Mobility Behaviour and its Associations with Sleep and Metacognition in Older Adults: Results from GPS-based Measurement in the MOASIS study

GEO 511 Master's Thesis

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ABSTRACT

The general trend of ageing societies is increasingly recognised as a serious, worldwide public health concern. Healthy aging and a good Quality of Life (QoL) should be possible for everyone including a person's ability to meet basic needs, make own decisions, contribute to society and engage in social contacts. Mobility becomes a basic prerequisite for partaking in social relationships and activities. In response to the demographic development towards older age in Switzerland, the *MObility, Activity and Social Interaction Study* (MOASIS) is being conducted by the University of Zurich. For this study, the focus is put on the mobility part, with the development of a sensor-based mobility and activity profile to describe the mobility behaviour of older adults, using *Global Positioning System* (GPS) and geographic information. The goal is further to examine the association between mobility behaviour and health-related variables such as sleep quality and cognitive capacities.

Traditionally, mobility behaviour has been assessed by measuring the mobility activity subjectively (i.e., by self-reports). In this MSc project, activity profiles were measured objectively and GPS trajectories and geographic information were used to detect and classify reasons to go outdoors and to investigate different *Life Space Levels* (LSL) visited by the participants for certain reasons. Reasons to go outdoors were detected successfully and results were found to be similar to those in other studies. Transport mode detection achieved, using a benchmark data set, an observed accuracy of 81% and a kappa value of 0.643 – a substantial strength of agreement – for minimum trip length of 4 minutes. Regarding the association of health-related variables and mobility behaviour, neither the repeated measures correlation analysis nor the moderated multiple regression revealed significant correlation.

Mobility and health do not seem to be related for the given sample of older adults. The MOASIS study was conducted with healthy older adults and it seems plausible that this sample contains barely any persons with major health restrictions. However, the objectively measured activity profiles can be used to gain further insights into mobility behaviour.

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NOMENCLATURE

API	Application Programming Interface
CV	Control Variable
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DV	Dependent Variable
EAR	Electronically Activated Recorder
GIS	Geographic Information System
GPS	Global Positioning System
H	Hypothesis
IV	Independent Variable
LMMs	Linear Mixed-effects Models
LSL	Life Space Level
LSQ	Life Space Questionnaire
M	Moderator
MIA	Metamemory in Adulthood
MOASIS	MObility, Activity and Social Interaction Study
OGD	Open Government Data
OSM	OpenStreetMap
POI	Point-of-Interest
QoL	Quality of Life
RMCORR	Repeated Measures Correlation
ROI	Region-of-interest
RQ	Research Question
URPP	University Research Priority Program
uTrail	Custom-built tracking device for the MOASIS study, including a GPS sensor

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1. INTRODUCTION

"Viewed as a whole the 'problem of aging' is no problem at all. It is only the pessimistic way of looking at a great triumph of civilization." - Notestein (1954)

1.1 Motivation

The world and its population are getting older. Increased age presents an issue not only in high-income countries, but worldwide. It is therefore a much broader, universal issue (Székely et al., 2011). Developed and developing countries are facing a demography of an increasingly older population. This growing percentage of older people and the consequential demographic transition is based on the increased longevity, declining fertility and the aging of the "baby boom" generations (Bloom et al., 2011; Tinker, 2002; Nations, 2017; World Health Organization, 2015). From a historical point of view the concept of an aging population is rather new. Looking at the year 1950, there was no country with more than 11% of its population aged 65 and over. However, this number is predicted to rise to 38% by 2050 (Rudnicka et al., 2020). The rising numbers can be linked to the improved living conditions, higher education, health, and sanitary conditions, reduced child mortality and economic growth (Baldanzi et al., 2019). There is no standard definition of when old age begins, but the most commonly used threshold in literature is the typical retirement age in Western countries, which is generally 65 (Rogerson, 1996). The age and size of the peak population varies in every country worldwide (Lutz et al., 2001).

According to the Bundesamt für Statistik (2020) the age structure of Switzerland's population is changing slowly and steadily. Its development can therefore be determined relatively well in the long term. The population group of people aged 65 and older will increase from 1.6 million in 2020 to 2.1 million by 2030 and to 2.7 million by 2050. Their share of the total population will rise from 18.9% in 2020 to 25.6% by 2050.

A higher life expectancy will be only beneficial for both the individual person and society as a whole when people live healthier and are able to extend the healthy years in order to minimize the gap between the total life expectancy and the active life expectancy. There is evidence that the next old age generation is relatively healthier than previous generations (Baldanzi et al., 2019; Rogers et al., 1990). Healthy aging and a good QoL including a person's ability to meet basic needs, make own decisions, contribute in society and move around/be mobile should be possible for everyone (Khaw, 1997; World Health Organization, 2015).

The World Health Organization (2020) published the *Baseline Report for the Decade of Healthy Aging (2021-2030)*. The report defines healthy aging as follows: healthy ageing is understood as the process of developing and maintaining the functional ability that promotes well-being in old age. Functional ability integrates the intrinsic capacity of the individual, the environment in which an individual lives in and the way in which people interact with their environment. Intrinsic capacity encompasses all the mental and physical capacities a person can access and includes the ability to walk, think, see, hear and remember. The level of intrinsic capacity is driven by multiple factors: the presence of disease, injury and age-related changes. The home, community and broader society including the built environment, people and their relationships, attitudes and values, health and social policies are all part of the environment. The ability to live in an environment that sustains and supports intrinsic capacity and functioning is the key to healthy ageing (World Health Organization, 2020).

Therefore, mobility is one of the most important components of healthy ageing and assessing it in the context of its relation with health in an older population is beneficial. This thesis specifically addresses the association between mobility and health related aspects (sleep quality and cognitive capacities) respectively environment. To improve the QoL, reasons to go outdoors such as social relations and activities (social visits, taking courses, eating out) are important factors for an increased mobility (Li-Tang et al., 2015). Growing older is associated with the possible loss of physical functions which have a negative impact on these two factors. In order to participate activities outside of residence, it is necessary to overcome spatial distances. Therefore mobility becomes a basic prerequisite for partaking in social relationships and activities (Gagliardi et al., 2007; Mollenkopf et al., 1997). Objectively measured mobility activity is detected by *Global*

Positioning System (GPS) data and the spatial behaviour and interaction with the environment is described by the definition of certain areas where people move within additional to the reasons people go outdoors. Furthermore, the association between the mobility and health such as sleep quality, metacognition and cognitive failures of the participants is investigated. Overall, the developed framework is designed for the deeper understanding in the MOASIS participants and the broader use for other studies and applications.

1.2 Thesis structure

First, a summary of related research addresses the mobility and health of older adults (Section 2.1). In the next step the research gaps are identified and the focus of the thesis is presented (Section 2.2). Furthermore, the research questions are developed with proposed methods, which are used to assess mobility and healthy aging (Section 2.2 - 2.4). In Section 2.5 the research questions are defined, and the research aims are explained. The data overview is presented in Chapter 3 with the specified data sources and meta information. The methodology is discussed in Chapter 4. The results are evaluated in Chapter 5, along with the mobility analysis and correlation analysis and eventually discussed in Chapter 6. Chapter 7 shows the main contributions, the potential further studies and the outlook.

2. THEORETICAL BACKGROUND AND FRAMEWORK

2.1 State of the Art: Mobility and Aging

2.1.1 Outdoor Mobility of Older Adults

The number as well as the length of trips decline with age and overall older people travel less than younger (Hill et al., 1999). This is due to the changing needs and circumstances in older age where no longer work trips are needed or possible fear of old-age poverty increase. With increasing age, limitations arise due to declining health and possible disabilities. The ability to go for a walk or to do household shopping declines drastically with older age (Jarvis et al., 1996). Outdoor mobility is defined by the ability to move from home to the outside world independently or with auxiliary tools, for example wheelchairs or other means of transportation (Webber et al., 2010). From a public health point of view, it is crucial to provide opportunities for the older adults to maintain their independent outdoor mobility and thus participate in social activities as long as possible (World Health Organization, 2002). The older population's mobility behaviours are influenced by the heterogeneous economic, social and cultural conditions of the older people (Beard et al., 2012; Davies and James, 2011). These heterogeneous differences are also detected between preceding generations and the next old generation, the baby boomers (Hugo, 2013).

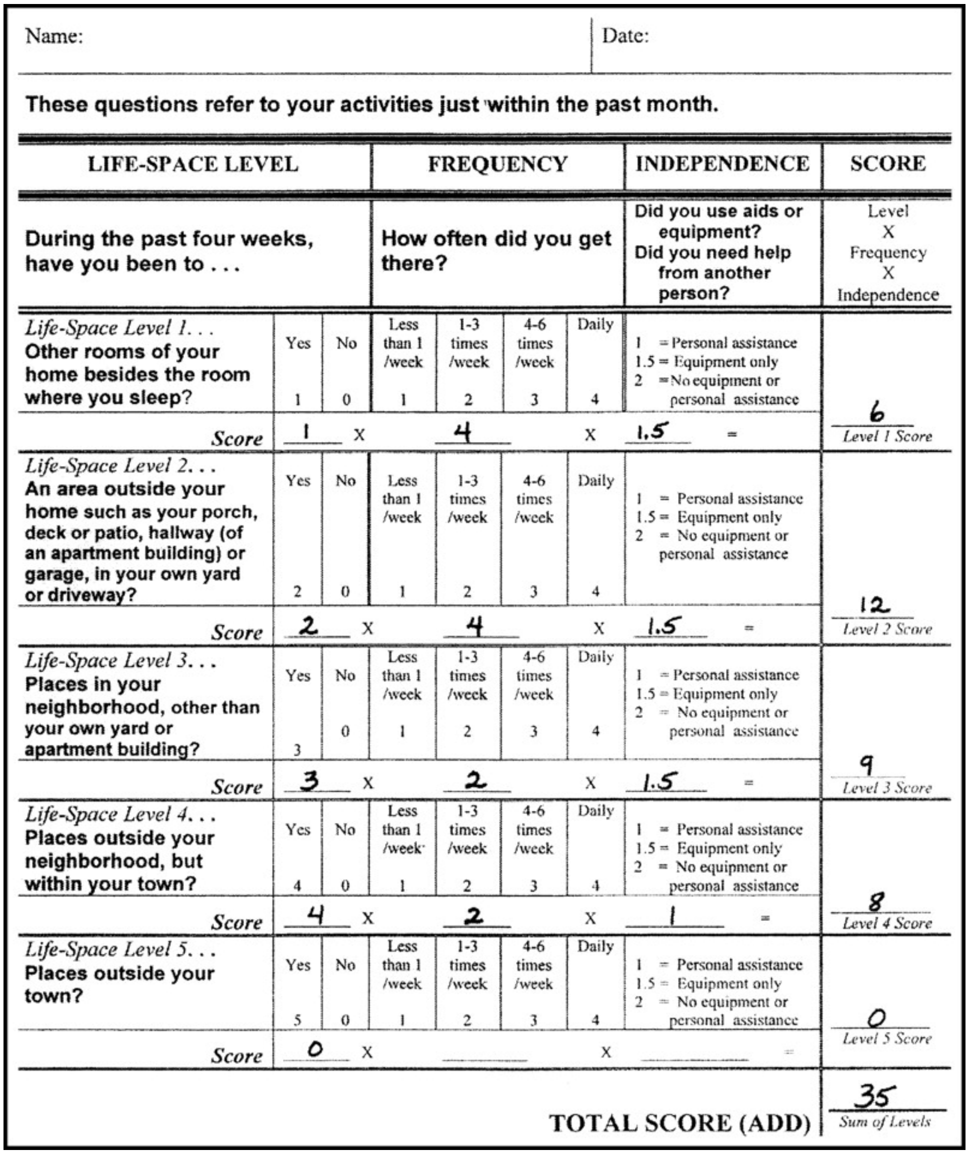
There are two most commonly used theoretical perspectives to explain the residential location and movement patterns of people as they age: the *Life Course Model* and the *Life Cycle Model*. The latter assumes that diversity of living space is a response to different stages of life cycle: families form, grow, shrink, and dissolve. Resident mobility is seen as a mechanism for families to adapt to their changing needs (Rossi, 1955). The life cycle stage is related to age and is considered to have a pattern of migration behaviour. Mobility is increasing during a young age, when important life changes occur. Young people's mobility reaches its peak with dating, starting a family and changes in jobs (Speare, 1970; Rindfuss, 1991). Elder (1975) criticizes the fixed life stages by pointing out that there could be disruptions in the stages, e.g. divorce, remarriage or voluntary childlessness.

Compared to the described model above, household transitions and age-related events such as retirement, illness and the death of a spouse are influential for the mobility behaviour and are described by the Life Course Model (Bailey, 2009; Crosnoe and Elder, 2002; Northcott and Petruik, 2011). In other words, mobility behaviour changes with different stages of life. Be it due to other life circumstances, opportunities or restrictions. Likewise, it cannot be defined in general terms as it is not possible to say that all people have the same mobility behaviour in a certain stage of life. Mobility has many different influencing factors and is very much dependent on the individual circumstances of each person (Beard et al., 2012; Davies and James, 2011).

2.1.2 Measuring Outdoor Mobility

Outdoor mobility is understood as the capability to move from one's own home to the outside environment (Webber et al., 2010). For older people walking is an important contribution to physical activity (Feskanich et al., 2002). It is also a prerequisite for being able to move independently through the life space areas (Collia et al., 2003). Even moving around with motorised vehicles requires physical ability to walk at least short distances and to get in and out of the vehicle. Motorised transport can reduce physical activity when used as a substitute for active locomotion such as walking or cycling. However, it can also enhance physical activity by compensating for eventual deficits in physical function and providing older people with more possibilities to participate in various activities (Baker et al., 2003). Mobility has been measured by several methods with different approaches. For example, by evaluating the participants ability to carry out activities of daily living, such as bathing, dressing and meal preparation or instrumental activities of daily living that involve spatial movement for activities, such as doing groceries or social visits (Clark et al., 1990). The mobility required to perform these tasks reflect motoric functions and coordination capabilities needed for home exercise. The evaluation of these measures can be used as a way to assess interventions to improve self-care and functional independence. Another way to study the mobility of older people is to determine risk factors for adverse consequences, such as falls (Cummings et al., 1995). The mobility assessments mentioned above fail to identify a key component of mobility: the spatial extent in which the participant travels in. Mobility is more than motoric function or coordination capabilities. It also includes travelling in, around and outside the house as well as attending social activities of everyday life. The mobility of an older person may be a reflection of several environmental factors: weather, neighbourhood crime rate or residential location; the persons resources, a vehicle ownership, public transport accessibility; or the intrapersonal factors for example like functional health, cognitive status, depression or education (Székely et al., 2011). One approach to measure spatial mobility is to assess it with subjectively self-recorded activity diaries. Subjectively measured methods involve a time consuming effort from the participants. Moreover, the accuracy of the self-reports may differ due to the fact that people struggle with quantitative estimates, such as time spent or distance travelled (Fillekes et al., 2019c). May et al. (1985) introduced the *life space diary* in 1985 where participants recorded their activity over a period of four weeks. Life space is an area that describes where participants have moved within a given time period (e.g., within a day). The life space is divided in five concentric levels/zones: *Bedroom*, *rest of the dwelling*, *garden/courtyard*, *block of the dwelling*, *area across a traffic-bearing street*. All participants recorded their movement in all these different levels during the day. Since 1985 many adaptions of the life space diary have been made and are still used in research. One of these adaptions is shown in Figure 2.1.

Székely et al. (2011) introduce the *Life Space Questionnaire* (LSQ) to characterize the mobility of older adults, to identify mobility patterns and to examine changes in mobility life space due to the loss of physical and cognitive functions. In recent years, data collection with GPS data loggers has gained attention. With GPS logging, mobility can be objectively recorded, eliminating the need for time-consuming work by participants. The data collected allows a better comparability, as the data is collected under the same circumstances (Klous et al., 2019). Objectively measured activity can be assessed by GPS-based systems which consist out of an interpretation and a validation process. GPS data loggers record the exact location and time, with an accuracy that could not be matched by traditional (subjective) methods (Bohte and Maat, 2009). Li-Tang et al. (2015) investigate the association among older people between reasons to go outdoors and objectively measured walking activity in different life space areas.



Name: | Date:

These questions refer to your activities just within the past month.

LIFE-SPACE LEVEL	FREQUENCY					INDEPENDENCE	SCORE
During the past four weeks, have you been to . . .	**How often did you get there?**					**Did you use aids or equipment? Did you need help from another person?**	Level X Frequency X Independence
Life-Space Level 1. . . **Other rooms of your home besides the room where you sleep?**	Yes 1 / No 0	Less than 1 /week 1	1-3 times /week 2	4-6 times /week 3	Daily 4	1 = Personal assistance 1.5 = Equipment only 2 = No equipment or personal assistance	
Score	1 x	4			x	1.5 =	6 *Level 1 Score*
Life-Space Level 2. . . **An area outside your home such as your porch, deck or patio, hallway (of an apartment building) or garage, in your own yard or driveway?**	Yes 2 / No 0	Less than 1 /week 1	1-3 times /week 2	4-6 times /week 3	Daily 4	1 = Personal assistance 1.5 = Equipment only 2 = No equipment or personal assistance	
Score	2 x	4			x	1.5 =	12 *Level 2 Score*
Life-Space Level 3. . . **Places in your neighborhood, other than your own yard or apartment building?**	Yes 3 / No 0	Less than 1 /week 1	1-3 times /week 2	4-6 times /week 3	Daily 4	1 = Personal assistance 1.5 = Equipment only 2 = No equipment or personal assistance	
Score	3 x	2			x	1.5 =	9 *Level 3 Score*
Life-Space Level 4. . . **Places outside your neighborhood, but within your town?**	Yes 4 / No 0	Less than 1 /week 1	1-3 times /week 2	4-6 times /week 3	Daily 4	1 = Personal assistance 1.5 = Equipment only 2 = No equipment or personal assistance	
Score	4 x	2			x	1 =	8 *Level 4 Score*
Life-Space Level 5. . . **Places outside your town?**	Yes 5 / No 0	Less than 1 /week 1	1-3 times /week 2	4-6 times /week 3	Daily 4	1 = Personal assistance 1.5 = Equipment only 2 = No equipment or personal assistance	
Score	0 x				x	=	0 *Level 5 Score*
						TOTAL SCORE (ADD)	35 *Sum of Levels*

Figure 2.1: Example of a self-reported life space diary adapted from May et al. (1985) excerpted from Peel et al. (2005).

