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Correlates of Older Adults' Out-of-Home Behaviour: Linking Health and Cognition with Mobility Indicators Derived from GPS-Trajectories

GEO 511 Master's Thesis

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"If I could get back my youth, I'd do anything in the world except get up early, take exercise or be respectable."

OSCAR WILDE, *The Picture of Dorian Gray*

Abstract

Background

Due to the global demographic development towards older age, interest in the topic of healthy ageing is increasing. Mobility was found to be a key component for maintaining a healthy, independent life in older age. Therefore, a profound knowledge of how older adults' out-of-home behaviour correlates with their health and cognition is of interest for future healthy ageing policies. Thanks to wearable sensors using GPS-technology, it is possible to track a person's mobility with a high spatiotemporal resolution. Various indicators representing a person's mobility can be derived from these trajectories. In this thesis, mainly the quantity of out-of-home activities as well as the timing of mobility are considered by the selected indicators.

Materials & Methods

The data used in this analysis stems from the *MObility, Activity and Social Interaction Study* (MOASIS), conducted by research teams at the University of Zurich. The sample consists of 93 community-dwelling healthy older adults (age: 65 – 88) living in Switzerland. Each participant carried a GPS-tracking device for at least a week, with an average of 18 study days. From those GPS-trajectories, the participants home location was derived, and subsequently multiple mobility indicators were calculated, which are based on time out of home (duration, variability, timing) as well as on place diversity (number of activity locations, revisits, entropy). These indicators are then compared to health indicators including physical, mental and cognitive health in order to reveal correlations on a between-person level.

Results

Little to no significant correlations between health and mobility were found in the analysis. The significant correlations found indicate that place diversity is higher for people with better cognitive health, out-of-home activity in the morning is more common with mentally healthy individuals, and further that the duration of time spent out-of-home is shorter for people suffering from depressive symptoms.

Conclusion

For the given sample of older adults, mobility and health do not seem to be related. Due to the criteria for participant selection, the sample is highly functional and hardly includes individuals with adverse health conditions. It seems plausible that these healthy older adults hardly experience any health-related restrictions in their everyday life, which allows for numerous patterns of out-of-home behaviour. Additionally, several other factors neglected in this analysis might influence a person's behaviour, e.g. their individual preferences or the geographical setting. In future research, these factors should be considered in order to reduce uncertainty.

Keywords

mobility, health, healthy ageing, older adults

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Glossary

ADS	Allgemeine Depressionsskala, German adaptation of the Center for Epidemiological Studies Depression Scale (CES-D)
AL	Activity Location
CES-D	Center for Epidemiological Studies Depression Scale
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
MBGP algorithm	time-based clustering algorithm developed by Montoliu, Blom and Gatica-Perez (2013)
MCS-12	Mental Component Summary of the SF-12 health survey
MOASIS	MObility, Activity and Social Interaction Study
OPTICS	Ordering Points to Identify the Clustering Structure
PCS-12	Physical Component Summary of the SF-12 health survey
PHQ	Patient Health Questionnaire
RQ	Research Question
SF-12	Short Form Health Survey, consisting of 12 items
TOH	time out of home
uTrail	custom-built tracking device for the MOASIS study, including a GPS sensor
VLMT	Verbaler Lern- und Merkfähigkeitstest, German version of the Rey Auditory Verbal Learning Test (RAVLT)
WHO	World Health Organization

1 Introduction

1.1 Motivation

We live in an ageing world: According to the United Nations Department of Economic and Social Affairs Population Division (2019), the number of people aged above 65 years globally is projected to double from 703 million in 2019 to 1.5 billion in 2050. Compared to other age groups, the group of older adults is growing more strongly: While the share of people aged 65 years or older globally was at 6 % in 1990 it grew to 9 % in 2019 and is projected to increase further to 16 % by 2050, meaning that by then one in six people will be in this age group. The growing number of older adults along with the demographic shift towards old age stresses the importance of research on ageing.

Even though Switzerland is a country with an already significant percentage of older adults, this age group is predicted to grow even further (Bundesamt für Statistik, 2020): As of 2020, 1.64 million people aged 65 years or older live in Switzerland. This number is projected to increase up to 2.67 million until 2050. According to Swiss population models, the number of people aged over 80 years will increase by a factor of 2.4. It is therefore safe to say that not only for the world in general, but for Switzerland in particular, ageing will become a more relevant topic in the near future.

With an increasing number of older adults worldwide, the focus lies on improving the quality of life for those people. Although the relationship is far from linear, ageing is usually associated with biological changes such as a general decline in the capacity of the individual and an increased risk of diseases, as well as psychosocial changes, with shifts in roles and social positions, and the need to deal with the loss of close relationships (Hébert, 1997; World Health Organization, 2015). Along with economic status, health was found to be a key predictor of life satisfaction in old age (Ng et al., 2017). The World Health Organization (2015) defines health as follows: "Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity." Additionally, cognitive capacities should be considered. In this thesis health will be characterised by three aspects: physical health, mental health and cognitive health. Their relevance for healthy ageing will be described later. Healthy ageing, defined as "the process of developing and maintaining the functional ability that enables well-being in older age" (World Health Organization, 2015), encompasses all three aspects of health mentioned.

Healthy ageing further includes important aspects such as independence, self-actualisation as well as participation in one's environment. Living an independent life usually requires moving to different places in order to accomplish everyday tasks. Outdoor mobility is thus crucial for maintaining independence in old age. Mobility is required for fulfilling basic needs, such as going shopping or seeing a doctor. Beyond these basic needs, mobility is crucial for an active participation in social life as well as for numerous further out-of-home activities (Gagliardi et al., 2007; Siren et al., 2015). Several studies have found correlations between mobility and health or well-being (Mollenkopf et al., 2004; S. R. Müller et al., 2020; Petersen et al., 2015; Wettstein, Wahl, & Diehl, 2014). While some relationships between mobility and health are evident, others remain unexplored. The interrelations between health and mobility of older adults in Switzerland will be analysed in this thesis. To this end, mobility behaviour will be expressed by simple indicators derived from GPS logs. Additionally, perceived health status will be used in order to search for potential interrelations.

Gaining knowledge on potential correlations between older adults' mobility behaviour and different health aspects might benefit future decisions in various fields, such as health systems, urban planning or general population satisfaction. Furthermore, monitoring the older adults' mobility behaviour could also benefit diagnoses of certain health issues: For instance, any change in out-of-home mobility may be an early sign of mild cognitive impairment (Wettstein et al., 2015).

1.2 Overview

First, an overview of the state of the art in research on mobility and health of older adults is given, including different approaches used in previous studies (Section 2.1). From there, the research gaps are identified and subsequently the research questions are developed (Sections 2.2 – 2.5.1). For each research question, the expected outcomes are described by referring to previous studies, allowing to formulate hypotheses (Section 2.5.2).

In Section 3, the data used as well as the methods applied in order to retrieve the different indicators are explained in detail. Furthermore, the statistical analysis is outlined. The resulting indicators and the outcomes of the statistical analysis can be found in Section 4, followed by a critical discussion and evaluation in Section 5, where the research questions are also answered. In Section 6, the main contributions of this thesis are summarised, and potential future studies are outlined.

2 Background

2.1 State of the Art in Research on Older Adults' Mobility

2.1.1 Mobility Studies Based on Self-Reports

For a long time, research on older adults' mobility and their daily activities was based on self-reports consisting of questionnaires and diaries (May et al., 1985; Stalvey et al., 1999). In such studies, participants are usually asked to keep a diary following a given structure. Another option is the use of questionnaires or even interviews, where the participants have to reflect on their experiences and activities of the previous day or week.

Self-reported data is often biased for various reasons: Participants tend not to accurately report on all of their activities due to lack of care, forgetfulness or sometimes even some deliberate decision (Brög et al., 1982). Especially with older adults, cognitive impairment and forgetfulness can become an issue when using questionnaires concerning longer time periods (Ho et al., 2020; Simões et al., 2018). As mentioned above, some participants rather conceal certain activities or places they have visited, as these might not be seen as socially desirable. These deliberate decisions not to report certain activities thus lead to the so-called social desirability bias (Fillekes, Kim, et al., 2019). Especially in studies on physical activity, the social desirability bias should not be underestimated as people tend to exaggerate the time they spend on activities which are considered healthy and therefore socially desirable (Adams et al., 2005).

Furthermore, as questionnaires and diaries are usually filled out retrospectively, the responses are often subject to a recall bias (Kitterød, 2001; Simões et al., 2018). For instance, older adults tend to overestimate positive affect when asked to report on their affect only once per day (Ready et al., 2007).

Apart from the bias within the reported action, there is a further problem: As the participants in these studies are constantly reminded of their participation through regular diary entries or questionnaires to be filled in, it is highly likely that they change their behaviour (Johnson & White, 1971). Although this change in behaviour due to self-observation might be unintentional, it still leads to a bias in the result as the reports may no longer reflect the normal routine of the participants, especially during the first days of a study.

Moreover, studies based on questionnaires and self-reports require an active participant involvement. Participants have to spend large amounts of time on reporting their activities, which can be felt as a burden for them. As a consequence, these studies are usually limited in duration so as not to overburden the participants.

Finally, the accuracy of the self-reports might need to be rather differentiated on a semantic level as to the description of which places were visited. Numerical measures such as distance travelled or time spent on a particular activity are often less accurate because people usually struggle more with these quantitative estimates (Fillekes, Röcke, et al., 2019).

Even though the points mentioned give the impression that relying on self-reports is an inappropriate approach to do research on older adults' mobility and their daily activities, it was the only feasible option for a long time. One should nevertheless not underestimate the progress in research done on those topics that were only possible thanks to such studies. Furthermore, studies based on self-reports also have distinct advantages, especially in terms of semantic, qualititative information included in the participants' answers.

2.1.2 Mobility Studies Based on Sensors

In recent years, thanks to the ubiquity of the Global Positioning System[1] (GPS) technology, the use of GPS devices in health sciences has become increasingly popular. GPS technology enables researchers to retrieve a detailed track log for each participant.

Compared to traditional methods based on self-reports, the use of GPS devices for assessing older adults' mobility behaviour holds several advantages: First of all, the objectivity of the data can be increased as most of the biases mentioned before can be avoided. Depending on the study design and sensor choice, participants are not constantly reminded of their involvement in the study and continue leading their lives as usual. Especially when using smartphones with GPS sensors, the obtrusion is minimal (Canzian & Musolesi, 2015). Secondly, it is possible to conduct studies over extended periods of time as the participant's burden is much smaller. Apart from regularly recharging the device and remembering to take it with them, the participant does not have to do anything actively. Longer studies are preferred because they provide a deeper insight into the lives of the participants and more of a process than a status perspective. The low level of active participant involvement makes it possible to include participants who not able to fill in self-reports, for instance people suffering from dementia (Lin et al., 2015; Oswald et al., 2010).

Moreover, using GPS devices leads to a significant increase in spatiotemporal resolution compared to self-reports (Isaacson et al., 2016). Thanks to high sampling rates and precise GPS measurements it is possible to gain a high-resolution insight to a person's whereabouts whereas with diaries and questionnaires the level of detail is much smaller. This high resolution makes it possible to precisely derive numerical mobility indicators such as the time spent at a particular location.

However, using GPS data also has its disadvantages. Whilst the objectivity of the data is undeniably increased, the subjective perspective included in diaries is lost. In contrast to diaries and questionnaires, GPS data does not contain any semantic information whatsoever. GPS measurements tell us where a person was at a certain time, however there is no information on why the person was there, with whom they were there, what they were doing there or what

[1] GPS is a specific type of the Global Navigation Satellite Systems (GNSS). As in health-related applications, the term GPS has become widely accepted it is used in this thesis although other GNSS might be used.

this place means to them. Semantic annotation of GPS data is therefore still a challenge in research, even though there are possibilities using inference algorithms (Boukhechba et al., 2015; Cao et al., 2010; Ghosh & Ghosh, 2016; Guc et al., 2008; Martin et al., 2018; Välimäki, 2020).

Even though the spatiotemporal resolution is high compared to self-reports, this is not true for indoor mobility, especially in the participants' home. While using self-reports, participants can indicate which room they spend their time in. Due to low accuracy or signal loss, this information is not contained in the GPS data. As a consequence, many mobility studies only distinguish between *at home* and *out of home* (Demant Klinker et al., 2015). Here, studies based on self-reports can give a deeper insight into the social rhythm of older people as activities such as an afternoon nap on the couch are recorded (May et al., 1985; Monk et al., 1992). This problem also affects multipurpose locations such as large shopping centres that might include shopping facilities, cinemas, hairdressers or restaurants and thus can be used in various ways (Bayat et al., 2020).

Another important issue with studies using GPS devices is compliance. Even though the participants' involvement is much smaller compared to diary- or questionnaire-based studies, the participants are still required to carry the device with them, make sure it is turned on and the battery is loaded (Isaacson et al., 2016). As older adults might not be overly familiar with using digital devices, a clear instruction on how to use the device is crucial. If necessary, there could be an additional meeting at the midpoint of the study to discuss compliance issues (Zenk et al., 2018). Unfortunately, compliance issues still arise – especially with cognitively impaired people (Isaacson et al., 2016). With only GPS data it is hardly possible to distinguish between a participant forgetting the device at home and the participant actually staying at home. The apparently high accuracy of GPS data should therefore not be interpreted as data without uncertainty.

2.1.3 Self-Reports Compared to Sensor-Based Studies to Measure Mobility

As mentioned, both studies based on self-reports as well as GPS sensor-based studies have their advantages and disadvantages respectively. Several studies have focussed on the comparison of mobility indicators derived from self-reports and GPS-based data. Depending on the aspect of mobility the level of agreement varies.

It is possible to compare life-spaces – a hierarchical classification of spatial areas introduced by May et al. (1985), e.g. the flat, the garden and the close neighbourhood. When comparing visits to such life-spaces derived from both GPS-data as well as traditional life-space questionnaires, Fillekes, Röcke, et al. (2019) found a high degree of agreement across participants. Other studies reported moderate to good correlations for the indicators mentioned, which might be explained by memory bias (Ho et al., 2020).

Another aspect of mobility is the detection of the mode of transport, meaning whether a person travelled e.g. by car or by bicycle. Whilst the classification of the mode of transport is similar disregarding the data source, participants seem to overestimate the traveling duration when using self-reports (Fillekes, Röcke, et al., 2019; Vanwolleghem et al., 2016).

Bayat et al. (2020) evaluated a stop-detection algorithm based on GPS-data using self-reports as ground truth. They were able to calculate an F-score of 87 % which can be interpreted as a reasonable accuracy. Similarly, Kestens et al. (2016) compared activity locations generated by a kernel-based algorithm with interview-based data and found the locations to be highly concordant. Ho et al. (2020) found sensor-based data to identify more stops compared to diaries, while nevertheless maintaining a good correlation between the two data sources.

Concerning the daily duration of out-of-home activities, Zhu et al. (2020) found GPS-derived measures to be a reasonable alternative to measures based on diaries, as the differences did not appear to be significant. In terms of trip frequency and duration, only moderate agreements were observed between GPS-derived indicators and self-reports (Zhu et al., 2020).

It can therefore be concluded that for most mobility indicators, the measures derived from GPS-trajectories as well as diaries or questionnaires seem to be correlated. It is however possible that some effects of over- or underestimation occur in either data source. Additionally, absolute values recorded might not necessarily represent the actual behaviour. With those potential challenges in mind, this thesis is based solely on GPS data and does not include any mobility indicators based on self-reports.

2.2 Research Gaps & Focus of the Present Thesis

The majority of previous studies using GPS devices to gain an insight in older adult mobility mostly focused on accurately measuring and describing their behaviour by writing improved algorithms and defining new mobility indicators. Meanwhile, studies in gerontology tend to focus on assessing older adults' health status and possible reasons for their health status. However, the direct comparison of mobility indicators derived from GPS data with health indicators is a more recent research field, which is still to be fully explored. A number of studies have been conducted, which mostly focus on one specific aspect of health, such as cognitive impairment (Shoval et al., 2011; Wettstein et al., 2015) or depression (Canzian & Musolesi, 2015; Saeb et al., 2016). On the other hand, there are studies which included a broader view on health while focusing exclusively on a narrow aspect of mobility (Petersen et al., 2015). While all these studies render valuable information on certain aspects of healthy ageing, only few studies give a more comprehensive overview (Giannouli et al., 2019).

Given the importance of mobility for healthy ageing, the goal of this thesis is to find interrelations between health and mobility on a between-person level. Other than most existing studies, both health as well as mobility should be considered comprehensively. This thesis aims at showing to what extent assessed health indicators correlate with mobility indicators derived from GPS data.

In order to statistically analyse interrelations between health and mobility, both aspects have to be transformed into numerical indicators. The following paragraphs describe the chosen mobility and health indicators as well as their significance.

2.3 Mobility Indicators Representing the Out-of-Home Behaviour

By applying different algorithms, numerous mobility indicators can be derived from GPS track logs. In a comparative approach, Fillekes, Giannouli, et al., (2019) come up with a framework of 20 mobility indicators explicitly for health and ageing studies (Figure 1). Based on a factor analysis, they find the following six dimensions required to obtain a comprehensive view of an older adult's daily mobility: extent of life space, quantity of out-of-home activities, time spent in active transport modes, stability of life space, elongation of life space, and timing of mobility. Within their framework, mobility indicators are grouped by space or time (or both). Additionally, they are categorised by movement scope categories, which can be supplemented with attributes.

Mobility indicator		Characteristic aspects											
		Space			Time			Mvt. sc.			Attribute		
Abbreviation	Full name	Count	Extent	Shape/distr.	Duration	Timing	Temp. distr.	Stop	Move	Trajectory	Out of home	Transport mode	Further attribute
MaxDist	Maximum distance to home		✓							✓			
CHull	Area of convex hull		✓							✓			
SDE	Area of standard deviational ellipse		✓							✓			
LocVar	Location variance		✓	✓						✓			
LengthPerTrip	Average trip length		✓	✓					✓				
DurPTM	Duration in PTM				✓				✓			✓	
DurATM	Duration in ATM				✓				✓			✓	
MaxDurATM	Duration of longest ATM trip				✓				✓			✓	
NumLoc	Number of locations	✓						✓			✓		
NumUniqLoc	Number of unique locations	✓					✓	✓			✓		
TOH	Time out of home				✓					✓	✓		
Entropy	Entropy in locations						✓	✓					
GravCompact	Gravelius compactness of cHull			✓						✓			
Maj2MinAxis	Major to minor axis of SDE			✓						✓			
RevisitedLS	% revisited area of daily life space						✓			✓			
AvgRevisitedLS	Avg. % overlapping daily life space						✓			✓			
SDDirMaxDist	Direction of max. distance fix						✓			✓			
TimeMaxDist	Time of day at max. distance to home					✓				✓			
TimeFirstMove	Time of day first move					✓			✓				
TimePeriodActive	Period of day with most OH activities					✓		✓	✓		✓		
Total # of indicators per category		**2**	**5**	**4**	**4**	**3**	**5**	**4**	**6**	**II**	**4**	**3**	**0**

Figure 1: The set of mobility indicators proposed by Fillekes, Giannouli, et al. (2019)

Out of the 20 mobility indicators, five indicators are used within this thesis. The mobility indicators are chosen to represent different aspects of mobility while maintaining simplicity, meaning that they can be calculated using similar code. Furthermore, the indicators should be rather easy to understand as this thesis should not only appeal to experts in mobility research. In addition, when selecting the indicators, attention is paid to the fact that they have already been used in previous studies in order to achieve comparability.

For the sake of conciseness, the selected indicators are divided into two main groups: *Time out of Home* and *Place Diversity*. The first group encompasses the indicators *TOH* (time out of home) as well as *TimePeriodActive* (period of day with most OH activities). The second group – *Place Diversity* – includes *NumLoc* (number of locations), *NumUniqLoc* (number of unique locations) as well as *Entropy* (entropy in locations). While *Time out of Home* is classified by time, *Place Diversity* is classified by place. Out of the dimensions of mobility described by Fillekes, Giannouli, et al. (2019), these indicators mainly represent the quantity of out-of-home activities (*TOH, Entropy, NumLoc, NumUniqLoc*). The indicators mentioned might also hold information on the extent of life space. Furthermore, the timing of mobility is considered with *TimePeriodActive*. While not all dimensions of mobility being considered, this selection of indicators allows a more comprehensive view on mobility.

2.3.1 Time out of Home

Duration

Time out of home (TOH) is one of the most commonly used mobility indicators as it is easily understandable: It is simply defined as the time a person spends out of their home (Brusilovskiy et al., 2016). In contrast to younger adults, for older adults TOH is no longer determined by employment or work characteristics (Rapp et al., 2018). It is therefore much more representative of an older person's choices and abilities. People can spend time out of their home for various reasons, that can be grouped into utilitarian and discretionary activities (Siren et al., 2015). Utilitarian activities encompass everyday activities fulfilling basic needs, for instance grocery shopping, health related errands as well as using public transport in order to get to the grocery shop. Discretionary activities are related to leisure and social activities such as visiting a friend, as well as outdoor exercise such as a walk in the forest. Both types of activities usually require people to leave their home and thus spend time out of home. Therefore, TOH is an indicator of how much time a person spends on these activities. In general, longer TOH duration is associated with a higher degree of autonomy and better health state. For example, being out of home was shown to increase the daily walking duration of older adults, which is thought to have a positive influence on physical health (Rapp et al., 2018).

Variability

A further aspect of TOH is its variability: While one person leaves their home for 5 hours every day, another person might leave for 10 hours every second day while fully staying at home every other day. While both persons show a similar average TOH duration, their behaviour varies significantly. Intra-individual variability in TOH might contain valuable information on a person's behaviour and should thus not be ignored (Brusilovskiy et al., 2016; Wang et al., 2012). While not specifically representing a mobility indicator proposed by Fillekes, Giannouli, et al. (2019), this indicator can be seen as an aspect of the indicator TOH duration.

