to the total number of stops and the count of the unique stops. X-axis being the number of counted stops or unique stops respectively, Y-axis being the frequency of participants with this amount of stops.

Additional we computed boxplots to further see into the distribution of the data. 1 being the younger group (65-72 years old) and 2 being the older group (73-89 years old). One can see that the distribution of the total number of stops (figure 41, left figure) is bigger in the younger group and the median is slightly higher than in the older group. For the unique stops (figure 41, right figure), the difference is a bit more visible, as the boxplots are more shifted. It is visible that the younger group visited more unique stops than the older group.

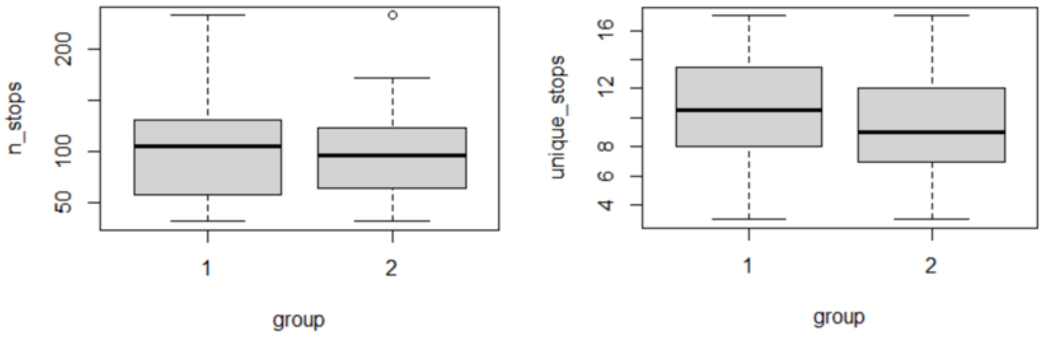


Figure 41: Boxplots of both age groups, regarding the total number of visited stops and the unique visited stops.

Further we test if these differences we have seen in the histograms and boxplots are significant. We use the Wilcoxon-Rank-Sum test for the relation total number of stops and age, because the data is not normally distributed.

We get the p-value of 0.7916, which is higher than the significance level of 0.05. This means, that the groups are not significantly different from one another (figure 42).

```
        Wilcoxon rank sum test

data:  n_stops by group
W = 1642, p-value = 0.7916
alternative hypothesis: true location shift is not equal to 0
95 percent confidence interval:
 -14.00000  20.99998
sample estimates:
difference in location
              1.999919
```

Figure 42: Wilcoxon rank sum test results to test the relation of the total number of stops and both age groups.

For the unique stops, we computed a t-test, because the data is normally distributed, and the variance is more or less similar (3.28 and 3.69). Therefore we can use the t-test for similar variances (figure 43). Here we tested if the younger group visited significantly more unique stops than the older group. We got a result of 0.0292 which is lower than the significance level of 0.05. So the younger group is therefore significantly visiting more unique stops than the older group, which is backing up our hypothesis posed in the section 4.

```
        Two Sample t-test

data:  summedup$unique_stops by summedup$group
t = 1.9124, df = 111, p-value = 0.0292
alternative hypothesis: true difference in means is greater than 0
95 percent confidence interval:
 0.1667544       Inf
sample estimates:
mean in group 1 mean in group 2
      10.642857        9.385965
```

Figure 43: Two sample t-test for the relation of the unique stops and both age groups.

8 Discussion

Regarding our first research question, we could partially show that the mobility of the older adults in the MOASIS dataset is similar to the mobility patterns found in the study of Gong et al. (2016). Participants tend to have more recreational stops on the weekends and showed less stops with the tag ‘Building’. This is an indicator that the participants are doing more activities outside on the weekends. We also showed that they are doing the shopping mostly during the week. Logically we found the least stops with the tag ‘Shopping’ on Sunday, which makes sense, since most of the shops are closed on this day. As for our last investigated tag ‘Transportation’, we found the most tags on Saturday. This also correlates with the finding of Saturday being one of the days the older adults are mostly outside and in nature, and the participants need public transport to go to their planned activity location. However the tags ‘Shopping’ and ‘Transportation’ do not really correlate with the findings of Gong et al. (2016). Their study showed that more shopping is done at weekends than during the week. ‘Transportation’ is really even distributed among the weekdays in their study. This may be because of the different age of the study participants. In the MOASIS dataset, the study participants were 65 years and older, whereas Gong et al. (2016) did not just focus on one age group. In addition, the study by Gong et al. (2016) focused on taxi trips, while the MOASIS study recorded the total mobility of healthy older adults for 30 days, as long as the participants wore the GPS logger. This of course included all trips, from public transport to walks to the grocery store and so on. Therefore we can answer our posed research question one, that there is a difference between the detected stop points on the weekends than on weekdays for the MOASIS participants, however the similarity to the study of Gong et al. (2016) is only partially visible.