2.2 Mobility, Activity and Social Interaction Study

How healthy older adults structure their daily lives in terms of activities is the research question of the ***MO**bility, **A**ctivity and **S**ocial **I**nteraction **S**tudy* (MOASIS). Psychological functioning is characterized by multidirectional trajectories of change and stability in later stages of life development (Röcke et al., 2018). The project represents a collaboration between lifespan psychologists, gerontologists and geographic information scientists. The study aims to collect rich within-person profiles of activities, performances and experiences of daily living and to assess the context of the activities. Furthermore, it aims to develop interventions to maintain health and to gain insights into how QoL can be improved in old age (Röcke et al., 2018). For this study, a costum-built single mobile sensor is developed, the uTrail. GPS and accelerometer data as well as sound recordings are gathered in order to get more objective information on spatial behaviour, physical activities, and social interactions. 161 community-dwelling older adults, aged 65 and over, have participated in the study and recorded their daily life movements across 30 days with the uTrail (Röcke et al., 2018). The MOASIS project is one of the national case studies, that highlight future pathways to address data gaps related to global healthy aging. The gathered information of older adults about their intrinsic capacities (incl. mental and physical abilities) and the spatial movement (collected with the uTrail) can be used to investigate the association between health related aspects and mobility behaviour. Moreover, it is possible to get insights for what reasons the participants move within a certain life space area.

World Health Organization (2020) define in their report healthy aging as the following: healthy ageing is understood as the process of developing and maintaining the functional ability that promotes well-being in old age. Functional ability includes five key domains: ability to meet basic needs; 2) to learn, grow and make decisions; 3) be mobile; 4) ability to build and maintain relationships; and 5) and contribute to society. Functional ability integrates the intrinsic capacity of the individual, the environment in an which an individual lives in and the way in which people interact with their environment. Intrinsic capacity encompasses all the mental and physical capacities a person can access and includes the ability to walk, think, see, hear and remember (World Health Organization, 2020).

2.3 Transport Mode Detection

2.3.1 Transport Modes

In recent decades, travel modes and travel patterns have become more complex as the population massively increased, and policy makers have demanded more detailed information. For a growing population, transportation is one of the most important challenges because it is an inevitable aspect of daily life (Bohte and Maat, 2009; Rasmussen et al., 2015). Travel patterns are affected by many factors in time and space: part-time work, homework, automation, and the increasing number of double-income families, family diversity, and number of cars per household. Due to the raising complexity of travel behaviour, current research on travel behaviour is focused on trip chains, complete daily and weekly activity patterns, and the relationship between detailed levels of spatial structure and travel behaviour (Bohte and Maat, 2009). Regional planning institutions have been relying on household travel diary surveys to gather data for transport modelling since the 1970s. In the early days of transportation planning, a large amount of data was collected through face-to-face interviews with families. The size of these samples contained usually 1-3% of the population. Another method in travel surveys is to examine the non-response rates with a computer telephone survey. A typical computer telephone survey usually produces a total response rate of about 36% (Stopher and Greaves, 2007). Telephone surveys were gradually becoming more difficult since more and more families rely more on mobile phones instead of fixed phones. Since most of the current ethical survey standards do not allow the use of mobile phones to conduct surveys, households are more difficult to reach and the quality of the data has been questioned by validation using GPS (Tuckel and O'Neill, 2002). The use of GPS data will further be discussed in the next chapter. A broad classification of transport modes is, for example, active (non-motorized) versus passive (motorized). The latter can be divided in public and private transport modes (Boissy et al., 2018). The active transport modes (biking, walking) are more health-beneficial (Carlson et al., 2015).

2.3.2 Transport Mode Detection using Global Positioning Systems (GPS) Data

The US Department of Defense developed GPS, a space-based positioning, navigation, and timing system. It originated in the late 1960s and early 1970s and is based on the research of the U.S. Air Force. GPS is widely known as a satellite navigation or a satellite positioning system, providing signals for geolocation, safe and efficient movement, measurement, and other objects anywhere from the surface of the earth to the geostationary orbit. In May 2000, the importance of these measures were significantly enhanced by the US government with the termination of selective availability accuracy degradation of the GPS signal transmissions (McNeff, 2002; Michael et al., 2006). In recent years, GPS-based technology has proven its value in collecting travel and activity data. Professional organizations are currently discussing the possibility of using GPS data to replace traditional measurement methods such as travel diaries or telephone surveys. With GPS latitude, longitude, speed, heading and altitude can be recorded (Du and Aultman-Hall, 2007). Feng and Timmermans (2013a) state, that some people believe that GPS technology reduces the burden on the participants as well as on the researchers and the quality of the data is considered to be more accurate than traditional methods. However, the traditional survey methods do not necessarily apply to all aspects of travel and activity diaries, as transportation and activity methods must be calculated based on GPS data (Feng and Timmermans, 2013b). Earlier studies have developed imputation methods, including ad hoc rules (Du and Aultman-Hall, 2007), rule-based (Gong et al., 2012; Kasahara et al., 2017), learning-based algorithms (Moiseeva et al., 2010) and regression models (Rudloff and Ray, 2010). The named methods are only partially correct in determining the means of transportation and the purpose of the activity. All these methods are based on speed and time information extracted from GPS tracks.

In some cases, these traces may even contain errors. For example, when traveling underground, GPS data can be incomplete or inaccurate, making it difficult to correctly assume certain aspects of movement and activity patterns. In addition, in some cases, the speed of use can cause classification errors. If the measured or calculated speed is kept within a range that is valid for several modes of transportation, no algorithm can accurately distinguish the modes of transportation based on

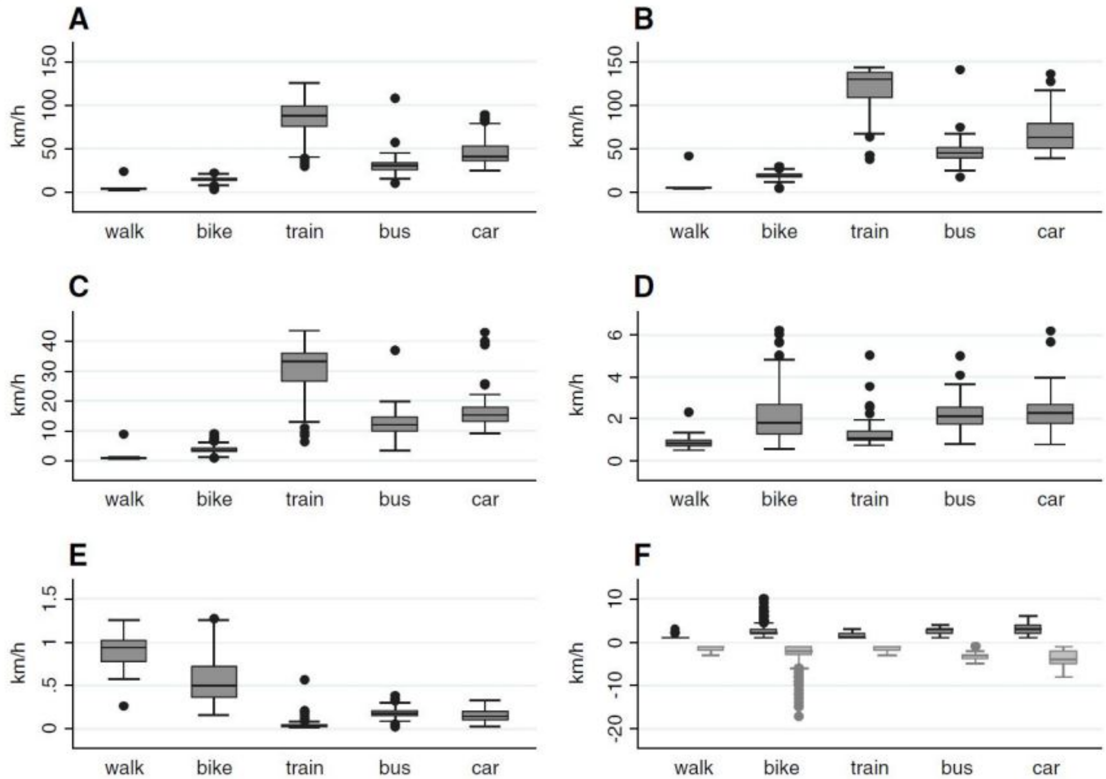


Figure 1 Speed metrics. Speed metrics per sequence for each type of transport mode, for sequences of at least one minute duration; Panels **A**: Mean; **B**: 95th percentile of speed; **C**: Standard deviation (sd); **D**: Rate-of-change (RCM); **E**: Standardized rate-of-change (RCMs) metric, **F**: Acceleration (positive values) and deceleration (negative values).

Figure 2.2: Speed metrics for different modes of transportation excerpted from Huss et al. (2014).

this information alone. In practice, this usually occurs in fast and slow cycling, buses and cars on crowded streets, trams, or light rails (Feng and Timmermans, 2013a). Figure 2.2 shows the diversity of the speed patterns across the evaluated transportation modes. A substantial strength of agreement is achieved and increased further when the motorised transport modes are summarised into one category. The median speed of all transportation modes is increased, if the duration of the trip is at least one minute (Huss et al., 2014).

2.3.3 Rule-Based Detection

In order to reduce the burden on the participants as much as possible, rule-based algorithms are developed, that use a combination from *Geographic information System* (GIS) data and data logs from the GPS loggers that were carried by the participants. A rule-based algorithm, which automatically processes GPS and GIS data to determine five modes is used by Gong et al. (2012). The algorithm combines GIS data (such as street centre lines, bus routes and stops, and subway lines) with GPS data to detect the transport modes and a promising 82.6% accuracy is achieved. Bohte and Maat (2009) introduced an architecture of a GPS-based system to detect transport modes and measure travel time and distance. Interpretation and validation are the two main processes in a GPS-based transport mode detection system. In Figure 2.3, the rule-based framework is shown. Firstly, unreliable track points are removed, and the data is divided into different trips. The defined threshold for a stop is 3 minutes. This threshold detected by Wolf et al. (2001) and resulted in the best prediction of the trip mode detection. In order to determine the trip purpose, GIS data is used. Lastly, the travel modalities are determined. Using average and maximum speed calculations, travel modes are defined as walking, cycling, or driving (Bohte and Maat, 2009).

1. Removing unreliable trackpoints and the division into trips	
1a	IF distance between trackpoint and previous trackpoint < 10 m THEN remove trackpoint[a]
1b	IF duration between trackpoint and previous trackpoint ⩾ '00:03:00' THEN split track[a]
1c	IF speed_trackpoint > 200 km/h THEN remove trackpoint
1d	IF adjacent trips are within same shopping centre polygon THEN merge trips
1e	IF speed_trackpoint < 5 km/h AND duration between trackpoint and previous trackpoint > '00:01:00' THEN trackpoint = trackpoint_garbage
	IF 3 * nr trackpoints_garbage within trip > nr trackpoints within trip THEN remove trip
1f	IF $\sqrt{((\text{trip xmax} - \text{trip xmin})^2 + (\text{trip ymax} - \text{trip ymin})^2)}$/triplength < 0.3 THEN remove trip
1g	IF nr trackpoints within trip < 4 THEN remove trip
2. Set the category of a trip	
2a	IF distance between trip end and POI < 50 m THEN set category = category POI ('shopping', 'recreation', 'culture', 'medical', 'kids' or 'railwaystation')
2b	IF endpoint trip is within railway station polygon THEN set category = 'railwaystation'
2c	IF endpoint trip is within shopping centre polygon THEN set category = 'shop'
2d	IF distance between home respondent and endpoint trip < 100 m THEN set category = 'home'
2e	IF distance between work respondent and endpoint trip < 100 m THEN set category = 'work'
2f	ELSE set category = 'unknown'
2g	IF distance between trip end and trip end with known category < 50 m AND category trip = 'unknown' THEN set category = known category
3. Set the modality of a trip	
3a	IF average trip_speed < 10 km/h AND max trip_speed < 14 km/h THEN set modality = 'foot'
3b	ELSE IF average trip_speed < 25 km/h AND max trip_speed < 45 km/h THEN set modality = 'bicycle'
3c	ELSE IF average trip_speed < 200 km/h AND THEN set modality = 'car'
3d	IF trackpoint is within railarea[b] THEN trackpoint = railpoint
	IF nr trackpoints within trip ⩾ 20 AND max trip_speed > 20 km/h AND 2 * nr railpoints within trip > nr trackpoints within trip THEN set modality = 'train' AND set category = 'railwaystation'
4. Merge and add train trips	
4a	IF modality adjacent trips = 'train' THEN merge trips
4b	IF distance between endpoint previous trip and railway station < 200 m AND general direction of previous trip is towards the station AND distance between startpoint next trip and railway station < 1500 m AND general direction of next trip is away from the station AND modality previous trip OR modality next trip = 'bike' OR modality previous trip OR modality next trip = 'foot' AND duration trip > '00:03:00' AND triplength > 5000 m THEN create new trip AND set modality = 'train' AND set category = 'railwaystation'

Figure 2.3: Rules used in the interpretation process to detect transport modes (Bohte and Maat, 2009).

After the validation process, the described GPS-rule based transport mode classification system achieved a 70% accuracy of correctly derived trips (Bohte and Maat, 2009). The model reaches its limits if, for example, the average speed and maximum speed of train and car trips in crowded cities are identical. In order to differentiate between various modes of transport in this kind of situation, a method of combining GPS data with GIS maps has been developed. In the method described by Tsui and Shalaby (2006), the average and maximum speeds and accelerations observed during the trip are recorded to calculate the activity time and transportation mode used from the records. In more than 90% of the cases, the means of transportation used were correctly determined (Tsui and Shalaby, 2006).

2.4 Health

2.4.1 Quality of Life

Over the last decades, the term *Quality of Life* (QoL) has become popular in medicine and health care. Originally, the term was an expression used to criticise policies that are aiming at an unlimited economic growth. Long-term effects (resource exhaustion) and side-effects (pollution) are especially pointed out and therefore QoL expressed a concern for the *quality of the external conditions for living* (Musschenga, 1997). In medicine, the term is considered regarding health decisions, for example effectiveness of medical treatments. The success of medical treatments is assessed by the extent to which health is fully restored or years of life are extended (Musschenga, 1997). *The World Health Organisation Quality of Life Group* defines the QoL as: *"an individual's perception of their position in life in the context of the culture and value systems in which they live and in relation to their goals, expectations, standards and concerns. It is a broad ranging concept affected in a complex way by the person's physical, health, psychological state, level of independence, social relationships, and their relationships to salient features of their environment"* (World Health Organization Quality of Life, 1993). It is well accepted that there is an important association between mobility and the QoL of older people. Decreasing mobility is related to a substantial reduction of well-being (Metz, 2000). For example, a person who is no longer able to drive a car safely or has an age-associated disability tends to have limited physical movement (Metz, 2000). Marottoli et al. (1997) concluded that driving attitude is one of the strongest predictors of enhanced depressive symptoms in older people. The effectiveness of interventions aimed at improving mobility is difficult to assess. Metz (2000) described different types of relevant interventions that influence the provision of transport: services used by older people, for example, through subsidy or regulation; the availability of supportive technologies which assist the movement of people with more severe mobility disabilities (Cowan et al., 1999); the availability of health and social services. A number of studies have shown that QoL is lower if people cannot move freely due to physical limitations or due to restrictions imposed on them by their environment (Breeze et al., 2005; Golant et al., 1979; Gabriel and Bowling, 2004).

2.4.2 Metacognition and Cognitive Failures

In psychology, the question of what individuals know about their own thinking is as old as time (Ach, 1905). Cavanaugh and Perlmutter (1982) state in their study, that any characteristics of methodological introspection are evident in the conceptualisations and methodologies of metamemory: conceptually, metamemory is based on the premise that memory is amenable to inspection and analysis by the memorizer; methodologically, self-report is the primary method of measuring knowledge of memory. Several studies have identified age disparities in favour of younger adults when metamemory is operationalized as, for instance, the capacity to assess the demands of the memory task, the anticipation of retrieval prior to exposure to the memory task, the readiness for retrieval, and the spontaneous use of effective acquisition tactics (Bruce et al., 1982). The *Metamemory in Adulthood* (MIA) questionnaire is used for examination of metamemory (Dixon et al., 1988). Younger adults perform better than older adults according to the MIA questionnaire. It is possible that metamemory as a construct is an even more multidimensional entity than assumed. Metamemory could consist out of several relatively independent modalities. Further elaboration of the technical details of a multidimensional construct and expansion of its empirical and theoretical relevance to cognitive development in adulthood are warranted (Dixon and Hultsch, 1983). Hertzog and Hultsch (2000) identify and address three main categories of metacognitions: Understanding cognition and cognitive functions, monitoring the present state of the cognitive system, and beliefs about cognition. They indicate that older people have relatively intact monitoring skill. Although, the older adults do not always use monitoring effectively to control learning and to maintain knowledge of effective strategies for cognitive performance (Hertzog and Hultsch, 2000).

2.4.3 Cognitive Map

A cognitive map contains spatial information about the environment, knowledge of potential and possible travel routes, including place and route identity, location, distance and direction (Downs and Stea, 1977). Travel experience and wayfinding are the primarily sources for developing cognitive maps (Golledge and Gärling, 2004). Systematic differences in cognitive maps and hence accessibility by variations in the experience of travel by different modes. The image of the city is shaped by whether the participant typically moves through the city on foot, by bus or train, or as an passenger. Slower speed interactions with places are involved while walking or bicycling than travelling by car or train. As well, walking, cycling and driving demand that the traveller actively makes wayfinding decisions throughout the journey (Mondschein et al., 2010). Spatial context decisions are possible by individuals with the combination of qualitative and spatial information (Suttles and Suttles, 1972). It is tempting to interpret a cognitive map as a mental version of a cartographic map (Golledge et al., 1999). However, between cognitive mapping and a cartographic representation of space is no simple one-to-one relationship. The cognitive map is rather a cognitive construct for which a cartographic map is only a metaphor (Downs, 1981). Similarly, other personal skills influence spatial learning, including spatial-sequential memory, topological knowledge, motor abilities, spatial awareness and general information-processing skills. Such abilities are partly inborn, but can be developed and enhanced through training and use (Golledge, 1997).

2.4.4 Sleep Quality

Many older adults experience difficulty in initiating sleep, are feeling tired throughout the day, are having trouble staying asleep or are waking up too early (Foley et al., 1995). Health and functioning are significantly impacted by subjective and objective sleep problems (Bliwise, 2000). Williams et al. (2007) state that self-reported sleep quality is assumed to generally overestimate the abnormalities that can be measured in the sleep laboratory. Nevertheless, self-reported sleep quality established a clear association between sleep quality and health outcomes; bad sleep quality results in poor health outcomes (Williams et al., 2007). There is also a strong correlation between sleep quality and QoL (Tel, 2013).