Timing

The aforementioned aspects of TOH focus mainly on duration. However, the aspect of timing is also important. While some people tend to spend most of their TOH in the morning, others rather go out during the afternoon or in the evening (TimePeriodActive*)*. The timing of TOH can be an indicator of sleeping problems, as some people might be awake very early while others struggle to get up in the morning (Ohayon et al., 2001). On a larger scale, there can be differences in the TOH timing between the seven days of the week (Horgas et al., 1998; Rapp et al., 2018).

2.3.2 Place Diversity – Activity Locations

Counts

Apart from the time spent out of home, it is also interesting to look at the places visited during TOH. Aside from recreational walks, people usually leave their home with the intention to visit a certain place – or multiple places (Zeitler & Buys, 2015). Typically, they visit this place in order to perform a certain activity, whether this might be shopping for groceries, getting their teeth cleaned by a dental hygienist, playing with their grandchildren or meeting up with a friend at a café. Consequently, such a place is called *Activity Location* (AL). For fulfilling basic needs, a certain number of visits to ALs are needed when living independently. Additionally, for some older adults activity locations are crucial as places for social interaction (van den Berg et al., 2015). The number of ALs can therefore hold important information about a person's behaviour.

These ALs can be extracted from the GPS data by applying different algorithms (Ebert, 2020; Montoliu et al., 2013; Thierry et al., 2013). The number of different locations can then be counted as well as the number of visits per AL (NumLoc). This makes it possible to extract the number of unique locations (NumUniqLoc). Depending on the number of revisits and uniquely visited ALs, a person's mobility behaviour can be further characterised.

Entropy – Temporal Distribution

Another indicator for place diversity is entropy, which shows how each participant's time was distributed over different location clusters (Fillekes, Giannouli, et al., 2019). In contrast to the aforementioned aspects of place diversity, this indicator is based on temporal distribution rather than spatial counts. Having a low entropy means a person spent most of their time in few places, while high entropy corresponds to a person spending their time at multiple places. Entropy seems to be relevant for health, as low entropy values were found to correspond with depressive symptom severity (Saeb et al., 2016).

2.4 Health Indicators

As mentioned before, health is a complex construct. Therefore, generating merely one simple indicator is not appropriate. In this thesis, health is divided into three components: physical health, mental health and cognitive health. This classification is common practice in research on health in old age (e.g. Richmond et al., 2011; Rosenberg et al., 2015). These three components cover a large part of the WHO's health definition. However, the aspect of social health is partly neglected. In the following sections, the three health components as well as their importance in later life are described.

2.4.1 Physical Health

Physical health is probably what most people think of when they talk about healthy ageing, as physical health often declines noticeably with age. Maintaining good physical health is crucial for an independent life in older age: It includes key aspects of health such as the ability to walk a certain distance, having sufficient eyesight and hearing, or having a good balance in addition to not suffering from health disorders such as strokes or respiratory diseases. Poor physical health can influence a person's mobility behaviour. For example, repeated falls as a result of poor balance or a lack of surefootedness can lead to a fear of falling and ultimately a reduction in mobility (Vellas et al., 1997).

In colloquial language one could say that good physical health means to be in good shape. However, physical health does not only include aspects of a medically defined states, such as chronic illness or sick days. It also includes social aspects such as self-maintenance and instrumental activities of daily living, as well as psychological aspects such as the subjective rating of physical health (Liang, 1986). This subjective assessment of physical health in particular plays an important role in terms of a person's well-being. Some people in later life maintain a positive perception of their own health, despite their health being poor when assessed objectively (K. Henchoz et al., 2008). These people feel less impaired by their health condition than one would expect. In several studies, self-reported health has been found to predict mortality, making it a good measure of overall health (Benyamini & Idler, 1999; Singh-Manoux et al., 2007).

2.4.2 Mental Health

The WHO defines mental health as "a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community" (World Health Organization, 2004). Following this definition, mental health is the basis for an individual's well-being and effective functioning.

Whilst the decrease of physical health in old age is a well-discussed topic, mental health issues with older adults were more likely to be ignored for a long time (Koenig et al., 1994; Reed, 1989). In recent years, however, mental health of older adults has become more of a focus for scientific research (Wu et al., 2012). Mental health is seen as an integral part of health, including subjective well-being, perceived self-efficacy, autonomy and self-actualisation of one's intellectual and emotional potential. Low mental health can lead to bad moods, low life satisfaction or even mental illnesses such as depression (World Health Organization, 2004).

Apart from negative effects on the individual, poor mental health is also an issue for the health care system. It has been shown that healthcare costs for depressive older adults are one third higher compared to non-depressive individuals even though most of them do not receive depression-specific treatment (Riedel-Heller et al., 2012).

In contrast to physical health, ageing can not only affect mental health in a negative way but often in a positive way, namely through psychosocial growth and improved coping strategies, which can lead to higher life satisfaction (Hamarat et al., 2001; World Health Organization, 2015). Furthermore, mental health disorders are less common among older adults than within other age groups, which goes along with a lower perceived need for mental health care in older adults (Klap et al., 2003).

2.4.3 Cognitive Health

Cognitive health can be defined in various different ways. Core elements of cognitive health usually include mental abilities, such as learning, thinking, reasoning, remembering, problem solving, decision making, orientation, and attention (Fisher et al., 2019; Folstein et al., 1975). Others define cognitive health as "improvement, maintenance, or minimal decline of cognitive function and absence, delay of onset, or slowing the progression of dementia" (Jedrziewski et al., 2007).

This thesis describes cognitive health by indicators of episodic and spatial memory.

Episodic memory

Episodic memory is a component of long-term memory, defined as the memory system that has to do with learning and retention of material presented in a particular place at a particular time (Tulving, 1972). Over time, the definition was refined as to include three key properties of episodic memory: Connection to self, subjective sense of time, and autonoetic consciousness (Tulving, 2002). It is however not bound to past events but also includes remembering ongoing life's experiences as well as the encoding and retrieval of items and associations (Braver & West, 2011; Tulving & Markowitsch, 1998).

As with most cognitive functions, episodic memory tends to decline in old age compared to younger adults (Braver & West, 2011; Trelle, 2016). However, it is important to note that age alone is not a sufficient predictor of episodic memory (Troyer et al., 1994). Having a good episodic memory is important for an older adult as it is needed for everyday situations, such as planning activities or remembering information. A reduced episodic memory can lead to less specificity with regard to past events or increased forgetfulness and temporal disorientation, which can make life difficult for those affected.

Spatial memory

Spatial memory is defined as the storage and retrieval of information within the brain that is needed both to plan a route to a desired location and to remember where an object is located or where an event occurred (Bisby & Burgess, 2019). Different nerve-cells in the hippocampus are involved in the different tasks requiring spatial memory (Olton, 1977). As most brain functions, spatial memory decreases with age, which can influence a person's behaviour (Barnes, 1988; Borella et al., 2014; Moffat, 2017). For instance, older adults were found to have more problems with memorising urban landmarks, route learning, or wayfinding than younger individuals (Burns, 1999; Evans et al., 1984; Head & Isom, 2010; Muffato et al., 2016). The inability to adequately apply orientation strategies can lead to spatial anxiety (Davis & Veltkamp, 2020). As a consequence, some older adults prefer to avoid unfamiliar routes and places (Burns, 1999). Especially in unfamiliar and inappropriately designed locations, older adults can be overwhelmed and may struggle performing spatial tasks (Phillips et al., 2013). Spatial cognition has been found to be predictive of an older adult's neighbourhood use (Simon et al., 1992). It is therefore interesting to see to what extent a participant's spatial memory level correlates with their mobility.

2.5 Research Questions & Hypotheses

2.5.1 Research Questions

Based on the mobility and health indicators mentioned above, the following research questions (RQs) shall be dealt with in this thesis:

RQ 1. How does time out of home (TOH) correlate with older people's health with regards to…

- a. duration?
- b. variability?
- c. timing depending on the day of the week?
- d. timing depending on the time of the day?

RQ 2. How does place diversity correlate with older people's health with regards to…

- a. the total number of activity locations?
- b. the number of repeatedly visited activity locations?
- c. the time distribution between different activity locations?

2.5.2 Hypotheses – Expected Results

RQ 1 Correlation Between Health and TOH

RQ 1a: Health and TOH Duration – Expected Results

Older adults are required to leave their home for various reasons, including both utilitarian and discretionary activities. However, the duration of TOH can vary among individuals.

Time spent at home is usually associated with utilitarian activities such as self-care, housework as well as discretionary activities such as napping, watching TV or reading. These discretionary activities tend not to include a lot of physical activity and thus classify as sedentary behaviour. Around 70 % of sedentary time is spent at home (Leask et al., 2015). It can be assumed that there is a negative correlation between TOH and sedentary behaviour, meaning people with low TOH tend to spend more time being sedentary (Harada et al., 2019).

Sedentary time is related to physical health, represented by gait speed, chair stands as well as self-reported physical functioning (Rosenberg et al., 2015). Physical health is lower for people with more sedentary time (Rosenberg et al., 2015). This also includes higher risks of being overweight for people with a great deal of sedentary time (Kikuchi et al., 2014). Furthermore, people with low cognitive health are found to have higher levels of sedentary behaviour (Ku et al., 2017). However, Copeland et al. (2017) argue that the relationship between sedentary time and cognitive health should not be oversimplified, as some sedentary activities such as solving a Sudoku or reading a book require higher levels of cognitive functioning.

While the correlation between sedentary time and physical activity as well as cognitive health seems persistent, it is not as clear for mental health: Multiple studies were not able to provide evidence for a correlation between sedentary time and mental health (Copeland et al., 2017; Kikuchi et al., 2014). Whereas the raw duration does not correlate with mental health, it has been shown that passive sedentary activities such as watching TV correlate with lower mental health (Kikuchi et al., 2014; Rosenberg et al., 2015). However, this information on the type of activity is missing in sensor-based data.

Apart from the inference of sedentary behaviour, TOH duration further allows to draw conclusions on an individual's out of home activities. In contrast to activities at home, out of home activities tend to be more challenging, both physically and cognitively. For people with physical impairments such as reduced vision or people who are dependent on a walking aid, moving through space out of home can be challenging due to uneven pavement, steps, or steep slopes (Brusilovskiy et al., 2016). These challenges can serve as a barrier for mobility and thus reduce physical activity (Rasinaho et al., 2007). Several studies have shown a positive correlation between TOH and physical activity (Fukushima et al., 2021; Harada et al., 2019). It is therefore not surprising that there is a relationship between TOH and physical health, as physical activity is closely linked to physical health. This correlation was shown by Petersen et al. (2015), who measured TOH with unobtrusive infrared sensors. They found better physical health to positively affect the TOH duration, while higher pain levels and slower gait speed were associated with less TOH (Petersen et al., 2015). These findings reinforce the hypothesis of a positive correlation between TOH duration and physical health.

As mentioned before, out of home activities tend to be more cognitively challenging compared to activities performed at home. Moving through unknown environments requires navigational skills. For people with reduced cognitive health, disorientation can become a problem (Lin et al., 2015). People experiencing disorientation can suffer from spatial anxiety, which can ultimately lead to a reduced use of the out-of-home space (Davis & Veltkamp, 2020; Phillips et al., 2013; Wettstein et al., 2015). Wettstein, Wahl, & Diehl (2014) found certain aspects of cognitive health, namely episodic memory, to be strongly related to TOH. This influence of episodic memory on the performance of activities of daily living was duplicated by de Paula et al. (2015). In a comparison among cognitively healthy individuals and people with mild cognitive impairment as well as persons with early-stage Alzheimer's disease, TOH was significantly lower for people with early-stage Alzheimer's disease, while there was no significant difference between the other two groups (Wettstein et al., 2015).

Furthermore, physical activity has been found to be beneficial for increased cognitive health (Hillman et al., 2004). Similarly, gait speed seems to correlate with cognitive performance (Holtzer et al., 2006). From these findings it can be expected that TOH is higher with cognitively healthy individuals compared to individuals with lower cognitive health. However, based on the findings by Wettstein et al. (2015), this trend might not be significant.

Apart from physical and cognitive health, mental health seems to influence out-of-home behaviour of older adults as well. Depressive symptoms were found to be a predictor of the ability to travel and use transportation (Bartley & O'Neill, 2010; de Paula et al., 2015). On the other hand, driving cessation, resulting most likely in reduced TOH, is also an important predictor of depressive symptoms (Marottoli et al., 1997). Previously, depressive symptoms were found to be related to physical activity, particularly outdoor physical activity (Herbolsheimer et al., 2018; Strawbridge et al., 2002). Kerr et al. (2012) concretised this correlation by showing that the correlation of depressive symptoms is even stronger with TOH compared to physical activity. Whilst the effect of depression on multiple mobility indicators was found to be negligible, there is a significant negative correlation between depressive symptoms and TOH (Wettstein et al., 2015). Apart from providing opportunities for physical activities, TOH also plays an important role for social interactions. Low levels of TOH were associated with being socially isolated, a predictor for depressive symptoms (Herbolsheimer et al., 2018).

RQ 1a – expected correlation	Physical Health	Mental Health	Cognitive Health
TOH duration	+	+	+

RQ 1b: Health and TOH Variability – Expected Results

While for some people TOH duration is similar each day, others show high variability. Compared to younger adults, life-style regularity appears to increase with older adults (Monk et al., 1997). This regularity is represented by similar wake hours and daily routines that do not vary too much from one day to another which can be measured using the Social Rhythm Metric SRM (Monk et al., 1992, 1997, 2002). As of today, only little research has been done in the field of possible correlation between life-style regularity and health in older adults. Some studies found high SRM-scores to relate to lower psychological distress and low SRM-scores to relate to higher social and emotional dysfunction (van Tienoven et al., 2014). Similarly, Margraf et al. (2016) found greater regularity to be related to better overall health state, life satisfaction, and positive mental health. However, both of those studies focus on the general population rather than older adults in particular.

It seems plausible, that life-style regularity does relate to health indicators. However, it seems reasonable to combine it with TOH duration in order to further distinguish different patterns of TOH.

Inferring life-style regularity from a rather short sample of GPS measurements is difficult, as regularity can occur on a much larger scale than only on a daily basis. For instance, a person can have choir practice every Tuesday evening and otherwise stay at home in the evenings. Their life would be very regular and at the same time show day-to-day variability. It is thus important to see that this indicator is not assessing the overall regularity of the participants' lives but rather whether the participants' days are similar to each other in terms of TOH duration.

One group of people that spends TOH regularly are dog-owners, who – disregarding weather and season – have to go for a walk with their dogs daily (Feng et al., 2014; Lail et al., 2011). Whilst this regular physical activity is beneficial for their physical health, it might also give information on their mental health, as pet ownership has previously been found to positively influence mental well-being of older adults (Raina et al., 1999). However, the influence of pet ownership on both physical and mental health is doubted by studies finding no health benefits for pet owners (Parslow et al., 2005).

RQ 1b – expected correlation	Physical Health	Mental Health	Cognitive Health
TOH variability	-	-	-

RQ 1c: Health and TOH Timing Depending on the Day of the Week – Expected Results

For the majority of the population, TOH timing between different weekdays is given by their working or teaching hours. This usually leads to a significant difference in behaviour between weekend days and days of the workweek (Bhat & Misra, 1999; Kitamura & van der Hoorn, 1987). However, TOH timing is no longer determined by the aforementioned factors after retirement. Nevertheless, according to the current state of research, differences in TOH timing can also be expected among retired people. Several studies found TOH to be lower on weekend days compared to weekdays (Horgas et al., 1998; Shoval et al., 2010, 2011). In other studies, no significant difference in TOH duration was found depending on the day of the week (Copeland & Esliger, 2009; Garatachea et al., 2010; Kaspar et al., 2015). Apart from factors such as weekday-related opening hours of facilities, public transport availability and other culturally defined opportunities, these differences in TOH duration might relate to various individual health indicators.

A study focussing on outdoor physical activity on weekdays and weekend days found the engagement in moderate to vigorous intensity of physical activity to be slightly lower on weekend days (Keskinen et al., 2020). This goes along with previous findings of reduced step counts on weekends compared to weekdays (Tudor-Locke et al., 2002). In contrast, another study on the activity of older people concludes that there is no significant difference in sedentary time between weekends and working days (Marshall et al., 2015). However, both studies agree that individuals with low overall physical activity and a lot of sedentary time show even less activity on weekend days compared to weekdays (Keskinen et al., 2020; Marshall et al., 2015). It can be assumed that physical activity mostly happens during TOH while sedentary time is rather spent at home. Therefore, people who have more TOH on the weekends are expected to more often engage in physical activity and thus be more likely to have better physical health.

The nature of out of home activity differs depending on the day of the week (Kaspar et al., 2015). Out of home activities during the workweek often classify as utilitarian, for instance medical appointments or grocery shopping. Due to restricted business hours, most of these activities are only possible during the workweek. On the other hand, certain discretionary activities are more likely to take place during the weekend. These include attending church on Sunday, engaging in cultural activities as well as visiting family members, who have limited time during the workweek. Dividing the week into five days of utilitarian activities and two days of discretionary activities would of course oversimplify the situation, as both kinds of activities are carried out on all days of the week. Heo et al. (2014) found a difference between weekdays and weekend days regarding discretionary activities: Compared to weekdays, the engagement in passive leisure such as watching television or relaxing increases at weekends, while the engagement in active leisure such as attending cultural events or doing sport remains the same. Older adults with a significant increase in engagement in passive leisure experience lower subjective well-being (Heo et al., 2014). This discrimination between active and passive leisure engagement can be transferred to this thesis' conceptualisation of TOH, as active leisure activities tend to happen out of home, while passive leisure activities are carried out at home. As a consequence, people with less TOH at weekends in comparison to weekdays are expected to have lower well-being. In a further study, Kaspar et al. (2015) found people's daily mood to increase when they spend more TOH during the weekend. Saeb et al. (2016) explored the relationship between time spent at home and depressive symptoms and found stronger positive correlations on weekends compared to weekdays. Even though this study was conducted with younger adults, this might also apply to people of old age. From the current state of research, a positive correlation between TOH at weekends and mental health can be expected.

The study by Kaspar et al. (2015) specifically aims at finding differences in TOH timing depending on cognitive health. They analysed TOH depending on the weekday for cognitively healthy individuals, for people with mild cognitive impairment and for individuals with early-stage Alzheimer's disease. However, for all three groups, TOH did not show a significant weekday-specific pattern. It is therefore unclear whether there is a correlation between TOH timing on a daily scope and cognitive health.

RQ 1c – expected correlation	Physical Health	Mental Health	Cognitive Health
TOH on weekends	+	+	?

RQ 1d: Health and TOH Timing Depending on the Time of the Day – Expected Results

The timing of TOH in terms of time of the day can be interpreted as the active period of a person. The timing of this active period largely depends on a person's chronotype, meaning whether they are a morning-type or an evening-type individual (Roenneberg et al., 2003). It can therefore be assumed that TOH timing is closely related to sleeping habits. In terms of chronotype, the percentage of people who can be classified as morning-type individuals is significantly higher with older adults compared to younger adults (Biss & Hasher, 2012; Fischer et al., 2017). Moreover, gender differences in chronotype common with younger adults are no longer significant with older adults (Castelli et al., 2020). This shift in chronotype might be due to differences in the likelihood of sleep at different circadian phases (Fischer et al., 2017). In several studies, correlations between a person's chronotype and their health were found. Morning-type individuals were found to report higher levels of positive affect compared with persons active in the evening (Biss & Hasher, 2012). People with depressive symptoms are more likely to be evening-types than morning-types (Drennan et al., 1991). Furthermore, evening-type individuals were found to have more unhealthy behaviours, such as smoking, low physical activity or sleep disturbance (Suh et al., 2017). Eventually, this even leads to increased mortality of evening-type individuals (Didikoglu et al., 2019). From this information it can be expected that participants spending TOH in the morning should show better overall health compared to participants who are out of home in the afternoon and evening.

Along with the shift in chronotype in old age, sleep disorders become a more common problem. More than one third of older adults report insomnia symptoms (Jaussent et al., 2011; Ohayon et al., 2001). These problems are seen as a consequence of inactivity, dissatisfaction with social life, the presence of organic diseases or mental disorders, rather than the ageing process per se (Ohayon et al., 2001). Physical activity has been found to be a possible solution for reducing sleep disturbances (Castelli et al., 2020). Sleep disorders can occur in different forms: Some people may have problems falling asleep or maintaining sleep after a disruption, while others suffer from non-restorative sleep, meaning they do not feel rested in the morning and therefore struggle with becoming active in the morning (Ohayon et al., 2001). It can be expected that for the second group of people, TOH probably is not spent in the early morning. However, non-restorative sleep among older people is rather rare (Ohayon et al., 2001). In contrast, there are a lot more people suffering from early morning awakening, meaning they wake up earlier than they intend to and are then unable to resume sleep (Jaussent et al., 2011; Ohayon et al., 2001). For these people, it is rather common to then get up early and thus have more TOH in the early morning. Even though insomnia most certainly plays a role in the TOH timing, it is difficult to predict the interrelation with TOH timing, as insomnia can lead to both high and low morning activity depending on the insomnia type.

Apart from sleep-related factors, the type of activities varies depending on the time of day. A diary-based study found physical activity as well as obligatory activities such as self-care or shopping to be dominant in the morning, whereas mental activities and socialising are predominantly carried out in the afternoon (Baltes et al., 1990). More recent studies based on accelerometery measurements have confirmed that physical activity occurs mainly in the morning (Copeland & Esliger, 2009). Furthermore, the periods of physical activity seem to be longer in the morning compared to in the afternoon and evening, which might be an indicator for out-of-home activities. Therefore, physical health can be expected to show a correlation with TOH timing, namely that the people who are active in the morning tend to be the ones with better physical health.