For the second research question we looked at the variables total recorded stops and number of unique visited stops in relation to the ‘home type’. We could not find a significant difference in mobility behavior when looking at participants that live in rural, sub-urban or urban areas. This is maybe caused due to the fact, that Switzerland already has a very well developed and functioning public transport system, and the accessibility is already very high. Additionally looking at figure 9, we see that the stop distribution of the participants is mostly in the canton of Zurich, where the connection to public services is really high also in rural areas. Therefore we could not prove our hypothesis that participants living in urban areas have a significant higher level of mobility.

Looking at the third posed research question, we showed that the mobility of older adults in the MOASIS dataset is significantly different when looking at the age of the participants and their unique visited stops. Younger participants of the study had a significantly higher amount of unique visited stops than the older participants. However when looking at the total number of visited stops, we could not find a significant difference. Hence we can verify our research question and hypothesis, that the older the participants, the less diverse are the stop visits of this age group are getting.

Our findings do partially correlate with the literature. Especially regarding the decreasing mobility regarding diverse stops with increasing age, which was as well shown by Yeom et al. (2008) and Hirsch et al. (2014). However Yeom et al. (2008) and Melzer & Parahyba (2004) showed that there is a difference when looking at the area the older adults live in. For our data, we could not prove this statement.

9 Limitations

9.1 OSM Data

The data of OSM has gaps when it comes to tag information, location and geometry. OSM data is user-generated content and can therefore be lacking important information. For example, the tag ‘building’ does not include additional information, of what’s inside of it. There could be different purposes: Probably there is a doctor, as well as a clothing store, which are two totally different POIs. Data can be missing entirely if it was not mapped by a user or can be outdated, if not maintained properly. Lastly, data in urban regions seem to be better than in rural regions. All those factors can lead to a wrong semantic annotation to a stop (Välimäki, 2020).

9.2 GPS

Thanks to GPS technology, it is possible to locate ones position globally. However there are some limitations to it as well. Lin and Hsu (2014) state three main limitations that are known to occur when collecting data with GPS devices. (1) Indoors as well as underground (e.g. in a tunnel), the GPS signal is usually blocked. (2) When using the GPS near tall buildings, interferences with the signal can occur and the position is therefore wrongly located. (3) If a large amount of GPS data is collected continuously, that may consume the energy of the GPS device quickly and prevent the collection of large high resolution GPS datasets over long durations.

9.3 Our Approach

Our semantic enrichment could have been enhanced with a descriptiveness score, like Bermingham and Lee (2019) did in their study. This would have led to a more detailed semantic enrichment.

Another limitation comes with the application of our algorithm. While searching for the nearest OSM feature, we chose the nearest point feature or the nearest boundary of a OSM polygon. This could have led to a tag ‘building’ of the polygon data, but ignored the fact that it would have been a restaurant point feature, and therefore with our method a lot of semantic information probably got lost.

Our classification approach of the OSM tags is probably too detailed. It is heavily skewed towards ‘Building’ tags. That’s why they occur so much in the dataset and in the results. Maybe in a future research one could leave the buildings out to get more specific semantic information.

9.4 MOASIS Study

MOASIS is a really big study with 159 participants and a huge trajectory dataset for the 30 day span of GPS tracking. In addition, there is the large metadata with all kinds of personal information, which is very extensive. However, no dataset is complete and there are gaps of data. For example, participants did not state their age or the area where they lived. Lastly not every participant seemed to wear the GPS logger for a consistent amount of time looking at the total stops some of the participants collected. Therefore it is very difficult and challenging to compare the collected GPS data and to be interpreted with care.