2.4.5 Control Variables

Control variables are factors that are added to the research analysis in order to rule out alternative explanations for possible outcomes or to minimize error terms and increase statistical significance (Schmitt and Klimoski, 1991; Schwab, 2013). Essential is the identification and isolation of factors that explain and predict the phenomena of interest, while controlling other relevant variables that may externally influence the relationships (Bernerth and Aguinis, 2016).

Age

The influence of age on subjective quality has been studied in the general population. Studies showed that age influences subjective perceptions of QoL. Older people expressed higher levels of satisfaction than younger people (Andrew and Withey, 1976; Campbell et al., 1976). Age has also been observed to have an effect on the objective living conditions and social integration of individuals with mental illness (DeSisto et al., 1995). The findings of Harding et al. (1987) have shown that age may contribute to social integration. As people grow older, they experience a number of challenges with regard to their outdoor mobility. The functional and cognitive changes that are associated with ageing often result in a limited outdoor mobility in later life (Zandieh and Acheampong, 2021). Older adults are possibly no longer able to drive and become more prone to accidents (Anstey et al., 2005; Bayam et al., 2005). Changes due to ageing also reduce the ability of older adults to cope with environmental limitations in walking and cycling (Black and Street, 2014). As a result, their spatial mobility range also reduces within their residential neighbourhoods (Glass et al., 2003).

Net income

This desire to remain engaged and connected to the outside world allows older people to physically get out and meet others and in this way, fulfill social and physical roles, and maintain their inner mental and emotional wellbeing (Metz, 2000). Chetty et al. (2016) and Koster et al. (2006) state that low-income of older adults have a greater proneness to reduced mobility (both physiological abilities and travel behaviour) than those with higher incomes. The desire of the participants to be involved and stay connected to the outside world and their ability to be resourceful enabled them to preserve a sense of independence and self-confidence (Franke et al., 2019). Franke et al. (2019) state that participants preferred grocery shopping multiple times a week in order to be able to take transportation. This resourcefulness helps also in other aspects, such as to maintain autonomy in daily tasks regardless of adverse circumstances (Rosenbaum, 1990), to improve self-assessed physical health (Zauszniewski, 1996) or to have a positive affect on coping skills which can eventually lead to a longer, healthier life (Jang et al., 2004).

2.5 Problem Statement and Research Aims

With the lack of an established association between mobility and QoL, the effectiveness of measures to improve mobility is difficult to assess (Metz, 2000). The research aim of this thesis is to get insights about the association of mobility behaviour of older people and their psychological well-being. For this purpose, a GPS-based analysis for detecting (objectively measured) mobility activity will be developed. In addition, a correlation between the detected mobility behaviour and the health conditions evaluated in the MOASIS project will be investigated.

First, there are two ways to measure mobility activity: subjectively with self-reports or objectively with GPS-based measurements. Activity diaries are used to assess the outdoor mobility and behaviours of participants. Li-Tang et al. (2015) used an open-ended questionnaire for a participant to self-report reasons to go outdoors and to track the corresponding life space area that she/he moves around. In order to overcome the limitations of self-reports mentioned in the theoretical background, objectively measured outdoor mobility methods are implemented. Bohte and Maat (2009) developed a GPS-based system with GIS data to collect travel times, transport modes, and trip purposes. After the validation, a classification accuracy of 43% on trip purpose and 70% on transport modes has been achieved. In this thesis, a GPS-based framework is developed to improve the assessment of outdoor mobility (trip purpose and transport mode). Furthermore, the associations between health related aspects and outdoor mobility described in above sections are investigated with the gathered information by the MOASIS questionnaire.

2.5.1 Research Questions and Hypotheses

The proposed research questions are grouped thematically. The first research questions (RQ) are focused on the assessment of the spatial and mobility behaviours of the participants. The second research questions cover the variables of interest out of the MOASIS project, sleep quality, cognitive failures and metacogniton, with the aim of linking these health related aspects to the mobility behaviours discovered by the first group of research questions.

Research Question 1: How do the detected mobility behaviour vary across different life space levels?

- **Hypothesis 1.1:** Transport modes of an older adult can be inferred based on GPS data.
- **Hypothesis 1.2:** Types of reasons to go outdoors vary with different life space levels.

Research Question 2: What is the association between the detected mobility and different health related aspects?

- **Hypothesis 2.1:** Participants with subjectively good daily sleep quality tend to have an increasing walking time, compared to those with not a good sleep.
- **Hypothesis 2.2:** The positive relationship between metacognition (low/high) and the number of new places visited is likely to be stronger among participants with low cognitive failures, compared to those with high cognitive failures.

2.5.2 Expected Results

The main contribution of this thesis is a proposed methodology to assess the objectively measured daily traveling activities and to get insights about the interplay between health and mobility behaviour. The developed framework of the mobility activity can potentially be applied to GPS-based individual behavioural studies, and further contribute to gaining insights into spatial behaviours of older adults and its relevance to the QoL in later life. Following the expected results of the hypotheses (H) are outlined.

RQ 1 - Objectively measured mobility behaviour

H 1.1: Transport modes of an older adult can be inferred based on GPS data.

This hypothesis provides the foundation and the initial basis for the subsequent hypotheses. Based on this analysis, the GPS data is enriched with related transport mode information. The knowledge of the transport mode provides valuable insights into the mobility behaviour of the participants. Insight regarding travel behaviour and travel demand is of ongoing importance for transport communities and agencies in any country (Edwards et al., 2009). Attempts are being made to automatically infer the means of transport from positional data, such as that collected with GPS devices (Bolbol et al., 2012). The applied method intends to be globally applicable. Therefore, the developed algorithm requires to be highly adjustable and parameterisable. The rule-based method fulfils these requirements completely. Previous Bohte and Maat (2009) and Gong et al. (2012) applied the same method and achieved an observed accuracy of 70% and 78-86%, respectively. It is expected to be capable of differentiating between the modes of walking, car and public transport.

H 1.2: Types of reasons to go outdoors vary with different life space levels.

One way to improve QoL is by going outdoors. Social interactions, relations and activities are important factors for a good QoL and are mostly outside the home (Li-Tang et al., 2015). Webber et al. (2010) describe outdoor mobility as the ability to move either independently or with assistance (e.g., assistive devices) in different life space areas. Life space is defined as the area where a person moves within throughout the day. Recent studies have investigated the association between physical activity and the life space area and detected a relationship between higher level of physical activity and the expansion of life space area (Baker et al., 2003; Li-Tang et al., 2015). Rantakokko et al. (2016) outlined that this relationship correlates with better QoL. To participate activities outside the home it is necessary to overcome spatial distances. Mobility thus becomes a basic prerequisite for participation in social relationships and activities (Gagliardi et al., 2007; Mollenkopf et al., 1997). Lifestyle regularity seems to increase over the lifespan in response to biological and psychosocial transitions and may reflect an adaptation to age-related changes. Regular behavioural rhythms may be beneficial for prolonged good health and well-being (Monk et al., 1997). Different people have varying patterns in their lifestyle regularity. Some people's daily routines are very regular: bedtime, eating and other behaviours are predictable and performed at the same time every day. Others are more "free-wheeling" and have little pattern or predictability about the timing of these daily events (Monk et al., 2006). The concepts of *Life Space*, outdoor mobility and physical activity are related, but it is unknown if walking activity varies according to reasons to go outdoors into different life space areas (Li-Tang et al., 2015). Reasons to go outdoors, specifically being in natural physical environments is associated with physical and psychological well-being (Pennebaker and Lightner, 1980; Pennebaker and Brittingham, 1982). De Vries et al. (2003) outline the positive effect of neighbourhood green spaces on self-reported health. Older adults have a wide range of reasons to go outdoors and shopping is the most common reason to go outdoors (Li-Tang et al., 2015). Li-Tang et al. (2015) state that reaching both the *Life Space Level* (LSL) of the neighbourhood and the greater area is associated with the highest walking activity. It is therefore assumed that there are differences between the types of reasons to go outdoors and the reached LSL.

RQ 2 - Association between the detected mobility and health related aspects

H 2.1: Participants with subjectively good daily sleep quality tend to have an increasing walking time, compared to those with not a good sleep.

Previous research has focused on the effect on walking with friends and regular longer walking on sleep quality and duration. Mostly experimental studies have investigated this association in relation to specialised populations: participants with depression, cancer and Alzheimer disease, nursing home residents, insomnia sufferers or women in transition to menopause(Elavsky and McAuley, 2007; Lam et al., 2015; Passos et al., 2012; Richards et al., 2011; Shih et al., 2017). In summary, the results indicate that walking can increase sleep quality in certain populations and situations (Sullivan Bisson et al., 2019). Older age is usually associated with gait abnormalities and a clinical diagnosis of gait deterioration is not uncommon in older people (Rosso et al., 2013). Agmon et al. (2016) outline the association between lower sleep efficiency with decreased gait speed. Moreover, Agmon et al. (2016) stress that abnormal sleep behaviour is linked to increased gait variability, which is related to an enhanced risk of falls. The loss of independence and a significant reduction in QoL is associated with the gait decline (Hartholt et al., 2011; Terroso et al., 2014). Sleep is seen as an important predictor of QoL and as an essential factor for adults in achieving work-life balance and life satisfaction (Grandner, 2017). Mindful walking has been identified as a potential intervention strategy to increase mental health and enhance well-being in adults (Yang and Conroy, 2019). Inconsistent findings where find by Kishida and Elavsky (2016); Youngstedt et al. (2003). They detected no evidence for within-person associations between walking and sleep in healthy, physically active adults.

Considered collectively, these contradictory findings justify further research on this topic. Therefore, the investigation of the association between sleep quality on walking can provide more prove in this manner.

H 2.2: The positive relationship between metacognition (low/high) and the number of new places visited is likely to be stronger among participants with low cognitive failures, compared to those with high cognitive failures.

Cognitive maps, respectively cognitive capacities are compulsory for navigating the world (Downs and Stea, 1977). Nonetheless, without sufficient spatial movement capacities, difficulties may arise, such as running in circles and getting lost (Yamasaki et al., 2018). Navigating through space requires an awareness of the current surroundings, which requires mental efforts such as assessing and verifying the present location (Lindberg and Gärling, 1983). This mental efforts and cognition capacities may be reflected in the assessed self-reports conducted in the MOASIS about metacognition and cognitive failures.

All places have different purposes and the person's needs, commitments and preferences can be described with the visited places (Gonzalez et al., 2008). Spatial behaviour and decision-making demand knowledge about the urban environment, including the possibilities and means available to reach it. Therefore, differences in spatial knowledge can lead to different degrees of effective accessibility even though there are similar locations, demographics and other factors that are widely believed to influence travel behaviour (Mondschein et al., 2010). Eagle and Pentland (2009) state that the routine in daily life can be represented by only a few places. Although, a variety of places is visited. A high degree of regularity in mobility patterns is known to exist and that people spend most time in a few locations (Halepovic and Williamson, 2005). Non-routine places were characterized by Quadri et al. (2018) and summarized as follows: people can have an explorer's streak that makes them want to abandon routine and go to undiscovered places in the city. Individuals visit a significant number of non-routine places during the observation period; The acceptance to pay the cost for non-routine places is higher and the places are farther from home than the places that are visited frequently; During leisure time undertaking activities increase; The daily schedules differ to the specific day of the week; People are more likely to visit places that are related to shopping, food, and night life (Quadri et al., 2018). A general trend was observed among participants with dementia that they were likely to visit fewer places in the community and give up cognitively or socially demanding activities (Chaudhury et al., 2021; Mitchell and Burton, 2010; Wettstein et al., 2015). It is therefore assumed that older adults with better cognitive capabilities visit more and various places.

3.1 MOASIS Data

This thesis analysed GPS trajectories and health related aspects collected from the *Mobility, Activity and Social Interaction Study* (MOASIS). The University Research Priority Program (URPP) "Dynamics of Health Aging" of the University Zurich conducted the MOASIS project. The goal of the MOASIS project is to examine how activity profiles (mobility, physical activity, and social activity) of healthy older adults in daily life look like, and extract the significance of the health relevance of activity profiles by linking them to interindividual differences in psychological functioning and health outcomes (Röcke et al., 2018). Each participant completed a comprehensive assessment of their physical health, social interactions, living circumstances, metacognition, sleep quality, cognitive failures, and subjective well-being. In this thesis, the collected GPS uTrail data and self-report measurements in MOASIS data on age, net income, daily sleep quality, metacognition and cognitive failures are further investigated. In the following section the different data availability is outlined, and subsamples are presented.

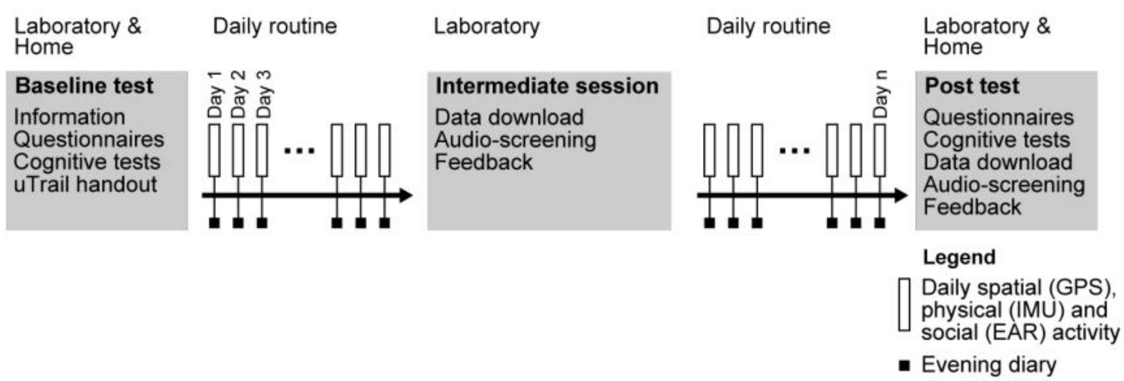


Figure 3.1: Study design of MOASIS excerpted from Bereuter et al. (2016).

Baseline tests, self-reports, evening diary complemented by the ambulatory assessment of the physical, spatial and social activity with uTrail are the study design of MOASIS (Figure 3.1). The uTrail is carried on a daily basis to conduct the activity (Bereuter et al., 2016).

3.1.1 MOASIS uTrail Data Description and GPS Data Processing

uTrail meta information

Participants carried a wearable mobile sensor device called uTrail in their everyday life (Figure 3.2). This tracker is specifically developed for the MOASIS project and employed to measure the spatial activity with GPS, physical activity with a 3-axis accelerometer and social interaction with a microphone (Bereuter et al., 2016). The participants were asked to wear the uTrail device around their waist at all times during the project period except at nights where the device was recharged. Due to measurement errors, the quality and quantity of GPS data varies greatly among participants. GPS data contain geographic coordinates (i.e., longitude, latitude), time (in the time zone of Universal Time Coordinated, UTC), elevation and the number of satellites. It also reports whether the device is being charged or the GPS signal is lost (Röcke et al., nd).

	Sensor	Variable	Sampling rate
Spatial mobility	GPS	timestamp, latitude, longitude	1 / sec
Physical activity	IMU	timestamp, Acceleration (x,y,z)	3 / sec
Social interaction	EAR	timestamp, sound samle (30 secs)	1 / 12.5 min

Figure 3.2: uTrail mobile sensor used in the MOASIS project excerpted from Bereuter et al. (2016).

GPS data (pre)processing

This thesis adopted the (pre)processed uTrail GPS data, produced by Kim et al. (2021). Kim et al. (2021) processed MOASIS uTrail GPS data with several procedures: 1) data filtering, 2) participant validation, 3) speed outlier removal, 4) home detection, and 5) stop-move detection, as follows.

Data filtering

First, raw GPS data were filtered by date and time range between 3:00 am (in the local time zone) on the next day of the first lab visit and 3:00 am of the returning lab visit day, resulting in usually multi-day 'real-life GPS data' per participant. In splitting multi-day GPS data into daily segments, the concept of functional midnight (i.e., 3 am) was employed assuming that activities are over at 3 am for the most people (Schneider et al., 2013; Fillekes et al., 2019a; Kim et al., 2021).

Participant validation

Second, with the real-life GPS data, participant validation analysis was conducted in Kim et al. (2021) and 116 valid participants were extracted based on an 8-hour threshold on the duration of GPS recordings in each study day and the requirement of the minimum 3 days (at least 2 weekdays and 1 weekend day), in order to avoid potential biases introduced by a short period of observations, referring to Fillekes et al. (2019a).

This validation was an essential step for Kim et al. (2021) because, due to GPS measurement errors, the quality and quantity of GPS data varies greatly among participants and they calculated daily mobility indicators. In this thesis, 141 valid participants were selected without the 8 hours/day, 3 days/week, and 1weekend day requirements. Because the analysis in this thesis was analyzed not on a daily basis, but on a trip basis (e.g., trip purpose, transport mode, travel time). Moreover, the daily routines during the week and at the weekend are no longer so widely differing as the older adults are retired.

Table 3.1: Investigation of the available MOASIS uTrail data excerpted from Kim et al. (2021).

Description	**Participants (n)**
Possible participants	161
Cancelled	4
Quitted	5
No GPS recordings	10
Real-life GPS recordings	141
Real-life GPS recordings of at least 8 hours/day, 3 days, and 1 weekend day	116

Table 3.1 shows the results of the MOASIS participant validation analysis Kim et al. (2021): invalid participants and valid subsamples for further analysis. 161 participants were initially recruited for the MOASIS project, but 9 participants left the project. Among completed participants, no GPS data were recorded at all for 10 participants. After filtering GPS data, only 141 participants were valid.

Besides, the definition of valid participants may differ depending on a research question. For example, to control study day selection bias, one needs to check GPS data distribution over weekdays or weekend days.

GPS outlier removal

Out of the real-life GPS data, the GPS points with speed outliers were excluded. The speed outliers were detected if the speed between a GPS point and its previous GPS point is beyond 250 km/h in consideration of the maximum speed achieved by trains in Switzerland (Fillekes et al., 2019c).

Home detection

The MOASIS project treats participant's home address as a confidential information to protect their privacy. To infer each participant's home location, Kim et al. (2021) applied the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm (Ester et al., 1996) with two input parameters, the radius of 60 meters and the minimum number of points of 3, based on the first and last GPS fixes of each of his/her study days, in the same manner of Fillekes et al. (2019a). Among the detected clusters, three largest clusters were considered as potential home locations, and then, the home location with the most GPS points within 60 meters was finally determined as the participant's home location.