Shoval et al. (2011) found people with mild cognitive impairment to usually spend their TOH in the morning rather than in the afternoon. Furthermore, they also found the timing to be age-dependent: While older old adults aged 77 – 90 tend to spend TOH in the morning and return home by the early afternoon, younger old adults aged 64 – 75 show greater variability in TOH timing (Shoval et al., 2011). This fits the observation of Baltes et al. (1990) that cognitively more challenging activities such as cultural activities, continuing education as well as socialising tend to occur during the afternoon and evening rather than in the morning. As people with lower cognitive health might struggle more with such activities, they tend not to participate in these and thus spend less TOH in the afternoon and evening.

To sum up people with good physical and mental health are expected to spend more TOH in the morning than people with lower physical and mental health. Concerning cognitive health, people who spend TOH in the afternoon and evening seem to show higher scores.

RQ 1d – expected correlation	Physical Health	Mental Health	Cognitive Health
TOH peak in the morning	+	+	-

RQ 2: Correlation Between Place Diversity (ALs) and Health

RQ 2a: Health and the Number of ALs – Expected Results

The number of places or ALs visited provides a different perspective on older adults' out-of-home behaviour and mobility. The correlation of the number of ALs visited and TOH was found to be highly significant (Wettstein, Wahl, Shoval, et al., 2014). In addition to TOH, the number of ALs visited gives information on where a person spends TOH.

Each AL visited can be seen as a performance of an activity of daily living whether it be grocery shopping or meeting a friend in a café. Therefore, a higher number of ALs visited can be interpreted as an independent life, including both utilitarian and discretionary activities. However, not every AL is an indicator of healthy ageing: appointments at the physiotherapist or doctor might actually imply health problems. Nevertheless, a small number of ALs visited implies that a person probably does not engage in many activities and might even not be able to perform all utilitarian activities independently. In order to perform the out-of-home tasks successfully, high environmental mastery is needed, which is defined as an older individual's feeling of being capable to use environmental resources (Wettstein, Wahl, Shoval, et al., 2014). For people with mild cognitive impairment as well as for people with early-stage dementia of the Alzheimer's type, this environmental mastery shows a significant positive correlation with the number of total ALs visited (Wettstein, Wahl, Shoval, et al., 2014). However, for cognitively healthy people, this correlation was not significant, implying that there might be other factors influencing these people's out-of-home behaviour. In line with this, in a sample of healthy older adults Boissy et al. (2018) found no significant correlation between the number of daily destinations and the Life-Space Assessment score by Baker et al. (2003). This Life-Space Assessment score itself does correlate with physical performance and self-reported function and can thus be seen representative for physical health (Baker et al., 2003). As this thesis is based on a sample of healthy older adults, the correlation between the number of activity locations and physical health is expected to be weak.

Apart from showing whether a person can perform utilitarian tasks by themselves, out-of-home locations play a significant role in terms of social interactions. According to van den Berg et al. (2015), social interactions at somebody's home account for only 35.7 % of the total social interactions. A low number of ALs could therefore imply a deficit in social interactions, which can lead to loneliness and reduced mental well-being (Herbolsheimer et al., 2018). Saeb et al. (2016) found the number of ALs visited to negatively correlate with depressive symptoms. It should be considered that social interactions are not only tied to mobility, but can be influenced by personal preferences as well (van den Berg et al., 2015). Although some people might prefer socialising at home, low numbers of ALs are generally expected to correlate with loneliness and lower mental health.

According to Wettstein et al. (2015), there is significant positive correlation between the number of AL and the episodic memory performance. The significance is even stronger when the activities are ordered by their cognitive demands: Cognitively healthy people tend to engage more in cognitively demanding activities compared to people with cognitive impairment (Wettstein et al., 2015). These activities include conducting business, such as visiting the bank, educational events or caring for others, for instance grandchildren. Unfortunately, it is hardly possible to assess the cognitive demands of a certain AL based on GPS-derived data. Nevertheless, a positive correlation between the number of ALs and cognitive health can be expected.

RQ 2a – expected correlation	Physical Health	Mental Health	Cognitive Health
Number of ALs	+	+	+

RQ 2b: Health and Revisits of ALs – Expected Results

By looking at the frequency of visits to each AL, it is possible to further distinguish between highly routinised out-of-home behaviour and a more diverse and varying lifestyle. It enables to assess place familiarity, which is seen as important for out-of-home behaviour of older adults (Mollenkopf et al., 2004). Some people might visit the same ALs every day, meaning they mostly navigate through familiar environments. Whilst this can result in a respectable total count of ALs visited, it might not represent the ability to move through the environment independently, as a person might be able to navigate through this familiar environment in a routine-like manner (Wettstein, Wahl, & Diehl, 2014). For instance, people with mild cognitive impairment tend not to venture out of their familiar surroundings but are able to move around in environments familiar to them (Shoval et al., 2011). Given the large cognitive demands needed for moving through unfamiliar environments, it can be expected that people with lower cognitive health tend to have a higher proportion of revisited places.

RQ 2b – expected correlation	Physical Health	Mental Health	Cognitive Health
Proportion of revisits	?	?	+

RQ 2c: Health and Time Distribution over ALs – Expected Results

Time distribution over different ALs – or entropy – sheds light on out-of-home behaviour from a different angle. Entropy was found to be higher in younger adults, leading to a smaller predictability of their mobility behaviour (Williams et al., 2012).

Compared to the other mobility indicators used in this study, only little research has been conducted on entropy and health. Saeb et al. (2016) made use of mobile phone location sensor data in order to assess the relationship between mobility and mental health. Low entropy values were found to correspond with depressive symptom severity (Saeb et al., 2016). In a similar approach, people with bipolar disorder displayed lower entropy values compared to healthy individuals (Faurholt-Jepsen et al., 2021). It can thus be expected that people who spend most time at fewer places show lower mental health values compared to people who show high entropy.

Hitherto, only studies on entropy and mental health have been conducted. It is therefore difficult to formulate hypotheses concerning physical and cognitive health, respectively.

RQ 2c – expected correlation	Physical Health	Mental Health	Cognitive Health
entropy	?	-	?

3 Materials & Methods

In Figure 2, the workflow of the analysis is visualised, indicating the section numbers where the corresponding steps are described. Starting with the data collection as part of the MOASIS project (Mobility, Activity and Social Interactions in the Lives of Healthy Older Adults), a subsample was built based on validity criteria. Both mobility and health indicators were calculated for this subsample. Subsequently, these indicators were subjected to a statistical analysis. In the following sections the approach will be explained in detail.

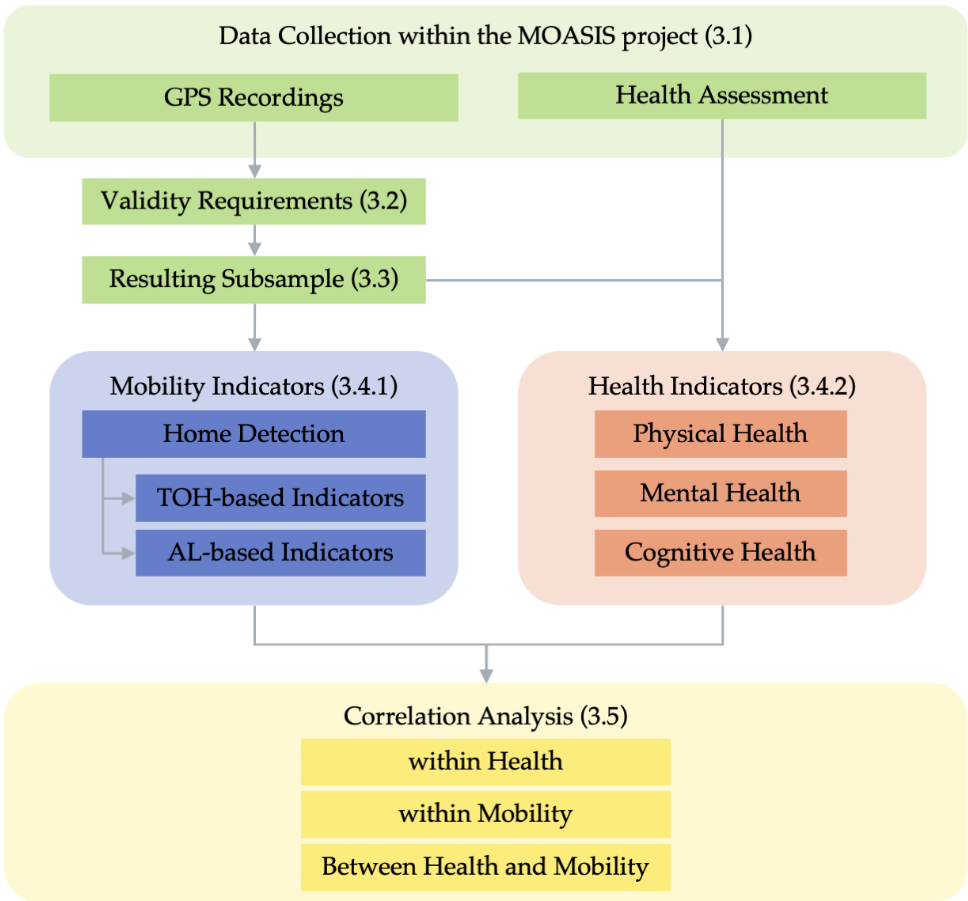

Figure 2: Workflow diagram for this thesis' analysis. The numbers refer to the corresponding sections

3.1 Data Collection

The data used in this thesis stem from the project "Mobility, Activity and Social Interactions in the Lives of Healthy Older Adults" (MOASIS). The MOASIS project is conducted by the University Research Priority Program "Dynamics of Healthy Aging" of the University of Zurich (Röcke et al., n.d.). The main study of the project consisted of a 30-day ambulatory assessment period during which the participants carried a tracking device, collecting positional data, acceleration measurements as well as ambient sound. In addition to the 30-day ambulatory assessment, all participants went through an extensive assessment of their physical health, living circumstances, subjective well-being, self and personality as well as their social relations and their metacognition.

The MOASIS study included 150 participants, of whom a subsample meeting the validity requirements will be analysed in this thesis. The inclusion criteria for this thesis are outlined in Section 3.2 *(Participant Selection)*. Participants included in the MOASIS study lived in Zurich and surrounding areas within Switzerland. In terms of age, participants of the study had to be aged 65 years or older. Even though age not necessarily definies an individual's health and behaviour, and people are not suddenly frail and morbid after retirement, it is still common to set an age threshold as an inclusion criterion. Only community-dwelling individuals were included. Further inclusion criteria for the study involved sufficient eyesight to operate a smartphone, having computer and internet access at home as well as absence of cognitive impairment as tested with cognitive screening.

During the ambulatory assessment period, the participants carried a custom-built tracking device called uTrail. The participants were asked to wear the uTrail device during wake time. They were instructed to clip it to the side of the waistband or pocket of their trousers (Figure 3). The uTrail device includes sensors collecting positional data based on a global navigation satellite system (GNSS, also referred to as GPS), IMU data (accelerometery) as well as ambient sound data. As for GPS data, a CAM-M8 module by u-blox was used which should reach a horizontal position accuracy of 2.5 m (u-blox, 2016). The sampling rate was set to be 1 Hz, i.e. the participants' whereabouts was recorded for every second.

Apart from the coordinates, each GPS fix from the MOASIS study included information on the number of satellites, the altitude, vertical and horizontal dilution of precision (VDOP & HDOP) and Doppler-based speed, as well as an indicator of whether the device is being charged (Röcke et al., n.d.).

The ambulatory assessment period took place in 2018, with the first measurements in April and the last measurements in November. The ambulatory assessment periods were thus not simultaneous for all participants.

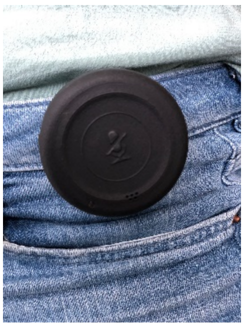

Figure 3: uTrail device used in the MOASIS study (Röcke et al., n.d.)

3.2 Participant Selection for the Subsample

Even though the data collection period was 30 days for all MOASIS participants, both quality and quantity of the GPS data vary significantly between participants due to measurement failures. In order to have a sound basis for the analysis, a subsample of participants fulfilling minimum criteria was selected fulfilling minimum criteria as described below.

First, all entries without valid GPS measurements were discarded. These entries might have occured due to signal loss, device failure or during charging. In order to delete noise points, measurements with a high recorded speed were deleted. The threshold value was set at 250 km/h, which corresponds to the maximum speed on the Swiss railway network (Tröndle, 2015).

The main criterion for the inclusion of a participant in this analysis is the number of valid days, i.e. days with a significant amount of data., which made it necessary to define the unit of a valid day.

A common approach for defining a valid day is to define a minimum wear time. Assuming the participants do not turn off their uTrail device during the day, the timespan between the first and the last measurement each day can be used as a proxy for wear time. In most human mobility studies, the minimum wear time is set between 8 and 10 hours (Boissy et al., 2018; Demant Klinker et al., 2015; Fillekes, Giannouli, et al., 2019; Fillekes, Kim, et al., 2019; Kerr et al., 2012; Loebach & Gilliland, 2016; Van Kann et al., 2016; Vanwolleghem et al., 2016). In other studies, a day is only labelled as valid when there is no consecutive period longer than 30 minutes during which there is no valid GPS data (Shoval et al., 2010). Fillekes, Giannouli, et al. (2019) compared several input thresholds and found the resulting factors to be fairly stable. They therefore argue for a less strict threshold. Thus, in order not to discard too much data, the minimum wear time for a valid day was set to be 8 hours.

Given the definition of a valid day, the minimum number of valid days needs to be defined. As with the minimum wear time, this decision is a trade-off between including as many participants as possible and only including participants with high data quality.

The number of days necessary to capture the participants' mobility strongly depends on their behaviour. Consequently, the minimum number of days with valid GPS data may vary depending on the sociodemographic characteristics of a sample as well as the desired mobility indicators. There is currently no standard for the minimum days in GPS-based mobility studies. Some studies accept a small number, such as 3 or 4 days (Fillekes, Giannouli, et al., 2019; Hirsch et al., 2014; Loebach & Gilliland, 2016; Vanwolleghem et al., 2016). It is to be noted that for most of these studies the total data collection period is much shorter compared to the 30 days of the MOASIS study. However, it seems unrealistic to grasp a person's mobility during such a short time period.

Holliday et al. (2017) recommend a threshold of 12 days for GPS based studies on physical activity. Other studies on detecting people's activity spaces indicate that the additional information about human mobility increases only marginally after 14 study days (Stanley et al., 2018; Zenk et al., 2018). Recent studies even go so far as to recommend a minimum duration of 15 weeks to obtain a stable data basis for human mobility studies (Dong et al., 2020). A comparison of various demographic groups also shows that mobility patterns are more regular for older people compared to younger study participants and therefore the study duration can be shortened to 10 weeks in studies on older adults (Dong et al., 2020). In the case of the MOASIS study, the data collection was already compleded and therefore such a high minimum number of days was unrealistic. Additionally, an evaluation of different inclusion criteria showed that strict thresholds such as 14 valid days lead to a significant loss of participants (see Table 1). This loss can be explained by the malfunctioning of the uTrail devices. Therefore, the minimum number of valid days for a participant to be included in this sample was set at seven days, intuitively representing one week.

Table 1: Number of valid participants depending on input variables of hours for a valid day as well as number of valid days for a valid participant, not including minimum weekend days (= chosen combination of variables)*

		number of hours for a valid day (timespan between first and last measurement)					
		6	7	8	9	10	11
minimum number of valid days for a valid participant	0	152	152	152	152	152	152
	1	139	139	138	134	132	128
	2	133	132	129	127	121	118
	3	128	127	122	122	116	109
	4	122	122	120	114	108	99
	5	121	119	115	108	99	93
	6	118	112	107	102	93	90
	7	111	106	**101***	95	91	85
	8	103	99	95	91	89	81
	9	98	94	91	85	84	74
	10	96	93	88	84	80	67
	11	92	88	83	80	73	59
	12	88	82	79	73	66	53
	13	81	75	73	67	59	48
	14	76	74	69	63	52	42
	15	73	72	63	60	43	37
	16	67	61	56	54	39	32
	17	59	54	51	44	37	27
	18	53	48	47	39	34	27
	19	48	44	41	32	26	24
	20	45	39	35	28	24	17
	21	37	32	28	22	20	14

In addition to the criterion of the mere number of valid days, it is also relevant for which days measurements are available. In order to investigate possible differences between weekends and weekdays, all participants should have a minimum number of valid days for both parts of the week. The minimum threshold was chosen as 2 weekend days (Saturday / Sunday) and 5 weekdays (Monday–Friday), so that for each participant there is data representing at least a full week. Including such a minimum number of weekend days is common for mobility studies (Boissy et al., 2018; Fillekes, Giannouli, et al., 2019).

As shown in Table 1, 101 participants fulfil the minimum criteria of 7 days with a minimum wear time of 8 hours. Out of these participants, six participants do not fulfil the criteria of having at least 2 weekend days and 5 weekdays. Additionally, two participants had to be discarded due to incomplete health data.

3.3 Resulting Sample

The resulting sample consists of 93 community-dwelling older adults aged 65 to 88 years (Mdn = 72.6). Of those participants, 43 (46.2 %) were female and 50 (53.8 %) were male. In terms of age, a Mann-Whitney U test indicated that the difference between men (Mdn = 72.6) and women (Mdn = 71.6) is not significant, $U = 921$, $p = .237$. 54 (58.1 %) participants indicated to be in a relationship during the time of the study while the remaining 39 (41.9 %) were single. 36 (38.7 %) participants lived on their own whereas 57 (61.3 %) participants shared their home with someone else.

All of these participants have between 7 and 30 days of valid GPS data, with a minimum wear time of 8 hours. The average number of valid study days is 18, the average recorded time is 9.7 hours per day. On average, 543,610 valid GPS measurements are available for each participant. The distribution of the number of valid days is shown in Figure 4. It should be noted that the majority of participants have more than double the minimum number of valid days, which should increase the significance of the results.

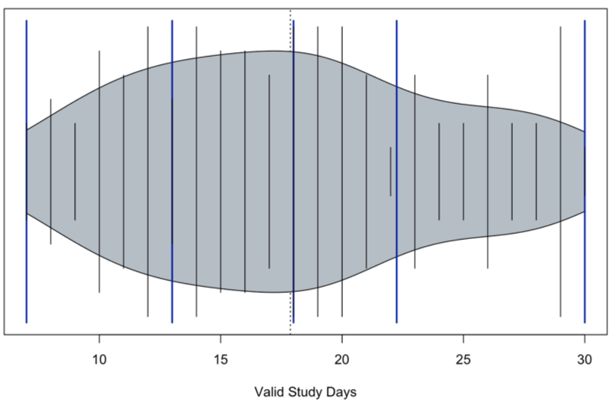

Figure 4: Beanplot of the number of valid study days (blue lines indicate quartiles, dashed line indicates the mean)

3.4 Calculation of the Mobility and Health Indicators

3.4.1 Deriving Mobility Indicators from GPS-Trajectories

Detection of the Place of Residence

In order to analyse the participants' out of home behaviour, the place of residence for each participant had to be defined as, for privacy reasons, the address information is stored separately from the study data and could therefore not be directly used.

As the participants were instructed to plug in the device overnight in order to fully charge it – which automatically turns off the GPS sensor on the uTrail device – it is to be assumed that for each day, the first and the last GPS-measurements are from the location where the person spent their night (Fillekes, Röcke, et al., 2019). Interpreting the place where a person spends most of the nights as their home, these first and last measurements can be used to derive a home location for each participant.

When a GPS-device is activated after being turned off for a few hours, it might take a while for it to generate reliable information. While being stationary, this so-called cold start might take up to one minute (de Jong & Mensonides, 2003). In order to reduce possible errors coming from such a cold start, the first minute of measurements was discarded.

Consequently, the last 5 minutes of GPS fixes as well as the GPS fixes from minute 2 to 6 were extracted for each day. On these points, DBSCAN spatial clustering (Hahsler et al., 2019) with minimum number of points = 250 and an epsilon distance of 60 m was applied to extract clusters of possible home locations. For each of the resulting clusters, the number of unique dates found within this cluster was counted. The cluster with the highest number of unique dates was subsequently labelled as home. In some cases, where no unambiguous cluster was detected on the basis of this criterion, the cluster with the highest number of GPS fixes in the first and last five minutes of each day was labelled as home.

Ambiguous Home Locations

Detecting the home location is complicated by the fact that some people own a second home and spend a lot of time there. This occurrence of second homes requires revisiting the definition of home. Many studies on housing ignore this fact by assuming there is such a thing as "*the* home" – defined as a single place (Paris, 2009).

Even though in Switzerland second homes are not as popular as in other regions such as Scandinavia (Hiltunen, 2004), on average 8.5 % of the Swiss households own a second home (Bundesamt für Raumentwicklung, 2009). Numerous participants spent time in Swiss cantons of Grisons, Valais or Ticino – all known for their large number of second homes, mainly used for leisure purposes (Bundesamt für Raumentwicklung, 2009). Second home ownership seems to increase significantly with increasing age (Bieger et al., 2005). Long-term studies have shown that second homes are used more frequently after retirement with some of them even being converted into the primary home (D. K. Müller & Marjavaara, 2012). This increase in time spent at the second home blurs the difference between primary and second home (Paris, 2009). Whilst the number of old-aged people with a registered second home is rather low compared to other age groups (Rieker, 2014), this mainly stems from the fact that people who stay in their second home for less than three months are not subject to any official registration obligation and thus are not included in the statistics. Most old-aged people with an official secondary address are residents of care institutions or retirement homes (Rieker, 2014).

