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Mobility patterns in university campuses: an example of the University of Tartu

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Annotation

Mobility patterns in university campuses: an example of the University of Tartu

The aim of the master thesis was to understand the spatiotemporal behaviour of UT students and academics depending on their socio-economic characteristics and the location of campuses. GPS data used for the research had been obtained through MobilityLog smartphone application, developed by the Mobility Lab, of the Department of Geography, UT. The data has been pre-processed by the Mobility Lab: sequential GPS points located close to each other have been aggregated into stops. To achieve the aim of the research, the number and duration of stops was analysed in relation to the meaningful places, pre-defined by respondents.

The day of the week, the starting hour of the stop, and the academic role of the respondent were proven to affect the duration of stops. The location of campus was not proven to be statistically significant alone, but had an effect in combination with other factors. The stop duration was affected by its location in relation to other meaningful places. The stops within the home domain were the longest, followed by stops in work and studies domain. Results indicated the shortage of services in Maarjamõisa campus comparing to the central campus.

Key words: Activity space, domains of meaningful places, GPS data, spatio-temporal behaviour

CERCS code: S230 – Social geography

Annotatsioon

Liikuvuse seaduspärad ülikoolilinnakutes: Tartu Ülikooli näitel

Käesoleva magistritöö eesmärgiks oli mõista üliõpilaste ja ülikooli akadeemiliste töötajate ajalis-ruumilist käitumist sõltuvalt nende sotsiaal-majanduslikust taustast ja ülikoolilinnakute asukohast. Uuringus kasutatud GPS andmed koguti MobilityLog nutitelefonirakenduse abil, mille väljatöötajaks on TÜ geograafia osakonna mobiilsusuuringute labor. Andmed eeltöödeldi mobiilsusuuringute laboris: üksteisele lähedal asuvad järjestikused GPS punktid olid ühendatud peatusteks. Uuringu eesmärgi saavutamiseks analüüsiti uuritavate peatuste arvu ja kestvust seoses teiste neile oluliste paikadega.

Nädalapäev, peatumise algustund ja vastanu akadeemiline roll olid analüüsi tulemusena statistiliselt olulised tegurid, mis mõjutasid peatumiste kestust. Ülikoolilinnaku asukoha statistilist olulisust peatumise kestuse kujunemisel üksinda võetuna ei tõestatud, kuid sellel oli mõju kombinatsioonis teiste teguritega. Peatumise kestust mõjutas selle asukoht seoses teiste isikule oluliste paikadega. Kõige pikemad olid enamasti peatumised kodupiirkonnas, millele järgnesid peatumised töökoha ja õpingute paiga piirkonnas. Tulemused viitasid teenuste puudulikkusele Maarjamõisa ülikoolilinnakus, võrreldes kesklinna ülikoolilinnakuga.

Märksõnad: Tegutsemisruum, isikule oluliste paikade piirkonnad, GPS andmed, ajalis-ruumiline käitumine

CERCS kood: S230 – Sotsiaalgeograafia

Table of contents

Introduction

The master thesis addresses the spatiotemporal behaviour of students and academics of the University of Tartu (further referred as UT) depending on the location of campus and socio-economic characteristics of respondents. UT students alone constitute almost 14% of the population of Tartu (Statistics Estonia, 2018; University of Tartu, 2019 [a]). For long time, UT has shaped the development of the city, and the historical campus is an integral part of it (Poom *et al.*, 2017). Thus, to balance the development of the city and the campuses of UT, it is necessary to understand mobility of people associated to the UT.

Human activities follow a certain spatial and temporal pattern that depends on the anchor points – home and work locations. Most of other activity locations are centred on these points. The anchor points explain person's choice of other activities, as well as their timing and location (Lee *et al.*, 2016). Home is the most important anchor in people's daily travel, with work or study location being at the second place (Schönfelder, Axhausen, 2003). Some researchers argue that the role of home location in determining locations of other activities is much more important than the location of workplace or commuting routes (Schönfelder, Axhausen, 2003; Li, 2016).

Understanding human behaviour and how people use time and space is crucial in urban planning, including transportation planning (Phithakkitnukoon *et al.*, 2010). Considering that today half of human population live in cities, and the number is growing (United Nations Organization, 2016), comprehensive urban planning has become crucial for city development.

Among other qualities of city, urban planning seeks to ensure liveability or suitability for living (Leach *et al.*, 2013). To foster liveability, it is necessary to understand how people use time and space. Studies on human activity spaces can help. Activity space is a subset of the locations which an individual usually visits daily (Schönfelder, Axhausen, 2003, Vich *et al.*, 2017) and describes person's spatial as well as temporal behaviour. It is affected by the built environment and the density of facilities (Shen *et al.*, 2015).

Most of historical UT study buildings are located within the historical city centre. However, the campus of Maarjamõisa is located on the edge of the city. One of the central points in Maarjamõisa campus is the university hospital. In 1910 Maarjamõisa was favoured for the development of hospital over several other locations because of the proximity to the railway. The campus nowadays has developed to a well-equipped study base for medical and natural sciences (Tohvri, Udumäe, 2013).

However, other facilities necessary for students, such as dormitories and the library, have remained in the city centre. Thus, the accessibility of the campus and its connectivity to the city centre is of crucial importance (Poom *et al.*, 2017). Further development of Maarjamõisa campus and reallocating significant numbers of students there might significantly affect daily dynamics of the city, including use of services and transportation, as well as perspective developments of the city.

Data used for the research has been provided by the Department of Geography, UT, and is obtained through MobilityLog mobile application, developed by the Mobility Lab, UT. The data was originally obtained for the needs of the project of Live Baltic Campus (Ahas *et al.*, 2017). The mobile application tracks the mobility of the respondents with help of global positioning system (further referred as GPS). The data set used for the analysis includes 71 respondents studying or working in UT (38 students and 33 academics; 31 persons from Maarjamõisa and 40 persons from the central campus), and covers two semesters of academic year 2016/2017. All the respondents have given their consent for the use of their data for scientific purposes. The author of the thesis has signed a contract for secure use and processing of the data for her master thesis. The author had access only to anonymized data, and results are presented in an aggregated form.

The data, provided by UT, had been pre-processed by the Department of Geography: sequential GPS points that were located within a certain radius had been aggregated into stops. Meaningful places had been pre-defined according to the information provided by the respondents in the interviews conducted by the Mobility Lab. Depending on the semantic meaning of meaningful places, they had been pre-classified into domains, such as home, work, study, hobbies, etc. In the master thesis, these stops are analysed in relation to the location of meaningful places.

Thus, the aim of the master thesis is to understand the spatiotemporal behaviour of the students and academics of UT in the spatial context of Tartu. To achieve the aim of the research, following research questions are stated:

1. How does the location of work and studies influence the duration and number of other activities of respondents?

2. What are the daily and weekly temporal rhythms of activities depending on individual's work or study location?
3. What are the differences regarding time use and locations of stops depending on individual's academic role?

The first part of the thesis gives an overview on interaction of campuses and cities, the concept of activity space, semantic and temporal differences of daily life, as well as GPS tracking in mobility studies. The data and methodology of the research is described in the second part. Finally, the results of the analysis are presented, the conclusions are made, and the questions for discussion are raised.

1. Theoretical overview

1.1. Interactions of campuses and cities

Today, 3.5 billion people live in cities, and it is estimated that this number will reach 5 billion by 2030 (United Nations Organization, 2016). Cities are the main contributors to welfare, as well as to negative environmental impacts. To mitigate negative effects, urban planning comes into play. One of the qualities of city that urban planning seeks to foster is liveability (Leach *et al.*, 2013).

Universities also contribute to the local economy and culture. They can be especially useful in knowledge management regarding smart city projects by acting as knowledge hubs (Ardito *et al.*, 2018). Smart city is a concept central in urban planning that covers technological developments, smart human resources, and collaborative governance (Meijer, Bolívar, 2015). However, the concept is so complex that it has become somewhat unclear (Nilssen, 2018). A part of smartness lies in the presence of higher education institutions and people with higher education (Shapiro, 2006; Winters, 2010). Often people moving to smart city for studies "play an important role in the relationship between human capital and urban population growth" (Winters, 2010), staying there after graduation. Thus the location and design of the campus can foster the inclusion of the campus into the city fabric and city life. It can significantly influence students' and academia's everyday choices as transport, dining, outdoor and leisure activities, etc.

Today's campuses involve not only premises for studies and research, but a much wider set of services, such as residences, student centres, shopping and recreational options (Witlox, 2017). Hence, the impact of campuses on urban environment becomes evident, and campuses are affected by this environment themselves (Witlox, 2017). A good campus is characterised by walkability, healthy and secure environment, and environmental sustainability (Hajrasouliha, 2017). Studies have shown that the reason why people are attracted to live in the city centre is the availability of services and convenience of being close to points of employment and consumption (Tallon, Bromley, 2004).

The presence of university in the city centre is a source of higher income in service sector, since students consume cultural and recreational products and, in many instances, are producers themselves" and their spending behaviour may differ from other residents' behaviour (Van den Berg, Russo, 2003). Students also have a major impact on housing market constantly requiring rent apartments (Van den Berg, Russo, 2003). That speaks in favour of a centrally located and compact campus with no need to use motorized transportation.

However, central location of the campus may not always be desirable. In fact, universities tend to compete with cities for land use. If universities expand in the city centres, it may cause inconveniences for other residents and decrease functionality of services (Van den Berg, Russo, 2003). In some cases influx of students into the city centre may cause the displacement of working class population by middle class students (Smith, 2002), while students are attracted to living in the city centre predominantly because of daily convenience and nightlife (Chatterton, 1999; Chatterton, Hollands, 2002; Smith, 2002).

On the other hand, locating the campus on the edge of the city may cause transportation issues. A study, analysing the mobility within campuses and their impact on wider mobility patterns, found out that daily journeys between home and the university campus can constitute a significant proportion of traffic problems in the neighbourhood where the university is located (Gurrutxaga *et al.*, 2017). Transportation on college campuses can generate unfavourable environmental impacts which disturb learning, harm environment, and affect health (Balsas, 2003).

However, people have different motives to choose a particular transportation mode. Fürst (2014) characterizes them as a spectrum, eco-friendly travellers being on one end of it and prestige-oriented travellers being on the other. Therefore, it is not enough to provide public transport or opportunities to use eco-friendly mobility means, but the attitudes of people must be changed to develop sustainable travel behaviour in the long term (Fürst, 2014; Gurrutxaga *et al.*, 2017). Transportation planning in campuses can encourage incentives for health- and environment-friendly transport modes not only in the campus but in a wider scale. Thus, university campuses can constitute laboratories for testing and implementing sustainable transportation alternatives (Balsas, 2003).

1.2. The concept of activity space

To analyse someone's spatial and temporal behaviour, the term of mobility is of use. This is one of the core concepts in the discipline of geography and can be used to describe daily travel, transportation modes, tourism, as well as social mobility (Kwan, Schwanen, 2016). In this master thesis, mobility is addressed as human movement over time and space, i.e., both as places where certain activities happen and commuting between these places.

Understanding human mobility in time and space is crucial in numerous fields, including urban planning (Phithakkitnukoon *et al.*, 2010).

In the course of their daily lives people visit certain places. A subset of the locations which an individual usually visits daily is classically called activity space (Vich *et al.*, 2017) or action space (Schönfelder, Axhausen, 2003) (further on – "activity space"). Activity space not only covers the places of person's everyday activities, but also describes person's spatial and temporal behaviour. Thus, it is a central concept that helps to understand why certain people visit certain places at certain time.

Activity space is a relatively old concept, but it still is of use to understand the spatial extent of daily mobility, the means of transport and the consequences in a broader scale (Vich *et al.*, 2017). The concept of activity spaces has been used beyond traditional one-dimensional approaches (i.e. travel distance) and it refers to two (spatial) and three (including time) dimensions. Activity spaces reflect the idea that physical spaces should not be observed in isolation from the processes that take place in them (Matos, 2008).

Thus, activity spaces serve not only for analysing individual behaviour, but also can be used as an indicator for aggregate level. On individual level they can describe the daily travels and give insight about the constraints regarding long travels and limited time (Vich *et al.*, 2017). They can also describe the use of other services (Lee *et al.*, 2016). On aggregated level they can show the busiest locations in the city, the main transport routes and modes, as well as the temporal differences in space use. Activity spaces are particularly relevant to transportation research because they frame the travel decisions made by individuals and can help us understand what features of an area draw people to it (Lee *et al.*, 2016). Individuals are facing different factors that shape the outlook of their activity space and their daily mobility. These factors are revealed in following chapter.

1.3. Diversity in daily mobility

Anchor points

The fixed activities in time and space (such as time spent at home or work) affect person's opportunities to participate in various activities at various time periods, thus resulting in constraints regarding the space-time prism (Hägerstrand, 1970), a concept to be explored in the following subchapter. These fixed activities can be referred as anchor points – the places that largely explain the choice of other activities, as well as their timing and location (Lee *et al.*, 2016). Typically, home and work locations are referred as such anchor points.

Although activity spaces are highly individual, they follow the same pattern – people interact less frequently with areas that are further away, while most of activities are centred on anchor points. The shape and size, as well as the inherent structure of activity spaces is determined by:

- home: location, the duration of residence, the supply of activity locations in the vicinity of home and the resulting neighbourhood travel;
- regular activities: mobility to and from frequently visited activity locations (anchor points), such as travel between home and work;
- irregular or flexible activities, such as travels between work and hobby-related activities or home and shops (Golledge, Stimson, 1997).

Studies have showed that home is the most important anchor in people's daily travel. In a study testing the relations between the size of the activity space and sociodemographic characteristics, it was acknowledged that the home location is the central anchor point of daily mobility and for most people the geometric shape of the activity space is ellipse-like with two focal points (Schönfelder, Axhausen, 2003). Consecutively, home-based sub-activity space is an essential component in person's activity space, while workplace-based and commuting trip-based sub-activity spaces are much smaller (Li, 2016). Some authors believe the distance between anchor points to be the key factor determining the shape and orientation of activity space (Sherman *et al.*, 2005).