Stop-move detection

In each study day of each participant, GPS points were classified into a stop, a move, or an unassigned segments using the threshold-based stop detection algorithm devised by Montoliu et al. (2013). In this algorithm, three input parameters are used as thresholds: 1) the minimum duration of stop, T_{min}, (2) the maximum duration of time gap between stops, T_{max}, (3) the maximum

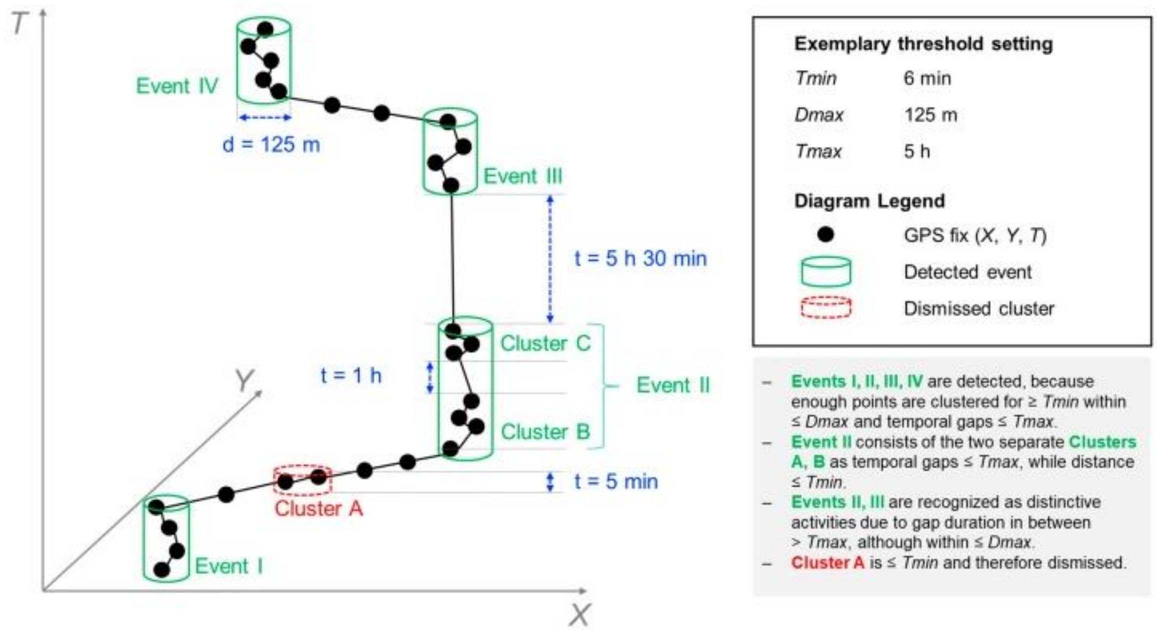


Figure 3.3: Schematic diagram of automatic activity location identification using spatial and temporal parameters excerpted from Fillekes et al. (2019b).

distance between consecutive GPS points , D_{max}. Kim et al. (2021) applied Montoliu et al. (2013) algorithm with $T_{min} = 5$ minutes, $T_{max} = 60$ minutes, and $D_{max} = 150$ meters to detect stops and moves. In Figure 3.3, an example of the estimation of stay points is shown excerpted from Fillekes et al. (2019b).

3.1.2 Self-report measurements in MOASIS

All used variables conducted in the self-report measurements in MOASIS are described. In Table (3.1.2) a summary of all available MOASIS data is shown.

Age and Net-Income

The baseline questionnaire of MOASIS includes questions concerning date of birth, sex, marital status, number of children, learned profession / education, current professional activity / date of retirement. Based on the baseline-questionnaire, the variables age and net income are used as control variables for the correlation analysis for the second research question.

Table 3.2: Self-report measurements in MOASIS to categorize the net income of participants.

Income Category	ID
Up to 3'000 Fr.	1
3'001 to 4'000 Fr.	2
4'001 to 6'000 Fr.	3
6'001 to 8'000 Fr.	4
8'001 to 12'000 Fr.	5
More than 12'000 Fr.	6

The question about the net income is personal and potentially incriminating. Therefore, the question is designed in a less objectionable way where the participant can select among broad net income categories (Cifaldi and Neri, 2013). In Table 3.2 the used categories to assess the net incomes is shown.

Metacognition and Cognitive Failures

The *Metamemory in Adulthood* (MIA) questionnaire is one of the most used methods to measure individual metamemory and is also applied as a questionnaire in MOASIS. The evaluation of the memory performance is assessed by the participants themselves (Dixon et al., 1988). The MIA questionnaire includes a Likert scale modified from a 5-point to a 7-point scale. Likert scale instruments are commonly used to investigate psychological constructs (Messick, 1989). Nemoto and Beglar (2014) outline the following advantages of Likert scales: data can be collected rather quickly from a large sample of participants; can deliver highly estimates of a person's abilities; data can be compared or combined easily with open-ended questionnaires or interviews. A Likert scale is always conceptualized from one extreme to another: small to large; negative to positive; low to high (Nemoto and Beglar, 2014).

Neutral category is not represented in the scale. This is due to the fact that a neutral category does not fit in a continuum of a scale. In the circumstance that a participant is not able to respond to some items, the participant should not answer. Missing answers to items do not pose a problem for modern approaches in psychological measurement (Nemoto and Beglar, 2014). The cognitive failures questionnaire is also conducted with a Likert scale and has modified ratings from 5-points

Table 3.3: Available participant information (MOASIS variables).

MOASIS variable	Participants (n)
age	153
net income	152
metacognition	153
cognitive failures	153

to 7-points, whereas 0 stands for *totally disagree* and 7 for *totally agree*. The questionnaire is about minor mistakes people make from time to time (Klumb, 1995). The available participant frequency is shown in Table 3.3.

Sleep Quality

The sleep quality is gathered by self-report measurements in MOASIS: *How was your sleep quality last night?* The assessment of the sleep quality is conducted each morning on a daily basis, in which each participant rates their last's night sleep quality from 0 (very bad) to 6 (very good). This item is created for the MOASIS project and is gathered with a Likert scale. In addition to sleep quality, the duration and detailed bedtimes were also recorded.

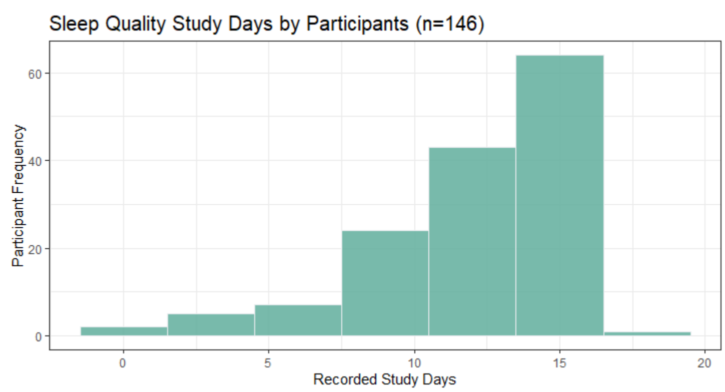


Figure 3.4: Frequency distribution of the participants' study days.

In Figure 3.4 the frequency of available sleep quality days by participants is shown. There are 146 out of 161 participants who recorded their sleep quality. Table 3.4 illustrates a brief summary of the available data. There are 1757 recorded sleep quality study days in total and subsamples of participants with different recorded minimum study days.

Table 3.4: Investigation of the available MOASIS Sleep Quality data.

Description	**n**
Sleep Quality Study Days	1757
Participants	146
Participants with 5 and more sleep quality days recorded	139
Participants with 10 and more sleep quality days recorded	116

3.2 Geographic Data and Information

Geographical data and information were used in the analysis to assess the reasons to go outdoors on the one hand, and as data input into the GPS-based system to detect the mode of transport on the other. Initially, data of the Federal Office for Topography swisstopo and federal Statistical Office were supposed to be used, but after first exploration the data turned out to be insufficient for the analyses. This is due to the fact that the information about the amenity or purpose of the building is not publicly accessible. The open source collaborative project OpenStreetMap (OSM) is suitable for further analyses, even though they need to be enriched with other GIS data.

3.2.1 Open Government Data

The majority of MOASIS participants live in the greater area of Zurich. Open data from administrative units and institutions of the Canton of Zurich (OGD) is free of charge. Anyone can access it, share it and use it freely. For the purpose of improving the quality of GIS data availability the OGD of the landuse of the Canton of Zurich is downloaded (OGD, 2021). In Table 3.5 the distribution by inferred residence locations are shown for all participants. The MOASIS project treats participant's home address as a confidential information to protect their privacy. Therefore, no specific locations are presented and only Cantons with at least 4 participants are shown. The percentages refer to the total number of participants. Canton Zurich has the most participants with 70 out of 141, which is almost 50%.

Table 3.5: Percentage and absolute numbers of participants (n=141) by inferred residence locations. Only Cantons with more than 3 inferred residence locations are shown.

Canton	Participants (n)	Participants (%)
Zürich	70	49.6
Aargau	13	9.2
Luzern	10	7.1
St. Gallen	8	5.7
Graubünden	7	5.0
Bern	6	4.3
Thurgau	4	2.8
Schwyz	4	2.8

3.2.2 OpenStreetMap

OSM is one of the most crowd-sourced and open-source collaborative projects in the world. In recent years OSM has become a serious alternative source for geodata (Arsanjani et al., 2015; Barron et al., 2014; Ramm et al., 2010). In the case of this thesis analyses it even outperforms Swiss state-funded GIS data. OSM data can be downloaded for free for every region in the world (OSM Planet, 2021).

All buildings of Switzerland are georeferenced in the OSM dataset but most of the data entries have no information about the purpose of the building. Only the following map features of the OSM data are included for the further data processing: building, amenity, craft, landuse, leisure, office, shop, sport, tourism. All available map features are documented on the wiki website of OSM (OSM Wiki, 2021). There are approximately 700'000 buildings with a specific purpose available and used for this analysis. The Federal Statistical Office reported about 1.7 million buildings with residential use (Bundesamt für Statistik, 2021). Therefore, the GIS data have room to improve.

3.2.3 Geocoding

In recent year, the availability of geographic data has resulted in a flexible and adaptive geocoding method (Wilson and Knoblock, 2007). Geocoding is a method for referencing data spatially. There are three different geocode indexes for location identification: nominal, ordinal, and cardinal (Dueker, 1974). Geocoding is used in this thesis for georeferencing addresses of grocery stores of the biggest retailers of Switzerland. Grocery shopping is one of the main reasons to go outdoors, even though this information is underrepresented in the OSM and OGD data. In Table 3.6 the retrieved addresses of the geocoding process in QGIS are shown.

Table 3.6: Retrieved addresses of Swiss retailers.

Retailer	**Branches (n)**	**Website for address information gathering**
Migros	731	filialen.migros.ch/de/
Coop	280	coop.ch/de/unternehmen/standorte-und-oeffnungszeiten.html
Lidl	97	tiendeo.ch/prospekte-kataloge
Aldi	164	tiendeo.ch/prospekte-kataloge
Volg	455	tiendeo.ch/prospekte-kataloge

The gathered addresses are geocoded in QGIS with the MMQGIS python plugin. With the nominal indexes (street names) and ordinal indexes (postal zip codes, numbered street names) as inputs, the georeferenced addresses are merged to the OSM data. Out of the 1727 retail addresses 1299 are successfully georeferenced.

3.3 Ground Truth Data

For the developed transport mode detection method in this thesis, the accuracy of this method has to be measured. For this purpose, ground truth data is used for the assessment of the accuracy of the inferences (Stopher et al., 2015). Isler (2018) focused in her master thesis on building a reference benchmark data set for transportation mode detection. This benchmark data set is used as the ground truth information for the transport modes detected in this study. The ground truth data were recorded at 16 different days in May and June 2018 with a sampling interval of every two seconds of GPS recordings.

3.4 Ethical Issues

The biggest concern is the information that can be retrieved and interpreted from the analysis of participant's GPS data and movements. With such information a lot about the participant's life can be revealed: workplace, political views (Protest participation), day routine (Michael et al., 2006). Michael et al. (2006) outline that most ethical issues are linked to the control aspect: suspected terrorists, employee monitoring, sex offenders and law enforcement. This control aspects arise a lot of unanswered questions. Does a company require the consent of their costumers to track their location and behaviour? Is the police force allowed to track a person if they expect an illegal activity? There is also a convenience use of GPS tracking. GPS tracking can be used to track individuals suffering from dementia. Due to the fact that it is difficult to keep a constant watch on individuals with a diagnosis of dementia. As a side effect the GPS tracking can lead to more freedom and independence and even allowing them a better QoL (Michael et al., 2006).

In this thesis the ethical framework is to respect the privacy of all participants. To do so, the gathered information with the uTrail sensor and the conducted information with self-report measurements in MOASIS are strictly separated. The information can only be linked with the participation ID. It is not allowed to move the data from the provided network. The data shown in this thesis is aggregated and it is not possible to reconstruct individual information and therefore it is not possible to identify individual information.

4.1 Workflow of the Analysis

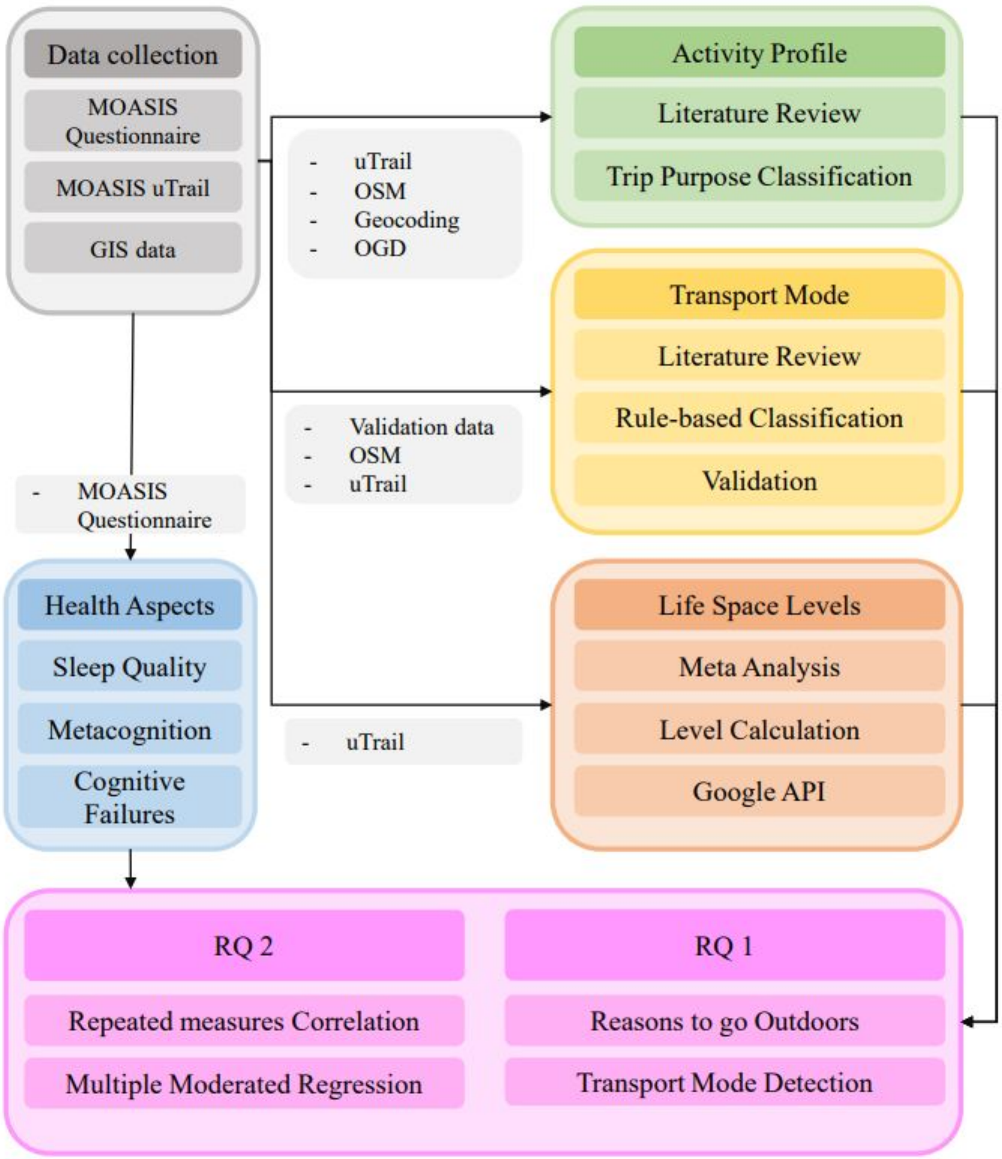


Figure 4.1: Workflow of the analysis of this thesis.

Figure 4.1 shows the workflow of the analysis of this thesis. First, the data collection is made. It includes the MOASIS related data and the gathered GIS data. Afterwards, the workflow shows the four major analysis blocks: *Activity Profile*, *Transport Mode*, LSLs and *Health Related Aspects*. Each block includes several steps which are part of the analysis. Finally, all parts are used for answering the research questions.

4.2 Life Space

4.2.1 Life Space Level (LSL)

In order to answer RQ 1.2, Life Space Levels (LSLs) are defined and constructed based on a meta-analysis of previous studies. There are 4 different frameworks used in the literature to assess the life space mobility with self-reports or interviewer (Taylor et al., 2015): The University of Alabama Life-Space Assessment (Baker et al., 2003); Life-Space Questionnaire (Stalvey et al., 1999); Nursing Home Life-Space Diameter; (Tinetti and Ginter, 1990); and the Life-Space at Home (Hashidate et al., 2013). All these questionnaires use between 4 and 9 scales to assess the LSLs and are used in other studies conducted in Mackey et al. (2014), Michael Parker DSW et al. (2002), Phillips et al. (2015), Sartori et al. (2012) and Hashidate et al. (2013). Figure 4.2 shows the conceptual design of the life space distribution assessment. The assessment of life space is based on a distribution range, categorized among different levels.

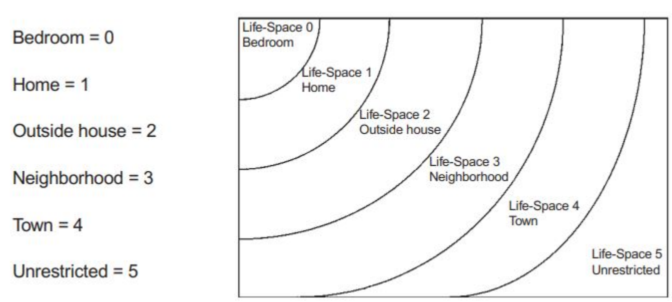


Figure 4.2: Conceptual framework of the life space distribution excerpted from Michael Parker DSW et al. (2002).