Second homes used for leisure purposes are not the only reason for people to not spend their nights at one place only. Other locations include hotel stays, visits to friends, or partners living separately. In recent times, such living apart together (LAT) relationships have become a more common way of living for old-aged people (Connidis et al., 2017; Strohm et al., 2009). In contrast to other age groups, old-aged couples mostly have LAT relationships by choice rather than by constraint; usually without any intention of moving in together despite an often long duration of their relationship (Régnier-Loilier et al., 2009; Strohm et al., 2009). Typically, people in LAT relationships previously experienced divorce or widowhood (de Jong Gierveld, 2004). Despite not sharing their residence, most LAT old-aged couples still visit each other frequently and also spend the night together on a regular basis (Karlsson & Borell, 2002).

As the home detection algorithm is based on the place where participants spend their nights, behaviour like staying at a secondary home location such as a holiday home or the LAT partner's home needs to be considered. Whilst a small number of nights spent out of home is completely normal and does not significantly affect the detection of the home location, an increasing percentage of nights spent out of home leads to an increased uncertainty of the home detection. Especially for analyses relying on TOH, this is critical, as all the time spent in a second home is treated as TOH, even though the participant might feel at home there as well. Therefore, the number of "days out of home" was counted for each participant, days out of home being defined as days on which the participant did not show a single measurement labelled "at home". For the participants whose number of days out of home was at least one third of their total valid days, the home detection algorithm was adapted. Thus, after performing the DBSCAN clustering, not only the cluster with the highest number of unique dates was labelled home but also the cluster with the second highest number of unique dates.

Accuracy of the Home Detection Algorithm

Complying with the MOASIS privacy policy, the coordinates of resulting home locations were compared to the addresses by a third person who was not able to access any study data. Likewise, the author had no access to the address data. In order to compare the home locations, the addresses were converted to coordinates, using a geocoding API provided by the Swiss Federal Office of Topography (swisstopo, 2019). The comparison showed that the algorithm for retrieving the home locations was accurate: The average distance between the computed home-location and the location derived from the addresses was around 9 metres. No participants were excluded on the basis of a large discrepancy between the computed home location and the indicated address. As shown in Figure 5 of the spatial distribution of the calculated home locations, the majority of the participants live in the canton of Zurich.

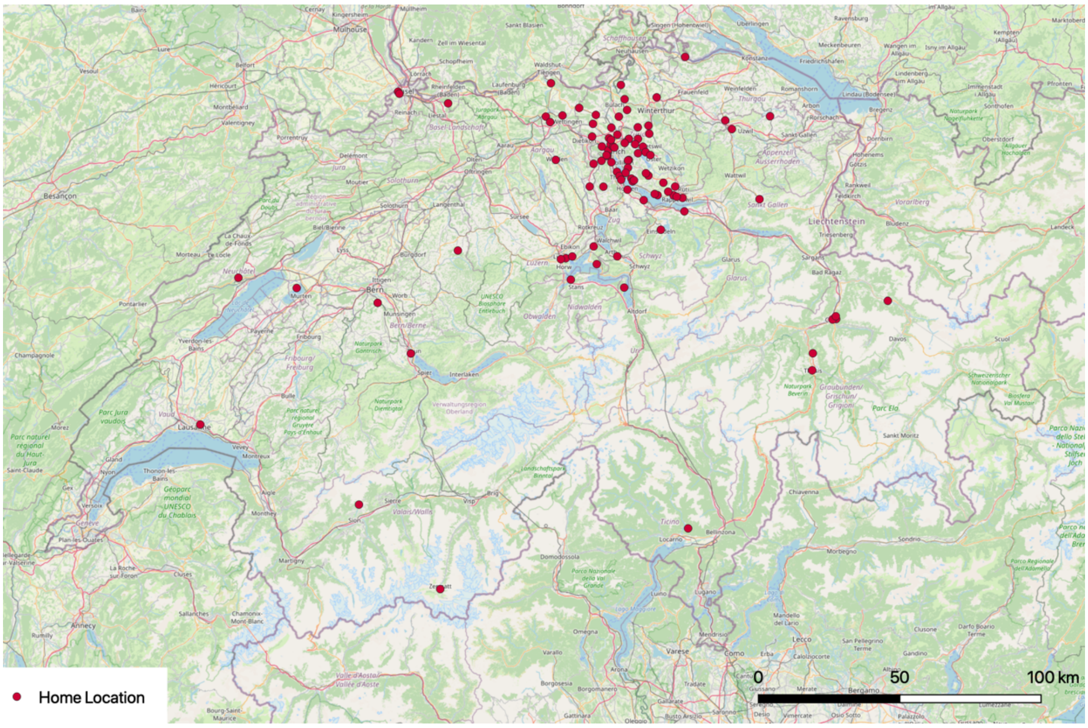

Figure 5: Spatial distribution of the participants' home locations (map data from OpenStreetMap)

TOH Calculation

Given the home locations, the analysis of TOH-related mobility indicators was possible. Following Fillekes, Giannouli, et al. (2019), a buffer of 150 m around the home location was drawn. GPS fixes outside this buffer were labelled as out of home (OH). Consequently, time spent in the garden or to some extent in the immediate neighbourhood is not counted towards TOH, even though they are technically out of home. However, a rather generous buffer helps to include all measurements with poor precision (Loebach & Gilliland, 2016). Using this buffer, all GPS fixes were classified as OH or at home (AH). In line with the approach of Fillekes, Giannouli, et al. (2019), data gaps up to 60 minutes were interpolated if both the preceding and subsequent fix were OH or AH respectively. Based on this classification, TOH was analysed on three different levels:

1. Overall
2. Depending on the day of the week
    a. on a daily level
    b. on an aggregated level: weekdays (Monday–Friday) and weekend-days (Saturday & Sunday)
3. Depending on the time of the day (on an hourly level)

For each of these three levels, statistical indicators such as mean, median and standard deviation were calculated. TOH was calculated both as absolute duration as well as the percentage of the total GPS fixes labelled as *out of home*. Days with less than 2 minutes of TOH were labelled as *fully at home*. For each participant, the percentage of days spent fully at home was calculated.

In order to analyse differences between the weekdays and weekend-days, weekday prevalence was calculated using the following formula:

$$Weekday\ Prevalence = \frac{median\ TOH_{weekday}}{median\ TOH_{weekday} + median\ TOH_{weekend}}$$

This calculation results in an indicator ranging from 0 to 1 with 0.5 representing equal distribution between weekdays and weekend-days, while values above 0.5 represent more TOH on weekdays compared to weekend-days.

Furthermore, the hour of the day with the highest TOH duration was derived for each participant. Thus, absolute TOH was used instead of relative calculations, as this would have led to biases where there was little data (e.g., late in the evening). Following the framework of mobility indicators of Fillekes, Giannouli, et al. (2019), this represents the indicator *"TimePeriodActive: Period of day with most OH activities"*, even though a higher temporal resolution was chosen. Instead of only classifying the day into morning, afternoon and evening, a temporal resolution of 1 hour was chosen. For a certain individual TimePeriodActive with the value 11 therefore means that this person had the most out-of-home measurements established in the time between 11:00 and 11:59, giving the information that this person is most likely to be out-of-home during this time of the day on a normal day. Additionally, TimePeriodActive was calculated for both weekdays and weekend-days.

Place Diversity

Detection of Activity Locations

For detecting the activity locations (ALs), only GPS fixes with valid coordinates were used. There are multiple stop-move detection algorithms that were previously evaluated on the MOASIS data (Ebert, 2020). According to this evaluation, the time-based clustering approach developed by Montoliu, Blom and Gatica-Perez (2013) – subsequently MBGP algorithm – yields the best results as there is a low number of input parameters, which nevertheless are intuitive and include both temporal and spatial aspects. In addition, the algorithm can handle gaps in the GPS data (Ebert, 2020; Toader et al., 2017).

The MBGP algorithm is a time-based clustering approach using on three input parameters (Fillekes, Kim, et al., 2019; Montoliu et al., 2013): Firstly, a maximum distance of two GPS fixes is defined (D_{max}) in order for those two points to belong to the same stop. Then, a minimum duration (T_{min}) of a group of GPS fixes is defined in order to count as a stop. This input has to be chosen carefully in order to include all significant stops while at the same time not including short activities such as waiting at a red light. The third parameter T_{max} represents the maximum allowed time gap between two consecutive GPS fixes points to be considered as one stop. A schematic representation of the activity location detection using the MBGP algorithm can be seen in Figure 6: The Stops I – IV are detected, because enough points are clustered for $\geq T_{min}$ within $\leq D_{max}$ and the temporal gaps are $\leq T_{max}$. Cluster A is dismissed, as the duration is less than T_{min}. Stop II consists of two separate Clusters B and C, as the temporal gap between those clusters is less than T_{max}. Stop III is classified as a distinctive stop, as the temporal gap to Stop II is longer than T_{max}.

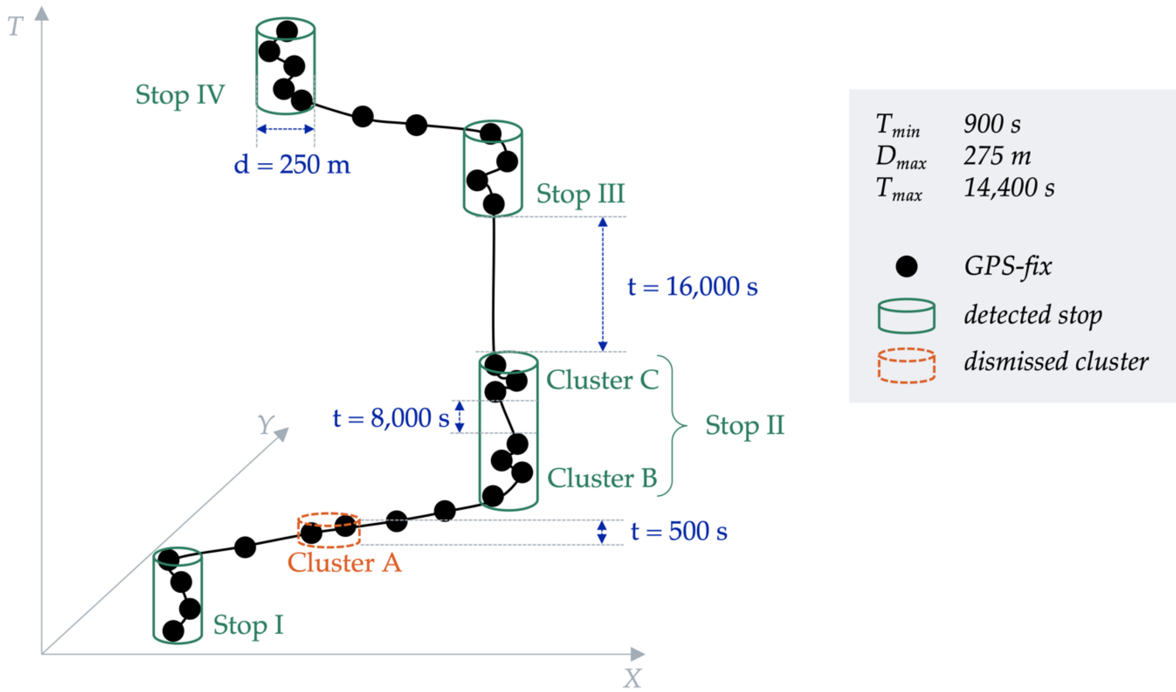

Figure 6: Schematic representation of the MBGP algorithm, modified from Fillekes, Kim, et al. (2019)

In the work by Ebert (2020), the most suitable input parameters for applying the MBGP algorithm on the MOASIS data were evaluated. Ebert (2020), found the following parameter set to yield the most promising results: D_{max} = 275 m, and T_{min} = 900 s, and T_{max} = 14,400 s.

Consequently, these proposed parameters are used in this analysis. In order to save processing time, the MBGP algorithm is applied on pre-processed data. This data only includes valid measurements out of home, as all the measurements taken at home are not relevant for activity locations.

The resulting stops were then post-processed, following the approach of Fillekes, Kim, et al. (2019): Short periods (< 3 min) initially labelled as *move* were handled as noise and thus removed. Consecutive stops which previously were separated by such short move-periods were merged if both spatial distance as well as temporal difference between those two stops were smaller than D_{max} and T_{max}, respectively. As the parameters by Ebert (2020) are only optimised for a raw use of the MBGP algorithm without post-processing, the values for D_{max} and T_{max} were taken from Fillekes, Kim, et al. (2019) and set to 3,600 s and 150 m, respectively. As with the MBGP algorithm, the median coordinates were used in case two or more stops were merged. This resulted in a shortened list of activity locations, still including attributes of date and time of the visit. However, for the majority of the participants, this list includes locations that were visited multiple times during the recorded time period. In order to derive information on unique and repeated visits, the activity locations represented by multiple entries in the list had to be found.

In order to achieve this, several common clustering algorithms such as DBSCAN or OPTICS were taken into consideration. Whilst DBSCAN gives good overall results, the algorithm struggles differentiating clusters with varying densities (Kanagala & Jaya Rama Krishnaiah, 2016). The OPTICS algorithm was designed to overcome this problem (Ankerst et al., 1999; Kanagala & Jaya Rama Krishnaiah, 2016). However, the results in this specific case were not convincing, which might be due to the fact that the overall number of activity locations is rather low, and the density is sparse. As an alternative to the density-based clustering approaches, an approach based on a nearest-neighbour graph was chosen. The activity locations are transformed into nodes of a graph, where each node is connected to its two nearest neighbours. The maximum length of these edges can then be defined as the distance up to which two points are considered to represent the same activity location. Unlike other clustering methods like DBSCAN or OPTICS, this approach is purely distance-based and is therefore intuitive. One disadvantage of this clustering approach is that the shape of a cluster is not taken into consideration. It would be possible to classify a whole street of shops as one location. However, neither DBSCAN nor OPTICS could prevent this problem too.

Using the R package *spatgraph*, a nearest neighbour graph of all activity locations was constructed (Rajala, 2010). However, edges that were longer than a defined threshold were discarded. Defining the threshold was challenging: The threshold should be large enough to encompass all points representing a particular activity location while at the same time it should not to be too large, as then multiple activity locations would be merged into one. After evaluating different distances, the threshold was set at 50 m. Whilst this threshold yields reasonable results overall, there are specific problems with activity locations covering wider areas. For instance, visiting a golf course results in numerous activity locations according to the MBGP algorithm. However, due to the large distances between the individual tracks, these points are not merged into a single activity location when applying a threshold of 50 m to the nearest-neighbour graph.

Finally, all components of the graph (i.e. inter-connected nodes as well as single nodes) were labelled as clusters and received a unique cluster ID. These cluster ID's made it possible to determine whether an activity location was visited uniquely or repeatedly during the recorded time period.

The detection of ALs is shown in Figure 7 where stops are first extracted from the raw GPS fixes by applying the MBGP algorithm. From these stops, ALs are inferred by clustering the stops. ALs can consist of only one stop (e.g., AL 2) or include multiple stops, not regarding the time and date of the individual stops (e.g., AL 1).

Figure 7: Example of the different steps in AL detection from raw GPS-fixes to Activity Locations (map data from Open-StreetMap)

Analysis of Activity Locations

Raw counts of activity locations as well as the number of places visited uniquely or multiple times strongly depends on the number of study days included. For instance, the probability that a particular place is visited more than once increases with each additional day of study. As the number of valid study days varies significantly between the participants (from 7 to 30 valid days), raw counts are not comparable. In order to ensure inter-individual comparability, the activity location counts were normalised for a week, the minimum number of valid days. This was achieved by using Monte Carlo Simulation, which is a computational algorithm relying on repeated random sampling (Raychaudhuri, 2008). Using this approach, the resulting indicators represent the case as if all participants had only seven valid study days. A sub-sample of seven days was drawn out of each participant's valid study days without replacement. For this sub-sample, the total number of activity locations as well as the number of uniquely and repeatedly visited activity locations was counted. Additionally, the total number of visits to activity locations and the total time spent at activity locations were calculated. Furthermore, entropy and normalised entropy were calculated, following the approach by Saeb et al. (2016), which is based on communication theory (Shannon, 1948):

$$Entropy = -\sum_{i=1}^{N} p_i * ln(p_i)$$

$$Normalised\ Entropy = \frac{Entropy}{ln(N)}$$

In the formula, N represents the total number of ALs, while p_i represents the percentage of time spent at AL i. Entropy values are either zero or positive. Normalised entropy is invariant to the number of ALs and ranges from 0–1.

Following the principle of the Monte Carlo Simulation, this procedure was repeated 2,000 times. From these 2,000 iterations, the median of each indicator was calculated. The number of iterations was empirically chosen; the median values of the indicators no longer change significantly with increasing iterations. An overview of the activity location-related mobility indicators is given in Table 2.

Table 2: Overview of AL-related Mobility Indicators

Indicator	**Description**
total stops	Count of all stops at ALs
total ALs	Count of all individual ALs
uniquely visited ALs	Number of ALs with only one visit (= number of visits at uniquely visited ALs)
revisits [%]	$\frac{\textit{total stops} - \textit{uniquely visited ALs}}{\textit{total stops}}$
revisited ALs [%]	$\frac{\textit{total ALs} - \textit{uniquely visited ALs}}{\textit{total ALs}}$
total time spent at ALs	Time spent at activity locations
entropy	Entropy (Saeb et al., 2016)
normalised entropy	Entropy normalised by the number of location clusters (Saeb et al., 2016)

3.4.2 Health Indicators

All indicators for physical and mental health are based on questionnaires of the MOASIS Main Study and are thus self-assessed (Röcke et al., n.d.). The indicators for cognitive health are based on lab-based tests. The SF-12 health survey was used to measure physical and mental health. The SF-12 survey is a shortened version of the SF-36 survey, which was developed to asses a person's health using 36 different patient-based measures (Ware & Sherbourne, 1992). The SF-12 survey uses only 12 of these items, whilst still providing adequate information on a person's health status (Gandek et al., 1998; Jenkinson et al., 1997). The SF-12 health survey includes questions on a person's own impression of their general health, their health-related limitations performing certain activities such as pushing a vacuum cleaner or climbing stairs, as well as general problems in daily activities as a result of their physical health (Ware et al., 1996). Further, the participants are asked questions about restrictions in their daily activities due to emotional problems, their perception of pain and how often they felt in certain way during the past four weeks, e.g. *full of energy*, *downhearted*, or *peaceful* (Ware et al., 1996).

Physical Health

Based on the SF-12 health survey, the Physical Component Summary (PCS) can be calculated by creating indicator values and weighing them according to the SF-12 scheme (Ware et al., 1995). The PCS is based on the following scales: Physical Functioning, Role-Physical, Bodily Pain as well as General Health (Ware et al., 1995). In order to differentiate between SF-36 and SF-12 scores, the score resulting from the SF-12 survey is referred to as PCS-12 (Jenkinson et al., 1997). Low PCS-12 scores indicate lower physical health.

Mental Health

As with physical health, a Mental Component Summary can be calculated from the SF-12 survey, which will be referred to as MCS-12. The MCS-12 is based on the following parameters: Vitality, Social Functioning, Role-Emotional as well as general Mental Health (Ware et al., 1995). It is seen as a valid measure of mental health and is a useful screening tool for depression and anxiety disorders (Gill et al., 2007). For older adults, the optimal cut-off score for depression was found to lie at 50.2 (Yu et al., 2015). Other studies suggest a cut-off score of 45 to identify depression and a score of 50 to identify any common mental disorder (Gill et al., 2007).

In addition to the MCS-12 score, the "Allgemeine Depressionsskala" (ADS) (translates as "General Depression Scale") was used, a German adaptation of the Center for Epidemiological Studies Depression Scale (Meyer & Hautzinger, 2001). ADS is commonly used for screening large samples for depressive symptoms (Stein et al., 2014). Like the SF-12 survey, ADS is based on self-assessment. The participants answer 20 questions, including emotional, motivational, cognitive, somatic and interactional factors (Borovac, 2017). From these questions, the ADS score is calculated ranging from 0 to 60. In contrast to the MCS-12 score, a low ADS score indicates mild or no depressive symptoms and thus better mental health. A common threshold for determining depression with the ADS is a score of 22 or 23 (Borovac, 2017; Hautzinger et al., 2012; Stein et al., 2014). Other studies found a score of 18 to be the optimal threshold (Lehr et al., 2008).

Cognitive Health

The indicators for cognitive health – episodic memory and spatial memory – were assessed during lab sessions at the University of Zurich. As with physical and mental health, this process was part of the baseline assessment.

Episodic memory

In order to assess the episodic memory, the German version of the Rey Auditory Verbal Learning Test (RAVLT) was used. This version is called “Verbaler Lern- und Merkfähigkeitstest” (VLMT) (translates as "Verbal Learning and Memory Test") and was developed to assess and differentiate verbal memory performance (Helmstaedter & Durwen, 1990).

The VLMT consists of five phases (Ptok et al., 2005):

1. A list of 15 words (List A) is read to the participants five times. After each reading, they are tested to see how many of the words they were able to remember.
2. This is followed by a one-time session with an interference list (List B), the procedure being identical to Phase 1.
3. Immediately afterwards, the participants are asked to recall the words from List A, without the list being read out again.
4. After a delay of half an hour, the participants are once again asked to recall the words on List A, without the list being read out again.
5. Finally, the participants are presented with a list of words from which they should select all the words that were on the original list (List A). This list contains all the words from both List A and List B, as well as phonologically and semantically similar words. In this phase, both correct and wrong answers are counted.

Similar tests based on noun lists were used in other studies to assess cognitive health (Langa et al., 2009). A particular advantage of the VLMT is that different performances of episodic memory can be recorded and evaluated (Volz-Sidiropoulou et al., 2010). The results of Phases 1 and 2 are an indicator for the participant’s learning performance and the data acquisition in short-term memory; the results of Phases 3 and 4 (loss after interference and over time, respectively) represent the consolidation in long-term memory (Ptok et al., 2005). Finally, the results of Phase 5 indicate a participant’s recognition performance. Thanks to these various indicators, a differentiated approach to episodic memory is possible. In this thesis, the indicators shown in Table 3 will be used.