Urban structure and access to services

Vich points out that the differences in the size of activity spaces can be caused by constraints, needs, preferences or resources available and can be grouped depending on whether they relate to individual or environmental characteristics (Vich *et al.,* 2017). Environmental characteristics represent the main constraints for spatial behaviour, reflected in the structure of the activity spaces of individuals (Vich *et al.,* 2017). These characteristics affect the extent of people using the different activity places that in turn influences the quality of urban space (Ahas *et al.,* 2010).

A study (Hasanzadeh, 2019), analysing centricity and clusterization of activity places, classified them into three groups of monocentric, bicentric, and polycentric. It was found out that the results could not be associated with socio-economic characteristics, but rather urban form. Travel mode and density of urban characteristics (services, housing etc.) were significantly associated with the form of centricity (Hasanzadeh, 2019).

Environmental exposure and accessibility are geographical notions that can help to understand the reason behind the variation of human behaviour in urban space (Kwan, 2013). People who have long commutes are forced to use motorised transport as private cars or public transport, while people who do not have to travel far, generally have smaller activity spaces (Vich *et al.,* 2017). This relationship works in both directions: people owning cars can afford longer travels than those who cannot afford a car. However, in the context of urban planning to influence the individual behaviour the first approach deserves more attention.

Flexibility of space-time use is important not only regarding transportation and travel behaviour, but also is affected by the built environment. Study in China reveals that the denser are the facilities around home location, the better the access to services is and people are not likely to choose analogue services elsewhere. However, density of facilities around other activity locations does not have such effect – people are equally likely to use services elsewhere (Shen *et al.,* 2015).

Socioeconomic differences

Age, gender and income are some of the individual factors that affect how people move (Weber, Kwan, 2015; Vich *et al.*, 2017). Some studies have shown gender differences in travel behaviour and mobility patterns, for example, on average men use cars more often than women and have larger activity spaces, while women tend to use more public transport and to make shorter work trips (Weber, Kwan, 2015). These gender differences in mobility and activity patterns are associated with women's increasing participation in paid employment, their gender roles in the domestic sphere, and their needs to balance their employment and household responsibilities (Weber, Kwan, 2015).

Mature adults are believed to have larger activity spaces than both younger adults and seniors, and wealthier households generally have larger activity spaces than those with lower income (Vich *et al.*, 2017). However, it does not necessarily mean that mature adults or people from wealthier households visit more places per day. Rather, the transportation mode is more likely to be blamed. A private car gives an opportunity to travel farther and thus to cover larger geographical space.

Multiple anchor points

Although daily mobility can be characterized by “a deep-rooted regularity” (Song *et al.*, 2010), diversity of space use both in time and space dimensions is characteristic especially for urban residents (González *et al.*, 2008). Nowadays people tend to be more mobile, and the nature of work is changing. In addition to traditional employment types, remote working or working at multiple jobs appears. Many people nowadays are not so attached to one job, but rather tend to work in multiple jobs, sometimes even simultaneously (Barley *et al.*, 2017). For example, in Canada already in 1994 one-third of employees was either working in part-time work, temporary jobs, were self-employed, or holding multiple jobs (Gunderson, Ridell, 1999).

If people are working or studying in higher education institutions, another important type of activity places must be considered: the study premises. Most students have their classes in different physical locations, and that causes them to commute both from home to these buildings and between them. Studies have shown that most of students’ time is distributed between resting and studying, and typically there are multiple study locations (Li *et al.*, 2015). The same applies to academics that may have their permanent work place at one location, but are giving classes in other locations or have to visit other university buildings for another reason, e.g., library, meetings, collaboration. The fact there are multiple work and study locations leads to a conclusion that the distance between home and work or study place cannot be measured as one continuous distance.

1.4. Semantic domains of daily life

Along with a rise of social network analysis the semantic meaning of the places is gaining attention (Mohamed, Abdelmoty, 2017). While mobility in general can be described as the interaction of human behaviour and spatiotemporal dimensions, the aim or the motivation is what initiates this interaction. It characterizes why a certain place is visited or reveals its semantic meaning.

Information as annotation of place or description of activities contains important semantics that helps to understand the motivation of visit. Such information can be derived from location-based social networks where people produce content themselves (Mohamed, Abdelmoty, 2017). Several attempts have been made to classify visited places. Some classifications, such as American Time Use Survey, are based on travel diaries, while other ones, such as Placer attempt for automated classification, are based on person’s demographic characteristics and timing of the visits (Krumm, Rouhana, 2013). Automated semantic labelling of places is a growing field in machine learning and is closely connected to fields such as navigation of mobile robots or personalized advertisements (Crespo *et al.*, 2017). However, the aim in both approaches is to capture the semantic meaning of the visit, describing the activities people engage with.

Some location-based social networks as Foursquare already provide place categories that are in principle grouped into semantic domains. These domains include residence, professional places, study-related places, and entertainment or recreation-related places. Studies demonstrate that taking semantic meaning of the place into account in addition to the spatial location and social characteristics can better describe users and their preferences (Mohamed, Abdelmoty, 2017).

Other studies have attempted to predict semantic meaning from mobile sensors data and timing. It was found out that there was a clear daily and weekly pattern, especially in semantic place labels related to home, workplace, and doing sports (Lex *et al.*, 2013). Another research showed that entertainment related activities are more typical during evening peak hours, while regular activities as trips to work are mostly taking part in morning rush hours (Huang *et al.*, 2018). Thus activities in certain domains are more likely to occur at certain time of the day.

Studies on human mobility in relation to the dominant function (e.g., shopping or recreation) of area have been conducted. The results show that regardless on physical location people working in the same type of area tend to have more similar daily activity patterns (Phithakkitnukoon *et al.*, 2010). This indicates that the characteristics of work area may have an effect on the daily activity pattern.

1.5. Temporal dimension of daily activities

The spatiotemporal patterns and rhythms of urban life have been the dominant focus of mobility researchers (Schönfelder, Axhausen, 2010). However, with the concept of time geography rising, temporal patterns started to gain more attention (Hägerstrand, 1970). Time geography discipline analyses human movement over space and time, as well as to conceptualise people's everyday activities (Zeng *et al.*, 2017). Hägerstrand's time geography concept pays much attention to the constraints and trade-offs individuals are facing because of limited time. Thus people are forced to make choices how to participate in spatially dispersed and temporally limited activities and how to commute between them (Hägerstrand, 1970; Miller, 2004).

In space-time-travel geographies "individual's movements are viewed as series of trips taken through time and space and are characterized by space-time diagrams". These diagrams reveal one or more space-time "prisms", covering all locations that can be reached within the time frame allocated by the traveller (Newsome *et al.*, 1998).

According to Hägerstrand (1970), a person's movements within a day can be described as a space-time prism that has time-space walls. These walls depend on the location and duration of stops – every stop makes the prism to shrink in a certain proportion to the length of the stop. Hägerstrand makes an example – if the work place is located far enough from home, a stay at work for eight hours might shrink the remaining prism so much it would disappear. That would mean a person has to spend most of the day at work and the rest of it on commute. However, as Hägerstrand marks out, a more typical prism is split in time before work, time at work, lunch hour, and evening after work (Hägerstrand, 1970). The components of space-time prism are both stops and movements, while activity space represents the spatial part of the prism (Hägerstrand, 1970).

The space-time framework has a potential in modelling human behaviour and aiding the planning of location of activities and infrastructure (Miller, 1991). The behaviour of people (location and movement) in urban space is a temporal pattern that can be used to measure the functional diversity of urban space (Ahas *et al.*, 2010; Ahas *et al.*, 2015). Hägerstrand (1970) points out that some activities common for most individuals (as working, shopping, being at home) tend to occur only at discrete locations for limited durations (Hägerstrand, 1970). Usual travel time expenditure is generally limited to 1–2 hours daily, so individuals will decide on the locations of their daily activities according to this limited travel time. People experiencing long working hours are forced to reduce the time spent in other activities and may even choose not to participate, thereby reducing the size of their activity space. Also, smaller activity spaces might lead to reduced access to opportunities in metropolitan regions (Vich *et al.*, 2017).

Considering that each individual is limited with their daily time budget, daily spatiotemporal rhythms become of interest, as they limit individual activity spaces. The daily movements of humans usually are regular and reflect circadian rhythms both in time and space (Zeng *et al.*, 2017). These rhythms are of essential importance for planning purposes, therefore understanding them is crucial for various fields, including urban and transport planning, business planning etc. (Zeng *et al.*, 2017).

The temporal variability is dependent on weekdays: the activities of people can vary depending if it is a work day or a weekend (Ahas *et al.*, 2010). A study exploring day-to-day variability of individuals' activity space found out for workers and students on workdays the activity locations are relatively stable from day to day (Susilo, Kitamura, 2005). Other researchers have found out that by using density maps of activity space, it is possible to find differences between weekday and weekend activity spaces (Lee *et al.*, 2016).

When analysing mobility patterns, it must be taken into account that while the semantic patterns of individuals might be similar, spatiotemporal patterns may significantly differ (Huang, Li, 2016; Zhang *et al.*, 2017). Studies, examining spatiotemporal behaviour of students in the Jinming campus of Henan University by collecting activity – travel diaries and seven day GPS data, revealed that during the workdays the daily rhythms are strongly expressed and similar for most of the students, while at weekend the time usage is distributed differently (Zhang *et al.*, 2017).

Now, time dimension is an inseparable part of a geographic research: accessibility is recognised to have both spatial and temporal dimensions. Without considering temporal dimension the conclusions about accessibility are not realistic (Urry, 2007; Kwan, 2013; Järv *et al.*, 2018). Consequently, time dimension should also be considered when studying peoples' activities.

1.6. GPS tracking data in mobility studies

The mobility can be tracked with traditional methods that include travel surveys, or with methods that involve technologies (Li, 2016). Conventional data sources involved self-reporting as surveys and travel diaries; however, such data has several challenges for the analysis. Because of the need of recruitment of the research participants and because of the consequent manual analysis of data, only a small proportion of population can be surveyed. It is hard to relate the results to general population, as small proportion of population is analysed. The time span of the research is limited, which may not give a representative picture of people's behaviour over time. Such data are also costly to collect or acquire (Li, 2016).

Technology-facilitated data sources include mobile phone based positioning such as call detailed record (CDR), as well as global positioning system (GPS), Wi-Fi, Bluetooth, etc. These sources have many advantages as better temporal and spatial resolution, larger sample sizes and they are less expensive to obtain (Li, 2016). GPS offers many privileges as reduction of subjectiveness, as the system is obtaining real-time data (Vich *et al.*, 2017). The widespread use of mobile phones and GPS technology offers very precise location tracking with high temporal resolution. It also allows obtaining large amounts of data while imposing minimal burdens to people (Ahas *et al.*, 2015; Vich *et al.*, 2017).

Hence, although conventional methods are less precise and less informative about the people's movement pattern, they give more contextual information on motivation to visit one or the other place. Therefore, it is common to combine qualitative methods as interviews with technology-facilitated sources of data to reach higher precision on mobility tracking, as well as to understand the motivation of mobility. As Korpilo points out, movement patterns alone do not provide the motives for root choice or visit, thus the research might benefit from combining GPS approach with questionnaires or another conventional method (Korpilo, 2017). A study on time use differences has approved that the use of travel diaries allows the interpretation of GPS data and facilitates its analysis (Zhang *et al.*, 2017).

To track GPS signal, either a special GPS logging device, or a smartphone can be used (Stopher *et al.*, 2018). In early studies with GPS data, usually a wearable GPS logger was used, but GPS loggers were frequently damaged or not returned. However, since smartphones have penetrated the market, it has become more popular to use smartphones with installed GPS tracking app. However, a study shows that generally respondents of surveys prefer to use a GPS tracking device over smartphones, because they are concerned about data safety and still not all the people have a smartphone (Stopher *et al.*, 2018).

Several aspects need to be considered in the context of analysing and using GPS data. GPS datasets are usually large, thus development of widely available tools for reducing and synthesising records into meaningful datasets is important (Pendyala, 2005). GPS data allow analysing day-to-day variability and weekly rhythms. Consequently, they hold within the information and can be used to analyse circadian and weekly rhythms, inter-person interactions, allocation of destinations and time of the visit, activity spaces etc. By implementing new techniques and solutions, GPS tracking datasets can be very informative and are considered as one of the best solutions in space-time activity studies (Pendyala, 2005).

2. Data and methods

2.1. Description of the study area

Tartu has the second largest population in Estonia: 97 thousands inhabitants in the beginning of the 2019 (Statistics Estonia, 2019). About one third of the population has higher education (Statistics Estonia, 2018). It is characteristic for Tartu that de facto population numbers fluctuate depending on the time of the academic year, as 12 thousands of inhabitants are UT students (University of Tartu, 2019 [a]).

In 2017, administrative reform was carried out, and Tartu city municipality was merged with Tähtvere rural municipality, thus more than doubling Tartu's area (Ministry of Finance, 2018). For the needs of this research, the old administrative borders are used, as the research concentrates only on the urban area.

At the moment, UT has 55 buildings in use across all Tartu (University of Tartu, 2019 [b]), over 30 of them within the city centre (Kesklinn) or in close vicinity of it, and 13 buildings in Maarjamõisa (see Figure 1). However, the borders of the campuses are not official and the campuses are rather dispersed.