Table 4.1: Meta-analysis of life space levels used in existing studies.

Life space levels [km]	**0.1**	**0.15**	**0.2**	**0.3**	**0.4**	**0.5**	**0.8**	**1**	**3**	**5**	**8**
Fillekes et al. (2019c)		x						x			
Frank et al. (2007)								x			
Song et al. (2013)								x	x	x	x
Coulton et al. (2001)						x					
Nelson et al. (2006)									x	x	
Haney and Knowles (1978)		x		x							
Vallée and Shareck (2014)					x		x				
Hirsch et al. (2014)			x		x		x				
Boruff et al. (2012)								x			
Berke et al. (2007)	x					x		x			

Methods to define areas where people move around are labelled as: spatial units, circular buffers, and polygon-based road network buffers (Boruff et al., 2012). The MOASIS study of Fillekes et al. (2019c) related to this thesis combined spatial units and circular buffers of LSLs: circular buffers such as neighbourhood ($<$ 1 kilometer), political boundaries such as residential municipality, residential canton, and the German-speaking part of Switzerland. Predefined political boundaries are not adequate as levels as they vary in size for each participant and the distance to the edge of the level may differ as well. However, if a participant lives close to a political border, he/she has to cover a much shorter distance in order to reach the next level. To overcome this problem and to guarantee the comparability between the participants circular buffers are used in this thesis. In Table 4.1 a meta-analysis of used circular buffers as LSLs in the literature is shown.

4.2.2 Travel Time Estimation

Getting insights into travel time estimation is the key task to answer RQ 1.1 requiring for the measure of walking time to use as a parameter in the transport mode detection method. This is due to the fact, that the mean gait speed is important to assess walking segments and differ between other modes. The walking time is also an indicator to describe the area of the participants neighbourhood. The walking time between 5 and 20 minutes defines the area of a neighbourhood and finds broad acceptance in the literature (Boruff et al., 2012). Travel time estimation is built up on a street network. A street network consists of a set of nodes and a set of edges connecting the nodes. Travel Time Estimation is usually done to find the (shortest) travel time between two points (Wang and Xu, 2011). Although, firstly, the gait speed has to be elaborated as the travel time may differ significantly based on the persons gait speed. The gait speed at which people walk is related to their functioning in the community (Robinett and Vondran, 1988).

Table 4.2: Descriptive meta-analysis of normal walking speed by age group excerpted from Bohannon and Williams Andrews (2011).

Strata gender (age in years)	**Source articles (n)**	**Subjects (n)**	**Gait speed (cm/second)**
Men (20 to 29)	10	155	135.8
Men (30 to 39)	5	83	143.3
Men (40 to 49)	4	96	143.4
Men (50 to 59)	6	436	143.3
Men (60 to 69)	12	941	133.9
Men (70 to 79)	18	3671	126.2
Men (80 to 99)	10	1091	96.8
Women (20 to 29)	11	180	134.1
Women (30 to 39)	5	104	133.7
Women (40 to 49)	7	142	139.0
Women (50 to 59)	10	456	131.3
Women (60 to 69)	17	5013	124.1
Women (70 to 79)	29	8591	113.2
Women (80 to 99)	17	2152	94.3

Bohannon and Williams Andrews (2011) made a descriptive meta-analysis of the measured mean gait speed of different age groups and gender. The summary of the meta-analysis is presented in Table 4.2. To investigate the mean *Travel Time Estimations* for the different LSLs the road network of each participant has to be taken into account. The method to estimating the origin-destination time matrix the Google Distance Matrix API is used. With this service the travel distance and time for a matrix of origins and destinations can be retrieved (Wang and Xu, 2011).

Figure 4.3: Schematic design of the routing calculations for the origin destinations matrix. The presented home location is fictitious.

In 4.3 the schematic design of the routing calculations for the origin destinations matrix are shown. The travel distance for 180 points on the edge of every LSL for each participants are calculated. The *Google Distance Matrix API* can be used for free for a limited number of queries. With the retrieved information and the descriptive meta-analysis of the mean gait speed, the travel times for each LSL can be calculated.

4.3 Transport Mode Detection

4.3.1 Define Transport Modes

Identifying transportation modes based on GPS data is key to answering RQ 1.1 and is critical information for all other RQs as well. Different studies investigated transport modes and focused on different types or modalities of transport modes: Chung and Shalaby (2005) differ between "walk", "bicycle", "bus", "passenger-car" or "taxi; Walking, driving and motorized are used by Bohte and Maat (2009); The detection of public transportation (buses, train) is investigated by Gong et al. (2012) and Rasmussen et al. (2015); "still", "walk" and "motorized" by Widhalm et al. (2012) and Gonzalez et al. (2010).

Speed as an input variable is an important feature to detect the transport mode. With the retrieved speed information and the derived variables (e.g., average, maximum, and minimum speed) from the GPS data characteristics of the different modes can be described (Gong et al., 2012). In this thesis, the focus of the transport mode detection is to differ between active (e.g., walking) and passive (e.g., motorized, including all public transport) transport modes as shown in Table 4.3. The detection of walking segments is important to investigate the walking time, the covered walking distance and to better detect reasons to go outdoors. To differ between public transport and a passenger-car is beneficial for insights about the participants mobility possibilities and behaviour. The detection of bicycle mode has been disregarded due to the circumstances that no significant amount of bicycle trips was recorded from the participants.

Table 4.3: The transport modes included in the transport mode detection framework of the thesis.

Transport Mode	
Active	Passive
walking	car, public transportation

4.3.2 Rule-Based Transport Mode Detection

A rule-based transport mode detection system with GIS and GPS data is implemented to detect 3 different transport modes: walking, car, and public transport. (Gong et al., 2012) developed a rule-based algorithm that detect 5 different modes with an accuracy of 82.6%. First, GPS data is divided into trips. A trip is defined as all the travel within two activity nodes. A cluster of points is defined as an activity node (location activity) and therefore, the end of a trip. A trip can have more than one transport mode. The trip segmentation is based on the mode change.

The defined rules are often based on the speed characteristics and are hierarchical. Bohte and Maat (2009) defined the trip modality as *foot* if the average trip speed is below 10 km/h and the maximum reached speed is less than 14 km/h. Else if the average trip speed is higher than 25 km/h and the maximum speed is less than 45 km/h the modality is *bicycle*. All other

Table 4.4: Adapted rules from the literature for the rule-based mode detection.

Rule-based Transport Mode Detection Framework
Pre-calculation
0a) IF speed > 61.1 [m/s] THEN remove observation 0b) Add speed moving average over 60 seconds 0c) Add speed moving maximum over 10 seconds
Classify GPS points into a transport mode for public transport
1a) IF distance of observation is WITHIN ROI *railway* THEN set mode *train* 1b) IF distance of observation is WITHIN 50m of POI *bus or tram stop* THEN set mode *near bus or tram stop* 1c) IF mean speed by POI *bus or tram stop* < 10 km/h THEN set mode *possible stop* ELSE mode *possible car* 1d) IF WITHIN the next 90 seconds another POI *bus or tram stop* THEN set mode *possible stop* AND IF mean speed BETWEEN *possible stop* > 25 km/h THEN set mode *bus or tram* THEN set mode *trip id* 1e) IF 1a-d not TRUE THEN set mode *unknown*
Classify GPS points into a travel mode: walk or car
2a) IF mode is *unknown* AND mean speed < 10 km/H AND max speed < 14 km/h set mode *walk* 2b) IF mode is *unknown* or *possible car* AND mean speed > 10 km/h and max speed > 25 THEN set mode *car*
Classify unassigned values into a transport mode
3a) IF NA value WITHIN detected walking mode THE set mode *walking* 3b) IF NA value WITHIN detected bus tram ride mode THEN set mode *public transport*

unassigned segments with an average trip speed less than 200 km/h get the modality *car*. Except the GPS points are located within the railway network, then the modality is *car*. With GIS data the detected modalities can be verified. Different distance thresholds are used in the applied rules in the literature. For example, Bohte and Maat (2009) defined the trip segment modality if distance of the detected trip end location is less than 50 m to the next POI (railway, bus stop, shopping, recreation, culture). A 75 meters threshold is used by Gong et al. (2012) to define the trip modality *bus*.

In Table 4.4 the applied rules of the mode detection framework are shown. First, pre calculations are made. All observations with a speed higher than 61.1 m/s are removed. This threshold is used by Fillekes et al. (2019c) and is the maximum speed achieved by trains in Switzerland. The moving average and maximum are calculated and used to detect possible speed outliers.

4.3.3 Validation of Detected Transport Modes

The validation is crucial to check the accuracy of the rule-based transport mode detection framework. The proposed framework is applied to the ground truth GPS data described in Section 3.3. One method to measure the accuracy of an algorithm is to calculate the observed accuracy. The observed accuracy is calculated by comparing the existing GPS data labelled with correct transport modes and the estimated transport modes classified by the rule-based algorithm proposed above. The mentioned studies above achieved an observed accuracy between 70% and 90% and the accuracy may differ with the selected trip length or the investigated transport mode (Chung and Shalaby, 2005; Bohte and Maat, 2009; Tsui and Shalaby, 2006).

Cohen's Kappa is another method to investigate the overall agreement between two attributes with a set of categories (Kvålseth, 1989). Statistical problems require the assessment of agreement between two or more classifiers. The method weighs the actual accuracy against the chance-expected accuracy: the accuracy that results from classification by chance (Berry and Paul W. Mielke, 1988). The kappa statistic (or kappa value) is a metric that weighs an observed accuracy versus an expected accuracy. The kappa value is used to not only evaluate a single classifier, but also to evaluate classifiers against each other (Viera et al., 2005). For example, a rule-based transport mode detection framework assigned 10 observations with two possible transport modes: *car*, *Public Transport*. Assuming there the two possible transport modes are equally represented. Ground truth; *car* (5), *Public Transport* (5). This means, the probability of observation being *car*, respectively being *public transport* is 50%.

Table 4.5: Example of confusion matrix to describe the Cohen's Kappa calculation.

	Classifiers	
	Car	**Public Transport**
Car	4	3
Public Transport	0	3

With the information of Table 4.5 the observed and chance-expected accuracy can be calculated. Observed accuracy is calculated by adding up the true assignments and divide by the total number of observations: $(4 + 3)/10 = 0.7$. Therefore, the observed accuracy is 70%. The *Classifier Car* detects the mode *car* with a probability of 40% ($(4 + 0)/10 = 0.4$) and the *Classifier Public Transport* detects the mode *public transport* with a probability of 60% ($(3 + 3)/10 = 0.6$). Therefore, the probability can be calculated where both agreeing: *car* with $0.5 * 0.4 = 0.2$; *public transport* with $0.5 * 0.6 = 0.3$. Out of the probability where both agreeing the sum represents the chance-expected agreement: $0.2 + 0.3 = 0.5$.

Equation of Cohen's Kappa (Berry and Paul W. Mielke, 1988):

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

$P_o =$ observed accuracy, $P_e =$ expected accuracy

The calculated kappa value is 0.4. In Table 4.6 the strength of agreement can be looked up. With a kappa value of 0.4 a *Fair* strength of agreement is achieved.

Table 4.6: Consistant nomenclature to describe the relative strength of agreement associated with kappa statistics (Landis and Koch, 1977).

Strength of Agreement	**Kappa Statistic Output**
Poor	<0.00
Slight	0.00-0.20
Fair	0.21-0.40
Moderate	0.41-0.60
Substantial	0.61-0.80
Almost Perfect	0.81-1.00

4.4 Objectively Measured Activity Profile

To investigate the mobility behaviour of participants, the reason why participants move within a certain area or why they go outdoors is important. In the mentioned studies above the activity was measured with an activity diary, where the participants track their behaviour with self-reports. (Li-Tang et al., 2015) An open-ended question was asked and the results were grouped into 18 categories: shopping (grocery shops, department stores); running errands (bank, post office, pharmacy); social visits; walking for exercise; other exercise (swimming, gym, ball games); health care; entertainment (movies, theatre, eating out); personal services (hairdresser); summer cottage; regular hobbies (fishing singing/instrumental practices); church-related activities; cemetery; helping others; social gatherings; participating in meetings; working; taking courses; and miscellaneous.

With the available data and the condition that the study includes only participants with an age over 65 not all reasons to go outdoors are considered or make sense to investigate. For example, working, helping others, social gatherings or participating in meetings are not beneficial due to the fact that the participants are retired or the detection of this reason with GPS data is difficult or even impossible.

The geographic information availability is crucial for the definition of the different reasons to go outdoors. In this analysis three different data sources are used: OSM, OGD from canton of Zurich and geocoded addresses of grocery stores. In the OSM dataset all buildings of Switzerland are available, but the majority have no information about the amenity or the purpose of the building. The classification of the OGD data is rudimentary with three types: residential, government and industry. The retrieved geocoded addresses can all assigned to shopping due to the fact that online addresses from grocery stores are geocoded. The allocation of the GPS points to the geographic information has following priority: first, geocoded grocery stores; second, OSM; third, OGD. These priorities were assigned according to the quality of the data. Geocoded geometries are definitely assignable to the shopping category. OSM has the more diverse classification than OGD.

In Table 4.7 the investigated reasons to go outdoors are shown. The categories were used and adapted from Li-Tang et al. (2015). Working, participating in meetings, helping others and social gatherings were excluded due to the mentioned reasons above. Walking for exercise was adapted to going for a walk, because of the research aim of the walking mobility and the difficulty to extract walking for exercise. The category of miscellaneous reasons was also not included since

Table 4.7: Adapted categories for reasons to go outdoors from Li-Tang et al. (2015).

Reasons to Go Outdoors
Shopping
Scoial visits
Entertainment
Church-related activities
Regular hobbies
Taking courses
Running errands
Health care
Going for a walk
Other exercise

the amenity/purpose information of all other buildings was not available, and the counting of these activities was not beneficial. After the adaption, the shown 10 different categories were left and used for the analysis.

4.5 Statistical Analysis

For all hypotheses of RQ 2 the correlations were explored among the selected variables and the suggested relationships. With QQ-plots and histograms the data were tested visually if it were normally distributed. For the second research questions, two different correlation analyses were needed: between-participant correlation analysis and a moderated multiple regression. For the between-participant analysis, a moderated multiple regression analysis was done. The relationship between the *independent variable* (IV) and *dependent variable* (DV) was moderated by *moderator variable* (M). Age and income were used as *control variables* (CV). In Figure 4.4 the conceptual framework of the moderated multiple regression model is shown.

There are different approaches to measure within-participant correlation, for example: *one-way ANOVA within participant*, *repeated measures correlation* (rmcorr), and *Linear Mixed-effects Models* (LMMs). For the ANOVA method normal distributed data is a prerequisite. For the within-participant analysis no normal distribution could be found and therefore the one-way ANOVA within participant was not suitable. Simple regression and correlation are often applied to non-

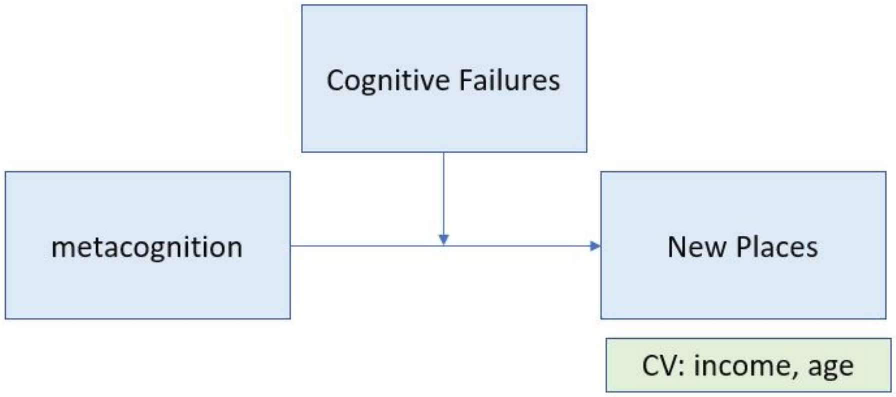


Figure 4.4: Conceptual framework of the moderated multiple regression model. The relationship between *metacognition* as an IV and *new Places* as a DV is moderated by *cognitive failures* as a M. Control variables: *age* and *income*.

independent observations or aggregated data what may lead to biased, specious results or differing patterns between-participants versus within-persons. Rmcorr is a statistical method for identifying the association within-participant with multiple measures for multiple participants (Bakdash and Marusich, 2017). Figure 4.5 shows how rmcorr captures the strong intra-individual relationship for multiple measures by participant and how the simple regression for averaged data by participant detects a small correlation and no significance.

Linear Mixed Effects Models (LMMs) are used widely within the psychological sciences and may become default method to analyse quantitative and multilevel data (Meteyard and Davies, 2020; Kuznetsova et al., 2017). LMMs are also recognised as hierarchical or multilevel or random effects models (Snijders and Bosker, 2000). LMMs are used when data is collected with multi-stage sampling or repeated measures design. Meteyard and Davies (2020) describe multi-stage sampling as when the data is gathered on the characteristics of participants: participants from a sample of hospitals in a sample of regions. Repeated measures are defined when, for example, all participants are reported with all available stimuli. This described designs have a multilevel or hierarchical structure (Meteyard and Davies, 2020). Each participant recorded its sleep quality every day over 30 days and the dependent variable is assessed on the same structure.