Table 3: Indicators of episodic memory derived from VLMT

Indicator	Description
VLMT Learning	The number of words from all five learning rounds (Phase 1)
VLMT Consolidation	The difference between the number of correct words of the last learning round (Phase 1) and the number of correct words of the delayed recall (Phase 4), divided by the number of correct words after the last learning. By using the percentage of words remembered after 30 minutes instead of the total number of words, a potential bias towards participants with large numbers of words in Phase 1 can be prevented.
VLMT Recognition	The number of correctly recognised words from Phase 5 minus the errors from the recognition-list.

The results of the VLMT were found to reflect the subjectively perceived memory impairment of older people in everyday situations (Volz-Sidiropoulou et al., 2010). Further, VLMT-scores correlate significantly with speech comprehension, implying that participants with high VLMT-scores have less problems with speech understanding (Meister et al., 2011, 2013). The VLMT-derived indicators therefore seem to represent possible constraints in older adults' lives due to reduced cognitive health.

Spatial memory

During the lab-based tests of cognitive abilities, spatial memory was assessed through a computerized object-location task similar to the card game "Concentration", also known as "Memory" or "Pairs", based on an approach developed by Rasch et al. (2007). In this test, the participants are required to visually learn the locations of 15 card pairs on a computer screen in a limited time. Upon presentation of a certain picture, they are then prompted to indicate the location of the matching card. The number of correctly matched pairs is counted. This procedure is repeated three times in total. Subsequently, an accuracy score between zero and one is calculated from the number of matched pairs (Rasch et al., 2007). In this thesis, the mean score of the three rounds is used. to calculate the indicator for spatial memory.

In research on spatial memory, tests based on the card game "Concentration" are commonly used (McBurney et al., 1997; Schumann-Hengsteler, 1996; Washburn et al., 2007; Washburn & Gulledge, 2002). However, it is unclear to what extent such small-scale visuospatial memory tests are representative of large-scale environmental tasks such as wayfinding in an urban environment (Mitolo et al., 2015). Comparisons of self-assessed sense of direction as well as spatial anxiety with scores in an object-location task suggest a correlation between the two (Mitolo et al., 2015).

3.5 Correlation Analysis

With all health indicators selected and the mobility indicators calculated, the data was searched for correlations. Spearman's rank correlation was used because normal distribution could not be assumed for most of the health and mobility indicators.

In order to prevent possible biases coming from skewed samples, stratified subsampling was applied. For this end, the sample was divided into three groups based on equal intervals. These three groups were expected to represent low, medium and high scores respectively. A subsample was then built consisting of the same number of participants from each group. The size of the subsample was determined by the number of participants in the smallest group. Following the principle of Monte Carlo Simulation, correlations were calculated for this subsample multiple times. However, stratified subsampling did not lead to a more reliable result. It did not increase the number of significant correlations but rather added to the uncertainty of the results, as some of the samples were rather small. Therefore, the results of the correlation analysis that included the *whole* sample are presented and discussed in the following sections.

Furthermore, as part of the correlation analysis, the participants were grouped by sociodemographic indicators (e.g., gender or relationship status) as well as by mobility indicators. These groups were then be compared using Mann-Whitney U test or Kruskal–Wallis H test, depending on the number of groups.

4 Results

The resulting health and mobility indicators as well as the outcomes of the correlation analysis are presented in this section. The comparison of the results with previous findings along with a critical evaluation can be found in Section 5 (*Discussion*).

4.1 Health Indicators

The distribution of the resulting health indicators is shown in the following figures and tables. The blue lines in the beanplots indicate the quartiles, the dashed line represents the mean value.

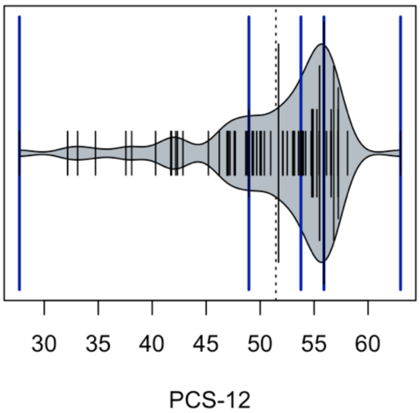

Figure 8: Beanplot of the Physical Health Scores

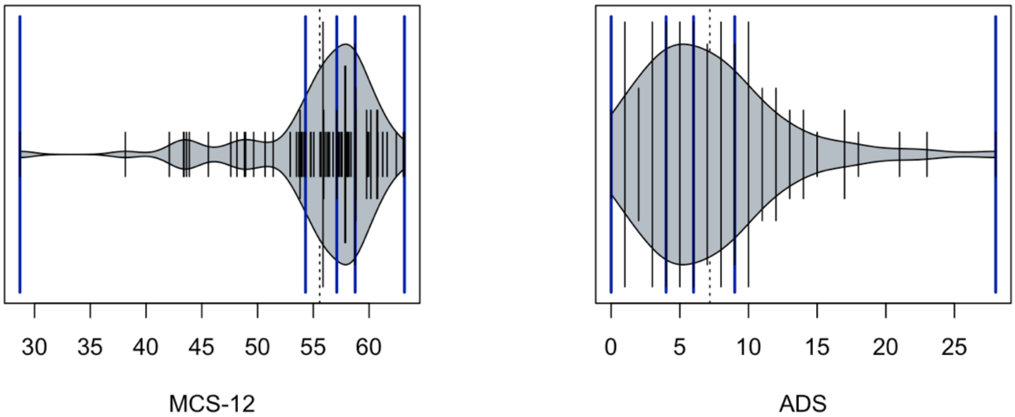

Figure 9: Beanplots of the Mental Health Scores

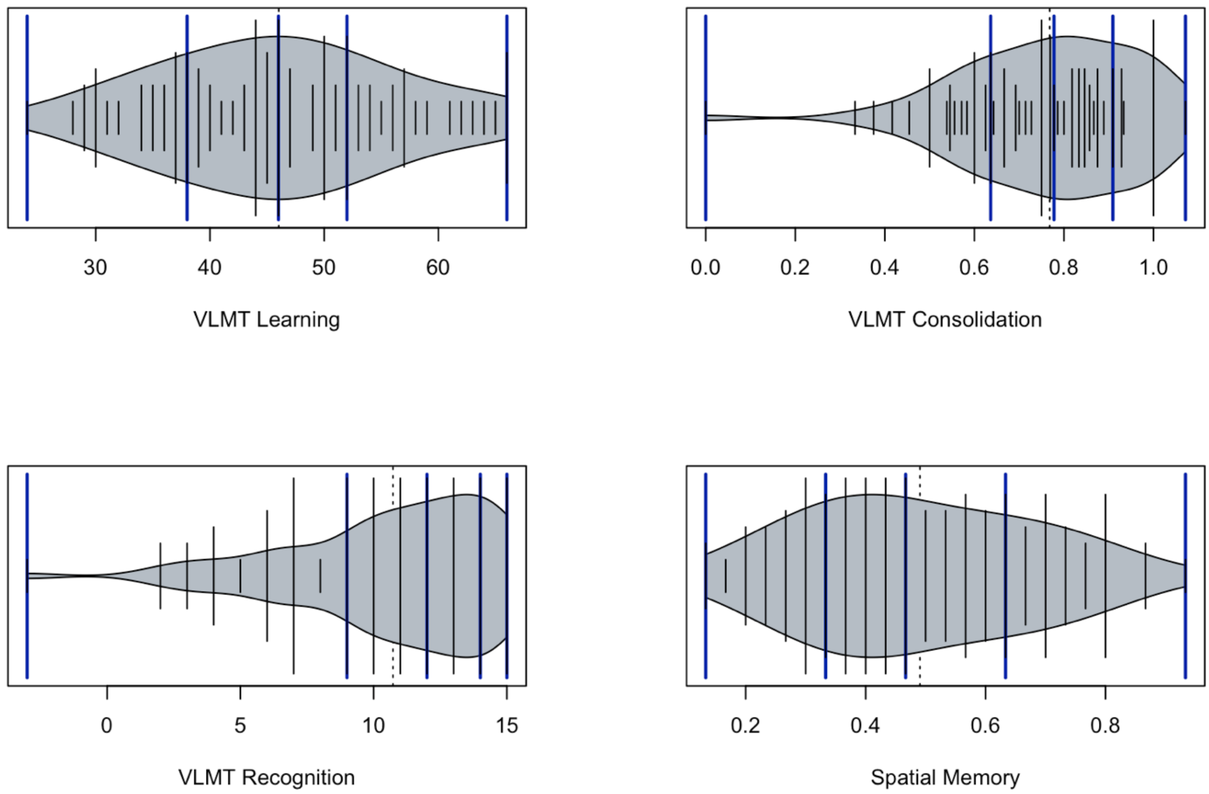

Figure 10: Beanplots of Cognitive Health Scores

Table 4: Descriptive statistics of the selected health indicators (p: physical, m: mental, c: cognitive)

Indicator		mean	sd	median	minimum	maximum
p	PCS-12	51.46	6.42	53.78	27.70	63.01
m	MCS-12	55.57	5.63	57.10	28.69	63.17
m	ADS	7.18	5.08	6.00	0.00	28.00
c	VLMT Learning	46.10	10.06	46	24	66
c	VLMT Consolidation	0.77	0.19	0.78	0.00	1.07
c	VLMT Recognition	10.75	3.74	12	-3	15
c	Spatial Memory	0.49	0.19	0.47	0.13	0.93

As shown in Figure 8 and Figure 9, the sample is highly skewed towards healthy individuals for both physical and mental health, as can be expected from the inclusion criteria and the demanding study design. With regards to cognitive health (Figure 10), a broader distribution can be found for learning performance and spatial memory. However, for long-term memory consolidation as well as recognition performance the sample is again skewed towards better scores.

A Shapiro-Wilk test implies that from all health indicators, normal distribution can only be assumed for *VLMT Learning* ($W = 0.98$, $p = 0.26$) and *Spatial Memory* ($W = 0.98$, $p = 0.12$).

4.1.1 Differences Regarding Sociodemographic Factors

All health indicators with possible differences depending on several sociodemographic classes, namely gender (male/female), relationship status (single/partnered), and housing situation (alone/shared flat) and pet ownership were analysed using a Mann-Whitney U test (see Table 5).

Table 5: Mann-Whitney U test results of health indicators depending on various factors (= p<0.05)*

Indicator		Gender		Relationship Status		Housing Situation		Pet ownership	
		U	*p*	*U*	*p*	*U*	*p*	*U*	*p*
p	PCS-12	912	.21	799	.05	1200	.17	630	.49
m	MCS-12	924	.24	1019	.79	1056	.81	740	.73
m	ADS	1232	.23	1166	.37	1060	.79	913	**.04***
c	VLMT Learning	1496	**<.001***	1017	.49	888	.80	484	.13
c	VLMT Consolidation	1521	**<.001***	1086	.42	814	.22	690	.88
c	VLMT Recognition	1588	**<.001***	1133	.40	768	.06	658	.73
c	Spatial Memory	1500	**.001***	1224	.19	782	.05	802	.34

As can be seen in Table 5, no significant differences between the groups were found concerning physical health. For mental health the only significant difference concerns a lower prevalence of depressive symptoms in pet owners compared to non-pet owners. As the sample includes only a small number of pet owners (n: 19), there is increased uncertainty of the resulting variance between pet owners and non-pet owners.

Regarding cognitive health, it becomes apparent that there is a highly significant difference for all indicators with respect to gender. Female participants significantly outperformed male participants in all aspects of the VLMT: On average, they were able to memorise 51 words in the learning rounds, whereas male participants only memorised 41. The female participants were able to remember 85.5 % of the previously learned words after a period of 30 minutes. In contrast, the male participants only memorised 69.5 % of the words they had previously learned. Finally, the women were able to correctly identify 13 words in a recognition-list, while the men on average identified nine words correctly.

Similarly, the female participants outperformed the male participants in the spatial memory test: The female participants on average achieved an accuracy of 56 % in matching the correct pair of pictures, with the male participants only achieving an accuracy of 43 %.

Other than the difference between men and women, no significant differences were to be found in cognitive health. Neither relationship status nor housing situation seems to be a decisive factor for the health of older adults in the MOASIS sample. These factors can therefore be ignored in the further process of analysing mobility behaviour.

4.2 Mobility Indicators

The resulting mobility indicators are described and visualised below. This is done separately for the mobility indicators concerning TOH and ALs.

4.2.1 Resulting TOH indicators

As shown in Table 6, 42 % of the measurements were labelled as out-of-home, which corresponds to an average TOH of 3 to 4 hours per day. As the mean daily TOH is strongly affected by extreme values and thus is less representative for an average day, median daily TOH is used for the following analysis. Using a Kruskal–Wallis H test, significant differences in TOH H (6) = 16.7, p = .01 were found on the different weekdays. The distribution of TOH across the individual weekdays are shown in Figure 11.

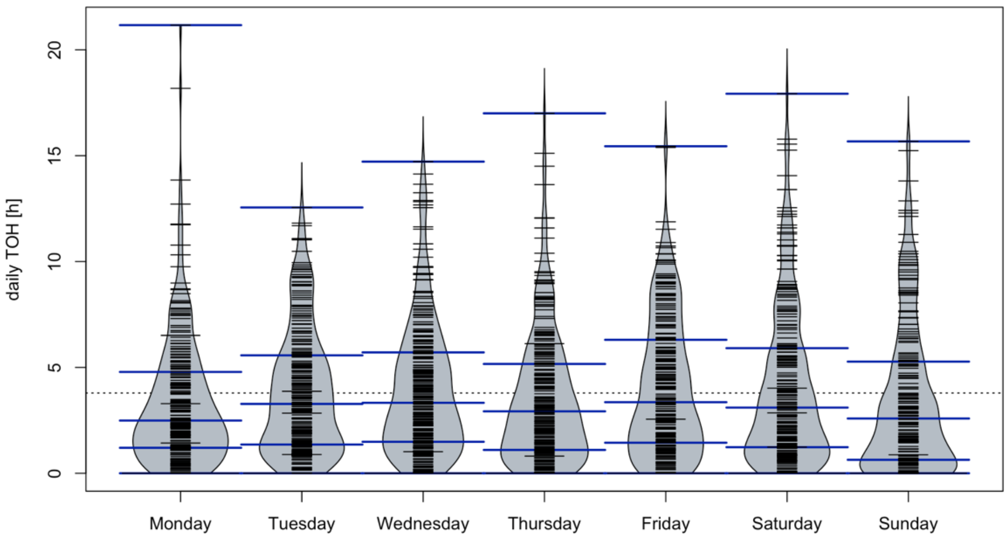

Figure 11: Daily TOH per day of the week

TOH duration is higher on weekdays compared to weekend days. However, a Mann-Whitney U test indicated that the difference between weekdays and weekend days is not significant, U = 273320, p = .202. It is to be noted that on weekend days, both lower minimum duration and longer maximum duration were recorded. Similarly, the standard deviation of TOH duration is higher on weekend days compared to weekdays, indicating higher TOH variability at weekends. In terms of the ratio of TOH between weekdays and weekends, the longer TOH spent on weekdays is visible as well, as the value for Weekday Prevalence is above 0.5. The maximum value of 1 indicates that there are participants who spend all of their TOH during the week and stay at home during the weekend.

Table 6: Descriptive statistics for the selected mobility indicators concerning TOH

Indicator	mean	sd	median	minimum	maximum
overall TOH [%]	42.27	19.53	39.37	2.01	95.31
mean daily TOH [h]	3.79	1.58	3.54	0.25	8.48
median daily TOH [h]	3.23	1.84	2.48	0	9.06
median daily TOH on weekdays	3.78	1.57	3.72	0.10	7.72
median daily TOH on weekends [h]	3.28	1.83	3.03	0.00	9.25
Weekday Prevalence	0.56	0.10	0.53	0.41	1.00
Days fully at home [%]	6.55	12.23	0	0	72.73
TimePeriodActive [h]	11.28	2.95	12	4	18
TimePeriodActive on weekdays	11.38	3.45	12	4	19
TimePeriodActive on weekends	10.45	3.04	10	4	19

In general, most participants leave their home almost every day and therefore have no days labelled as fully at home. However, some individuals spend up to 72 % of the days fully at home and thus increase the overall mean. Therefore, in spite of a mean of 6.55 %, days spent fully at home remain an exception for the majority of the participants.

TimePeriodActive gives information on when the participants spend most of their time out-of-home. Overall, most out-of-home measurements were taken between 11:00 and 11:59. While this is true for weekdays as well, on weekends participants tend to be out-of-home earlier, with 10:00–10:59 being the hour with most TOH recorded. A more detailed analysis of the TOH timing regarding the time of the day can be found in Section 5.2.1 (TOH Timing).

Figure 12 shows the median TOH duration plotted against the standard deviation. It becomes evident that duration alone might not be a sufficient indicator for the out-of-home behaviour, as there are participants with similar TOH durations showing vast differences in the standard deviation.

By applying Ward's method for hierarchical cluster analysis, the participants were grouped into five clusters. The resulting clusters can be seen in Figure 12, each representing a different type of out-of-home behaviour. For example, participants in Cluster 1 tend to have consistently low TOH durations, whereas participants in Cluster 2 show more variability while still having rather short median TOH durations. These clusters will be used for answering RQ 1b, which is about the correlation of TOH variability and health.

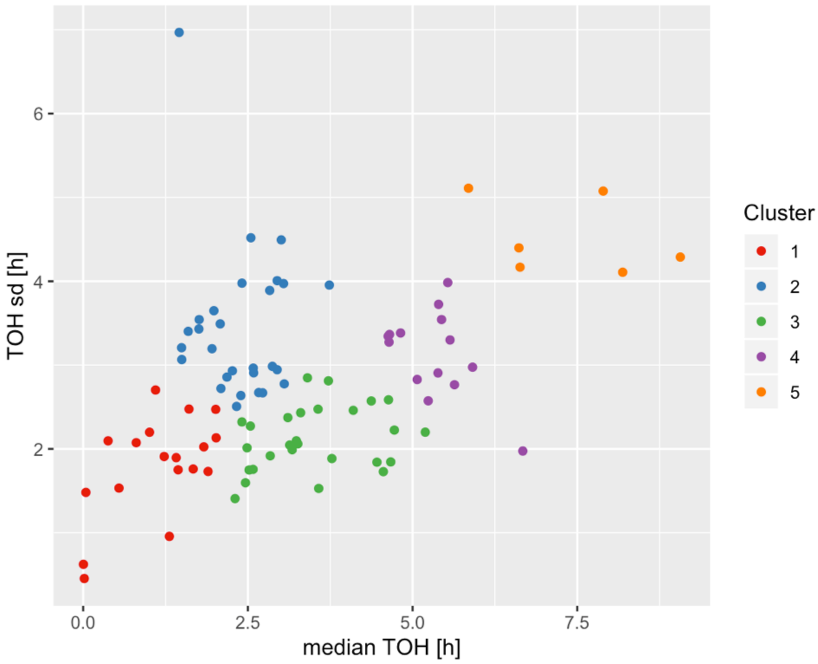

Figure 12: Median TOH including variability, expressed by standard deviation

4.2.2 Resulting AL indicators

As shown in Table 7, the participants spent time at an out-of-home AL on average 17 times per week. The inter-individual differences are rather large, ranging from two to 32 stops per week. On average, these 17 stops spread over 13.6 ALs, with 11.5 ALs being visited only once. The remaining stops happen at ALs with multiple visits and are thus counted as revisits. These revisits account for an average of 30 % of the total stops. As with the counts of total stops as well as total ALs, there is a broad distribution for the indicator *revisits*, ranging from no revisits to almost two out of three stops being a revisit. The results of a Shapiro-Wilk test imply that normal distribution can be assumed for *total stops* ($W = 0.99$, $p = 0.57$), *total ALs* ($W = 0.98$, $p = 0.12$), *revisited ALs* ($W = 0.97$, $p = 0.07$), and *total time spent at ALs* ($W = 0.99$, $p = 0.59$).

A weekly average of 25 hours results for time spent at ALs. Once again it is to be noted that the range of time spent at ALs is broad, ranging from less than 4 hours to over 50 hours. This indicator combined with the total number of stops makes it possible to calculate entropy as well as normalised entropy.

Table 7: Descriptive statistics for the selected mobility indicators concerning ALs, all indicators are confined to seven days (cf. "Analysis of Activity Locations", Section 3.4.1)

Indicator	mean	sd	median	minimum	maximum
total stops	17.12	6.54	17	2	32
total ALs	13.56	5.03	13	2	27
uniquely visited ALs	11.50	4.45	11	2	25
revisits [%]	30.76	14.25	31.58	0.00	64.29
revisited ALs [%]	14.19	8.06	13.64	0.00	33.33
total time spent at ALs [h]	25.25	9.84	26.07	3.90	51.84
entropy	2.10	0.45	2.16	0.61	3.00
normalised entropy	0.83	0.08	0.86	0.49	0.94

Comparing entropy and normalised entropy, entropy shows a broader distribution, while normalised entropy scores tend to be concentrated towards the upper end of the scale (Figure 13).