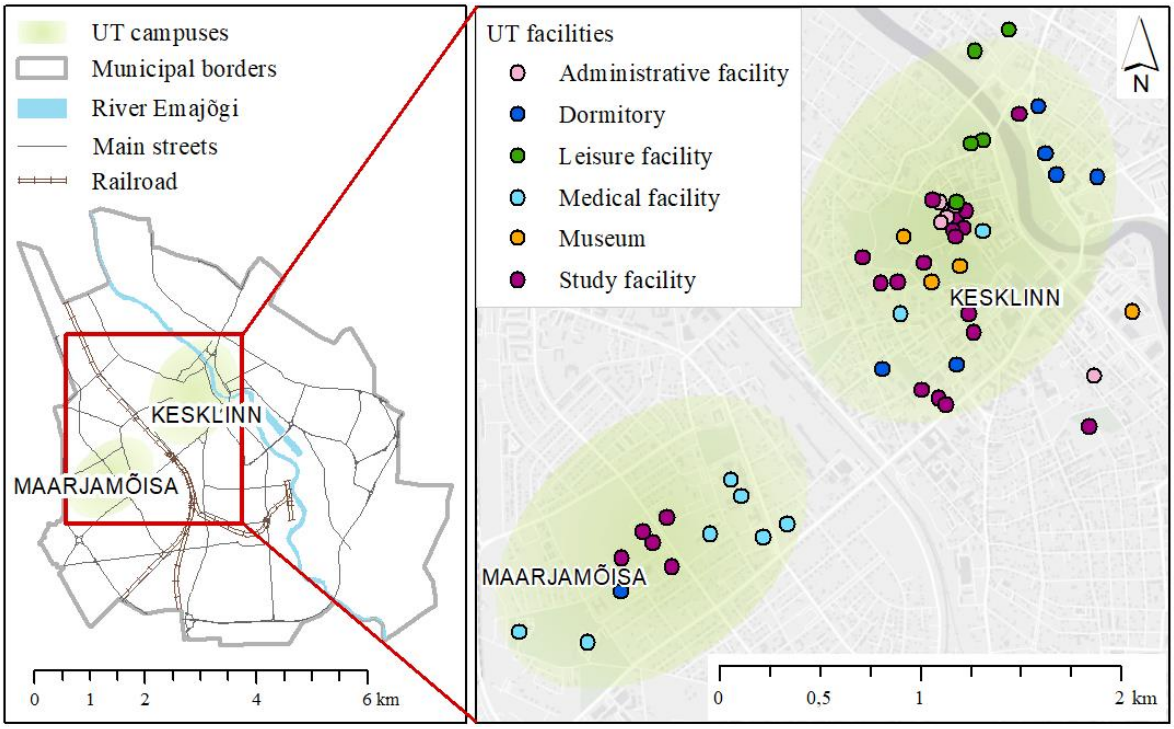

Figure 1. UT facilities.

(Author: Daiga Paršova. Data: University of Tartu, 2019 [b], 2019; Geoportal, 2019; Open Street Map, 2019; World Light Grey Canvas Base map)

Historically UT has been located in the city centre, with most of the buildings in the old town. However, in 1910 it was decided to relocate the university hospital to Maarjamõisa because of its proximity to the railway. The campus nowadays has developed to a medical centre of national importance, as well as to a well-equipped study base for medical and natural sciences (Tohvri, Udumäe, 2013). The campus is however still located in the fringe of the city.

The historical centre does not accommodate much of housing. Mostly public buildings, business-related buildings, and different services are located there. The fringe on the centre accommodates also low-rise apartment buildings. Along with active leisure activities, the centre offers access to historical old town and various green areas. The compactness of the historical centre makes it accessible by foot or bicycle from surrounding living districts. The cycling infrastructure includes marked cycling ways on the biggest streets and multiple bicycle parking places. In close vicinity to the centre there are affordable housing facilities, including dormitories and shared apartments. Currently, most of the student dormitories are located in close vicinity of the city centre.

The Maarjamõisa campus quarter that is to be developed according to the detailed plan (Detailed plan, 2015) belongs to UT and is marked in the general plan of Tartu as an area for educational needs (Municipality of Tartu, 2017). However, the campus area in fact is wider. Maarjamõisa district mostly accommodates public buildings (State Archive), UT study and research premises (Physicum, Biomedicum, Chemicum, and Institute of Technology) and other educational institutions (Tartu Health Care College and its dormitories, Tartu Tamme Gymnasium and Tartu Adult Gymnasium), the hospital with its clinics, greenery areas, and individual dwelling houses. There are very few grocery shops in close vicinity of UT premises and hospital and practically no recreational or entertainment services. The study buildings though include lounge areas and cafes.

At the moment, there is one dormitory belonging to UT in the Maarjamõisa campus (Tartu Student Village, 2019). Students are mostly commuting via public transportation or bicycles from the dormitories located close to the city centre. Maarjamõisa campus is approximately in 2.5 km distance from the centre, and two main routes (Riia Street and Näituse Street) include crossing the railway. The cycling ways and bicycle parking places are available in vicinity of the study buildings and hospital.

2.2. Data acquisition and preliminary processing

Initial dataset and data collection purpose

Within the Live Baltic Campus project, the Mobility Lab of the Department of Geography, UT, in collaboration with other scientists and officials conducted a study to understand the effect of workplace on the space and time use (Ahas *et al.*, 2017). The respondents included students and academics of the UT, as well as the employees of the Estonian National Archives and Estonian National Museum (in total 260 respondents). The GPS data was collected via MobilityLog smartphone application, developed by the Mobility Lab, UT. The GPS data was complemented with information from two interviews conducted with respondents to add semantic dimension to the visited places (Ahas *et al.*, 2017).

The data collection period was from March 2016 to October 2017. During the research period, the Estonian National Archives and Estonian National Museum both were relocated to the fringe of the city. The results showed that the relocation of the institutions increased home-to-work distance, forced commutes through the central city, and reduced time spent within the city centre. The study introduced an approach combining GPS tracking data with semantic information acquired from interviews, thus uncovering the motives for visits (Ahas *et al.*, 2017).

Preliminary analysis and processing of data sample

To answer the research questions stated in the master thesis, the data collected within the Live Baltic Campus project is used: both GPS data and data from associated interviews. The data set is narrowed to two semesters: 29.08.2016-16.12.2016 (Semester 1) and 06.02.2017-26.05.2017 (Semester 2). The sample used in the thesis is also narrowed according criteria discussed in chapter 2.2.2. The author of the thesis has signed a contract for secure use and processing of the data for her master thesis. The student accesses pseudonymized data only, and results are presented in an aggregated form.

The data has been pre-processed by the Mobility Lab in order to distinguish stops: sequential GPS points that were located within a certain radius have been aggregated into stops. In the master thesis, these stops are analysed in relation to the location of meaningful places. Meaningful places were pre-defined according to the information provided by the respondents in the interviews conducted by the Mobility Lab. Depending on their semantic meaning, the meaningful places were pre-classified into domains, such as home, work, study, hobbies, etc.

In order to light up the differences between students and academics studying and working respectively in the city centre and Maarjamõisa, they are divided into subgroups regarding their academic role (student or academic) and place of studies or work (city centre or Maarjamõisa).

The number of data days per user for each of the subgroups is presented in Figure 4 and Table 1. The median value for all the respondents is 83 data days, while the standard deviation is 25 data days. The mean value is lower than the median value indicating that there are more outliers in the first quartile.

Table 1. Data days per one semester.

	Respondents	Mean	Standard deviation	Median	Minimum	Maximum
Academics: Centre	26	77	25	86	4	107
Academics: Maarjamõisa	21	69	27	78	2	108
Students: Centre	34	75	26	85	2	106
Students: Maarjamõisa	23	77	23	83	6	106
In total	**104**	**75**	**25**	**83**	**2**	**108**

According to Figure 2, the upper quartile in all groups is relatively similar, while the minimum number fluctuates significantly, and there are outliers present. In order to have a comparable number of data days for all the groups, 60 days will be minimum threshold (standard deviation subtracted from median). 60 days constitute two months, while a semester is either four or five months long. Thus, using data from users with less than 60 data days might not give a true impression about the space and time use throughout the semester. On the contrary, setting minimal threshold higher may result in too few data for analysis.

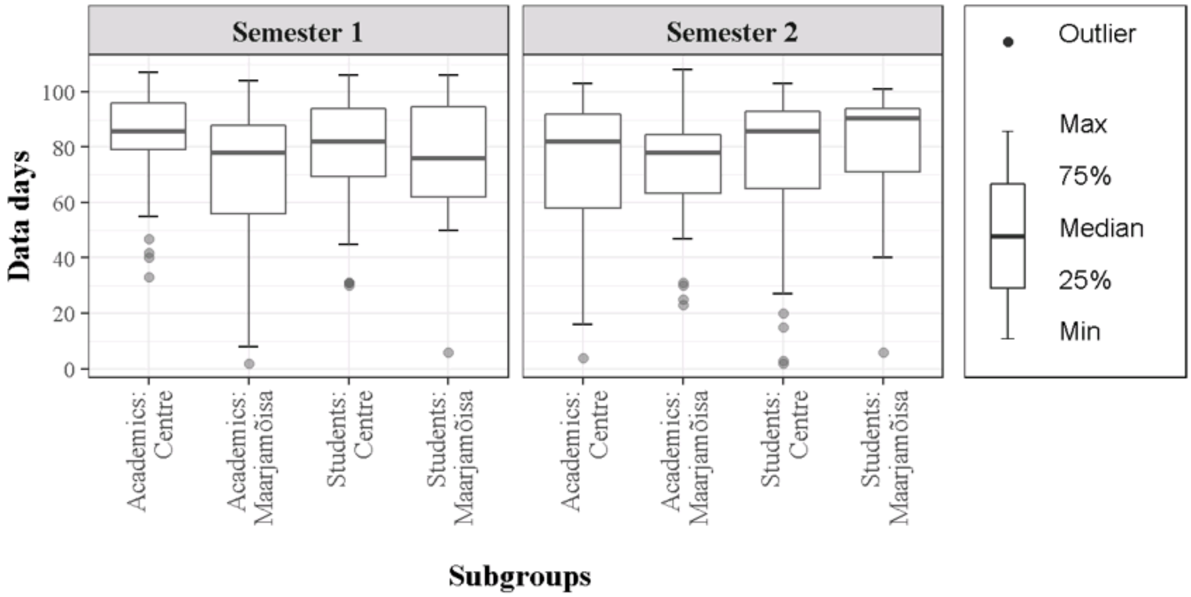

Figure 2. Number of days per semester for each subgroup.

The minimum number of stops is common for all the groups, and it is one (see Figure 3). However, if there is only one stop per day, it is not possible to analyse distribution of time between the domains of stops, therefore the minimum threshold is set to two stops per day. The mean value and the median value in this case both were around five stops per day. According to Figure 3, in 95% of the observations the number of stops per day was up to ten stops per day. Thus, the maximum limit for analysis is set to ten stops per day. After cropping the data, the data days are reduced from 14 440 to 12 305.

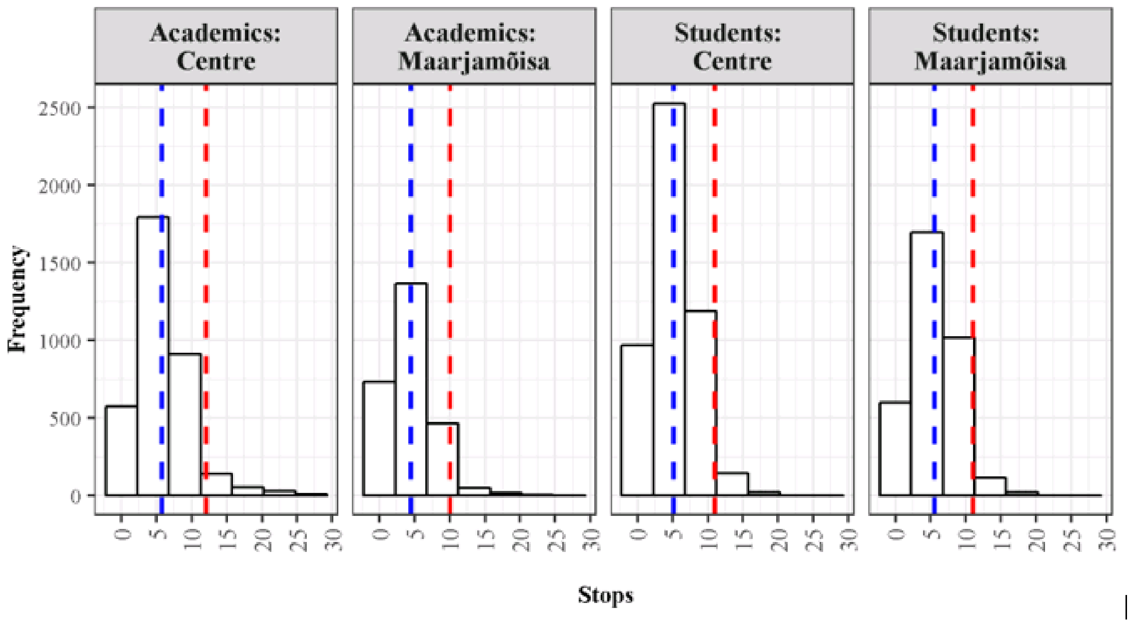

Figure 3. Histogram of number of stops per day.

(Blue line – mean value; red line – border of 95% of observations)

Duration of a stop is displayed in Figure 4. The minimum duration of a stop is 5 minutes, while the maximum values reach 3 236 minutes (54 hours). It is necessary to set a minimal limit to the number of stops, as there are stops that are longer than daily time budget. However, the median values are 39 to 68 minutes depending on a subgroup. The upper limit of the third quartile for all groups is around 100 minutes.

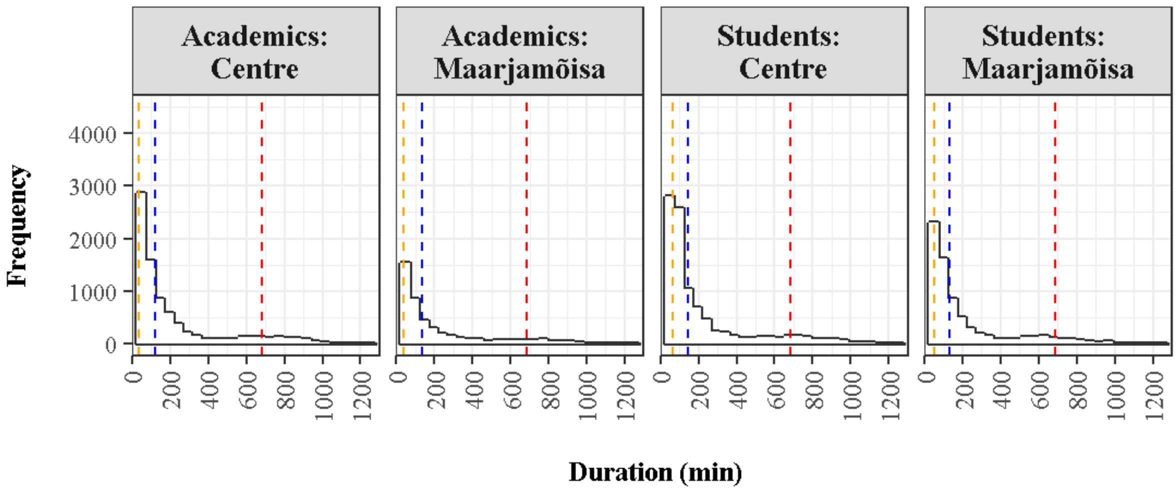

Figure 4. Histogram of duration of a stop.