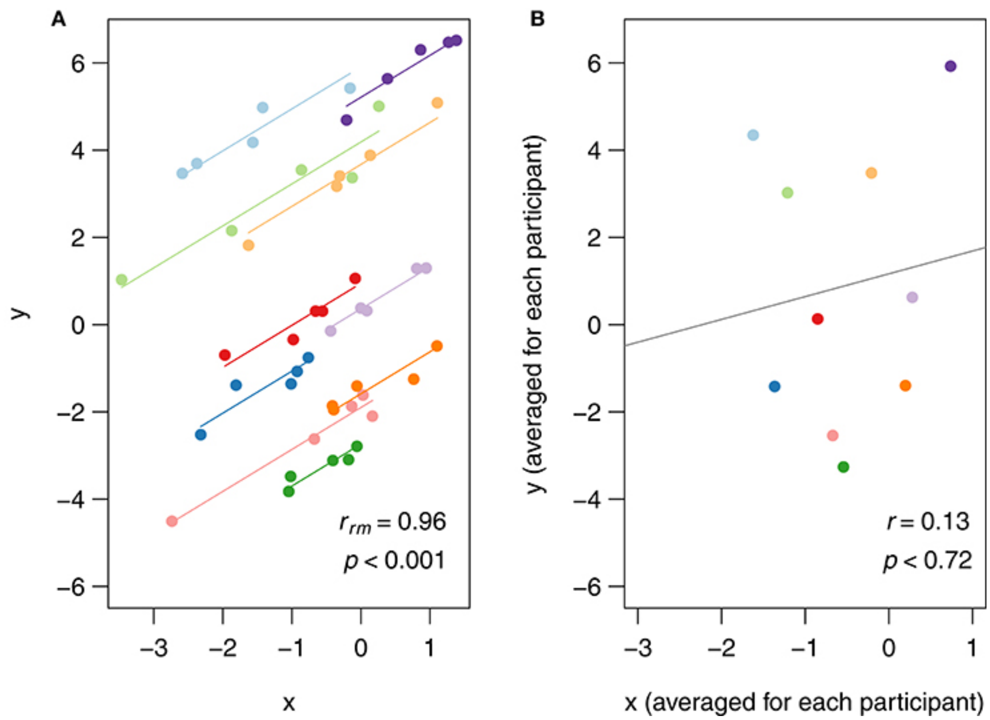


Figure 4.5: (A) Rmcorr method for 10 persons with 5 measures (left) and (B) the corresponding regression plot for the averaged data by participant excerpted from Bakdash and Marusich (2017) (right).

5. RESULTS

5.1 Life Space Levels

With the meta-analysis in Section 4.1 the LSLs of an individual can be described with circular buffers, which defines areas, where people move in. The centre of each circular buffer is the participant's residency. There are six different LSLs defined and used for the analysis.

Table 5.1: Spatial definition of the LSLs with circular buffers based on the meta-analysis in Section 4.1.

Level Nr.	Life Space Level	Circular Buffer [m]
1	Home/Garden	150
2	Close Neighbourhood	300
3	Neighbourhood	1000
4	Greater Neighbourhood	3000
5	Greater Area	8000
6	Further away	>8000

Table 5.1 shows the defined LSLs for this thesis. Level 1 is defined as a 150 meters circular buffer, including the participant's *home and garden area*. Studies investigated by Fillekes et al. (2019c) have identified the identical circular buffer of the first and third Level as used in this analysis and illustrated in Table 5.1. The 1000 meters circular buffer in Level 3 used by Fillekes et al. (2019c) is defined as a *close neighbourhood*. However, other studies claim a much smaller circular buffer of the neighbourhood area: Coulton et al. (2001) state, that the neighbourhood remains within 500 meters; Haney and Knowles (1978) see suburban residents with a 300 meters and inner-city residents with 125 meters radius; whereas Nelson et al. (2006) define neighbourhood with a circular buffer of 3000 meters. A key aspect of mobility behaviour are reasons to go outdoors within the neighbourhood. In order to support this claim and to form a deeper understanding, a more precise segmentation of the neighbourhood is required. In addition to the two circular buffers

of Fillekes et al. (2019c), two more circular buffers will be applied: the *close neighbourhood* with a 300 meters area and the *greater neighbourhood* with a 3000 meters radius. Mobility does not stop in the neighbourhood, however, but is especially crucial for outdoor activities with greater distances. To investigate the mobility behaviour of the participants beyond the neighbourhood, different approaches apply. For example, Fillekes et al. (2019c) utilised political borders such as municipality, Cantons or German-speaking part of Switzerland for mobility patterns. Song et al. (2013) on the other hand identified 1, 3, 5 and 8 kilometers circular buffers in a national-level analysis of neighbourhoods. The described problems in Section 4.2.1 of political borders lead to the last two levels: 8000 meters circular buffer for the *greater area* and everything above is summarised in last Level *further away*.

5.2 Travel Distance Calculation

The natural and built environment varies for each participant. Figure **??** illustrates different LSL conditions: rural vs. urban surroundings; natural boarders such as lakes, rivers, forest and built environment such as road network, bridge and interstates. All these conditions either complicate or facilitate the moving within and to the edge of a certain LSL.

The *googleway* R package provides methods to plot a *Google Map* and grants access to Google Map APIs. With the Google Matrix API, the distances and travel times of each travel mode (driving, walking, bicycling, transit) can be retrieved (Cooley, 2020). In Table 5.2 the average mean distance of each LSL is shown. The average distances are calculated out of the retrieved distances within two standard deviations of the data mean. To determine the mean walking time of older adults to cover the retrieved mean distances of the LSLs, the discussed meta-analysis of the mean gait speed of different age groups in Section 4.2.2 is applied. As the average age of the participants is 73 years; the mean gait speed of the age group 70 to 79 is used for further calculations. Bohannon and Williams Andrews (2011) detected a mean gait speed of 126.2 cm/s for men, respectively 113.2 cm/s for women. For the purposes of simplifying the calculation, the average speed of both women and men is used as a reference for the analysis: 119.7 cm/s. The data suggests that walking is the least used transport mode in Levels 5-6, outside the neighbourhood. Therefore, two

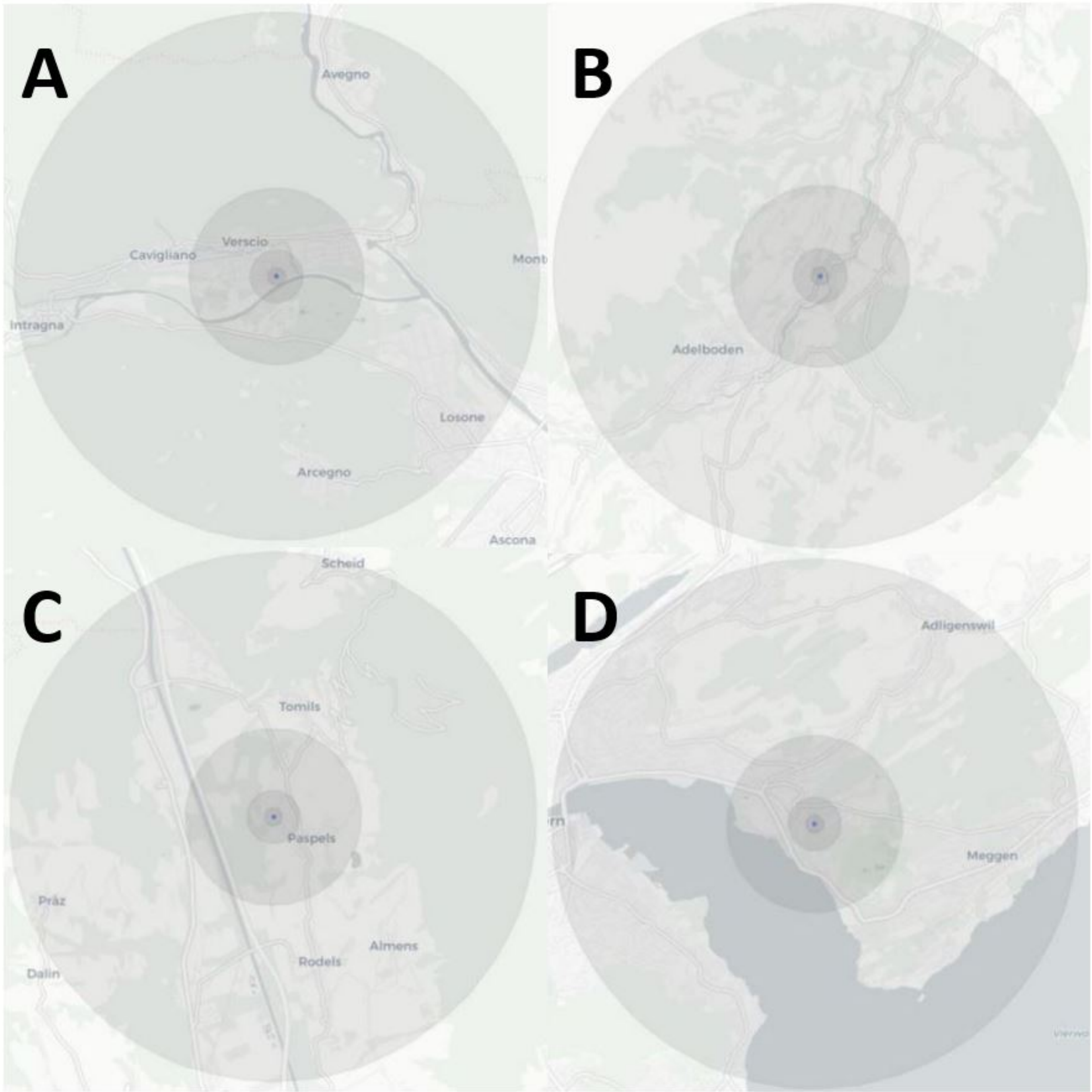


Figure 5.1: Examples of different life space level conditions for travel distance calculations: A) river as a natural boarder, B) high in the mountains with one main road towards *Adelboden*, C) interstate as a man-made boarder and D) urban location near the lakeside.

more transport modes are taken into consideration: bicycling within *greater neighbourhood* (3000 meters) and driving within *greater area* (8000 meters) and *further away* (>8000 meters).

5.3 Visual Examination of Classified Transportation Modes

The detected transport modes are visualized in the Figures 5.2 and 5.3. For example, Figure 5.2 shows transport modes in the city of Zurich classified after step 1 and 2 of the rule-based transport

Table 5.2: Retrieved mean distances of the Google matrix API and the calculated mean walking time.

LSL buffer [m]	Mean Distance [m]	Mode	Walking Time
150	220	Walking	4min 23s
300	487	Walking	9min 43s
1000	1662	Bicycling	
3000	5607	Driving	-
8000	13838	Driving	-

mode detection algorithm in Table 4.4 are applied with five different classes: 1) *bus or rail* 2) *bus or tram* 3) *potential bus stop* 4) *potential walk or drive* 5) *unknown* 6) *walking*. The available geographic information enabled the differentiation of several public transport modalities: train, tram, and bus.

Figure 5.2: An example of detected transport modes in the city of Zurich.

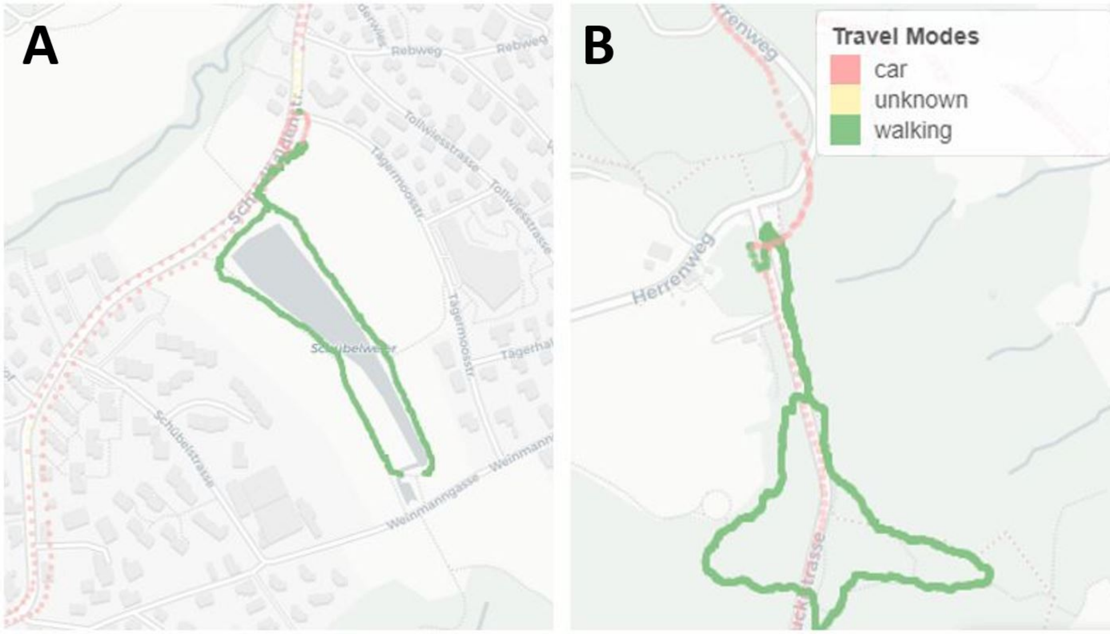


Figure 5.3: An example of the detected transport modes in rural area: a car trip with a stop A) for a walk around a pond and B) a walk in the forest is detected.

However, if any of these vehicles used the same travel route, for example a bus and tram were using the same stops along *Bahnhofstrasse*, it was hardly possible to distinguish which is which by the constructed data of this study. 5.2 shows the overlapping transport modes in this case. The walking segments were detected in *District 1*, *District 2*, and *Oerlikon* in the city of Zürich. No car segments are detected and therefore not visualized. Notably, only in the proximity of the *Hardbrücke* bridge did the algorithm have difficulty identifying a specific transport mode and assigned the GPS trajectories as "unknown". This means that it was not possible to allocate a specific transport mode.

A car trip with a stop for a walk in the forest and a walk around a pond is detected in Figure 5.3. Although there is missing data while walking around the pond, the succeeding GPS points are still classified correctly as visualized in illustration A. In illustration B the walking segment is not discontinued even though it overlaps with a road. This demonstrates that the environment plays a secondary factor and the modes are still correctly classified. The final rule-based transport mode detection system distinguished three different classes in this case: 1) car 2) unknown 3) walking. Unknown observations are classified right before the participant stops, as soon as the car is slowing down. The walking parts around the pond and in the forest are fully identified, as well as the driving along the street.

5.4 Validation of Detected Transport Modes

The key aspect of this thesis is to establish a rule-based transport mode detection framework with an accuracy as high as possible. To do so, first, the observed accuracy is calculated. Observed accuracy is the percentage that is classified correctly throughout a given confusion matrix: The number of observations classified as *walk* and then labelled as *walk* by the rule-based transport mode detection framework. Table 5.3 shows the observed accuracy of each combination of transport modes and different minimum trip length parameters. The results show a 68.4% overall accuracy for classifying all transport modes without the minimum trip length requirement. With an increase in the minimum trip length, the observed overall accuracy increased as well. The highest overall accuracy of 80.9% for all transport modes was reached with the minimum trip length of 4 minutes. Walking segments were detected with a higher accuracy with the minimum trip length of 6 minutes and car trips were classified with the 90.8% accuracy. Furthermore, the observed accuracy was calculated for the active and passive transport modes, whereas the best classification performance was achieved with the minimum trip length of 180 seconds.

The best classification performance was achieved with a minimum trip length of around 4 minutes. This value was used for further calculations of the kappa value, which describes the strength of the agreement. In Table 5.4 the results of the calculated confusion matrix and the kappa value output is shown. The rows represent the ground truth information. Therefore, *car* is 4589 times correctly classified as *car*. The columns represent the classifiers. For example the classifier *walk* classified 290 times ground truth data wrongly as *public transport*. The calculation is based on the described methods in Section 4.3.3. Moreover, with the achieved kappa value of 0.643 a substantial strength of agreement is reached for the rule-based transport mode detection framework. The classifiers of the *car* and *walk* mode have a high expected accuracy. The classifier *Public Transport*

Table 5.3: Observed accuracy of the detected transport modes in terms of transport mode and various minimum trip length parameters.

Transport Mode	**Minimum Trip Length [s]**	**Accuracy**
All	0	68.4%
All	120	77.2%
All	180	77.1%
All	240	80.9%
Walk	0	58.5%
Walk	300	71.0%
Public Transport	0	35.0%
Car	0	63.4%
Car	120	86.6%
Car	240	90.8%
Active/Passive	0	75.8%
Active/Passive	60	79.4%
Active/Passive	120	80.7%
Active/Passive	180	81.2%

categorises 2625 times incorrectly an observation as public transport. Impressively, the classifiers for *walk* and *car* reach high numbers in the confusion matrix correctly.

Table 5.4: Confusion matrix retrieved from the applied rule-based transport mode detection framework on the ground truth data.

		Classifiers	
Transport Mode	**Car**	**Public Transport**	**Walk**
Car	4589	235	131
Public Transport	385	1648	290
Walk	18	2625	6224
Kappa Value Output		**Strength of Agreement**	
	0.643		Substantial

5.5 Objectively Measured Activity Profile

The reasons to go outdoors of the participants ($n = 128$) are detected and described with the objectively measured activity profile. In particular, they are identified for each LSL a participant has been in and combined with their motives to go outdoors. In Table 5.5 all distinguished reasons to go outdoors are displayed and are ordered in descending manner. The most common reasons were going for a walk, social visits, entertainment and running errands. Interestingly, church related activities have no significant number and even regular hobbies and taking courses are not revealed.

Table 5.5: Detected reasons to go outdoors with the objectively measured activity profile.

Reason to Go Outdoors	**Detected Trips**
Going For A Walk	5506
Social Visits	2710
Entertainment	1183
Running Errands	822
Other Exercise	568
Shopping	244
Health Care	142
Church Related activities	16

Figure 5.4 shows the number of participants that reached a certain LSL in relation to the most common reasons to go outdoors. To establish more insights about the individual distribution of these motives, a within participant analysis was conducted. As a brief recapitulation: The neighbourhood was represented by the 300m and 1000m circular buffer, the greater neighbourhood was described with a 3000m buffer. A participant that moved within more than one level was counted multiple times in each category of LSLs.