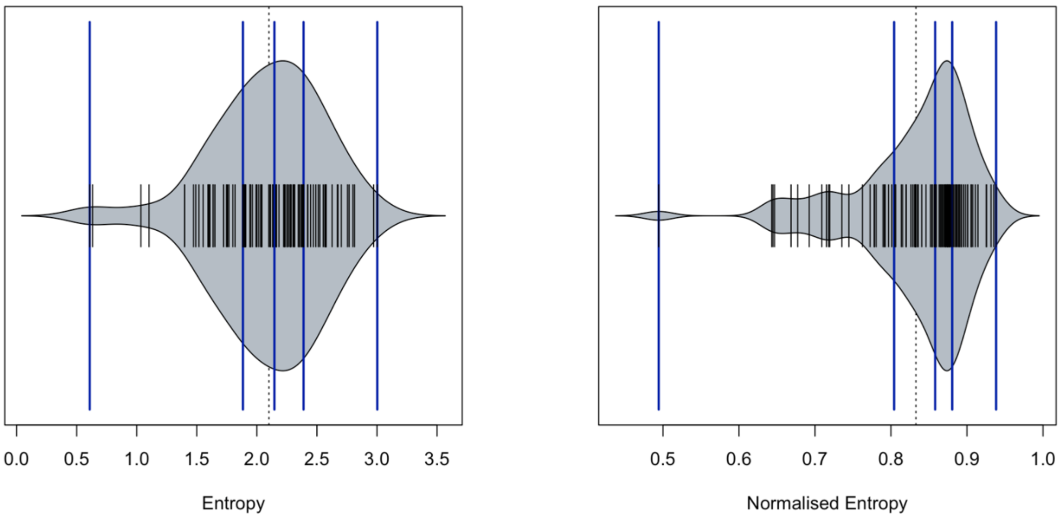

Figure 13: Distribution of the mobility indicators Entropy and Normalised Entropy

4.3 Correlation Analysis

Spearman's rank correlation was calculated for all health and mobility indicators. In a first step, the correlations within the health indicators are presented, followed by the correlations within the mobility indicators. Finally, the resulting correlations between the health indicators and the selected mobility indicators are described.

4.3.1 Within Health Indicators

The correlations within the health indicators are presented in Table 8.

Table 8: Spearman's ρ and p-values for correlations within the health indicators (= p < .05)*

	PCS-12		MCS-12		ADS		VLMT Learning		VLMT Consolidation		VLMT Recognition		Spatial Memory	
	ρ	p	ρ	p	ρ	p	ρ	p	ρ	p	ρ	p	ρ	p
PCS-12			-.02	.88	-.23	**.03***	.11	.31	.10	.36	.11	.30	-.04	.61
MCS-12	-.02	.88			-.38	**<.001***	-.12	.22	-.10	.37	-.22	**.02**	.03	.67
ADS	-.23	**.03***	-.38	**<.001***			.02	.88	-.02	.87	-.07	.49	-.06	.54
VLMT Learning	.11	.31	-.12	.26	.02	.88			.42	**<.001***	.64	**<.001***	.46	**<.001***
VLMT Consolidation	.10	.36	-.10	.36	-.02	.87	.42	**<.001***			.49	**<.001***	.32	**.002***
VLMT Recognition	.11	.30	-.22	**.03**	-.07	.49	.64	**<.001***	.49	**<.001***			.37	**<.001***
Spatial Memory	-.04	.61	.03	.76	-.06	.54	.46	**<.001***	.32	**.002***	.37	**<.001***		

Within the health indicators, there are several significant correlations. Both the physical health indicator (*PCS-12*) and the mental health indicator (*MCS-12*) show a significant negative correlation with depressive symptom severity (*ADS*). The negative correlation coefficient is due to the inverted scales of the ADS and the SF-12. The correlation between the two indicators representing mental health is highly significant.

Similar to the mental health indicators, all cognitive health indicators are significantly correlated. Although the indicators are derived from two different tests, the correlation between the indicators is highly significant.

Additionally, the mental health indicator (*MCS-12*) shows a significant positive correlation with the long-term memory indicator *VLMT Consolidation*.

4.3.2 Within Mobility Indicators

In a first step, Spearman's rank correlation was calculated within TOH- and AL-based mobility indicators. The results can be found in the appendix (Table 14 & Table 15). Unsurprisingly, there are numerous significant correlations within these mobility indicators. This was to be expected, as the calculations of these indicators were all based on the same measurements. The only exceptions were indicators such as *TimePeriodActive* or *normalised entropy*, which are unrelated to the extent of out-of-home mobility.

In a second step, the correlations between the indicators based on TOH and AL respectively were analysed using Spearman's rank correlation. The results are shown in Table 9.

There are numerous significant correlations between TOH-based mobility indicators and AL-based mobility indicators; only a few indicators do not show significant correlations. These are the same indicators that do not show any significant correlation to the indicators in the same group: Firstly, these are the three TOH indicators based on *TimePeriodActive*. Further, *normalised entropy* does not show any correlation with the TOH-based indicators. Unlike all other mobility indicators, these indicators are not influenced at all by time spent out of home, which probably explains the missing correlation. All other indicators depend strongly on TOH duration.

All in all, the correlations within mobility indicators is often significant, disregarding whether they are based on TOH or ALs.

Table 9: Spearman's ρ and p-values for correlations between the two groups of mobility indicators (= p < .05)*

	total stops		total ALs		uniquely visited ALs		revisits		revisited ALs		total time spent at ALs		entropy		normalised entropy	
	ρ	p	ρ	p	ρ	p	ρ	p	ρ	p	ρ	p	ρ	p	ρ	p
overall TOH	.70	**<.001***	.67	**<.001***	.63	**<.001***	.26	**.01***	.22	**.03***	.60	**<.001***	.56	**<.001***	.03	.79
mean daily TOH	.79	**<.001***	.70	**<.001***	.62	**<.001***	.39	**<.001***	.30	**.004***	.79	**<.001***	.49	**<.001***	-.20	.06
median daily TOH	.82	**<.001***	.76	**<.001***	.69	**<.001***	.34	**<.001***	.28	**.01***	.73	**<.001***	.61	**<.001***	-.03	.76
median daily TOH on weekdays	.77	**.001***	.70	**.002***	.63	**.001***	.35	**<.001***	.31	**.002***	.68	**<.001***	.53	**<.001***	-.11	.28
median daily TOH on weekends	.73	**<.001***	.67	**<.001***	.61	**<.001***	.35	**<.001***	.30	**.003***	.64	**<.001***	.53	**<.001***	-.04	.73
Weekday Prevalence	-.46	**<.001***	-.40	**<.001***	-.39	**<.001***	-.28	**.01***	-.21	**.04***	-.40	**<.001***	-.37	**<.001***	-.04	.69
Days fully at home	-.46	**<.001***	-.41	**<.001***	-.36	**<.001***	-.34	**<.001***	-.30	**.004***	-.48	**<.001***	-.34	**<.001***	.06	.54
TimePeriodActive	.11	.27	.13	.21	.17	.11	-.06	.58	-.07	.51	.17	.10	.06	.55	-.09	.40
TimePeriodActive on weekdays	.10	.36	.12	.27	.16	.14	-.11	.30	-.14	.17	.18	.09	.02	.85	-.10	.34
TimePeriodActive on weekends	-.03	.80	.00	.98	.03	.76	-.10	.35	-.13	.21	.00	.99	.03	.79	.02	.86

4.3.3 Health Indicators and TOH-Based Mobility Indicators

In order to answer the research questions, the relationship between health- and mobility-indicators was analysed using Spearman's rank correlation. The resulting statistical measures are displayed in Table 10.

The vast majority of the TOH-based mobility indicators do not show any significant correlation to the health indicators, which would indicate some kind of interrelation between mobility and health. However, there are three exceptions showing significant correlations, which are described below and visualised in Figure 14.

Table 10: Spearman's ρ and p-values for correlations between health indicators and TOH-based mobility indicators (= p < .05)*

	PCS-12		MCS-12		ADS		VLMT Learning		VLMT Consolidation		VLMT Recognition		Spatial Memory	
	ρ	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*
overall TOH	-.07	.52	-.03	.77	-.05	.65	-.05	.67	-.13	.23	.07	.50	.10	.32
mean daily TOH	.02	.85	-.03	.80	-.13	.23	-.04	.72	-.07	.49	.12	.24	-.05	.64
median daily TOH	.03	.80	.04	.69	-.23	**.03***	.03	.77	.02	.86	.17	.10	.02	.85
median daily TOH on weekdays	.07	.48	-.04	.69	-.12	.25	-.05	.67	-.08	.44	.09	.40	-.03	.75
median daily TOH on weekends	.07	.53	.00	.98	-.14	.19	.02	.84	-.02	.87	.14	.18	.03	.81
Weekday Prevalence	.06	.54	.03	.75	.03	.78	-.15	.17	-.07	.50	-.16	.12	-.11	.31
Days fully at home	-.02	.88	.06	.55	.12	.24	.18	.09	.22	**.04***	-.05	.63	.04	.69
TimePeriodActive	.00	1.00	-.27	**.01***	.12	.27	.08	.44	.10	.35	.12	.25	.01	.90
TimePeriodActive on weekdays	-.02	.84	-.10	.36	.08	.42	-.02	.88	.06	.55	-.02	.89	-.05	.66
TimePeriodActive on weekends	-.15	.17	-.10	.34	-.04	.70	-.06	.55	-.12	.25	.07	.49	.12	.25

Firstly, a significant negative correlation was found between depressive symptoms (*ADS*) and the *median daily TOH*. This finding suggests that participants with stronger depressive symptoms spend less TOH compared to participants without or fewer mental health issues.

Further, there is a negative correlation between the mobility indicator *TimePeriodActive* and the *MCS-12* score, indicating that participants with lower mental health tend to spend most TOH later in the day compared to participants with better mental health.

The third significant correlation found in the data is between the indicators *Days fully at home* and *VLMT Consolidation*, indicating that participants with better episodic memory spend a higher proportion of their days fully at home.

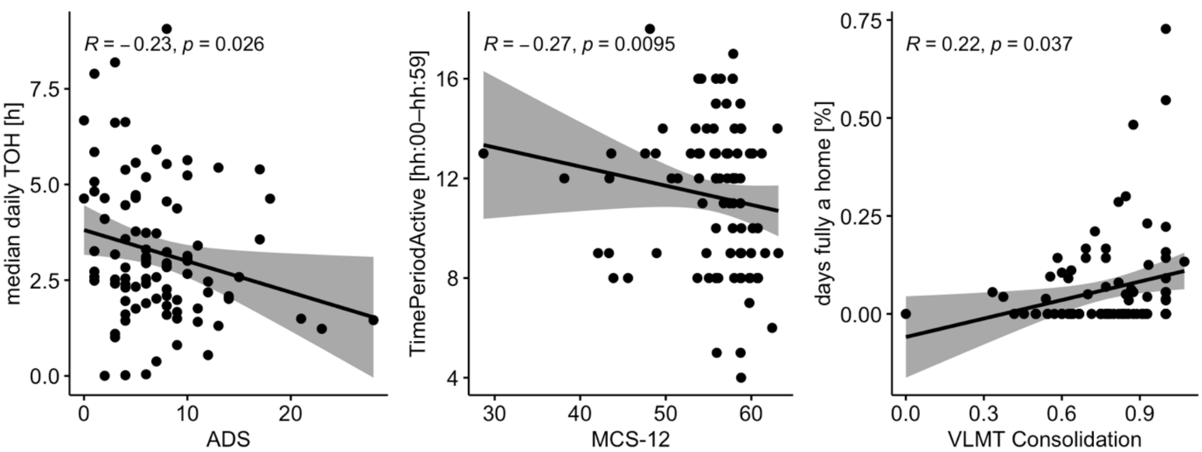

Figure 14: Three significant correlations between health indicators and TOH-based mobility indicators

In addition to the analysis based on Spearman's rank correlation, potential differences were assessed depending on the out-of-home mobility. For that use, the five clusters of Figure 12 were compared using a Kruskal–Wallis H test. The results are displayed in Table 11.

Table 11: Results of the Kruskal-Wallis H test (df = 4) on differences in health depending on TOH including variability

	TOH including variability	
	H	*p*
PCS-12	2.55	.64
MCS-12	5.29	.26
ADS	8.43	.08
VLMT Learning	3.78	.44
VLMT Consolidation	4.41	.35
VLMT Recognition	9.48	.05
Spatial Memory	2.11	.72

The results of the Kruskal–Wallis H test indicate no significant difference in health between the five groups. Two health indicators, *ADS* and *VLMT Recognition*, are very close to reaching significance. Given these results, it is questionable whether including TOH variability leads to an improved analysis, at least for the given sample of participants. As no significant health differences were detected, no further analysis was performed using this data set including TOH variability.

4.3.4 Health Indicators and AL-Based Mobility Indicators

As with TOH-based indicators, Spearman's rank correlation was calculated for AL-based mobility indicators and health indicators. The results are displayed in Table 12.

Table 12: Spearman's ρ and p-values for correlations between health indicators and AL-based mobility indicators (= p < .05)*

	PCS-12		MCS-12		ADS		VLMT Learning		VLMT Consolidation		VLMT Recognition		Spatial Memory	
	ρ	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*
total stops	.01	.96	.13	.21	-.20	.06	-.06	.61	-.10	.35	.04	.69	.01	.96
total ALs	.03	.76	.12	.26	-.13	.20	-.05	.63	-.08	.45	.06	.55	.03	.80
uniquely visited ALs	.00	.98	.06	.56	-.08	.45	-.05	.63	-.05	.64	.08	.46	-.01	.95
revisits	-.03	.74	.04	.67	-.13	.23	.04	.73	-.21	**.04***	.00	.98	-.01	.89
revisited ALs	-.02	.85	.13	.22	-.15	.16	.07	.53	-.21	**.04***	-.03	.77	.06	.59
total time spent at ALs	.06	.57	-.11	.29	-.08	.46	.11	.29	-.04	.69	.16	.13	.07	.51
entropy	.00	.98	.13	.22	-.10	.33	-.01	.91	-.09	.38	.05	.63	.08	.47
normalised entropy	.00	.98	.14	.19	.02	.82	.04	.74	.03	.77	-.06	.60	.07	.53

As shown in Table 12, from all AL-based mobility indicators only two indicators – namely *revisits* and *revisited ALs* – show any significant correlation with a health indicator. These two indicators show a negative correlation with the cognitive health indicator *VLMT Consolidation* representing long-term memory performance. This correlation indicates that participants with better long-term memory performance tend to have a lower percentage of revisits as well as a lower share of repeatedly visited ALs.

5 Discussion

In this chapter, it is first discussed in Section 5.1 to which extent the health of the MOASIS sample is representative for older adults in Switzerland. This is done by comparing the resulting health indicators to results from previous studies as well as potential deviations thereof.

Furthermore, in Section 5.2 the resulting mobility indicators will be analysed in terms of their significance and representativeness. Wherever possible, the mobility indicators will be compared to results from other studies with a similar approach.

In a next step, in Section 5.3 the correlation between health and mobility will be critically discussed. The correlations found in the analysis as well as the non-correlations will be reviewed and compared to previous findings. The research questions are answered based on the results of this analysis.

Finally, in Section 5.4 potential reasons for hypotheses that could not be confirmed are discussed by pointing out limitations of the chosen approach.

5.1 Health Indicators – Critical Evaluation

In the following paragraphs, the measured health indicators of the MOASIS subsample used for this thesis (Table 4) are compared to results from previous studies. It is important to note that comparability might be constrained depending on the date of the study: Older adults in Switzerland have been found to perform better in physical health but worse in cognitive health compared to previous generations (Y. Henchoz et al., 2020).

5.1.1 Physical Health

For people aged 65–74 in the United States, the PCS-12 score was previously found to be in the range between 13 and 59 (mean: 43.65, sd: 11.02); for people above age 74, the range was 17–57 (mean: 38.68, sd: 11.04) (Ware et al., 1995). For Switzerland, there is normative data for SF-36 scores. PCS and MCS scores calculated from the SF-12 survey usually do not differ significantly from the scores based on the SF-36 survey (Jenkinson et al., 1997). For people in Switzerland (age ≥66 years), the mean PCS score lies at 44.51 (sd: 12.19) (Roser et al., 2019).

In comparison, the MOASIS sample scores higher and includes less variation (mean: 51.46, sd: 6.42). It can be concluded that in terms of physical health, the MOASIS sample is highly functional and not representative for the whole population of older adults in Switzerland.

5.1.2 Mental Health

As with physical health, mental health scores in this sample tend to be much better compared to representative samples. For people aged 65–74 in the United States, the MCS-12 score was previously found to lie in the range between 19 and 70 (mean: 52.1, sd: 9.53); for people above age 74, the range was 19–70 (mean: 52.1, sd: 9.53) (Ware et al., 1995). In a Swiss sample, the mean MCS score was found to be at 54.13 (sd: 8.97) (Roser et al., 2019).

In contrast to the American sample, the MOASIS sample shows higher scores and less variation (mean: 55.57, sd: 5.63). Even though the mean value of the Swiss sample is more similar to the MOASIS sample than the American sample, the standard deviation in the MOASIS sample is nevertheless considerably smaller, indicating a less diverse sample.

In terms of ADS-scores, no norm values for older adults are available. A study based on CES-D, i.e. the original English version of the ADS-questionnaire, resulted in an average score of 7 for adults aged 60–79 (Hertzog et al., 1990). Lewinsohn et al. (1997) found the average CES-D score for adults aged 70 and older to lie at 8.74 (sd: 6.63). Compared with these values, the MOASIS sample (mean: 7.18, sd: 5.08) does not seem to deviate too far from a representative population. However, in terms of prevalence of depressive symptoms, the MOASIS sample seems to miss out on people showing depressive symptoms. While in the sample of Lewinsohn et al. (1997), 16.81 % of people aged 70 and older had a CES-D score above the cut-off score of 16, the MOASIS sample shows a prevalence of only 6.45 %. Using a higher cut-off score of 20, around 7.33 % of the participants are expected to be classified as showing depressive symptoms. However, in the MOASIS sample only three participants or 3.23 % show ADS-scores higher than 20. In Switzerland, the Patient Health Questionnaire (PHQ) is used for official statistics. This score can be transformed into a CES-D score following the conversion table by Choi et al. (2014). In 2017, around 3.2 % of Swiss adults aged 65 or older did show PHQ values corresponding to CES-D values above a cut-off score of 20 (Bundesamt für Statistik, 2018b). This further underlines the lack of people with depressive symptoms in the MOASIS sample as well as the general good mental health of its participants.

5.1.3 Cognitive Health

Volz-Sidiropoulou et al. (2010) developed age norms for the VLMT particularly for older adults. They found the average number of words learned in the first five rounds to be 49.4 (sd: 10.4), which corresponds to the indicator VLMT Learning found in the sample used for this thesis (mean: 46.10, sd: 10.06). The age norms from Volz-Sidiropoulou et al. (2010) are valid for people aged 60–82 years old and therefore encompasses more younger people than the MOASIS sample. As the number of words learned depends on age, this might explain the slightly lower score measured with the MOASIS sample.

For the indicator VLMT Consolidation, the sample of Volz-Sidiropoulou et al. (2010) suggest a score of 81 %, while the MOASIS sample resulted in a score of 77 %. Similarly, with 11.6 words, Volz-Sidiropoulou et al. (2010) found a slightly higher average score for VLMT Consolidation compared to 10.75 correctly recognised words in the MOASIS sample. Taking into consideration the slightly younger sample of Volz-Sidiropoulou et al. (2010), it seems that in terms of episodic memory, the deviation of the MOASIS sample from the general population of older adults well comprehensible.

Even though there are studies applying a spatial memory test based on the “Concentration”-game (Schumann-Hengsteler, 1996), there are no age norms available for the specific test applied in the MOASIS project.

Concluding, the results show that in contrast to physical and mental health, the cognitive health scores seem to be more representative for the general population and less skewed towards high functioning. This might also be a consequence of increasing physical functioning and decreasing cognitive capacity found in older adults in Switzerland, compared to previous generations (Y. Henchoz et al., 2020).

5.1.4 Differences Regarding Sociodemographic Factors

In the MOASIS sample, no significant gender difference was found in the scores for physical and mental health. Nevertheless, male participants tend to score insignificantly higher in the SF-12 questionnaire, for both physical and mental health. This difference was noted previously, suggesting that men refrain from answering the questions honestly, which could indicate weakness, rather than actual differences in health (Fleishman & Lawrence, 2003).

In contrast, significant gender differences were found in the domain of cognitive health. Female participants significantly outperformed males in the domain of episodic memory, tested by VLMT. This finding is in line with earlier study results, which were explained by women’s strength in verbal tasks (Herlitz & Rehnman, 2008; Volz-Sidiropoulou et al., 2010). Previous studies found females to outperform males in spatial memory tests based on “Concentration” (McBurney et al., 1997). This pattern was also found in the MOASIS data.

Even though previous studies suggested that for older adults, relationship status is connected to health (Goldman et al., 1995), no such trends are visible in the MOASIS sample. Only the relationship between physical health and relationship status comes close to reaching significance.

Older adults living alone have been found to show worse physical and mental health compared to individuals living with relatives (You & Lee, 2006). However, in the MOASIS sample no significant difference between people living alone and people sharing their home with others can be seen. Sakurai et al. (2019) found that having a poor social network is a factor for adverse health rather than simply the fact whether someone is living on their own.

5.2 Mobility Indicators – Critical Evaluation

While the health indicators used in this study are mostly standardised tests with age-based normative data available, the mobility indicators are far less common. Therefore, a direct comparison of the mobility indicators is often impossible. Nevertheless, is it possible to discuss the resulting indicators in terms of their range and distribution as well as their patterns.

5.2.1 TOH

TOH Duration

A diary-based study found older adults in Germany to spend 72 % of their wake time at home (Baltes et al., 1990). Based on interviews, Horgas et al. (1998) reported the time spent at home to be 80 % of the wake time. A sensor-based study found older adults to spend on average 66 % of their wake time at home (Boissy et al., 2018). In contrast, in the sample of this thesis the average percentage of GPS-measurements classified as *at home* lies at 58 %, indicating significantly more TOH (TOH = 42 %). However, when looking at the absolute TOH duration, the results from this thesis do suggest the exact opposite, namely rather low TOH duration.

Harada et al. (2019) found the average daily TOH to be 4.6 hours with a standard deviation of 2.5 hours. Similar TOH durations were reported by Fillekes, Kim, et al. (2019) (4.5± 3.7 hours), Petersen et al. (2015) (4.2 ± 2.7 hours), as well as Wettstein et al. (2015) (4.0 ± 2.3 hours). In a dairy-based study, Rapp et al. (2018) reported an average daily TOH of 3.8 hours (± 2.8 hours), which is almost identical with the mean TOH found in this thesis. There is however a difference regarding the variability, with the MOASIS sample showing a lower standard deviation (1.58 hours) compared to the sample of Rapp et al. (2018).