(Stops 1200 – 3236 min. omitted from histograms, counted into statistics; orange line – median value; blue line – mean value; red line – border of 95% of observations)

From 11 555 data days, on 11 211 days (97%) the tracking application has been switched on all day long. Other cases (344 data days) are depicted in histogram (Figure 5). Time being offline is different for each subgroup.

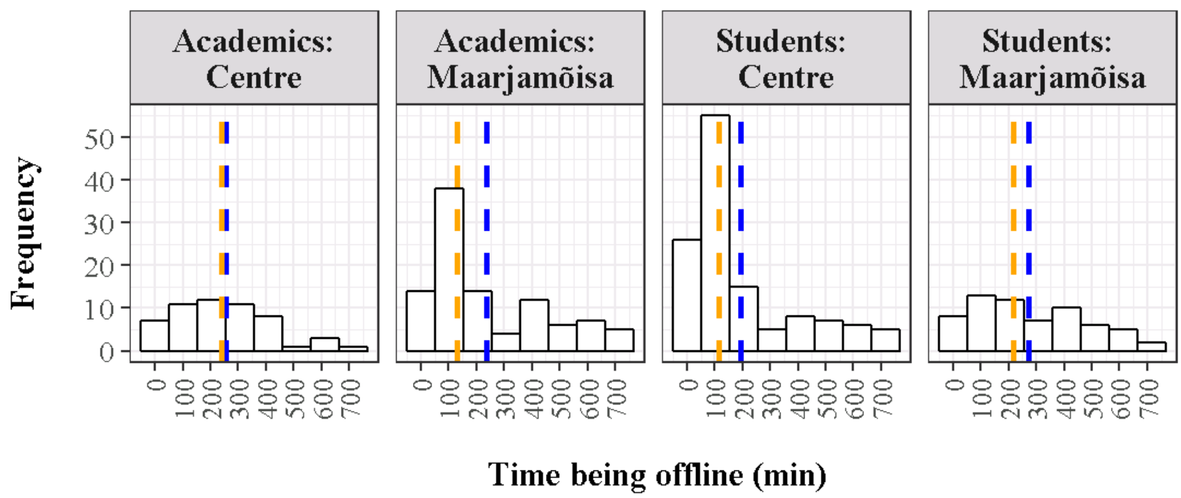

Figure 5. Histogram of time being offline.

(NA values omitted; blue line – mean value; orange line – median value)

However, for all four groups the mean value is between 200 and 300 minutes, while median value is lower (see Figure 5). In case of academics working in the central city, mean and median values are very close. Considering the effect of this variable on the number and duration of stops, the threshold is set to 200 minutes or 3 hours and 20 minutes.

The students' birth year is different for the students from each campus; however, there are more students who are younger (see Figure 6). To include only typical students in the sample, maximum age limit was set to 26 years (year of birth starting from 1993). After 26 years of age students typically have accomplished bachelor's and master's studies. Thus, everyday mobility patterns might change: students might spend more time at work. Therefore, such students are excluded from the sample.

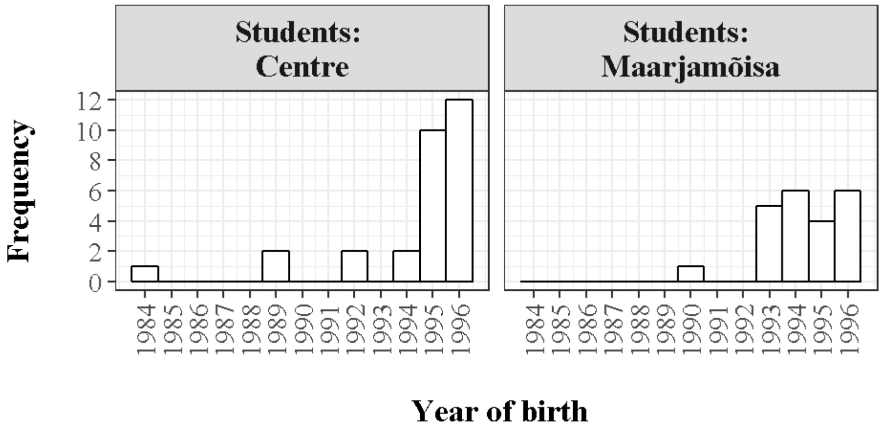

Figure 6. Histogram of the year of birth of students.

After selecting data according to the described conditions, the sample consists of 71 users in total: 38 students and 33 academics, as presented in Table 2.

Table 2. Number of respondents in each step of pre-processing.

	Initial dataset	Filtering data days	Filtering stops	Filtering time offline	Filtering year of birth:
Academics: Centre	26	20	18	18	18
Academics: Maarjamõisa	21	17	15	15	15
Students: Centre	34	30	30	27	22
Students: Maarjamõisa	23	22	22	18	16
In total	**104**	**89**	**85**	**78**	**71**

The description of subgroups is depicted in Table 3. Both genders are represented relatively equally. No students have children. Most of the respondents are car users.

Table 3. Sample description after filtering.

	Gender		Children		Car user		
	Men	***Women***	***TRUE***	***FALSE***	***Yes (1-3 cars)***	***No***	***NA***
Academics: Centre	8	10	15	3	14	4	0
Academics: Maarjamõisa	10	5	6	9	11	3	1
Students: Centre	10	12	0	22	15	7	0
Students: Maarjamõisa	6	10	0	16	11	5	0

Data structure

The data available for analysis includes:

- a list of UT students and academics, whose home is located in Tartu or within a spatial buffer of 1 km from the city border;
- socio-demographical characteristics of respondents, declared in the interviews;
- location and classification of meaningful places, declared in the interviews;
- home locations of respondents with the relevant residence periods, declared in the interviews;
- a classification of places into domains and types;
- stops within Tartu, related to the meaningful places if the stop had occurred within a pre-defined radius of that place;
- data frames derived from the table of stops: the dates and number of workdays per semesters.

The structure of the database and relations between tables are depicted in Figure 7. Some tables are related via one field, while others have several common fields.

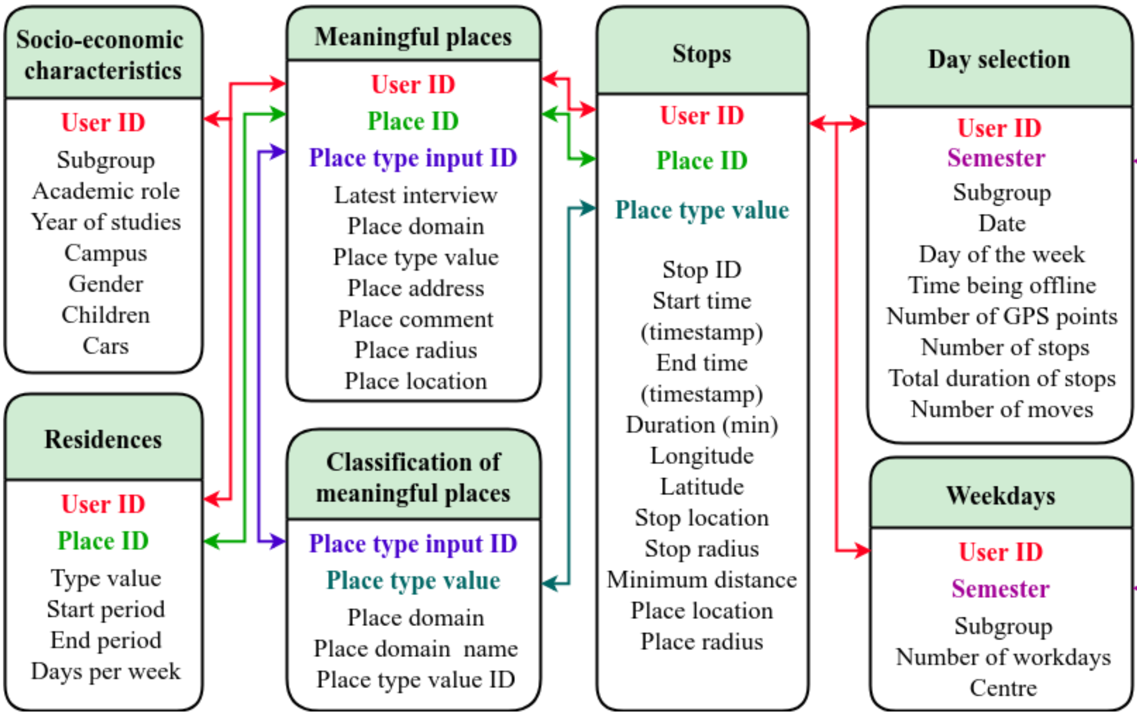

Figure 7. Structure of the database of input data.

The stops are linked with meaningful places that have been assigned domains according to their semantic meaning, derived from the interviews with the respondents. The domains of meaningful places and sub-domains are listed in Annex 1. Analysis regarding semantic meaning of the stops concentrates on the domains of meaningful places. However, subdomains can help with the interpretation of data. The domains are to be aggregated based on the preliminary analysis of data.

2.3. Methodological outline

2.3.1. Methods

The flowchart (see Figure 8) shows the main steps of the data pre-processing and analysis. First, preliminary analysis and filtering was conducted to narrow down the sample. Then, new variables were calculated and joined to the respective data tables. Finally, statistical analysis was run.

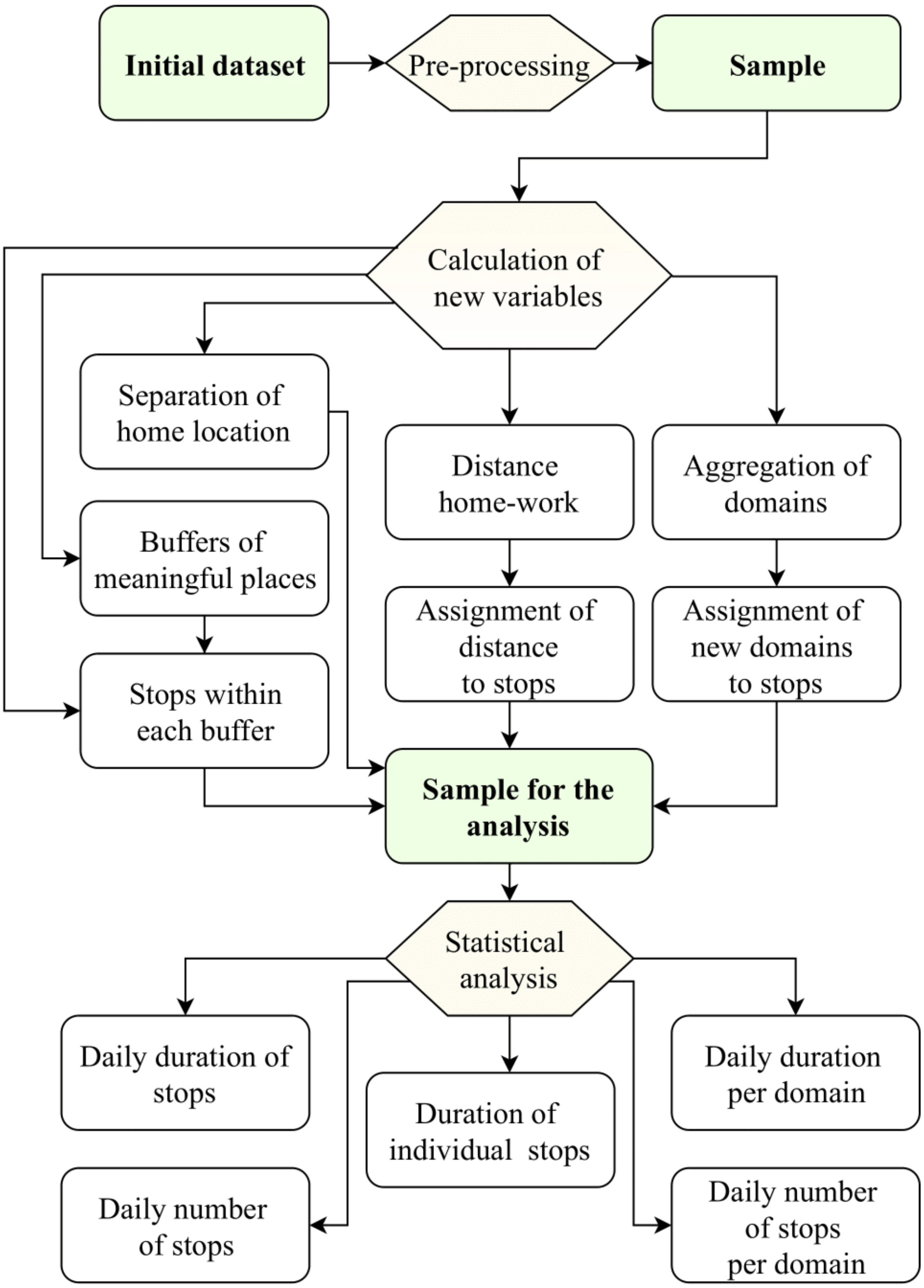

Figure 8. Flowchart of the work process.

To describe spatiotemporal behaviour of UT students and academics, the stops were analysed in relation to their location to meaningful places, defined in the interviews, and to the domains of meaningful places. The methods of analysis were selected to answer the research questions.

The data was pre-processed using SQL queries and PostGIS functionality. Statistical analysis was performed in RStudio using R. To gain overall understanding of time and space use of the respondents, as well as to choose appropriate methods and to prepare sufficient queries, descriptive statistics were used.

To analyse the spatial distribution of stops regarding the home or work/studies location, spatial analysis methods were used: it was tested how many stops fell into the buffer area of home or work/study place or other meaningful places and to which domains they belonged (SQL queries included in Annexes 2 and 3).

Statistical analysis was performed to explore whether there was a statistically significant difference between the groups depending on their academic role and work or study location and other factors. Analysis of variance (ANOVA) was used to determine if variability between and within each population was significantly different (Molugaram, Rao, 2017). To reveal the differences regarding time use and location of stops depending on individual's academic role and other characteristics, repeated measures ANOVA was used.