10 Conclusion

We performed a semantic enrichment on the detected stops of the MOASIS study participants. Further we analyzed their annotated stops regarding different influencing variables like age (Yeom et al., 2008), weekday differentiation (Gong et al., 2016) and home type (Melzer & Parahyba, 2004, Yeom et al., 2008).

We showed that there is no significant difference regarding the activity locations (total number of detected stops and unique visited stops) when looking at the home types of the participants. However there is a significant difference when focusing on the mobility of older participants (73-89 years old) in relation to the younger participants (65-72 years old). Older participants showed significant less diverse stop visitation than their younger counterparts. This is particularly interesting as the total number of visited stops in relation to the two age groups did not show a significant difference.

We also found interesting place visitation patterns when looking at the different weekdays. We showed that on weekends, recreational stops were more frequent than during the week. Shopping mostly occurs during the week, while on the weekends it is less frequent. Finally we showed that participants are less often near buildings on the weekends.

Our semantic enrichment process could have also been done with other methods, which would have led to other results. For example adding descriptive scores or weighted tags, to find the most important semantic tag, would have changed the results of this thesis with certainty. Further mentionable is the skewness of the OSM tags, in which we had a huge amount of polygon ‘building’ tags, which resulted in a lot of stops being annotated with this tag. This tag is not very useful in the aftermath, because more insight is needed, in what exactly the purpose of this building is.

Further research in this field may not focus on the stops and activity locations of the older adults, but concentrate on the move episodes of the MOASIS participants, and look onto the different modes of transport participants use. This could be useful for transport planners to obtain valuable information regarding the public transport use of the older adults. Another approach would be to look further into trajectory patterns of the participants and do a sequence alignment of different stop episodes of individuals.

This would be interesting in analyzing individuals mobility patterns and finding similarity or differences to other participants.

We did not focus in this thesis on the relation between men and women and their total stop count and unique visited stops. Li et al. (2017) did show in their study that men tend to have a higher daily step count than women. So this question could be of great interest as well, whether there is a difference in activity locations when looking at the different gender of participants.

However further research of our findings are necessary, to deepen the understanding of the mobility of healthy older adults and the preferences of daily place visitation. Maybe these findings then can help to improve healthy aging promotion programs or help urban planners and policy makers to integrate the older population to prevent social isolation and loneliness.

Appendix

OSM Tags (independently developed classification)

Grouping of related point shapefile tags: 43 tags in total

Polygon tags were not grouped, as there already were only 29 tags.

accomodation
alpine_hut
bed_and_breakfast
camp_site
caravan_site
chalet
guesthouse
hostel
hotel
motel
shelter

art
museum
artwork

attraction
attraction
viewpoint
wayside_cross
wayside_shrine
memorial
monument

bank
bank

bench
bench

catering_drinking
bar
biergarten
cafe
pub

catering_eating
fast_food
food_court
restaurant

graveyard
graveyard

health
dentist
doctors
hospital
pharmacy
veterinary

historical
castle
fort
ruins
archaeological
battlefield

leisure_nightlife
cinema
nightclub
theatre

leisure_park
park
playground
dog_park

leisure_sport
golf_course
ice_rink
pitch
sports_centre
stadium
swimming_pool
tennis_court
track

nature
beach
cave_entrance
cliff
glacier
peak
spring

nursing_home
nursing_home

parking
parking
parking_bycicle
parking_site
parking_multistorey
parking_underground

picnic_site
picnic_site

place_of_worship
buddhist
christian
hindu
jewish
muslim
shintoist
sikh
taoist

poi_education
college
kindergarten
school
university

poi_emergency
police
fire_station

shopping_other
laundry
travel_agent

poi_publicbuilding
town_hall
public_building
arts_centre
community_centre
courthouse
embassy
post_office
library

poi_recycling
recycling_clothes
recycling_glass
recycling_metal
recycling_paper

poi_water
fountain
wastewater_plant
water_mill
water_well
water_works

prison
prison

service_station
fuel
service

shopping_car_bicycle
car_dealership
car_rental
car_repair
car_sharing
car_wash
bicycle_rental
bicycle_shop