While at first glance it may seem inconsistent to have rather high TOH percentages while at the same time showing rather low TOH durations, there are several plausible explanations. Firstly, individual patterns suggest that many participants did not turn on their uTrail sensor as soon as they woke up in the morning, but rather attached it shortly before leaving the house. Similarly, they might have turned it off as soon as they got home. As a consequence, a disproportionate amount of TOH was recorded, leading to a higher percentage of recordings that are labelled as *out-of-home* compared to other studies. The rather low TOH durations can possibly be explained by poor data quality. Compared to other studies, the uTrail sensor used in the MOASIS study performed rather poorly in terms of signal loss and resulting data gaps (Fillekes, Röcke, et al., 2019). As a consequence, the overall daily recordings with valid GPS signal are rather short in the MOASIS study. While in their study, Harada et al. (2019) recorded an average of 14.3 hours per day, the analysis of the MOASIS data resulted in a daily average of only 9.7 hours. With a lower total recorded time per day, shorter TOH durations are a logical consequence. In addition to the aforementioned technical issues, there is another potential explanation for the lower TOH durations: In this study, a rather generous definition of home was chosen, consisting of a buffer of 150 m around the calculated home coordinates. This of course includes not only the participant's flat or house, but also their garden and possibly also the close neighbourhood. It is therefore likely that time spent weeding flower beds, reading on the bench beneath the apple tree in one's garden or drinking tea at a neighbour's flat is not counted to TOH. Depending on the definition of *home*, these activities would be labelled as TOH. Furthermore, using different sensors, such as the infrared sensors inside the participant's flat used by Petersen et al. (2015), TOH can be assessed with higher accuracy.

TOH Timing

Looking at the distribution of TOH over the course of the day as well as across different days of the week, Shoval et al. (2010) found distinct patterns which are visualised in Figure 15 (left). There is a peak in out-of-home movement in the late morning hours and a second peak in the afternoon, which is however much lower.

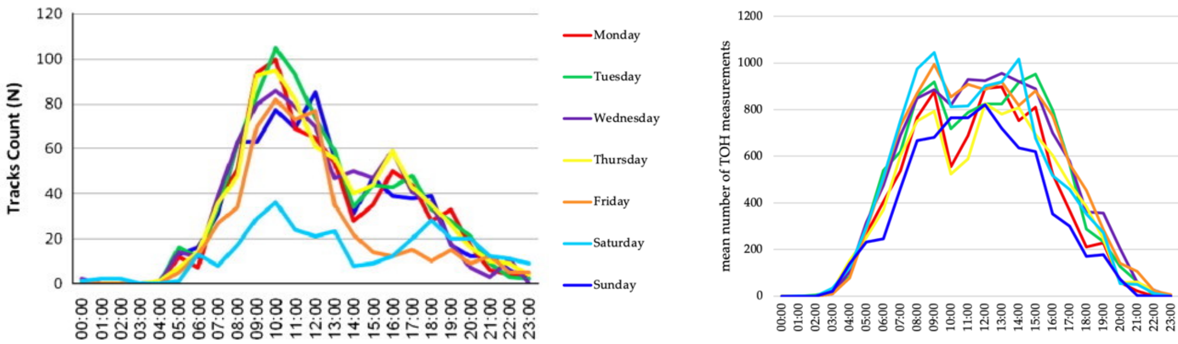

Figure 15: GPS measurements out-of-home per hour and per the day of the week in the study by Shoval et al. (2010) (left) and the MOASIS study (right)

There is also a clear difference between weekdays and weekend days. Note that the study by Shoval et al. (2010) was conducted in Israel, meaning that the weekend is observed on Friday and Saturday. There is significantly less out-of-home movement at the weekend, which can be explained by religious and cultural context, as for instance all shops are closed on Saturday in Israel (Shoval et al., 2010). In contrast to the study by Shoval et al. (2010), the patterns in the MOASIS sample are less distinct, though there are certain similarities. For example, both samples show a peak in out-of-home activity in the morning. However, in the MOASIS sample, the afternoon activities are only marginally lower than the morning activities. Further, in both studies the second day of the weekend (Saturday for Shoval et al. (2010), Sunday for the MOASIS study) shows an overall low TOH compared to the other days. In the MOASIS study, however, this tendency is considerably less pronounced compared to the study by Shoval et al. (2010). There are several possible explanations for the differences: Firstly, the due to the different sampling location there are different cultural influences. This can be seen in the significantly lower mobility on Saturday in the study by Shoval et al. (2010), which is due to closed shops, shut down public transport as well as reduced driving on Shabbat in Israel.

While in Switzerland most shops are closed in on Sundays, the majority of restaurants and cultural institutions are open. Further, public transport is barely reduced. Hence, there are is still numerous possibilities to spend TOH on Sundays.

Another explanation is the health status of the study participants. While the MOASIS sample is highly functional, the sample of Shoval et al. (2010) includes individuals of around 65 % with mild cognitive impairment or mild dementia. It is possible that these people tend to spend most of their TOH at once and prefer to stay at home for the rest of the day, resulting in a pronounced peak of TOH in the morning.

The difference in TOH between different days of the week has also been observed in other studies: A interview-based study found the time spent out of home to decrease on Sundays (129 min) compared to the other weekdays (196 min) (Horgas et al., 1998). A sensor-based study indicated an average reduction of 33 minutes of TOH on Sundays compared to the other days of the week (Rapp et al., 2018). In a comparison between different age groups, Bhat & Misra (1999) found older adults to spend less TOH compared to younger adults. This difference is even more pronounced on weekends (Bhat & Misra, 1999).

Thus, the distinction between weekdays and weekends is apparently not the most suitable for the MOASIS sample. While the distinction between weekdays and weekends is common, there are studies that group the days into one group consisting of the days from Monday to Saturday and a second group including only Sundays (Rapp et al., 2018).

In the MOASIS sample, Sundays do show significantly less TOH compared to the other days of the week, however, mean TOH is actually the highest on Saturdays. Combining these two days may have led to an effect of cancelling of itself out, which would explain the non-significant difference between weekends and weekdays.

The fact that on average most TOH was recorded on Saturdays might be explained with the high functionality of the sample. As most of the study participants are in good health, it is likely that they participate in various discretionary activities such as attending cultural events, hiking in the mountains, and meeting their family and friends. These activities are likely to happen on Saturdays, as they involve other people who might be at work during the week. In order to prove this hypothesis, it would be necessary to look at the places visited as well as the activities performed on Saturdays.

Whilst the TOH timing in terms of the day of the week has been addressed in several studies, there has been less detailed research on TOH timing in relation to the time of day. Apart from the study by Shoval et al. (2010), an analysis on an hourly level is not common. Further comparison is therefore not possible.

5.2.2 Place Diversity – Activity Locations

Number of Stops/ALs

Compared to TOH, ALs as an indicator are less common in research on older adults' mobility. A study found healthy older adults in Canada to visit on average 5.6 ALs per day (Boissy et al., 2018). A further sensor-based study from Singapore found the average daily number of ALs for older adults to lie around 2.9 (Ho et al., 2020). For the participants in the MOASIS sample an average of only 2.4 daily stops at ALs were recorded. This number corresponds to the findings of Fillekes, Kim, et al. (2019), who reported an average of 2.6 ALs per day while using a similar definition and approach for AL detection, namely the MBGP algorithm. As different studies define stops and ALs differently, a direct comparison is problematic. Even if the same algorithm is used for AL detection, varying input parameters can still significantly influence the result (Ebert, 2020). Although Fillekes, Kim, et al. (2019) used slightly different input parameters, it seems as if the result of the MOASIS sample is appropriate.

It is important to note, that though the MBGP algorithm was deemed most suitable for detecting stops and ALs in the MOASIS data set, it is not perfect. Comparing its results with manually labelled ground truth revealed that in terms of accuracy there is still room for improvement. In her comparison Ebert (2020) found the median F-score to lie at 0.86, indicating that the algorithm nevertheless falsely detects stops as well as misses out on true stops. This result is in line with results by Bayat et al. (2020), who calculated an F-score of 0.87 for their stop detection algorithm in comparison with ground truth. As the MOASIS participants were not required to keep diary throughout the data collection, it is not possible to assess the precision and accuracy for the given sample. Therefore, uncertainty must not be underestimated.

Revisits & Entropy

Unfortunately, there are no studies providing numerical information on how many places are revisited by an individual over a certain amount of time. Also, for entropy, there are only few studies providing data. Furthermore, a direct comparison of these indicators would be problematic, as they are dependent on the duration of the data collection.

In a study with college students, Saeb et al. (2016) calculated an average normalised entropy of 0.26 which is significantly lower compared to the normalised entropy in the MOASIS sample. However, due to the age difference in the sample as well as different definitions of what an AL is, and more importantly due the fact that Saeb et al. (2016) included time spent at home, a direct comparison is not feasible.

As the indicators on revisits and entropy aimed at representing place diversity and place familiarity, they were compared with an indicator based on daily assessments the participants did during the data collection period. Every evening, they were questioned on whether they had spent time in unusual places on that day, 'unusual places' defined as places that were typically visited less than twice a month. The answers were coded into a binary scale with 0 representing *No* and 1 representing *Yes*. The results were then averaged over the whole data collection period, resulting in an indicator of place diversity where values close to zero signify that this individual hardly ever spent time at unusual places. This participant indicated place diversity was then plotted against the GPS-derived mobility indicators and Spearman's rank correlation was calculated (Figure 16).

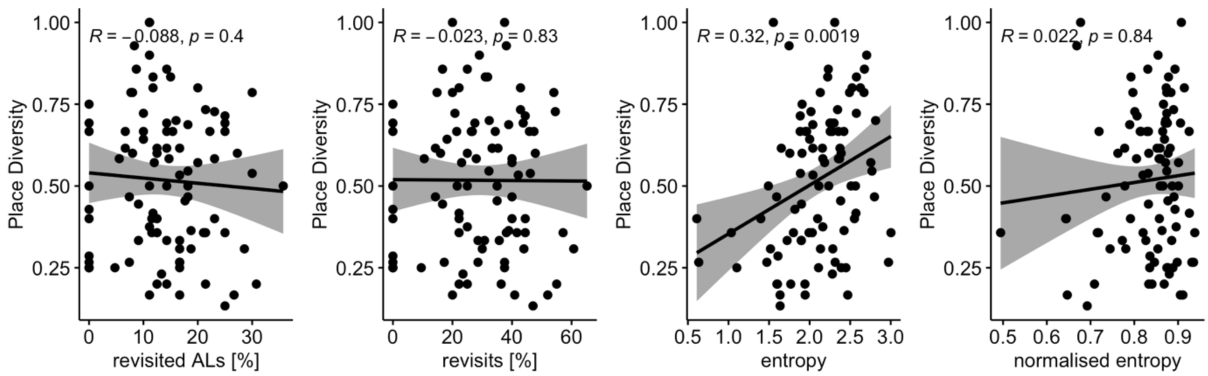

Figure 16: Participant indicated place diversity (0 = never visited unusual places, 1 = visited unusual places every day) plotted against GPS derived mobility indicators of place diversity.

Out of the four mobility indicators, only entropy shows a significant correlation with the participant indicated place diversity, meaning people with higher entropy values tend to visit unusual places more often. This correlation could also be as entropy being the best proxy for place diversity or place familiarity respectively.

5.3 Correlation Analysis – Critical Evaluation

5.3.1 Correlations Within Health

Both the MCS-12 and the ADS score were previously found to be valid measures of mental health and depressive symptoms (Gill et al., 2007; Stein et al., 2014). It is therefore not surprising that the two scores show a significant correlation. Similarly, the VLMT scores as well as the score for spatial memory represent the functioning of the episodic memory which explains correlation between those scores. Further, the VLMT Recognition score shows a positive correlation with the MCS-12 score. Individuals with mental health issues were previously found to perform worse in the VLMT, lending plausibility to the correlation found in the MOASIS sample (Listunova et al., 2016).

Interestingly, the physical health component of the SF-12 survey does not show a correlation with the mental health component of the SF-12 survey, although the PCS and MCS scores were previously found to show a positive correlation (Farivar et al., 2007). The correlation between self-reported physical health and depressive symptom severity was previously in numerous studies (Geerlings et al., 2000; Murrell et al., 1983).

5.3.2 Correlations Within Mobility

Given that all mobility indicators are based on the same GPS-trajectories, it is not surprising that there are numerous significant correlations within these indicators. Similar to the results of this analysis, the correlation between TOH duration and AL counts was previously found to be significant (Wettstein, Wahl, Shoval, et al., 2014). Even if only some correlations between health and mobility are found to be significant, the generally good correlations within the mobility indicators may allow to draw certain overall conclusions.

5.3.3 Correlations Between Health and Mobility

Overall, there are less significant correlations between health indicators and mobility indicators than were to be expected taking into consideration the results of the previous studies in this field. In the following paragraphs, the resulted correlations are discussed in order to answer the research questions of this thesis. On the one hand, this includes the discussion of the five correlations between health and mobility that were found to be significant. On the other hand, correlations that were expected to be significant but did not meet the threshold of significance are also be looked at.

Research Question 1: Correlation Between TOH and Health

Three significant correlations were found between TOH-based mobility indicators and health indicators. Out of these correlations, two seem reasonable and mirror results from previous studies. The third correlation, i.e. between *Days fully at home* and *VLMT Consolidation* seems somewhat spurious. Rather than showing an actual relationship, the resulting correlation might be due to the fact that for the majority of the participants *Days fully at home* is zero, leading to a distortion.

The remaining significant correlations concern depressive symptoms and TOH duration on the one hand, as well as mental health and TOH timing on an hourly scale. The sub-questions of research question 1 will be answered in the following sections.

Research Question 1a: Health and TOH Duration

The hypothesis of lower overall health with lower TOH duration could not be confirmed as neither physical health nor cognitive health showed a significant correlation with TOH duration. However, a negative correlation between depressive symptom severity and TOH duration, previously described by Wettstein et al. (2015), was found in the sample. Similarly, Saeb et al. (2016) found a positive correlation between depressive symptoms and time spent at home. Even though the MOASIS sample hardly includes participants with severe depressive symptoms, the difference in behaviour depending on the ADS score was found to be significant. This thesis can thus not only reinforce previous findings but further evince that depressive symptom severity and TOH duration certainly show a positive correlation even in samples of highly functional older adults.

Research Question 1b: Health and TOH Variability

The analysis including TOH variability, expressed as the standard deviation did not lead to any significant results (Table 11). Even though some trends are visible, grouping the participants according to their TOH duration and standard deviation does not lead to a more distinct correlation with health indicators. It is likely that TOH variability does not sufficiently represent regularity and routine of an individual's life and that there is a relationship between health and TOH regularity that was not detected in this analysis.

Research Question 1c: Health and TOH Timing Depending on the Day of the Week

No significant correlations were found regarding health and the TOH timing on weekdays and weekends respectively. Unlike the results from previous studies, the highest amount of out-of-home activity is found on Saturdays. Due to this fact, the overall TOH at weekends is not significantly different from the rest of the week, even though TOH duration is low on Sundays. This contrasts with various studies that have found significant differences in TOH timing depending on the day of the week (Heo et al., 2014; Keskinen et al., 2020; Marshall et al., 2015; Tudor-Locke et al., 2002).

As a consequence of the lacking difference in mobility behaviour with regards to weekends and weekdays, the hypothesis of better physical and mental health with increasing TOH at weekends could not be confirmed. Similarly to the results by Kaspar et al. (2015), no significant correlations were found regarding cognitive health. It is possible that for this highly functional sample a comparison with the mobility behaviour of younger adults at weekends would result in more similarities, as they seem to have fewer health restrictions.

Research Question 1d: Health and TOH Timing Depending on the Time of the Day

The results indicate that people with better mental health tend to be out-of-home earlier compared to people with lower mental health. Other than that, no significant correlations between health and TOH timing depending on the time of the day were found.

As Ohayon et al. (2001) pointed out, low morning activity can be caused by nonrestorative sleep, which by itself can be a consequence of low mental health. The trend of increasing mental health in morning-type individuals was also found by Biss & Hasher (2012). This circumstance also seems to be reflected in the behaviour of the MOASIS participants. The hypothesis of more morning activity of individuals with better mental health can thus be confirmed. On the other hand, there does not seem to be any significant correlation with both physical and cognitive health in the MOASIS sample.

Research Question 2: Correlation Between Place Diversity (ALs) and Health

Two significant correlations were found between AL-based mobility indicators and health indicators, both of them concerning revisits and cognitive health. The sub-questions of research question 2 are answered in the following sections.

Research Question 2a: Health and the Number of ALs

No significant correlations were found between the number of stops or ALs visited and the chosen health indicators. This mirrors the results of a study by Boissy et al. (2018), who reported a weak, non-significant correlation between AL counts and physical health. In contrast to the findings of Saeb et al. (2016), the correlation between depressive symptom severity and the number of stops just missed the significance threshold. Given results from previous studies, a positive correlation between the number of ALs and cognitive health might be expected (Wettstein et al., 2015). Yet, this hypothesis could not be confirmed. A possible reason is the absence of cognitively impaired individuals in the sample and hence the generally high cognitive functioning of the participants.

Research Question 2b: Health and Revisits of ALs

The only significant correlations between AL-based mobility indicators and the selected health indicators relate to the revisits of ALs and stops respectively, which both correlate with the episodic memory indicator *VLTM Consolidation*. Participants who remembered a smaller number of words in the VLMT assessment, and thus are considered having lower cognitive health, tend to show a higher percentage of revisits to ALs and stops compared to participants with a better cognitive health. This confirms the hypotheses of more revisits with lower cognitive health. This relationship was previously found in older adults with mild cognitive impairment (Shoval et al., 2011). The analysis of the MOASIS sample, consisting of cognitively healthy individuals, now suggests that people tend to have a higher proportion of revisited places with declining cognitive health even when their cognitive health is in general higher.

Research Question 2c: Health and Time Distribution over ALs

Based on the research by Saeb et al. (2016), individuals with lower entropy were expected to have higher depressive symptom severity compared to individuals with high entropy. However, this trend could not be found in the MOASIS sample. Neither entropy nor normalised entropy showed a significant correlation with any of the given health indicators.

A plausible explanation might be the lack of individuals in the MOASIS sample that actually show depressive symptoms. As described in section 5.1.2, the sample used in this study includes but three individuals that show ADS scores above 20 and are therefore likely suffer from depression. It seems that within a generally healthy sample, there is no correlation with entropy.

5.4 Critical Evaluation of the Results

Given the amount of mobility indicators and health indicators, reporting only five significant correlations is underwhelming. Especially since multiple studies previously reported connections between mobility and health in later life, which could not be reproduced in this analysis. In the following sections, possible explanations for the outcome of this thesis is discussed. This includes approach-related limitations, differences in both approach and sample to previous studies as well as an overview of factors ignored in the analysis.

5.4.1 Approach-Related Limitations

Within this study, the older adults' mobility behaviour was characterised purely by mobility indicators derived from GPS-measurements. However, it is challenging to comprehensively characterise the multidimensional concept of outdoor mobility through those indicators (Bayat et al., 2020). General disadvantages of using GPS-sensors for research on mobility and ageing were already presented in section 2.1.2. In the following, only specific limitations with regards to this thesis are discussed.

Missing Semantic Information

An important aspect ignored in this study is the semantic information on the type of places that the participants visited as well as the exact activities they pursued. Instead, the mobility indictors used in this thesis are based on raw counts, ignoring the fact, that some places and activities are more positively associated with different health aspects than others. For instance, visits to green spaces such as parks have been found to have a positive effect on well-being and are often related to physical activity (Irvine et al., 2013). In contrast, ALs such as a doctor's surgery are associated with health issues and thus tend to indicate an adverse health condition. Whilst it is possible to align the calculated ALs with a dataset of potential points of interests, the accuracy of such approaches is limited due to the uncertainty coming from AL detection. A previous study aiming at retrieving meaningful semantics from MOASIS data was not able to provide convincing results in terms of the relationship between place visits and health (Välimäki, 2020).

Even if semantic information could be accurately retrieved, more information would be needed in order to draw meaningful conclusions on potential effects on health. Apart from being unable to tell what people do at the ALs they visit, it is further difficult to estimate the social interactions they experience when they are at an AL. Assuming that visiting more ALs represents more social interactions might be misleading, as there is no information on whether a person is alone or with other people. Furthermore, technological innovations might be able to enable social interaction without having to visit ALs physically. More research is needed on to what extent ICT-mediated contacts might serve as a replacement for social interaction happening at ALs (Barbosa Neves et al., 2019; van den Berg et al., 2015).

Similar to missing semantic information on locations, there is also a lack of information on movement. Movement from one location to another can be achieved by various means of transportation which require different capabilities. Possibly this missing information explains why there is no correlation between the number of ALs and the chosen health indicators. Minor mobility restrictions due to health issues might be irrelevant as there are coping and adaption strategies: Some people with impaired vision might only use the car in the daytime and during good weather conditions while others might switch to public transport (Zeitler & Buys, 2015). However, for individuals in generally good health, many adaptions are possible without actually influencing the total AL count. By combining GPS data with accelerometery measurements it is possible to infer the transportation mode which could then provide valuable information on a person's health (Corti, 2020).

5.4.2 Differences to Previous Studies on Mobility and Ageing

The research focus of this thesis was not the primary research objective of the MOASIS project during which the data used here was collected. The data therefore does not perfectly suit the research focus of this thesis and differs to datasets used in previous studies on similar questions. The main characteristics of the data which differ from previous studies as well as their influence on the analysis are discussed in the following passages.