Mixed design ANOVA allowed assessing the effect of both fixed and random factors, as well as describing relationships between variables in case of repeated measures data, i.e., measurements that are taken from the same subjects over time (Pinheiro, Bates, 2000).

Repeated measures needed specific handling because using conventional statistical tests would have led to pseudoreplication. Firstly, the observations were not independent because they were taken from the same subjects, and secondly, they were correlated over time (Pinheiro, Bates, 2000). Thus, the repeated variable needed to be explicitly indicated in the model. This was done by referencing them as random factors.

Furthermore, several correlation structures were tested indicating one-level or nested correlations. It was found out that autocorrelation AR(1) in time between the subjects, assuming that sequential observations of the same subject are more similar than those further away in time (Package 'nlme', 2019) was the most suitable to analyse the data.

Models were compared through ANOVA function (*anova()*). The output included a data frame with all the comparable models, their degrees of freedom, the Akaike Information Criterion (AIC), and other. In case the models had different number of degrees of freedom, a likelihood ratio statistic and the associated p-value was calculated (Package 'nlme', 2019). Lower AIC presented better model fit. However, inclusion of too many factors in the model can result in lower AIC. Thus, the number of factors had to be balanced with the research interest.

After choosing the best model, ANOVA was performed and assumptions about normal distribution of residuals were tested. Variables used in the models are presented in Annex 4. In case the distribution of residuals was not normal, data transformation was performed. As the data was unbalanced, type III or "marginal" ANOVA was performed, therefore each factor was tested as if it had been entered last into the model, instead of testing factors sequentially.

To uncover the effect of independent variables, statistical analysis was performed in several dimensions of data. First, total daily duration and total daily number of stops was analysed. Then, the duration of individual stops was analysed. Finally, the duration of stops per domain was analysed.

When analysing the factors affecting number of stops and daily duration of stops, the dependant variables – total duration of stops per day and number of stops per day were transformed to normalize the distribution of data. The models are presented in Annex 5 and 6 respectively. The models' residuals after the transformation had normal distributions (see Annex 5, Figure A.5 and Annex 6, Figure A.6, respectively).

The duration of individual stops was not normally distributed. To normalize the distribution of the variable, natural logarithm was used. The model is presented in Annex 7. The distribution of the model's residuals is presented in Annex 7, Figure A.7 and corresponds to normal distribution.

The distribution of stops' duration per domain was not normal even after the variable was transformed using square root. The model is presented in Annex 8 The model's residuals however were normally distributed and are presented in Annex 8 Figure A.8.

To uncover the factors affecting the duration of stops within each domain, a separate analysis was performed. Residuals for the analysis of stops in the domain "Work and studies" are presented in Annex 9, Figure A.9. Residuals for the analysis of stops in the domain "Maintenance" are presented in Annex 10, Figure A.10. Residuals for the analysis of stops in the domain "NA" are presented in Annex 11, Figure A.11.

2.3.2. Preparation of variables for the analysis

Before performing further analysis, several variables were derived from the data set, formed for the analysis. The process of preparation is described in the following chapter.

Buffers of meaningful places

In order to assess the location of the stops in respect to the meaningful places for each user, the buffers around meaningful places were created. Further, it was assessed how many stops were located in the buffer area of each of the domains (Annex 2 and 3).

In the data set provided for the analysis, each meaningful place had been originally assigned a radius in order to find stops that are located close-by. The stop radius varied from 50 m to 275 m depending on their location (places located in the downtown had a smaller radius). When designating a new buffer radius to the meaningful place, it was taken into account that the distance had to be walkable. Secondly, it was necessary to prevent or minimize overlapping of the buffers.

Considering the compact spatial structure of Tartu, the radius for the buffer was calculated by adding 100 m to the initial radius, but not exceeding 300 m in total. Thus, the new radius of the buffer area varied from 150 to 300 m. Further it was assessed how many stops had occurred within the buffer area of each of the meaningful places and how many stops had occurred outside of any buffer area. In case the buffer areas of meaningful places were overlapping, the stop was added to the buffer area of the place being closer.

Classifying home location into centre or suburbs

Each of the home locations was assigned a value: either “centre” or “suburbs”. To define the borders of the city centre, an expert estimation, based on the available services in the area, was used. The area of the centre had been defined by experts from the Department of Geography, UT within the project Live Baltic Campus (Live Baltic Campus, 2017).

Distance from home to work/study place

As the respondents had multiple meaningful places related to work or studies, the distance from home to work or study place could not be calculated as a distance between two single locations. Considering that respondents might visit several study or work locations during day without visiting home in between, an average distance between home and all the study and work places was calculated (SQL query in Annex 12). For users who had several residences in the study period, the distance was calculated for each or the residences for respective time period and joined to the stops, based on the date of the stop and validity period of the respective residence.

Aggregation of domains

As seen in Figure 9, the total daily duration of stops per user differs depending on domains. For example, there is only one stop in second home domain, thus the duration of stops is close to zero. There are relatively low durations of stops in domains related to children, hobbies, social life, and service.

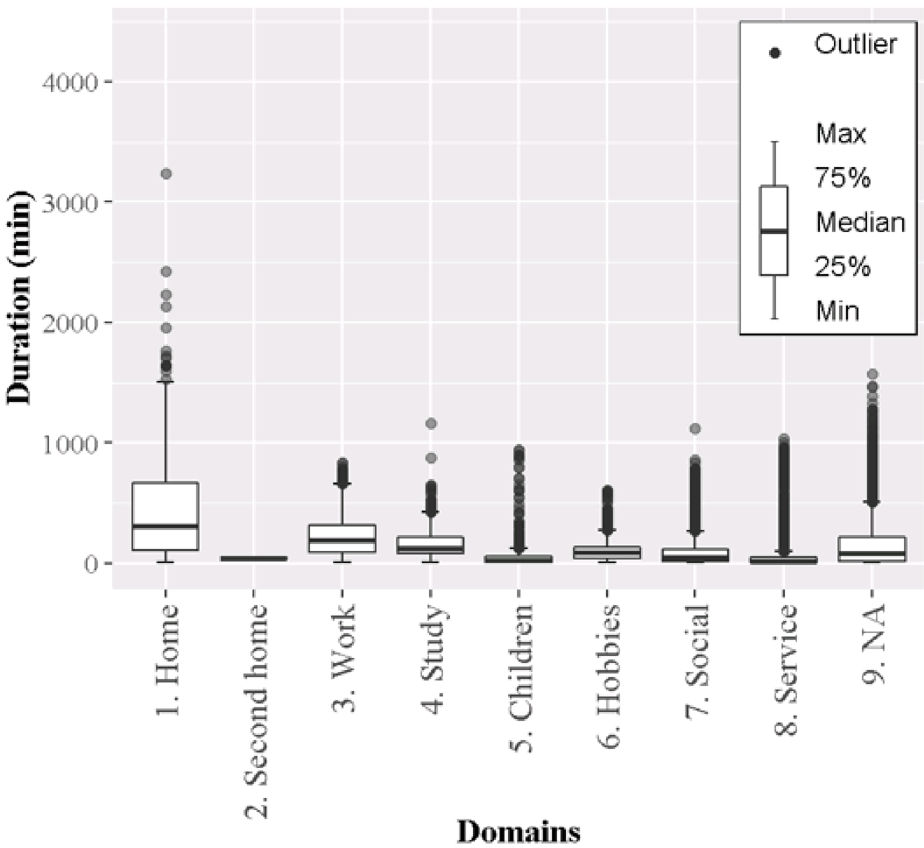

Figure 9. Daily duration of stops per user in each domain of meaningful places.

To concentrate the analysis on the research questions stated before, the domains were aggregated as displayed in Table 4.

Table 4. Aggregation of domains of meaningful places.

Domain ID	Place domain	New domain ID	New domain
1	Home	1	Home
2	Second home		
3	Work	2	Work and studies
4	Study		
6	Hobbies	3	Recreation
7	Social		
5	Children	4	Maintenance
8	Service		
[null]	NA	5	NA

3. Results

3.1. Factors affecting daily duration of stops and number of stops

ANOVA showed that the most important factors affecting the total duration of stops are type of day of the week (whether it is work day or weekend) ($F_{1,9305} = 31.57$, $p < 0.01$), academic role of the respondent ($F_{1,64} = 4.28$, $p = 0.04$), and the interaction between the two factors ($F_{1,9305} = 4.89$, $p = 0.03$). Value for workday was typically 1.6 units higher (SD 0.28) than for weekend. Students had 1.88 units higher value than academics (SD 0.91); however, the type of the day has a greater impact on academics, compared to students. (Figure 10).

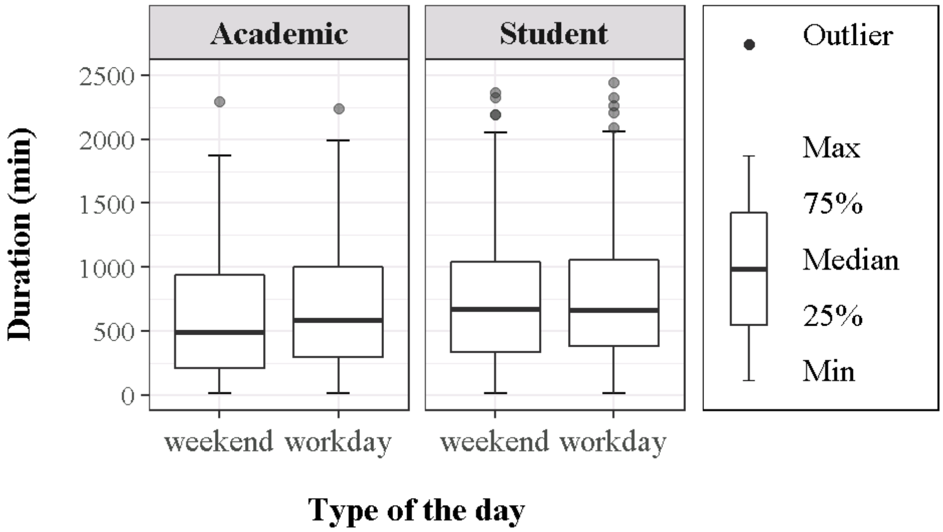

Figure 10. Total duration of stops starting at one day depending on academic role and type of the day (One outlier of 3545 min omitted)

Factors such as work location, average distance from home to work, gender, ownership of cars, or having children were not proven to have a statistically significant impact on the total duration of stops.

Regarding the number of stops per day, type of day of the week (workday or weekend) ($F_{1,9305} = 11.05$, $p < 0.01$) was statistically significant. Academics tended to have higher values on weekends, compared to workdays, while it was opposite for the students (Figure 11). Another statistically significant factor was ownership of a car ($F_{1,9305} = 3.59$, $p = 0.03$), as well as the interaction between day of the week and academic role ($F_{1,9305} = 12.13$, $p < 0.01$). However, academic role itself was not proven to be statistically significant. Factors such as gender, children, average distance from home to work, or work location were also not proven to be statistically significant.

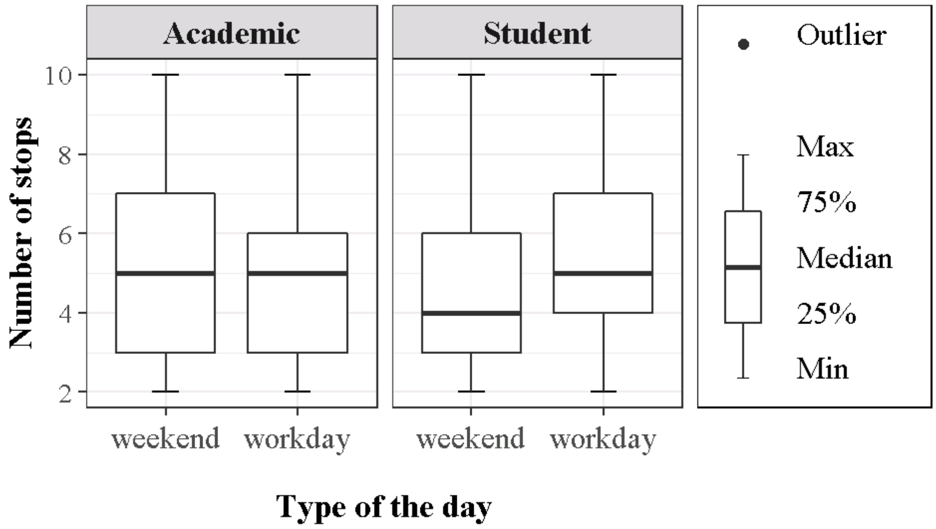

Figure 11. Total number of stops per day depending on academic role and type of the day.

3.2. Factors affecting duration of individual stops

ANOVA revealed that domain of the stop had a statistically significant effect on the logarithm value of duration of the individual stops ($F_{4,47481} = 1842.53$, $p < 0.01$). Home domain had stops with the highest duration, and the second longest stops were in work and studies-related domain (see Figure 12).

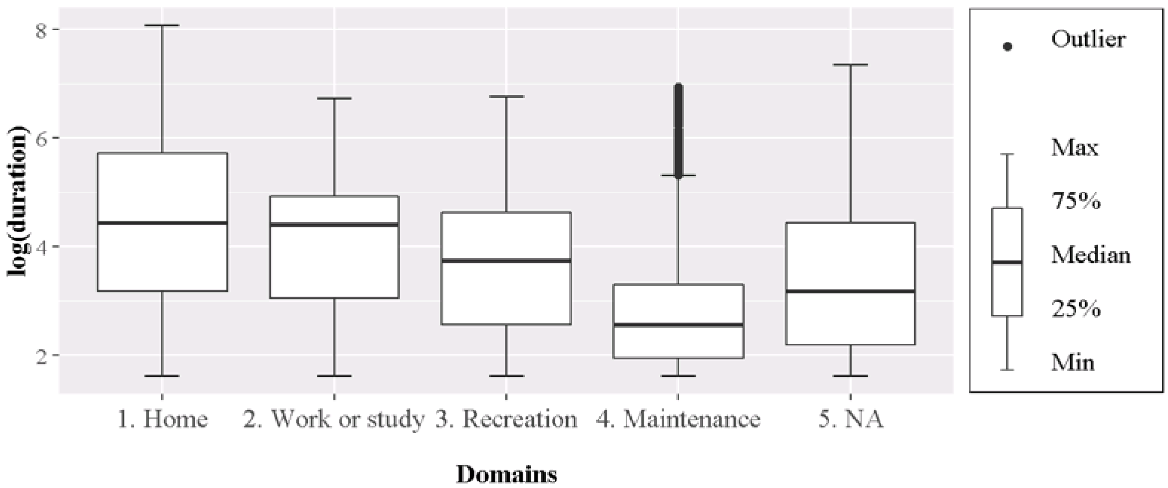

Figure 12. The logarithm of stop duration regarding the domain of meaningful places.