Naturally, the data show that most participants moved within multiple levels to pursue the most common reasons to go outdoors. Likewise, all participants moved around multiple LSLs to go for a walk. It also shows that some participants moved only within the greater neighbourhood for

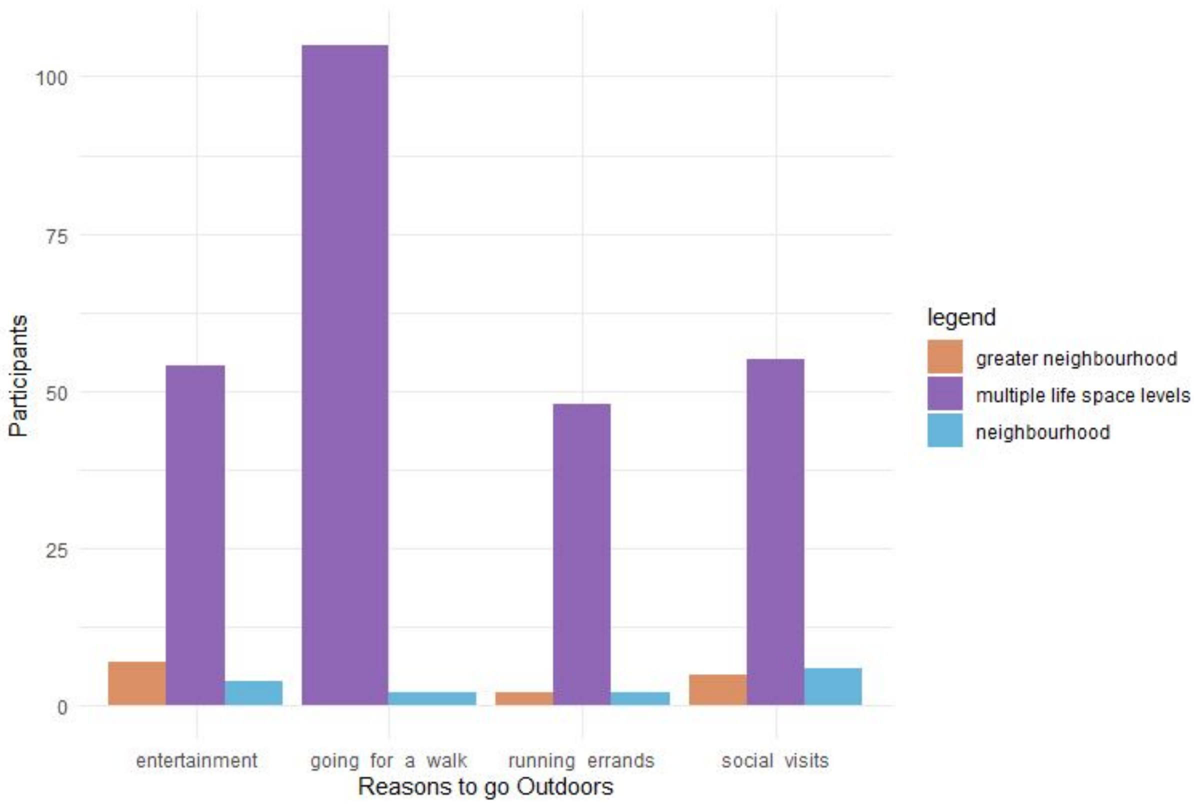


Figure 5.4: Distribution of participants (n=128) that moved to the extent of each life space level for the four most common reasons to go outdoors.

entertainment and social visit purposes. From the data in Figure 5.4, it is apparent that there are some participants who moved only within the neighbourhood for certain reasons.

The frequency of each reason to go outdoors according to LSLs is displayed in Table 5.6. Each characterisation of the levels used in this section is described in Section 5.1. In the first part of the Table 5.6, the most prevalent reasons to go outdoors are shown in terms of frequency and percentage within each level. In the second part, all other identified reasons for spending time outdoors are listed. The most striking observation is that participants covered greater distances in order to run their errands (61.92%) and entertainment purposes (69.81%). Surprisingly, going for a walk is rather done in further distances (64%) than in any other level (approximately 10% in each other level). A similar pattern is shown in the context of social visits, where only one fifth takes place within the close neighbourhood and almost 60% further away. LSLs in further area also play

Table 5.6: Frequency of reasons to go outdoors varying with life space levels.

	Neighbourhood			Further	
Life Space Level [m]	**300**	**1000**	**3000**	**8000**	**>8000**
Most common reasons to go outdoors, n (%)					
Entertainment	45 (3.80)	201 (17.00)	111 (9.38)	281 (23.75)	545 (46.07)
Running Errands	29 (3.53)	154 (18.74)	130 (15.81)	268 (32.60)	241 (29.32)
Going For A Walk	578 (10.50)	403 (7.32)	458 (8.32)	538 (9.77)	3529 (64.00)
Social Visits	533 (19.67)	231 (8.53)	156 (5.75)	202 (7.45)	1588 (58.60)
Other reasons to go outdoors, n (%)					
Other Exercise	0 (0.00)	31 (5.45)	44 (7.75)	209 (36.80)	284 (50.00)
Church Related	0 (0.00)	2 (12.50)	6 (37.50)	3 (18.75)	5 (31.25)
Health Care	27 (19.01)	10 (7.06)	20 (14.08)	24 (16.90)	61 (42.95)
Shopping	5 (2.04)	30 (12.31)	49 (20.08)	57 (23.36)	103 (42.21)

an important role in exercise purposes: Participants seem to have never moved within the close neighbourhood and rather cover further distances. Another interesting insight is that participants went for health care purposes one fifth within the close neighbourhood and each a quarter within the greater neighbourhood and greater area. The highest percentage for church related activities are achieved within the greater neighbourhood. Finally, the highest percentages are most often detected in the farthest LSLs.

5.6 Correlation Analysis

5.6.1 Within-individual Analysis

Two different approaches are used to measure within participant correlation: a repeated measure's correlation method and a linear mixed-effects model. The aggregated walking time includes the active walking without the detected stop points and is calculated for each study day of each participant.

In Figure 5.5 the mean walking time and the sleep quality is visualised with boxplots. A boxplot presents graphical information about the location and dispersion of the data and potential outliers are pointed out. These six boxplots are ordered from bad (0) to good (6) sleep quality. No significant difference of the median is visible between the boxplots. The interquartile ranges are reasonably similar, except for boxplot 1. The exact distribution of each group is hidden behind boxes; therefore, the individual observations are added. The overall data range is greater, and more observations are reported as the sleep quality gets better.

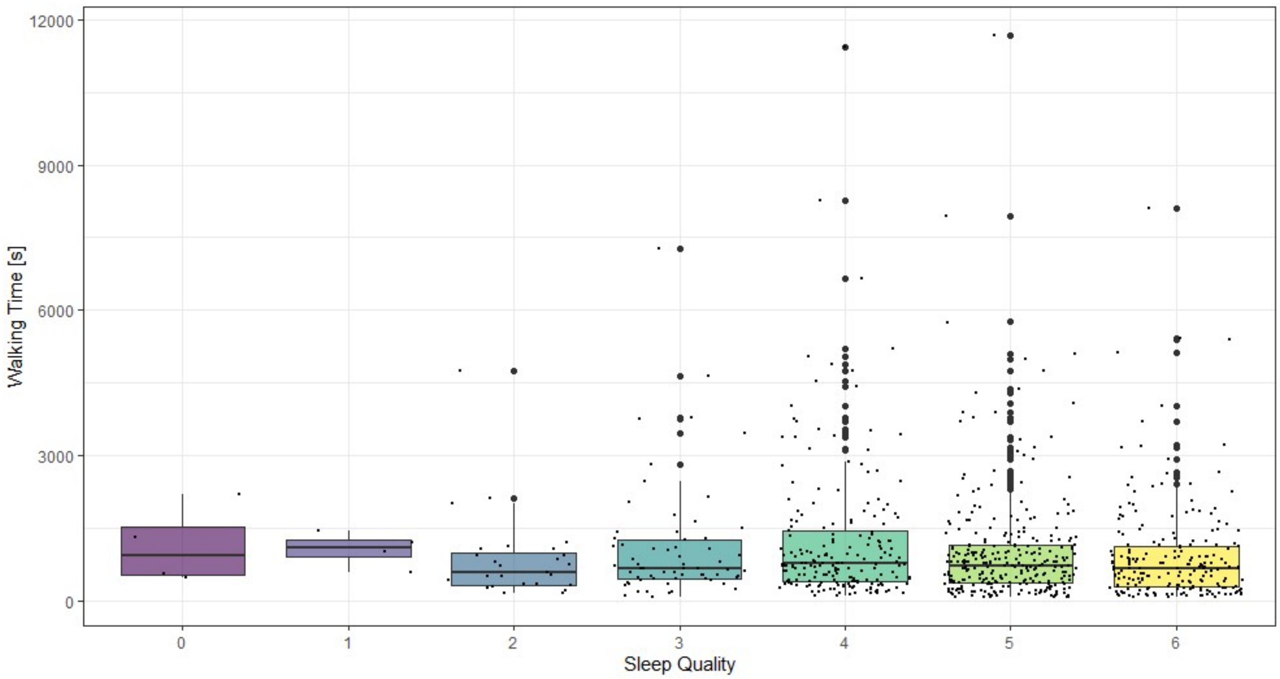


Figure 5.5: Distribution of walking time and sleep quality.

With the linear mixed-effects model, negative correlation between daily sleep quality and daily walking time is detected $(p - value = 0.0254, correlation = -0.95)$ and illustrated in Table 5.7. Negative correlation indicates a statistical relationship: As sleep quality decreases, walking time increases. The random effect of the participant is meant to capture all the influences of participants on walking times. Furthermore, the random effect part tells how much of variance can be found among the levels of the grouping factor, plus the residual variance. For this analysis, 105 participants with 821 observations are implemented.

Table 5.7: Linear mixed-effects model output.

Random effects:					
Formula:	~ 1 | participantID				
	(Intercept)	Residual			
	581.6505	988.7277			
Fixed effects:					
Trip Duration ~ Sleep Quality	Value	Std. Error	DF	t-value	p-value
(Intercept)	1389.322	219.564	715	6.3276	0.0000
Sleep Quality	-81.597	36.424	715	-2.2401	0.0254
Correlation:		(Intr)			
	Sleep Quality	-0.95			
Standardized Within-Group	Min	Q1	Med	Q3	Max
Residuals	-2.29683	-0.46557	-0.15824	0.22431	9.84491
Number of Observations:	821				
Number of Groups:	105				

With the repeated measure correlation method, a p-value of 0.0193 and a correlation of -0.087 are achieved. Therefore, no significant correlation is revealed. A value of near zero indicates no relationship between the two variables.

5.6.2 Moderated Multiple Regression

The moderated multiple regression is applied to describe the relationship between metacognition (IV) and new places visited (DV) moderated by cognitive failures (M). Metacognition and cognitive failures are tested to see whether the variables have a normal distribution. The histograms in Figure 5.6 are an ideal way to visualise the distribution of a single variable and check for normal distribution. According to the histograms, there is a normal distribution. In Figure 5.6 quantile-quantile (QQ) plots are shown to check, whether the variables are normally distributed. The points on the QQ-plots follow a straight line, therefore normal distribution is given for these two variables.

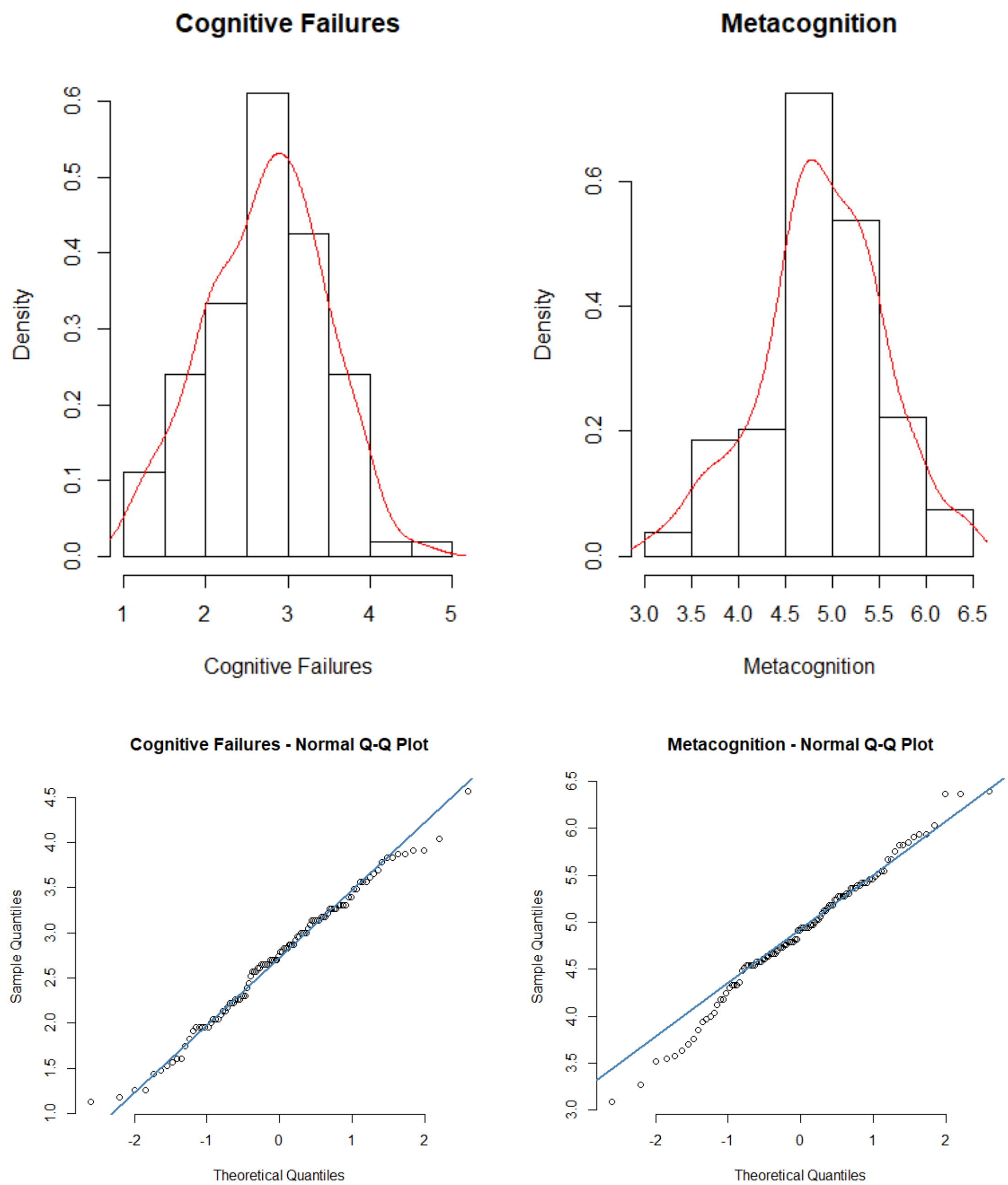


Figure 5.6: QQ-plots and histograms for the metacognition and cognitive failures data.

Table 5.8 reveals no significant correlation for the moderated multiple regression analysis. P-value is 0.4838 which is much higher than 0.05. Likewise, the control variables, age and net income, do not show any significant correlations.

Table 5.8: Output of the moderated multiple regression analysis.

Residuals					
	Min	1Q	Median	3Q	Max
	-0.4826	-0.17127	0.00168	0.17456	0.52433

Coefficients:				
	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.033694	0.363352	0.093	0.926
Cognitive Failures	-0.033286	0.035307	-0.943	0.348
Metacognition	0.015129	0.035441	0.427	0.670
Age	0.002350	0.004262	0.551	0.583
Income 3001 - 4000 CHF	0.283976	0.233867	1.214	0.228
Income 4001 - 6000 CHF	0.239747	0.232780	1.030	0.306
Income 6001 - 8000 CHF	0.328456	0.234028	1.403	0.164
Income 8001 - 12000 CHF	0.282767	0.239868	1.179	0.241
Income < 3000	0.332307	0.232953	1.427	0.157
Income > 12000	0.091296	0.251466	0.363	0.717
Cognitive Failures:Metacognition	-0.031627	0.045565	-0.694	0.489

Residual standard error: 0.2265 on 97 degrees of freedom
Multiple R-squared: 0.89999, Adjusted R-squared: -0.003822
F-statistic: 0.9593 on 10 and 97 DF, p-value: 0.4838

6. DISCUSSION

In this chapter, the presented results of the previous Chapter 5 are discussed in depth, in regard to answering the research questions. Subsequently, core components of the analyses, including (1) life space levels (LSLs), (2) transport mode, and (3) objectively measured activity profile are explained and discussed in more detail. This is necessary, because those components are a critical part of the research questions and hypotheses, because those components are a critical part of the research questions and hypotheses.

6.1 Life Space Levels

Following 1) the challenges and implications of defining life space levels, 2) the possibility of the use of network buffers for life space, and 3) the use of different spatial segmentation are discussed.The previous described frameworks of the four questionnaires in Section 4.2.1 contain some differences to the applied LSLs. That is due to the fact, that often subjectively interpretable levels are used. For example, Michael Parker DSW et al. (2002) does not define LSLs with a specific metric value, but rather has the participants state whether they are outside the house, in the neighbourhood or in the city. By using this method, LSLs are recorded subjectively. This also implies that participants might perceive the extent of the neighbourhood or the city differently. Another approach is applied by Fillekes et al. (2019c): they combine metric LSLs with political boundaries, which has the advantage, that LSLs have a semantic meaning and are more tangible. However, political boundaries also have their constraints. Firstly, political boundaries (residential municipality, residential Canton, or German-speaking part of Switzerland) vary among participants and secondly, LSLs can overlap. Furthermore, predefined and rigid areas, such as political boundaries, do not necessarily represent the area of participants movement patterns. However, these subjective levels are useful for self-reports. People are better able to judge when levels have a semantic meaning. However, it is difficult to determine whether someone is moving 300 or 400 meters away from home. Based on the meta-analysis in Table 4.1 of the buffers found in the literature, the different LSLs used in this thesis have been defined. This approach of circular buffers allows to eliminate the described disadvantages of the political boundaries. The LSLs allow a comparability between participants and can be implemented with little cost. A limitation of the chosen LSLs is, that the built environment is not taken into consideration. Rural and urban areas differ greatly in terms of road network density and general accessibility. Duncan et al. (2013), for example, use street network buffers in addition to circular buffers. In Figure 6.1 the differences can be seen quite clearly: with a poorer street network, the edges of the circular buffers can be reached less well.

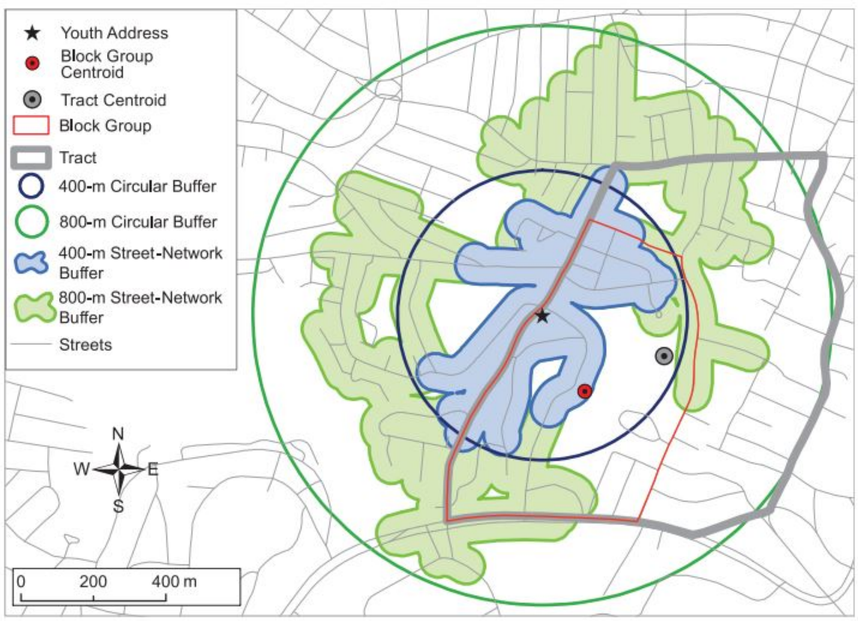


Figure 6.1: Combination of circular and street network buffer excerpted from Duncan et al. (2013).