shopping_crafting
doityourself
garden_centre

shopping_grocery
bakery
butcher
beverages
convenience
greengrocer
supermarket

shopping_health
chemist
optician
beauty_shop

shopping_nonfood
bookshop
clothes
department_store
florist
furniture_shop
gift_shop
hairdresser
jeweller
kiosk
mall
newsagent
outdoor_shop
shoe_shop
sports_shop
stationery
toy_shop
video_shop

poi_other
windmill
hunting_stand

shopping_technology	themepark_zoo	tourist_info	tower
computer_shop	zoo	tourist_info	tower
mobile_phone_shop	theme_park		comms_tower
			tower_observation
			water_tower
			lighthouse

traffic_water	transport_air	transport_bus	transport_railway
dam	aerialway_station	bus_station	railway_halt
marina	airfield	bus_stop	railway_station
pier	airport		
waterfall	apron		
weir	helipad		

transport_taxi	transport_tram	transport_water	
taxi_rank	tram_stop	ferry_terminal	

OSM Tags classified according to Gong et al. (2016)

Building
industrial
residential
buildings
prison
poi_publicbuilding
bank

Transportation
traffic_water
transport_air
transport_bus
transport_railway
transport_taxi
transport_tram
transport_water
parking

Schooling
military
poi_education

Shopping
commercial
retail
shopping_car_bicycle
shopping_crafting
shopping_grocery
shopping_health
shopping_nonfood
shopping_other
shopping_technology
poi_recycling
service_station

Dining
catering_drinking
catering_eating

Lodging
accomodation

Medical
health
nursing_home
poi_emergency

Recreation	Recreation (cont.)	Recreation (cont.)	Recreation (cont.)
allotments	orchard	dock	leisure_nightlife
forest	park	themepark_zoo	leisure_park
cemetery	recreation_ground	tourist_info	leisure_sport
farmland	reservoir	tower	nature
farmyard	river	poi_other	picnic_site
glacier	riverbank	poi_water	place_of_worship
grass	quarry	art	
heath	scrub	attraction	
meadow	vineyard	bench	
national_park	water	graveyard	
nature_reserve	wetland	historical	

Pseudo Code of the Semantic Enrichment

```
## Load modules
    library(sf)
    library(dplyr)
    library(readr)
    library(stringr)
    library(ggplot2)

## Define functions
## Get stops and process
stops <- readxl::read_xlsx('StopFile.xlsx') %>%
    select(mergeTypeId, participantID, studyDay, mergedType, medianX, medianY, totDur, sDateTime, durMin) %>%
    filter(., mergedType == 'stop') %>%
    st_as_sf(coords = c("medianX", "medianY"), crs = 32632) %>%
    st_transform(3857)

## Function to process shapefiles
load_data <- function(path){
    data <- st_read(path) %>%
    st_set_crs(4326) %>%
    st_transform(3857) %>%
    select(osm_id, fclass, name)
    return(data)
    }

## Get table with nearest features and distances
near_table <- function(stops, feature){
    nearest <- st_nearest_feature(stops,feature)
    dist <- st_distance(stops, feature[nearest,], by_element = TRUE)
    table = cbind(stops, st_drop_geometry(feature)[nearest,])
    table$dist = dist
    return(table)
    }
```

```
## Get shapefiles information
files <- list.files(pattern = "\\.shp$")
for (f in files){
    cat('Processing',f)
    table <- st_drop_geometry(near_table(stops,load_data(f)))

write.csv(table,paste(substr(f,1,nchar(f)-4),'.csv'),append=FALSE,row.names = FALSE)
}

## Execute functions
## Merge dataframes into single one
stopsMerged <- list.files(pattern = "\\.csv$", full.names = TRUE) %>%
    lapply(read_csv) %>%
    bind_rows

## Group per Stop and get minimum distance feature across all shapefiles
stopsFeature <- stopsMerged %>%
    group_by(mergeTypeId, participantID) %>%
    slice(which.min(dist))
## Process non utf-8 characters and get weekdays
stopsFeature$name <- gsub("[^ -~]+", "", stopsFeature$name)
stopsFeature$weekday <- weekdays(stopsFeature$sDateTime)
## Save in csv
write.csv(stopsFeature,"stopsFeature.csv")
```

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Personal declaration

I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

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