Another statistically significant factor was the start hour of the stop (a full hour when a stop starts) ($F_{23,47481} = 50.42$, $p < 0.01$). According to Tukey's range test, all the hours had lower stop duration, comparing to midnight (Figure 13). The shortest stops started between 6 and 19 o'clock. Academic role, work location, gender and having children were not proven to be statistically significant factors.

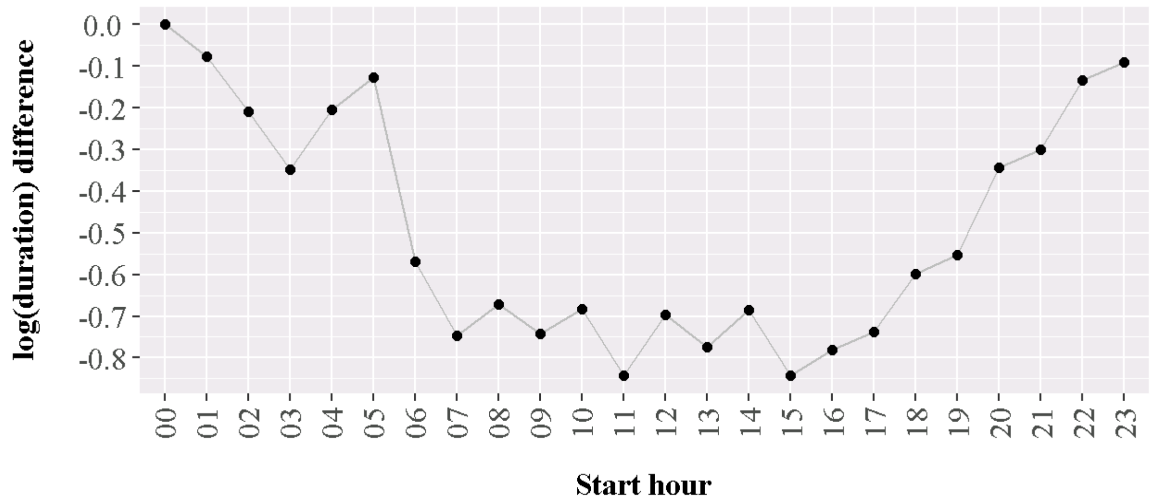

Figure 13. Tukey test of difference of log(duration) of stops per starting hour ("00" = 0).

The effect of the starting hour on the number of stops for each group is seen in Figure 14. The lowest number of stops was at 5 and 6 o'clock. It started to grow after 6 o'clock. At 12 o'clock there was an increase in the number of stops indicating lunch break. The daily peak of stops around 17 or 18 o'clock indicated the end of work and studies. For academics, the increase of stops after the working hours in Maarjamõisa started at 18, while in the centre it started already at 17. For students, there was an increase in number of stops at 16 and for those from the centre also at 18.

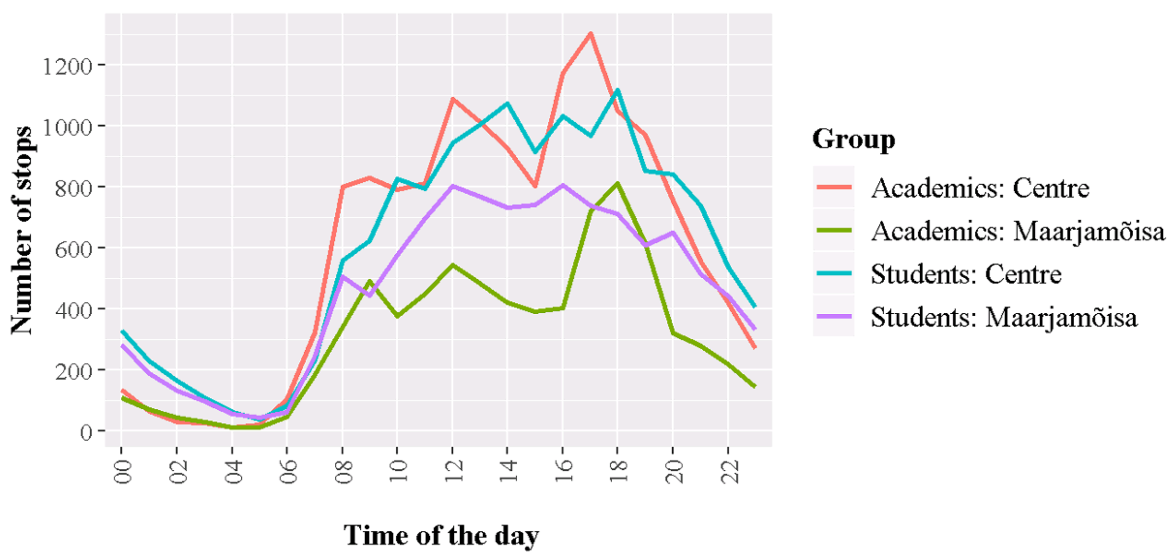

Figure 14. The number of stops starting at each hour of the day.

Factor of day of the week was statistically significant ($F_{6,47481} = 5.16$, $p < 0.01$). According to Tukey's range test, comparing to Monday as ground level (0), Tuesday (0.03), Wednesday (0.001) and Sunday (0.07) typically had higher values, while Thursday (-0.05), Friday (-0.006) and Saturday (-0.01) had lower values.

3.3. Factors affecting duration and number of stops per domain

Stop duration within the domain was affected only by the type of the day (workday or weekend) ($F_{1,24074} = 143.36$, $p < 0.01$) and stop's domain ($F_{1,24074} = 3083.73$, $p < 0.01$). Factors as academic role, work location, gender, having children, average distance from home to work, or car ownership were not proven to be statistically significant.

Figure 15 presents percental distribution of stops occurring at each hour according to their domains (SQL query for the aggregation of data is presented in Annex 13). Vast majority of the stops throughout the day were occurring at the place of residence or in vicinity of it. Thus, home was approved to be the most important anchor point. Students from Maarjamõisa tended to have the smallest proportion of home-related stops, comparing to other groups (Figure 15).

Percentage of stops at work or study place or in vicinity of it was rather small. Students from Maarjamõisa tended to spent most time in vicinity of their work or study place, compared to other groups (Figure 15). Stops in vicinity of recreational facilities were mostly taking place in working hours. Throughout the day, students had larger percentage of stops attached to recreational domain than academics.

For students, maintenance-related stops were equally poorly represented throughout the day. However, for academics from centre most of the maintenance-related stops were taking at 17 to 9 o'clock, while for academics from Maarjamõisa stops in this domain were taking place mostly during working hours – from 10 to 17 o'clock. Rather large proportion (5-20%) of stops at each hour had not been assigned a domain. These stops had not occurred in any of the buffer zones of meaningful places.

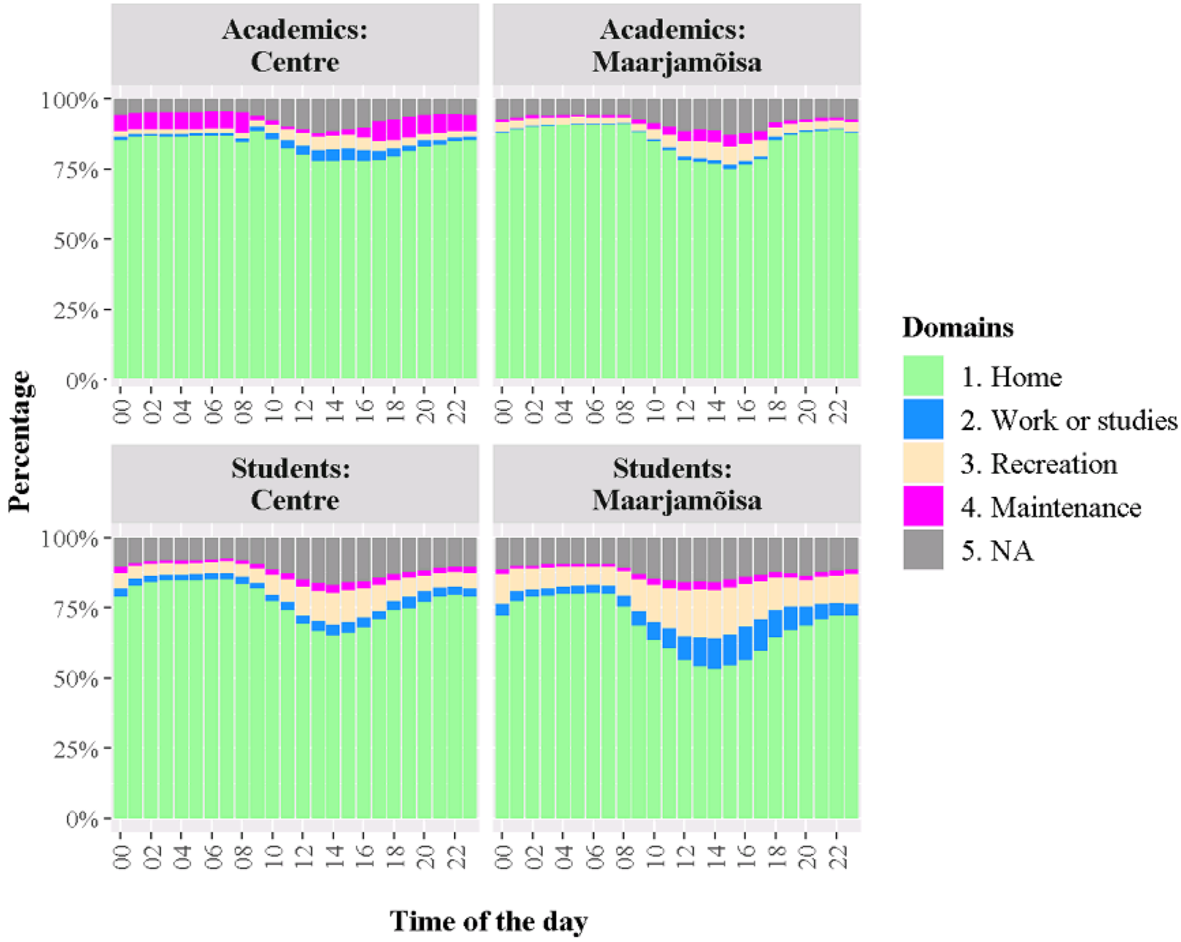

Figure 15. Percentage of stops taking place at full hour in each domain of meaningful places.

To assess the effect of combined factor of academic role, work location, and type of the day, as well as the other factors as having children, car ownership, home - work distance, and gender, ANOVA was performed on stops of each domain separately. For home domain, none of these factors was statistically significant indicating that time spent at home or in vicinity of it did not depend neither on socio-economic characteristics, nor on the day or time of the day.

However, in the domain "Work and studies" combined factor of academic role, work location, and type of the day proved to have statistical significance ($F_{1,4736} = 11.51$, $p < 0.01$), while another factors were not proven to be statistically significant.

According to Tukey test (Figure A.14.1., Annex 14), academics regardless of their work location spent more time at their work place or in vicinity of it on workdays comparing to weekends. However, on weekends, academics working in suburbs spent significantly less time in vicinity of their work place than those working in the central campus. On workdays academics working in Maarjamõisa spent more time in vicinity of their work place than academics working in centre. For students, the trend was opposite, although the differences between type of the day were small. Students tended to spend more time in vicinity of their work or study place on weekends, comparing to workdays. Students studying in the centre spent almost same time there on weekends and workdays. However, students studying in Maarjamõisa campus spent more time in vicinity of it on weekends than on workdays (Figure A.14.1., Annex 14).

In the domain “Maintenance” combined factor of academic role, work location, and type of the day proved to have statistical significance ($F_{1,4372} = 3.44$, $p < 0.01$), while another factors were not proven to be statistically significant. Academics working in the central campus spent more time in vicinity of maintenance-related places on workdays than weekends, while for academics working in Maarjamõisa campus the tendency was opposite (Figure A.14.2., Annex 14). Students regardless of their study place spend more time in vicinity of maintenance-related places on weekends comparing to workdays, and the difference in slope is approximately the same for students from central campus comparing to Maarjamõisa campus. However, students from Maarjamõisa in general spend more time in vicinity of maintenance-related places, comparing to students from the centre.

In the domain “Recreation” none of the factors listed before was statistically important. However, the combined factor was proven to be statistically significant also regarding the stops not associated to any domain, but for the sake of analysis grouped into domain “NA” ($F_{7,3292} = 100.71$, $p < 0.01$). A clear weekly rhythm could be noticed: both students and academics, regardless of their work or study place, had longer duration of stops in NA domain on weekends comparing to workdays, while academics and students from centre typically spent more time in NA domain than those from Maarjamõisa (Figure A.14.3., Annex 14). Having children was also proven to be statistically significant factor ($F_{7,66} = 5.87$, $p < 0.01$). Average distance from home to work was not proven to be statistically significant, but was close to that ($F_{7,3292} = 3.66$, $p < 0.056$).

4. Discussion

As underlined in literature, home is the most important anchor point for human mobility (Schönfelder, Axhausen, 2003; Li, 2016). It was confirmed in this research that most of the stops occurred at home or in the vicinity of it. These stops were also the longest ones, comparing to stops in other domains. The effect of the home place did not depend on its physical location either in the centre or elsewhere in the city of Tartu. To explain time spent in home domain, none of the analysed socio-economic factors was proven to be statistically significant, indicating that the time spent at home or in vicinity of it did not depend on type of the day, academic role, or work location.

The second domain with the longest stops was work and studies-related domain. Stops occurring in vicinity of work and studies-related places were the second longest and they followed a certain weekly and daily rhythm, mostly occurring during working days and working hours. However, when analysing their share at a certain hour, stops close to work were rather negligible part of all stops. This approves the superior role of home as the main anchor point, work and study place lagging behind.