Highly Functional Sample

As pointed out in section 5.1, the sample used in this study is not representative for the whole population of older adults in Switzerland in terms of health. It is highly skewed, as it includes almost exclusively very healthy individuals and thus leads to an underrepresentation of people with low health. There are several reasons for this: Firstly, there is most likely a recruitment bias. Voluntary study participants in studies on the subject of older adults' mobility and activity were previously found to be fitter and healthier than average, while people with adverse health tend to refrain from study participation (de Souto Barreto et al., 2013; Martinson et al., 2010). Apart from this participation bias, the selection process for the MOASIS study included a cognitive screening in order to exclude people with cognitive impairment. Further, sufficient eyesight in order to use a smartphone was required. Thus, an additional selection bias resulted. Even though the vast majority of older adults in Switzerland live in their own home, the focus on community-dwelling individuals excludes 4 % of the older adults, who live in nursing homes or other care facilities (Bundesamt für Statistik, 2018a). Nursing home residents typically need more assistance in their everyday life and thus most certainly show a significantly different mobility behaviour.

As a consequence of both the nature of a voluntary study participation and the inclusion criteria, the MOASIS sample is highly functional in terms of all three aspects of health. Many of the participants hardly experience health-related constraints in everyday life. Moreover, there is a very small variance in terms of health scores within the sample compared to previous studies; most of the scores lie within a narrow range. Both the generally good health status and the low variance in the sample limit the possibilities of the analysis as it makes it difficult to infer trends and correlations regarding mobility for a broader population of older adults. A more diverse sample including people with adverse health conditions could possibly help to improve an analysis.

Short Sampling Period – Small Amount of Data

In the MOASIS study, 150 participants were tracked for a period of one month. However, due to a rather low data quality resulting from various sampling problems, only a subset of 93 participants could be used in this study (see section 3.2, *Participant Selection*). On average, 18 days of valid GPS logs were available for each participant. Other studies with a similar approach were able to use significantly more data. For instance, Petersen et al. (2015), who reported several interesting relationships between mobility and health, had an average of 227 valid days per participant. Given that this is more than ten times the amount of data used for this thesis, it is not surprising that the analysis by Petersen et al. (2015) is more conclusive. Another study by Rapp et al. (2018) is based on a shorter sampling period of one week. However, a much larger sample consisting of 1289 older adults was used for this study, which again results in a dataset roughly five times larger than the one used in this thesis. In a smaller data set, single events or behavioural patterns, e.g. as a weekend spent in a hotel or a day of heavy rainfall spent indoors, have a stronger impact on the result, leading to increased uncertainty. For some indicators concerning revisits of ALs, an even shorter period of only seven days was used in the analysis. It is rather difficult to decide whether someone often spends time in familiar locations if all you know is whether a place has been visited several times in the course of a week. Many locations might be perceived as familiar even though they are visited less frequently than at least twice per week. It seems likely that the resulting correlations would be more pronounced if the sampling period was longer and thus more representative of the older adults' mobility behaviour.

5.4.3 Further Influencing Factors

It is important to note that health status is by far not the only factor determining the mobility behaviour of older adults or vice versa. Further influencing factors which are neglected in this thesis as well as their potential effect on mobility or health are discussed in the following sections.

Age

Compared to other age groups, the diversity in terms of health is larger by far with older adults (World Health Organization, 2015). Nevertheless, some trends based on chronological age are visible in the data. An analysis based on Spearman's rank correlation reveals a significant correlation between several health indicators with the participants' chronological age (Table 13). Physical health as well as two cognitive health indicators show a significant decrease with increasing age. In contrast, mental health scores are significantly higher with increasing age.

Table 13: Spearman's ρ and p-values for correlations between health indicators and chronological age (= p < .05)*

	Chronological Age	
	ρ	p
PCS-12	-.25	**.02***
MCS-12	.20	**.05***
ADS	.14	.17
VLMT Learning	-.27	**.01***
VLMT Consolidation	-.04	.74
VLMT Recognition	-.24	**.02***
Spatial Memory	.02	.88

Concerning mobility, fewer correlations with age are found (see Table 16 & Table 17 in the appendix). Only the mean daily TOH duration as well as the time spent at ALs are found to be significant. Horgas et al. (1998) compares the behaviour of older adults in their 70s, their 80s and people aged over 90 and found significant differences in time spent outdoors as well as time spent on obligatory and discretionary activities depending on the age group.

These findings of age dependent differences in both health and mobility suggest that a further age differentiation within the population aged 65 or older might lead to significant results.

Character Traits – Personal Preferences

Representing human behaviour through numerical indicators bears the risk of ignoring the fact that the research is about human beings with diverse personal preferences and individual character traits. Some people just like being at home more than others, disregarding their health state.

In the MOASIS study, the participants were asked to assess themselves whether they were more of an indoor- or outdoor-type of person on a scale from one (*I would always like to be at home*) to seven (*I would always like to be outside*). Of course, this assessment can by itself already be influenced by a person's health status. When looking at the median daily TOH depending on the participants self-characterisation, it becomes evident that people who prefer being outdoors spend more TOH compared to individuals who see themselves as more of an indoor-type person (Figure 17).

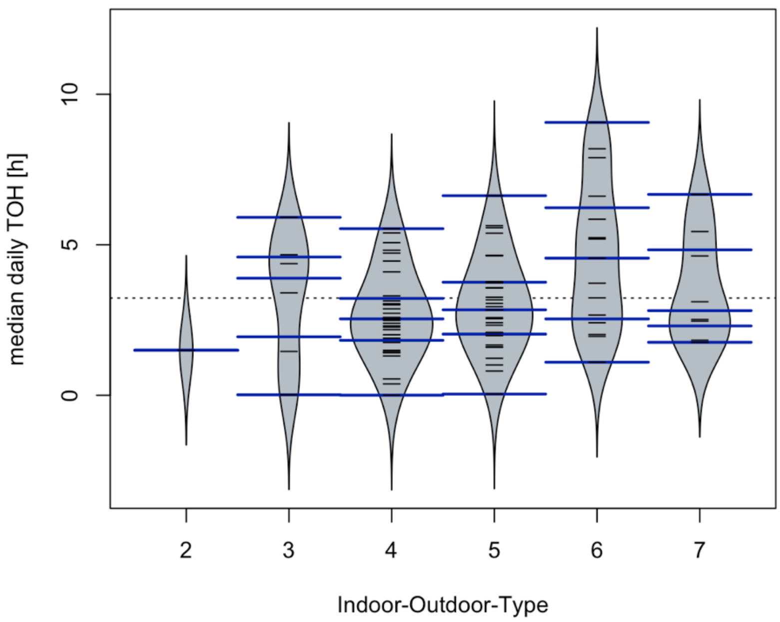

Figure 17: TOH by self-assessed outdoor/indoor preference (1 = strong indoor preference, 7 = strong outdoor preference)

This strongly supports the idea that, at least within this highly functional sample, the mobility behaviour is strongly influenced by a person's interest rather than by the limitations they experience through adverse health. These personal preferences could be compared to the actual mobility behaviour regarding potential discrepancies. However, the information on personal preferences cannot be derived from GPS logs and still requires input from the participant involved.

Influence of the Weather – Varying Sampling Periods

It has been shown that there are effects of maximum temperature, global radiation, precipitation, humidity and wind speed on the TOH duration of older adults (Klenk et al., 2012; Petersen et al., 2015). These effects can be rather large: Adults in Canada were found to on average spend 148 minutes outdoors in summer, while they only spent 33 minutes outdoors in winter (Leech et al., 2002). At the same time, time spent indoors at home increased in winter compared to summertime (Leech et al., 2002). Similarly, a decrease in physical activity from summer to winter as well as with increasing precipitation was found in a sample of older adults from Norway (Aspvik et al., 2018). However, other studies did not find any relationship between maximum temperature and mobility indicators (Giannouli et al., 2019).

The sample used for this thesis includes data collected from April to November and thus contains a wide variation of weather conditions: While the average temperature in Zurich was 21.1 °C in July 2018, it was only at 5.4 °C in November (Bundesamt für Meteorologie und Klimatologie, 2020). Similarly, there were big differences in precipitation: In August 2018, 113.3 mm of precipitation were measured in Zurich, whereas in April shows only about a tenth of this amount was measured (12.2 mm) (Bundesamt für Meteorologie und Klimatologie, 2020).

Given these large differences and the previous research on the subject, a bias resulting from different sampling periods is likely. Using a Kruskal–Wallis H test, significant differences $H\,(7) = 33.8$, $p < .001$ were found between the eight months of data collection. The distribution can be seen in Figure 18. The mean daily TOH was highest in July and lowest in November, which is in line with previous findings of increased out-of-home activity in warmer seasons (Aspvik et al., 2018; Leech et al., 2002).

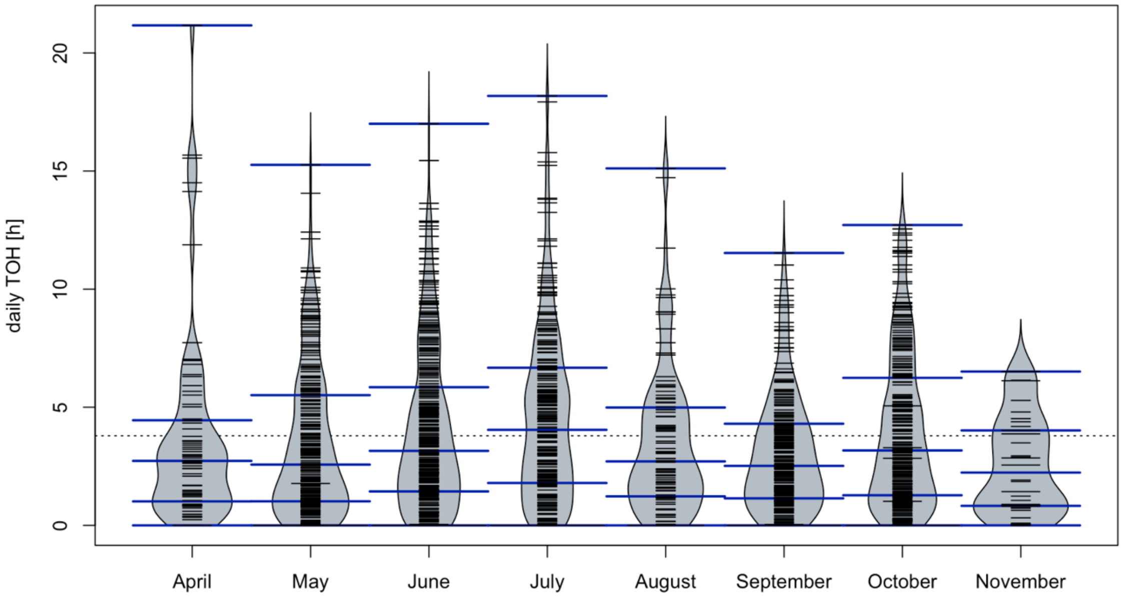

Figure 18: TOH measurements across the different months of recording

Given this significant difference, the sampling period, or even exact meteorological information, should be used as a correction factor. However, more research is still needed in order to accurately weigh the effects of the weather on TOH and other mobility indicators.

Geographical Setting

Even though most participants of the MOASIS study live in the Zurich metropolitan area, the environment varies significantly between the different home locations with some participants living in more urban areas while others have their home in a more rural environment. When comparing rural environments with urban environments, the population density is lower in rural areas, which can have implications on social contacts. Furthermore, places of interest (ALs) tend to be further apart in rural areas, therefore requiring more mobility. At the same time, public transport service is often worse in rural areas compared to urban environments. Likewise, health service accessibility is usually worse in rural areas (Blazer et al., 1995).

A person's spatial environment was found to be related to their health status in various ways: For instance, due to varying public transport access and usability, older adults in rural and suburban environments are more dependent on their car compared to individuals living in urban areas. This dependency on driving may impede older adult's mobility and thus their participation in social life (Zeitler et al., 2012; Zeitler & Buys, 2015). Moreover, in rural areas people are more prone to social isolation than older adults living in urban environments (Baernholdt et al., 2012). In contrast, depression prevalence was found to be higher among urban residents (Purtle et al., 2019). Additionally, the factors associated with depressive symptoms were found to vary depending on the environment (St John et al., 2006). Norstrand & Xu (2012) thus argue that the geographical setting should be taken into account when analysing older adults' health status.

Environmental factors do not only influence older adults' health on a large scale (urban vs. rural) but on a smaller scale as well: Neighbourhoods can vary in accessibility and attractivity, which can impact both the mobility behaviour as well as the health status of older adults. Natural and green areas are associated with more physical activity (Keskinen et al., 2020). On the other hand, busy roads with bustling traffic, short green times at pedestrian crossings and fast changing urban environments can discourage older adults from spending TOH (Phillips et al., 2013). Similarly, steep terrain slopes were found to reduce out-of-home activity (Keskinen et al., 2020). It is therefore relevant whether a person lives in a quiet, green neighbourhood which is pedestrian-friendly or in a busy neighbourhood where pedestrians, especially older adults, are not a priority. Even microscale features such as benches have been found to positively influence older adults' mobility experiences and thus lead to an increased use of the outdoor space (Ottoni et al., 2016). Furthermore, neighbourhood perception is linked to mental well-being: Toma et al. (2015) found decreased well-being in older adults with a negative neighbourhood perception, including perceived disorder or a feeling of distrust towards other residents. When including environmental factors into the analysis, it is important to look at the real-world action spaces of an individual rather than assuming a neighbourhood based on defined thresholds (Cummins, 2007).

As multiple studies have shown, environmental factors, whether on a larger or smaller scale, do have an influence on older adults' health and should therefore be taken into account in studies dealing with healthy ageing. However, due to the already small sample size, a further distinction depending on the participants' home environment was discarded in this thesis.

6 Conclusion

6.1 Main Contributions

In this study, simple mobility indicators based on TOH and ALs were derived from GPS-trajectories collected in the MOASIS study. As a basis, the participants' home locations were successfully deduced from the trajectories. The following statistical analysis showed that within this sample of healthy, highly functioning older adults, health and mobility do not seem to be related for the most part.

Most of the hypotheses formulated based on the relevant literature, suggesting an interrelation between older adults' health and their mobility behaviour expressed through indicators derived from GPS-trajectories, could not be confirmed. Only few correlations were significant, indicating that place diversity is higher for people with better cognitive health, out-of-home activity in the morning is more common with mentally healthy individuals, and further suggesting that the duration of time spent out-of-home is shorter for people suffering from depressive symptoms. Other than that, no significant correlations were found.

Apart from methodological limitations and other factors which potentially influence health and mobility ignored in the analysis, these results seem plausible given that most previous studies were done on samples including a broad spectrum of health conditions. Given the broad diversity in the mobility behaviour manifested in the MOASIS sample, contrasted by little variance in health and the small number of significant correlations found, it seems plausible that for a highly functional sample such as the MOASIS participants, health and mobility are not related. Nevertheless, mobility behaviour varies significantly between individuals, which goes along with the notion of diversity within the population of people aged 65 or older.

In conclusion, healthy and highly functional older adults in Switzerland show a broad diversity in mobility behaviour which does not seem to correlate with their health status to a great extent. This can be seen from a positive point of view, namely that there is no single right path to healthy ageing but that there are various types of mobility behaviours that allow a healthy life in older age.

6.2 Outlook

Due to the ongoing demographic development, the topic of healthy ageing is bound to gain increased importance in the future. Even though hardly any significant relationships were found within this highly functional sample, further studies exploring the correlates of health and mobility in later life should be conducted.

There are still many mobility indicators proposed by Fillekes, Giannouli, et al. (2019) that have not yet been analysed in terms of a potential correlation with health. Given the outcome of this thesis it is however questionable whether any of the mobility indicators would show a significant correlation when looking at a highly functional sample. Based on previous studies, on the other hand a more diverse sample in terms of health status would be likely to reveal correlations.

For future studies, better data quality as well as a larger amount of data will be crucial. In order to comprehensively describe an individual's mobility behaviour, a longer data collection phase or fewer data gaps, respectively, are necessary. Given a more extensive dataset, further aspects of mobility in relation to healthy ageing could be analysed.

One aspect which is of interest are intra-individual patterns in mobility and well-being. Although mobility and health seem to be only weakly associated, there might be interrelations on a smaller scale. Given the amount of data used in this analysis, it seemed unrealistic to focus on this aspect. A profound insight into the short-term effect of mobility patterns on well-being could however be enlightening.

Further, it would be interesting to conduct long-term longitudinal studies which could detect changes in behaviour and well-being over extended periods of time and thus might uncover causations between health and mobility rather than just point out at correlations derived from cross-sectional studies. This knowledge of how mobility behaviour changes with age and decreasing health could be valuable for the diagnosing of certain health issues.

An important point for future studies is diversity: Most knowledge on mobility in old age comes from regions of the world which experienced the demographic shift towards old age already in the twentieth century, such as Western Europe, North America as well as East Asia, Australia and New Zealand. Needs of older adults may differ across cultures. It is therefore important to be aware of cultural biases when drawing conclusions for healthy ageing policies.

7 References

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8 Appendix

8.1 Additional Tables

Table 14: Spearman's ρ and p-values for correlations within the TOH-based health indicators (= p < .05)*

	overall TOH		mean daily TOH		median daily TOH		median daily TOH on weekdays		median daily TOH on weekends		Weekday Prevalence		Days fully at home		TimePeriod-Active		TimePeriod-Active on weekdays		TimePeriod-Active on weekends	
	ρ	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*
overall TOH			.80	**<.001***	.78	**<.001***	.79	**<.001***	.70	**<.001***	-.39	**<.001***	-.44	**<.001***	.07	.79	.05	.65	.11	.30
mean daily TOH	.80	**<.001***			.89	**<.001***	.92	**<.001***	.78	**<.001***	-.39	**<.001***	-.47	**<.001***	.12	.06	.11	.29	.00	.97
median daily TOH	.78	**<.001***	.89	**<.001***			.86	**<.001***	.88	**<.001***	-.60	**<.001***	-.44	**<.001***	.02	.76	.04	.71	-.01	.92
median daily TOH on weekdays	.79	**<.001***	.92	**<.001***	.86	**<.001***			.88	**<.001***	-.45	**<.001***	-.42	**<.001***	.10	.28	.11	.30	-.05	.61
median daily TOH on weekends	.70	**<.001***	.78	**<.001***	.88	**<.001***	.88	**<.001***			-.77	**<.001***	-.35	**<.001***	.02	.73	.08	.47	-.08	.44
Weekday Prevalence	-.39	**<.001***	-.39	**<.001***	-.60	**<.001***	-.45	**<.001***	-.77	**<.001***		**<.001***	.21	**<.001***	.16	.69	.07	.53	.10	.36
Days fully at home	-.44	**<.001***	-.47	**<.001***	-.44	**<.001***	-.42	**<.001***	-.35	**<.001***	.21	**.04***			-.03	.54	.05	.61	-.11	.30
TimePeriodActive	.07	.50	.12	.26	.02	.83	.10	.32	.02	.88	.16	.12	-.03	.81			.73	**<.001***	.39	**<.001***
TimePeriodActive on weekdays	.05	.65	.11	.29	.04	.71	.11	.30	.08	.47	.07	.53	.05	.61	.73	**<.001***			.17	.10
TimePeriodActive on weekends	.11	.30	.00	.97	-.01	.92	-.05	.61	-.08	.44	.10	.36	-.11	.30	.39	**<.001***	.17	.10		

Table 15: Spearman's ρ and p-values for correlations within the AL-based health indicators (= p < .05)*

	total stops		total ALs		uniquely visited ALs		revisits		revisited ALs		total time spent at ALs		entropy		normalised entropy	
	ρ	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*	*ρ*	*p*
total stops			.93	**<.001***	.84	**<.001***	.38	**<.001***	.35	**<.001***	.76	**<.001***	.78	**<.001***	.06	.54
total ALs	.93	**<.001***			.97	**<.001***	.08	.43	.09	.37	.63	**<.001***	.91	**<.001***	.25	**.01***
uniquely visited ALs	.84	**<.001***	.97	**<.001***			-.10	.35	-.10	.34	.52	**<.001***	.91	**<.001***	.32	**.002***
revisits	.38	**<.001***	.08	.43	-.10	.35			.93	**<.001***	.55	**<.001***	-.09	.41	-.50	**<.001***
revisited ALs	.35	**<.001***	.09	.37	-.10	.34	.93	**<.001***			.44	**<.001***	.00	.98	-.34	**<.001***
total time spent at ALs	.76	**<.001***	.63	**<.001***	.52	**<.001***	.55	**<.001***	.44	**<.001***			.41	**<.001***	-.23	**.03***
entropy	.78	**<.001***	.91	**<.001***	.91	**<.001***	-.09	.41	.00	.98	.41	**<.001***			.58	**<.001***
normalised entropy	.06	.54	.25	**.01***	.32	**.002***	-.50	**<.001***	-.34	**<.001***	-.23	**.03***	.58	**<.001***		

Table 16: Spearman's ρ and p-values for correlations between TOH-based mobility indicators and chronological age ($* = p < .05$)

	Chronological Age	
	ρ	*p*
overall TOH	-.11	.29
mean daily TOH	-.21	**.04***
median daily TOH	-.18	.08
median daily TOH on weekdays	-.19	.07
median daily TOH on weekends	-.13	.22
Weekday Prevalence	.06	.55
Days fully at home	.18	.08
TimePeriodActive	-.12	.27
TimePeriodActive on weekdays	-.08	.46
TimePeriodActive on weekends	.17	.10

Table 17: Spearman's ρ and p-values for correlations between AL-based mobility indicators and chronological age ($* = p < .05$)

	Chronological Age	
	ρ	*p*
total stops	-.20	.06
total ALs	-.19	.07
uniquely visited ALs	-.19	.06
revisits	-.09	.37
revisited ALs	-.05	.63
total time spent at ALs	-.23	**.03***
entropy	-.12	.26
normalised entropy	.02	.82

8.2 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.

Pascal Griffel, 26 January 2021