The network buffers were discarded because additional requirements would always have to be met. Street network data is not available comprehensively everywhere in the world, and small streets possibly are not even mapped. Furthermore, not all available stay points can be included in street network buffers. Nevertheless, the decision was made to focus on circular buffers. In order to get a better understanding of the chosen LSLs, the Google Matrix API is applied in Section 5.2.

This allows a precise calculation of the average distance, that had to be travelled to reach the edge of the level. Other studies define neighbourhood area by a walking time between 5 and 20 minutes. This approach finds broad acceptance in the literature (Boruff et al., 2012). This is in line with the found walking times for the levels 1 and 2, which represent the neighbourhood.

By implementing LSLs, spatial segmentation of the environment is easily achieved. Additionally, the use of these levels contributes to a precise understanding of the spatial behaviour. The LSLs are vital components of the objectively measured activity profile. Through the used levels, the reasons to go outdoors outlined in Section 4.4 are spatially mapped and serve a broader understanding of the spatial behaviour of participants. Conclusively, the implemented framework builds on existing research and the concept of LSLs could be improved.

6.2 Transport Mode

This section 1) describes the successfully implemented rule-based transport mode detection algorithm and 2) compares the achieved accuracies with other studies. For the objectively measured activity profile it is crucial to know the transport mode of every given observation of the GPS trajectories. It is essential for the detection of the reasons to go outdoors to only use observations, that have an assigned transport mode or are defined as walking. The achieved observed accuracy and the expected accuracy are both considered satisfactory and sufficient for further analysis. The accuracy improves with increasing trip length. The best accuracy for walking trips is achieved at a trip duration of 3 minutes (71.0%), for public transport at 0 seconds (35.0%) and for car trips at 4 minutes (90.8%). The comparatively low accuracy of public transport could be due to the fact, that the transport mode of the ground truth data was too complex to capture by the framework. However, the observed accuracy in the Section 5.3 seems to be convincingly good. With a trip length of 4 minutes, an observed accuracy of 80.9% and a kappa value of 0.643 (substantial strength of agreement) is achieved. Other rule-based transport mode detection frameworks achieve similar accuracies: Bohte and Maat (2009) at 70% and Gong et al. (2012) between 78-86%. The rule-based transport mode detection framework can be applied globally with OSM data and can be simply enriched with local GIS data. Nevertheless, the accuracies achieved could be exceeded with alternative methods. Stenneth et al. (2011) describe that machine learning achieve accuracies up to 93%.

Transport mode detection could be improved for the purpose of recognising public transport segments. This can be achieved with additional data (e.g., public transport timetable) and enhanced implementation of public transport stop-and-go patterns. Based on the above arguments, the developed framework can contribute to transport mode detection and can be easily transferred to other regions as well as being sufficient for the analysis. The framework is composed of few rules and yet is able to identify particular modes effectively. Based on existing research (Bohte and Maat, 2009; Gong et al., 2012), the framework was implemented and the concept of rule-based transport mode detection was successfully applied.

6.3 Objectively Measured Activity Profile

With the previous two discussions on transport mode detection and the definition of LSLs, the key components of the objectively measured activity profile are addressed. It is now possible to assign a transport mode and a specific LSLs to each GPS point. The objectively measured activity profile extends the previous understanding about the participants of the MOASIS project by connecting the reasons to go outdoors and the movement within different LSLs.

As indicated earlier, the most common reasons for being outdoors are walking, social visits, entertainment and running errands. These results build on existing evidence of the study from Li-Tang et al. (2015): they identified the same most common reasons for going outdoors, except for shopping. In the case of shopping, however, this result contradicts the claims of several studies suggesting that shopping is the most common reason for going outdoors among older people (Barnett et al., 2015; Li-Tang et al., 2015). This is surprising, as shopping is listed only fifth of the detected reasons to go outdoors. Although, the geocoded addresses of over 1000 branches of the largest retailers in Switzerland are retrieved and joined to the used GIS data. Tongren (1988) has discovered that older people have a tendency to make joint buying decisions. This could be the reason behind the decreased number of detected shopping trips, as the OSM data information is partly not as accurate and different shops in a shopping centre are not recorded individually, but only the centre itself. Shopping also offers older people the possibility to move around in a moderately convenient and controlled environment. For example, the ability to walk considerable distances in shopping centres while examining the goods is often welcomed (Mason and Bearden, 1978). These assumptions may lead to the conclusion that many of the participants do their shopping in a shopping centre.

Social visits are the second most common reason for going outdoors. Among these reasons is the visit of children and grandchildren. Time spent with children and young people also enhances the QoL (Gabriel and Bowling, 2004). Furthermore, Gabriel and Bowling (2004) point out that older people enjoyed seeing friends for socializing purposes and having the possibility to do activities with others, particularly if they were widowed. In terms of social relationships, social participation has been shown to correlate with a reduction in the harmful effects of stress and life-threatening illnesses (Welin et al., 1985).

The most common reason to go outdoors is simply going for a walk. In this context, it is important to note that this only includes the frequency of journeys made on foot for recreational purposes, not trips made to places such as the theatre, grocery shop or post office. It is emphasised that walking is the transport mode of last choice. It is accessible to many older people who are unable to drive or cannot use public transport (Gagliardi et al., 2007).

The majority of participants reach multiple LSLs for commonly used reasons to go outdoors. It is particularly noteworthy that almost all participants reach several LSLs by simply taking a walk. Then again, for the other most common reasons (entertainment, running errands and social visits), individual participants only move within the neighbourhood or the greater neighbourhood. A possible explanation might be the influence of the built environment. A participant who lives in the city probably has every essential shop or leisure activity close by. However, a participant living in a rural area has to travel longer distances to do the same. The distribution of reasons for going outdoors differs greatly between the LSLs. All reasons except running errands are most often done further away than 8000 meters. Section 3.2.1 shows that most participants are from the Zurich region. In this case, one possible explanation could be that many participants travel to the city for entertainment, to run errands or to go shopping, which is further than 8000 meters away. This assumption is also supported by Mouratidis (2019) who states that the distance to the city centre and neighbourhood density have an effect on leisure satisfaction. In the future, it could be beneficial to distinguish the LSLs more precisely or to consider region of interests (ROI), such as Zurich city centre or the old town.

6.4 Discussions for Research Questions and Hypotheses

RQ 1 - How do the detected mobility behaviour vary across different life space levels?

H 1.1: Transport modes of an older adult can be inferred based on GPS data.

With the results presented in Chapter 5, the hypothesis can be confirmed. The developed rule-based transport mode detection framework manages to distinguish between walk, car and public transport. The accuracy improves with increasing trip length. The best accuracy for walking trips is achieved at a trip duration of 3 minutes (71.0%), for public transport at 0 seconds (35.0%) and for car trips at 4 minutes (90.8%). Transport mode detection achieved, using the benchmark data set from (Isler, 2018), an observed accuracy of 81% and a kappa value of 0.643 – a substantial strength of agreement – for minimum trip length of 4 minutes. Other studies with an implemented rule-based transport mode detection achieve similar results: Bohte and Maat (2009) at 70% and Gong et al. (2012) between 78-86%. Given differences in the available data set and validation with different ground truth data, performing a direct comparison with existing studies on rule-based transport mode detection is challenging.

In summary, however, it is indeed possible to determine the means of transport of an older adult by using GPS data. Nevertheless, the comparatively low recognition accuracy of public transport still leaves room for improvement.

H 1.2: Types of reasons to go outdoors vary with different life space levels.

The objectively measured activity profile achieves very promising results (Section 5.6) and is also in line with other studies (Li-Tang et al., 2015). The existing limitations have been described above. There are three main components to this hypothesis, LSLs, reasons to go outdoors and GIS data. The LSLs in this thesis are defined with circular buffers. However, there are many different approaches to defining habitat in the literature: political boundaries (Fillekes et al., 2019c), circular buffers (Berke et al., 2007; Boruff et al., 2012; Coulton et al., 2001; Frank et al., 2007; Fillekes et al., 2019c; Hirsch et al., 2014; Nelson et al., 2006; Song et al., 2013), street network buffers (Duncan et al., 2013) and self-reports (May et al., 1985; Peel et al., 2005). Nevertheless, advantages of the chosen buffers are comparability among participants, inexpensive to implement and finally and no overlaps. Constraints of this approach are, on the one hand, that the built environment is not taken into consideration and the area of the last LSL (further away, 8000 meters) is most likely too large and, secondly, that too many GPS points are proportionally assigned to this level.

With the help of the objectively measured activity profile and the reasons to go outdoors it is possible to determine within which LSL the participants move for a certain reason. The literature claims (Li-Tang et al., 2015) that reasons are employed that are not associated with a specific location and are therefore difficult to distinguish by GIS data. For example: helping others or social gatherings. Although OSM already has a wealth of data, there are still weaknesses when precise information about the purpose of buildings is needed. In order to better identify the variability of reasons to go outdoors between levels, it would be necessary to optimise the GIS data and expand the levels so that a finer distinction is possible. However, the analysis and the distribution of reasons to go outdoors found, provides additional results for further research within the MOASIS project. To better understand the implications of these results, future studies could address other associations. For example, between walking time and the reached LSL. Li-Tang et al. (2015) state that there are significant differences in the walking distances for different reasons to go outdoors and for a certain LSL. The hypothesis can therefore be confirmed, but the results could be improved with further work.

RQ 2 - What is the association between the detected mobility and different health related aspects?

Reasons to go outside can help maintain older people's walking activity. In the context of daily activities, reaching multiple LSLs may even promote walking. However, activities that are only carried out in the locations far from home do not necessarily increase walking activity. In addition to the greater risk of falls, hospitalisation (Cesari et al., 2009) and poor QoL (Oh et al., 2014), there is growing evidence of the close relationship between aspects of mobility and cognitive processes, involving executive functions, memory, and processing speed Demnitz et al. (2016). The MOASIS project collected with the MIA questionnaire the metamemory skills and assessed the cognition failures with another questionnaire of all participants.

H 2.1: Participants with subjectively good daily sleep quality tend to have an increasing walking time, compared to those with not a good sleep.

This hypothesis cannot be confirmed. The statistical evaluations carried out do not provide consistent results and it is not possible to establish a significant correlation between the variables sleep quality and walking time.

Sleep quality varies with the normal ageing process, both in terms of shortened duration and consolidation (Espiritu, 2008). Evidence suggests that sleep quality is crucial in maintaining cognitive function in older people and helps reduce the risk of developing dementia (Lim et al., 2013). More than half of adults over 65 have at least one chronic sleep disorder, the most prevalent being the inability to stay asleep at night (Foley et al., 1995). With the world's ageing population, understanding how changes in sleep quality can contribute to cognitive decline in older people has become a research necessity (Landry and Liu-Ambrose, 2014). However, sleep quality is a complex construct, making it difficult to evaluate empirically.

Although the participant slept well, the weather is not good for walking, then the walking time gets shorter. This issue can be addressed by controlling the weather variables (temperature or precipitation) of each study day, which will be future work. Previous research has focused on the effect on walking with friends and regular longer walking on sleep quality and duration. Mostly experimental studies have investigated this association in relation to specialised populations: participants with depression, cancer and Alzheimer disease, nursing home residents, insomnia sufferers or women in transition to menopause(Elavsky and McAuley, 2007; Lam et al., 2015; Passos et al., 2012; Richards et al., 2011; Shih et al., 2017).

In summary, the results indicate that walking can increase sleep quality in certain populations and situations (Sullivan Bisson et al., 2019). Inconsistent findings where find by Kishida and Elavsky (2016); Youngstedt et al. (2003). They detected no evidence for within-person associations between walking and sleep in healthy, physically active adults. Considered collectively, these contradictory findings justify further research on this topic. Therefore, the investigation of the association between sleep quality on walking can provide more prove in this manner. Likewise, no significant correlations were found between walking and sleep quality. The relationship between walking and sleep quality remains unsolved. Further research is needed to gain significant insights.

H 2.2: The positive relationship between metacognition (low/high) and the number of new places visited is likely to be stronger among participants with low cognitive failures, compared to those with high cognitive failures.

This hypothesis cannot be confirmed. The statistical evaluation carried out does not provide consistent results and it is not possible to establish a significant correlation between the variables. Previous studies have shown that the routine in daily life can be represented by only a few places. Although, a variety of places is visited over time (Eagle and Pentland, 2009). A high degree of regularity in mobility patterns is known to exist and that people spend most time in only a few locations (Halepovic and Williamson, 2005). A cognitive map contains spatial information about the environment, knowledge of potential and possible travel routes, including place and route identity, location, distance, and direction (Downs and Stea, 1977). Spatial context decisions are possible by individuals with the combination of qualitative and spatial information (Suttles and Suttles, 1972). The cognitive map is a cognitive construct for which a cartographic map is only a metaphor (Downs, 1981). No cognitive relation is detected. The positive relationship between metacognition and the frequency of new places visited has no significant correlation. Further research is needed to determine the causes of between cognition and mobility behaviour.

6.5 Overall Limitations

This section focuses on the overall limitations of the thesis as other specific limitations on the analysis were already mentioned above. By clarifying the limitations of this work and the methods used, future researchers get a better understanding of the conditions under which the results ought to be interpreted.

Participant profile

The participants in the MOASIS project have similar prerequisites, which makes it difficult to identify significant distinctions. Almost all participants have their residence in the Zurich region. This means that the largest city within Switzerland with the greatest number of offers is nearby and may have an impact on the reasons to go outdoors. Furthermore, only healthy older people were included, which has an impact on the variability in the scores of the metacognition and cognitive failures variables.

Methods

The used methods are accurate for the research aim, but also has its limitations. For example, the analysis of the association between cognition and newly places visited by the participant has the limitation, that only the places within four weeks are considered. Some occasional events that happen only every other year have strong impact on the results. For example, the 4-yearly motor vehicle inspection coincides with the measurement period. Furthermore, the variable selection for hypothesis 2.1 is not completely suitable. It would be beneficial to further invest time to select a better fitting variable. For example, investigate the daily life routine. For the analysis of the reasons to go outdoors, ground truth data would have been important to validate the retrieved reasons.

Data Collection Process

The geographic data from OSM provide a good foundation for the analysis and produce feasible results. However, it would have been beneficial for the whole study if the data contained enhanced meta information. It is unfortunate that neither swisstopo nor the statistical office could provide better information about the purpose or amenity of the Swiss buildings.

7. CONCLUSION

7.1 Main Contributions

This thesis intended to provide answers to the following two research questions. The first objective developed and implemented a framework to detect objectively measured mobility behaviour using Global Positioning System (GPS). The second objective had the aim to link the relationships between mobility and health related aspects.

To address these objectives accordingly, the following approach was applied. Insights into the mobility behaviour of healthy older people were derived from GPS trajectories collected in the MOASIS project. Three core components were developed and implemented for the analysis of the GPS trajectories. First, the *Life Space Levels* (LSLs) for the segmentation of the habitat had to be defined. For this purpose, a meta-analysis was applied to define the best fitting life space levels. This segmentation can be used cost-effectively for future analyses and is easily adaptable. Second, a transport mode detection was required to assign the GPS trajectories to a transport mode. For this purpose, a rule-based transport mode detection algorithm was developed, which is optimally suited for global use. Therefore, the algorithm can process any GPS trajectories regardless of its location, as it only requires OSM data. Three transport modes are therefore identified: walk, car, and public transport. These are further differentiated between active (walk) and passive (car, public transport). Third, objectively measured activity profile can potentially replace the subjective self-report diary. Reasons to go outdoors were defined, which were tried to detect from the GPS data using GIS data.

The first research question and hypotheses were confirmed by using the developed framework. This framework enabled gaining insights into the mobility behaviour of participants. The developed transport mode detection framework achieved promising results with the observed accuracy of 81% and the kappa value of 0.643 – a substantial strength of agreement – for the minimum trip length of 4 minutes. The framework provided a deeper understanding on reasons to go outdoors and the participant's movement patterns within a certain LSL. Apart from methodological or data limitations, the retrieved results were consistent with other studies (e.g. Li-Tang et al. (2015)). Furthermore, the conceptualisation of the LSLs has been revised and the defined levels can be used for further studies. This research extended the knowledge about the participants of the MOASIS project.

The second research question and the hypotheses, however, could not be effectively answered, and no significant correlations were found. Mobility and health related aspects do not seem to be significantly related for the given research questions and samples of older adults. As the MOASIS study was conducted with only healthy older adults, it seems plausible that this sample contains barely any persons with any type of major health restrictions. Hypothesis 2.1 aligns with the findings of previous research, which found that the relationship between sleep quality and walking is yet unresolved. In conclusion, healthy older adults in the German-speaking area of Switzerland show an active mobility behaviour beyond their residence, but such mobility behavior is not significantly correlated with their cognition or sleep quality.

Conclusively, this thesis provides a deeper understanding in the MOASIS participants and a broader use for other studies and applications.

7.2 Outlook

The world is getting older and further research in healthy ageing will be necessary in order to understand the ongoing developments and to better cope with the problems that will arise. Although, no significant correlation was found within the statistical analyses, further studies should be conducted to investigate the correlations of health related aspects and mobility in later life. This master thesis is one of the first few attempts that used GPS trajectories of the recording period of the MOASIS study. Therefore, there are a lot of other mobility aspects that could be investigated within this data. For future research, a more in-depth analysis of how to detect the reasons to go outdoors, that can be used to characterise the mobility behaviour, should further be examined. Finally, it would be beneficial to further investigate the within-person relationships between mobility behaviour and health related aspects.

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APPENDIX A

SOFTWARE

Table A.1: Used software for the thesis analysis.

Software	**Description**
QGIS 3.16.2-Hannover	A Free and Open Source Geographic Information System
Overleaf	Online LaTex editor; used to write the thesis.
R 3.6.0	Language and environment for statistical computing and graphics.
R-Studio 1.2.1335	Free and open-source IDE for R; used as the main tool for the processing and visualization of the collected data and all calculations for segmentation and classification.

The R scripts developed for this project are not included in this thesis but are stored on the DYNAGE server.

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.

Zurich, 30 June 2021

Oliver Eberli