Academics working in the central campus spent more time in vicinity of maintenance-related places on workdays than weekends, while for academics working in Maarjamõisa campus the tendency was opposite. This may indicate that in the vicinity of Maarjamõisa campus the service supply was poor, as the domain of maintenance included children- and service-related places as schools, kindergartens, and shops.

None of the social characteristics of respondents was proven to have a statistically significant effect neither on the duration of individual stops, nor on the time spent per domain. However, academic role was statistically significant to explain variance in daily duration of stops, students having higher total duration of stops than academics. This may indicate that academics were more mobile and spend more time on commute. Academic role in combination with the work location and type of the day was proven to be statistically significant to explain the stop duration in the domains of work and studies, maintenance, and NA.

The main work or study place did not prove to be significant factor affecting the number or duration of stops. The distance (approximately 2.5 km) between the central campus and Maarjamõisa campus is a walking distance, and the public transport in Tartu is affordable and convenient. In bigger cities where the distance between central campus and campus in suburbs is longer, the results can be different, as the distance between the anchor points can play a major role in the composition of activity space (Sherman *et al.*, 2005). Considering relatively small distances in Tartu, people can satisfy their needs elsewhere. However, further development of suburban Maarjamõisa campus must take into account the need for sufficient services to avoid unwanted effects, such as increase in car usage.

Ownership of a car was only proven to affect the total number of stops per day. That is understandable, since car provides easier mobility options. Having children was only statistically significant to explain stop duration in NA domain. That indicates that people with children tend to have more unplanned or irregular places to visit. Gender was not proven to be statistically significant factor affecting the time use. Thus the research results do not approve gender being one of the most important factors affecting activity space (Weber, Kwan, 2015; Vich *et al.,* 2017).

The number of individual stops and time spent for a domain both were highly affected by the type of the weekday and by time of the day. Total duration of stops on workdays was higher than on weekends. Sunday, Monday, Tuesday, and Wednesday typically had higher duration of stops, compared to Thursday, Friday and Saturday. While it does not completely follow workday versus weekend approach, it certainly follows a weekly rhythm. Both students and academics had lower duration of individual stops on workdays, comparing to weekends. This indicates that both students and academics tended to spend weekends in fewer locations, while being more mobile during workdays.

There was a clear daily rhythm of stops. The longest stops occurred at night time, while the shortest ones – during working hours. Most of the stops at night time were related to home domain, thus they were longer. The stops taking place in working hours or shortly after were shorter, since they were related to other domains. However, most of the stops started during working hours indicating respondents' mobility during the day. This finding is in compliance with the Hägerstrand (1970) point that individual activities in certain semantic domains are highly affected by their timing and location. However, the percentage of home-related stops at each hour was surprisingly high. Partly it can be explained by overlapping buffer zones of meaningful places.

The average distance between home and work (studies) was not proven to be statistically significant, but was proven to have higher statistical significance on both duration and count of the stops, comparing to the binary approach of classifying the work place. Therefore in future research this methodology can be further developed.

Method of analysing stops in vicinity of pre-defined meaningful places is informative to develop understanding on spatio-temporal behaviour of respondents. However, it does not substitute analysis of activity space. Rather, these can be viewed as sub-activity spaces, attributed to a specific semantic domain of activities. Knowing where people spend their time is crucial information for numerous fields, including city planning and transportation. However, this approach does not uncover the motivation of visit. Technical challenges must be solved regarding overlapping buffer areas, and the solutions depend on the scope and aim of the research.

When interpreting the results of the analysis, the limitations of the study must be considered. The results of the study were affected by the provided dataset and by data pre-processing, described in chapter 2.2. In the sample used for the analysis, not all the respondents were represented on every day of the research period and not all the domains were represented daily for each respondent, causing unbalanced levels of variables. Several variables were not measured directly, but were derived from the sample according to the methodology described in chapter 2.3.2.

The compact spatial structure of the research area also had an effect on the results, causing buffer zones of meaningful places to overlap. Furthermore, the short distance (approximately 2.5 km) between the central campus and Maarjamõisa campus may have caused the campus location to be not statistically significant factor affecting the duration and number of stops.

Therefore, the filtered sample cannot be considered random and cannot be ascribed to general population. However, in order to entirely uncover the patterns of spatio-temporal behaviour of UT students and academics, another sample design should be considered, but similar methodology can be used.

Summary

Mobility patterns in university campuses: an example of the University of Tartu

Daiga Paršova

The master thesis addresses the spatiotemporal behaviour of students and academics of the University of Tartu (further referred as UT) depending on the location of campus and socio-economic characteristics of respondents. UT plays an important role in the city of Tartu – for long time it has shaped the development of the city (Poom *et al.*, 2017), and nowadays UT students constitute almost 14% of the population of Tartu (Statistics Estonia, 2018; University of Tartu, 2019 [a]). Therefore understanding the effects of the location of the campus can contribute the development of the city and UT itself.

In the master thesis, the space and time use is analysed. Activity space or a subset of the locations which an individual usually visits daily (Schönfelder, Axhausen, 2003; Vich *et al.*, 2017) is affected by the built environment and the density of facilities (Shen *et al.,* 2015).

Home and work locations are believed to determine both spatial and temporal pattern of human behaviour. Most of other activity locations are centred on these points (Lee *et al.*, 2016). Home is believed to be the most important anchor in people's daily travel, with work or study location being at the second place (Schönfelder, Axhausen, 2003; Li, 2016).

Although most of historical UT study buildings are located within the historical city centre, the campus of Maarjamõisa is located on the edge of the city. The campus nowadays has developed to a well-equipped study base for medical and natural sciences and to a medical centre of national importance (Tohvri, Udumäe, 2013). However, other facilities have remained in the city centre forcing students and academics to commute. Thus, the accessibility of the campus and its connectivity to the city centre is of crucial importance (Poom *et al.*, 2017).

The aim of the master thesis was to understand the spatio-temporal behaviour of the students and academics of UT in the spatial context of Tartu. To achieve the aim of the research, following research questions were stated:

1. How does the location of work and studies influence other activities of respondents?
2. What are the daily and weekly temporal rhythms of activities depending on individual's work or study location?

3. What are the differences regarding time use and location of stops depending on individual’s academic role?

Data used for the research had been provided by the Mobility Lab of the Department of Geography, UT, and had been obtained through MobilityLog mobile application. The mobile application tracked the mobility of the respondents with help of global positioning system (further referred as GPS). The data set for the analysis included 71 respondents studying or working in UT (38 students and 33 academics; 31 persons from Maarjamõisa and 40 persons from the central campus), and covered two semesters of academic year 2016/2017. The author of the thesis had signed a contract for secure use and processing of the data for her master thesis, and all the respondents had given their consent for the use of their data for scientific purposes. The author had access only to pseudonymized data.

The data had been pre-processed with the algorithm, developed by the Mobility Lab: sequential GPS points that were located within a certain radius were aggregated into stops. In the master thesis, these stops were analysed in relation to the location of meaningful places. Meaningful places were pre-defined according to the information provided by respondents in the interviews, conducted by the Mobility Lab. Depending on the semantic meaning, they were pre-classified into domains as home, work, study, hobbies, etc.

The author of the thesis used spatial analysis methods to create buffer areas around the meaningful places, to find stops within the buffers, and to assign respective domain to those stops. In the master thesis, the duration and number of stops were analysed. Repeated measures analysis of variance was used to find out the spatiotemporal patterns.

It was found out that most of the stops had occurred at home or in the vicinity of it, thus approving home being the most significant anchor point of daily activities. The second domain with the longest stops was work and studies-related domain.

None of the social characteristics of respondents was proven to have a statistically significant effect neither on the duration of individual stops, nor on the time spent per domain. However, academic role was statistically significant to explain variance in daily duration of stops. Academic role in combination with the work location and type of the day was proven to be statistically significant to explain the stop duration in the domains of work and studies, maintenance, and NA. Academics working in Maarjamõisa were found to spend less time in maintenance-related places on workdays, compared to weekends. For academics working in the central campus, the tendency was opposite. This indicates poor service supply in the vicinity of Maarjamõisa campus.

The main work or study place did not prove to be a statistically significant factor affecting the number or duration of stops, possibly because of relatively short (approximately 2.5 km) distance between the campuses. Ownership of a car was proven to have a positive effect on the number of stops per day, since car provides easier mobility. Having children was only statistically significant to explain stop duration in NA domain, indicating that that people with children visit more unplanned places. Gender was not proven to be statistically significant factor affecting the time use.

The number of individual stops and time spent for a domain both were highly affected by the type of the weekday and by time of the day. Both students and academics tended to spend weekends in fewer locations, while being more mobile during workdays. The longest stops occurred at night time, while the shortest ones – during working hours, indicating respondents' mobility during the day.

The interpretation of the results of the research is limited by the composition of data sample that was specifically designed for the needs of this research and hence was not random. Likewise, the compact urban structure of Tartu may have affected the results.

Liikuvuse seaduspärad ülikoolilinnakutes: Tartu Ülikooli näitel

Daiga Paršova

Kokkuvõte

Magistritöö käsitleb Tartu Ülikooli (TÜ) üliõpilaste ja akadeemiliste töötajate ajalis-ruumilist käitumist sõltuvalt ülikoolilinnaku asukohast ja vastanute sotsiaal-majanduslikust olukorrast. TÜ on pikka aega mõjutanud linna arengut (Poom *et al.*, 2017). TÜ üliõpilased moodustavad peaaegu 14% Tartu linna rahvastikust (Statistics Estonia, 2018; University of Tartu, 2019 [a]).

Linna muude omaduste hulgas püüab linnaplaneerimine tagada linna elatavuse ehk elamiseks sobivuse (Leach *et al.*, 2013). Elatavuse soodustamiseks on vaja mõista, milline on linnaelanike ajalis-ruumiline käitumine. Siin võib abiks olla inimeste tegevusruumi uurimine. Tegevusruumi ehk tegevuspaikade alamhulk, mida isik tavaliselt iga päev külastab (Schönfelder, Axhausen, 2003; Vich *et al.*, 2017), ning see kirjeldab nii isiku ruumilist kui ajalist käitumist. Seda mõjutab ka tehiskeskkond ja teenuste tihedus (Shen *et al.*, 2015).

Inimtegevus järgib teatud ruumilist ja ajalist seaduspära, mis sõltub ankrupunktidest – kodu ja töökoha asukohast. Enamik muudest tegevuspaikadest keskendub nende punktide ümber. Ankrupaigad selgitavad isiku teiste tegevuste valikuid nagu ka nende ajastust ja asukohti (Lee *et al.*, 2016). Kodu on inimeste igapäevase liikumise kõige tähtsam ankrupaik, millele järgneb töökoha või õpingute paiga asukoht (Schönfelder, Axhausen, 2003; Li, 2016).

Inimeste käitumise ning nende aja- ja ruumikasutuse mõistmine on kriitilise tähtsusega sisend linnaplaneerimises, sealhulgas transpordiplaneerimises (Phithakkitnukoon *et al.*, 2010). Arvestades, et tänapäeval elab pool inimkonnast linnades ja see arv kasvab (United Nations Organization, 2016), on põhjalik linnaplaneerimine muutunud linna arengu jaoks ülioluliseks.

Kui enamik TÜ ajaloolistest õppehoonetest asub Tartu vanalinnas, siis Maarjamõisa ülikoolilinnak asub linnaservas. Üks Maarjamõisa ülikoolilinnaku keskseid punkte on ülikooli haigla. Üks põhjusi, miks 1910. aastal eelistati Maarjamõisat haigla ehitamise paigana teiste paikade ees, oli raudtee lähedus. Tänapäevaks on ülikoolilinnak arenenud meditsiini- ja loodusteaduste hästivarustatud uurimisbaasiks ja riikliku tähtsusega meditsiinikeskuseks (Tohvri, Udumäe, 2013).

Samas on muud üliõpilastele vajalikud teenused nagu ühiselamud ja raamatukogu jäänud kesklinna. Seepärast on ülikoolilinnaku juurdepääsetavus ja ühendus kesklinnaga olulised ruumilised aspektid (Poom *et al.*, 2017). Maarjamõisa ülikoolilinnaku edasine arendus ja

olulise osa üliõpilaste sinna kolimine võib oluliselt mõjutada linna igapäevast dünaamikat, sealhulgas teenuste ja transpordi kasutamist, samuti linna tulevast arengut.

Seega on käesoleva magistritöö eesmärgiks mõista TÜ üliõpilaste ja akadeeliste töötajate ajalis-ruumilist käitumist Tartu ruumilises kontekstis. Uuringu eesmärgi saavutamiseks püstitati järgmised uuringuküsimused.

1. Kuidas mõjutavad töökoha asukoht ja õpingute paiga asukoht vastanute muid tegevusi ning nende kestust ja sagedust?
2. Kuidas sõltub ajakasutuse päevane ja nädalane rütm isiku töökoha või õpingute paiga asukohast?
3. Millised erinevused ajakasutuses ja peatumiste asukohtades on põhjustatud isiku akadeemilisest rollist?

Uuringu andmed on saadud TÜ geograafia osakonna mobiilsusuuringute laborist, kasutades GPS-põhist mobiiltelefonirakendust MobilityLog. Andmekogu hõlmab 71 vastanut, kes õpivad või töötavad TÜ-s (38 üliõpilast ja 33 akadeemilist töötajat; 31 isikut Maarjamõisas ja 40 kesklinnas paiknevast ülikoolilinnakust), ning katab 2016./2017. õppeaasta mõlemad semestrid. Kõik vastanud on andnud oma nõusoleku enda andmete teaduslikel eesmärkidel kasutamiseks. Magistritöö autor on sõlminud lepingu andmete turvaliseks kasutuseks ja töötlemiseks seoses oma magistritööga. Autoril oli juurdepääs ainult pseudonümiseeritud andmetele ja tulemused on esitatud koondatud vormis.

Mobiilsusuuringute laborilt saadud andmed sisaldasid labori väljatöötatud algoritmi abil GPS punktide põhjal leitud peatumisi. Algoritmi järgi loeti järjestikused GPS punktid, mis asusid teatud raadiuse sees, ühe ja sama asukoha sisse kuuluvateks ja koondati peatumiseks. Magistritöös analüüsiti neid peatumisi seoses isiku jaoks oluliste tegevuskohtade asukohtadega. Olulised tegevuskohad olid eelnevalt välja selgitatud uuringus osalenutega peetud intervjuude käigus, mille tulemusena olid tegevuskohad jaotatud semantilise tähenduse järgi klassidesse nagu kodu, töö, õpingud, hobid jne.

Magistritöö autor kasutas ruumilise analüüsi meetodit, et luua eelnevalt tuvastatud oluliste tegevuskohtade ümber puhveralad, leidmaks peatumised, mis jäävad neisse puhveraladesse, ning omistamaks neile peatumistele semantilise tähenduse. Magistritöös analüüsiti tegevuste kestust ja sagedust. Kasutati kordusmõõtmiste meetodil varieeruvusanalüüsi, et leida ajalis-ruumilised seaduspärad sõltuvalt vastanute akadeemilisest rollist, töökohast või õpingute paigast ja muudest sotsiaal-majanduslikest tunnustest ning leida seaduspärad seoses peatumiste asukohaga oluliste tegevuskohtade ja piirkondade kontekstis.

Seoses peatumiste ajalise seaduspäraga tõestati nii nädala rütmi kui peatumiste algustunni statistiline olulisus peatumiste kestuse mõjutajana. Nii üliõpilased kui akadeemilised töötajad peatusid tööpäevadel lühemat aega kui nädalavahetustel; samas olid nädalalõppude ja tööpäevade vahelised erinevused üliõpilaste hulgas selgemini väljendatud. Tööajal toimuvad peatumised kaldusid olema kõige lühemad, samas kui õhtuti toimuvad peatumised olid pikemad.

Sotsiaalmajanduslikest joontest oli akadeemiline roll kõige tähtsam peatumisi mõjutav tegur. Auto omamine mõjutas päeva jooksul tehtavate peatumiste koguarvu, sest auto teeb liikumise lihtsamaks. Samas ei leidnud tõestamist auto olemasolu mõju peatumiste kestusele. Sugu ei leitud olevat statistiliselt oluline tegur seoses peatumiste kestuse ega arvuga.

Ülikoolilinnaku ega kodu asukohal ei olnud eraldi võetuna statistiliselt olulist mõju, kuid neil oli selline mõju kombinatsioonis teiste teguritega. Kodu piirkonnas tehtud peatumised olid enamasti pikimad, millele järgnesid peatumised töökoha ja õpingute paiga piirkondades. Peatumiste kestust mõjutas nende asukoht seoses teiste oluliste tegevuskohtadega. Inimesed veetsid rohkem aega oma kodu ja töökoha (või õpingupaiga asukoha) läheduses. Kodu piirkonnas veedetud aja kestus ei sõltunud päeva tüübist, vastanu akadeemilisest rollist, töökoha või õpingute paiga asukohast ega muudest sotsiaalmajanduslikest teguritest.

Maarjamõisas töötavad akadeemilised töötajad veetsid nädalalõppudel vähem aega töökoha läheduses kui kesklinna ülikoolilinnaku akadeemilised töötajad. Viimased kulutasid teenustega seotud kohtades rohkem aega tööpäevadel kui nädalalõppudel. Maarjamõisa ülikoolilinnakus töötavate akadeemiliste töötajate puhul oli see trend vastupidine. Samas üliõpilased veetsid teenustega seotud kohtades ülikoolilinnaku asukohast sõltumata rohkem aega nädalalõppudel kui tööpäevadel. See näitab teenuste puudulikkust Maarjamõisas võrreldes kesklinna ülikoolilinnakuga, kus on kogu nädala jooksul palju teenuseid ja mis on külastustele atraktiivne ka nädalavahetustel.

Uurimistöö tulemuste tõlgendamine on piiratud andmekogumi koosseisuga, sest see oli koostatud konkreetselt käesoleva magistritöö jaoks ja seega pole juhuslikult valitud. Käesolevas uuringus analüüsiti ainult peatumisi, jättes tähelepanuta nende vahelised liikumised. Samuti võis tulemusi mõjutada Tartu kompaktne linnaplaan.

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Annexes

Annex 1. Domains and subdomains of meaningful places

Domain ID	Place domain	Sub-domains	
1	**Home**	Main residence	Hotel / guest house
		Residence on workdays	Other type
		Parents'/ children's residence	Dormitory
		Friend's home	Not known
2	**Second home**	Summer cottage	Apartment
		Cottage	Other type
		Farmhouse	Not known
		Other individual house	
3	**Work**	Work place	Work-related irregular place
		Work-related regular place	
4	**Study**	Study building	Studies-related irregular place
		Studies-related regular place	
5	**Children**	Kindergarten	Playground
		School	Other type
		Hobby group / sports	Not known
		Home of a child's friend	
6	**Hobbies**	Indoors sports facilities	Culture-related place
		Outdoors sports facilities	Other type
		Other regular hobby place	Not known
7	**Social**	A place to pay visit to	Travel (irregular) related to paying a visit to someones
		Dining and recreation	
		Recreation (irregular place)	Not known
8	**Service**	Grocery store	Institution
		Other special purpose shop	Other type
		Multifunctional shopping centre	Not known
		Self-service place	
[null]	**N/A**	Irregularly visited places	

Annex 2. Code for finding stops within buffers

```
SELECT s.user_id, s.new_sub, s.stop_id, s.duration_min, s.stop_radius, s.semester_no, s.dow, s.start_date, s.start_time, s.time_median, s.median_hour, s.start_hour, s.est_stop_geom, s.home_type_value, s.home_id, s.home_address, s.home_geom, s.home_start, s.home_end, s.dist_hw, s.home_loc,

p.place_domain as b_place_domain, p.place_type_value as b_place_type_value, p.place_type_description as b_place_type_descr, p.place_id as b_place_id, p.place_address as b_place_addr, p.est_place_geom as b_est_place_geom, p.buff, p.buffgeom,

ST_Distance(est_stop_geom, est_place_geom) as dist_stop_place

INTO stops_allbuff

FROM public.stops_distances s

LEFT JOIN public.places_joined_res p ON (s.user_id=p.user_id)

WHERE ST_within(s.est_stop_geom, p.buffgeom)=TRUE

      AND p.est_place_geom IN

            (SELECT est_place_geom FROM public.stops_distances a

            LEFT JOIN public.places_joined_res pl ON (a.user_id=pl.user_id)

            WHERE ST_within(a.est_stop_geom, pl.buffgeom)=TRUE AND a.user_id=s.user_id

            and a.stop_id=s.stop_id

            ORDER BY ST_Distance(s.est_stop_geom, pl.est_place_geom)

            LIMIT 1)

GROUP BY s.user_id, s.new_sub, s.stop_id, s.duration_min, s.stop_radius, s.semester_no, s.dow, s.start_date, s.start_time, s.time_median, s.median_hour, s.start_hour, s.est_stop_geom, s.home_type_value, s.home_id, s.home_address, s.home_geom, s.home_start, s.home_end, s.dist_hw, s.home_loc,

b_place_domain, b_place_type_value, b_place_type_descr, b_place_id, b_place_addr, b_est_place_geom, p.buff, p.buffgeom, ST_Distance(est_stop_geom, est_place_geom);
```

Annex 3. Code for finding stops without a buffer

```
CREATE TABLE stops_allbuff_2 AS

SELECT bu.user_id, bu.new_sub, bu.stop_id, bu.duration_min, bu.stop_radius, bu.semester_no, bu.dow, bu.start_date, bu.start_time, bu.time_median, bu.median_hour, bu.start_hour, bu.est_stop_geom, bu.home_type_value, bu.home_id, bu.home_address, bu.home_geom, bu.home_start, bu.home_end, bu.dist_hw, bu.home_loc, bu.b_place_domain, bu.b_place_type_value, bu.b_place_type_descr, bu.b_place_id, bu.b_place_addr, bu.b_est_place_geom, bu.buff, bu.buffgeom, bu.dist_stop_place

	FROM public.stops_allbuff_1 bu

UNION

SELECT un.user_id, un.new_sub, un.stop_id, un.duration_min, un.stop_radius, un.semester_no, un.dow, un.start_date, un.start_time, un.time_median, un.median_hour, un.start_hour, un.est_stop_geom, un.home_type_value, un.home_id, un.home_address, un.home_geom, un.home_start, un.home_end, un.dist_hw, un.home_loc, un.b_place_domain, un.b_place_type_value, un.b_place_type_descr, un.b_place_id, un.b_place_addr, un.b_est_place_geom, un.buff,  un.buffgeom, un.dist_stop_place

	FROM public.stops_unique un

WHERE un.stop_id NOT IN (SELECT bu.stop_id FROM public.stops_allbuff_1 bu);
```

Annex 4. List of variables in the models

cars	– ownership of a car
children	– children
cnt_stops	– number of stops per day per one respondent
dist_hw	– average distance from home to work
dow	– day of the week
duration_min	– duration of individual stop
gend	– gender
new_dom	– domain after aggregation
new_dom	– aggregated domains
soc_role	– academic role (student or academic)
socworktdow	– combination of soc_role, work_location, and tdow
start_date	– date when the stop has started
start_hour	– full hour when the stop has started
tdow	– type of the day of the week (workday or weekend)
tot_dur	– total duration of stops per day per one respondent
user_id	– respondent’s unique ID
work_loc	– work location (Maarjamõisa or centre)

Annex 5. Daily total duration of stops

```
total_duration <- lme(sqrt(tot_dur) ~ tdow + soc_role + work_loc  +
                      dist_hw + gend + cars + children +
                      soc_role:tdow,
                      random = ~1|user_id,
                      data = cnt_dur, method = 'ML',
                       correlation=corAR1(~start_date|user_id, value=0.5))
```

Repeated measures ANOVA of daily total duration of stops

	numDF	**denDF**	**F-value**	**p-value**
(Intercept)	1	9305	347.5376	<.0001*
tdow	1	9305	31.5719	<.0001*
soc_role	1	64	4.2792	0.0426*
work_loc	1	64	0.2110	0.6475
dist_hw	1	9305	0.7915	0.3737
gend	1	64	0.4886	0.4871
cars	2	64	0.3248	0.7239
children	1	64	1.4279	0.2365
tdow:soc_role	1	9305	4.8934	0.0270*

* - statistically significant difference

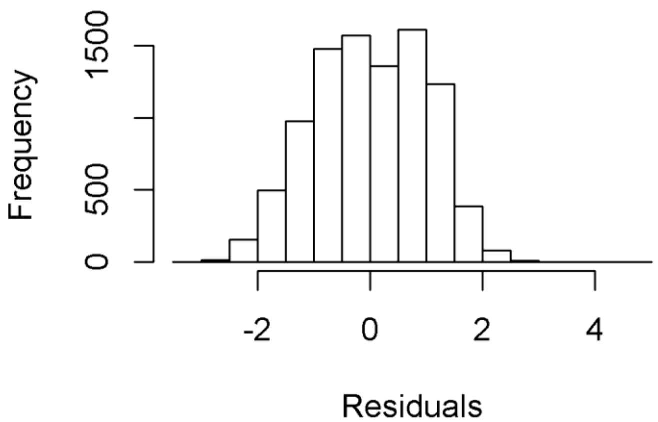

Figure A.5. Histogram of normalized residuals (square root of total duration, min)

Annex 6. Daily total number of stops

```
number_of_stops <- lme(sqrt(cnt_stops) ~ tdow + soc_role + work_loc  + dist_hw +
                       gend + cars + children +  soc_role:tdow,
                       random = ~1|user_id,
                       data = cnt_dur, method = 'ML',
                       correlation = corAR1(~start_date|user_id, value=0.5))
```

Repeated measures ANOVA of daily total number of stops

	numDF	denDF	F-value	p-value
(Intercept)	1	9305	357.6701	<.0001*
tdow	1	9305	11.0539	0.0009*
soc_role	1	64	2.8431	0.0966
work_loc	1	64	0.3893	0.5349
dist_hw	1	9305	1.5316	0.2159
gend	1	64	3.8819	0.0531
cars	2	64	3.5874	0.0334*
children	1	64	3.1141	0.0824
tdow:soc_role	1	9305	12.1331	0.0005*

* - statistically significant difference

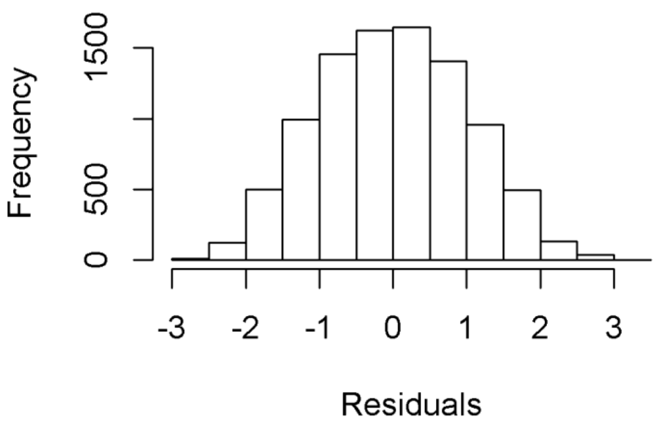

Figure A.6. Histogram of normalized residuals (square root of number of stops per day)

Annex 7. Duration of individual stops

```
individual_duration <- lme(log(duration_min) ~ dow + soc_role + work_loc +
                           gend + dist_hw + children + cars +
                           new_dom + start_hour,
                           random = ~1|user_id,
                           data = stops, method = 'ML',
                           correlation = corAR1(~start_date|user_id,
                           value=0.5))
```

Repeated measures ANOVA of duration of individual stops

	numDF	denDF	F-value	p-value
(Intercept)	1	47481	1754.7107	<.0001*
dow	6	47481	5.1583	<.0001*
soc_role	1	64	0.0035	0.9532
work_loc	1	64	0.6162	0.4354
gend	1	64	3.1061	0.0828
dist_hw	1	47481	0.6409	0.4234
children	1	64	3.5591	0.0638
cars	2	64	1.5727	0.2154
new_dom	4	47481	1842.5347	<.0001*
start_hour	23	47481	50.4224	<.0001*

* - statistically significant difference

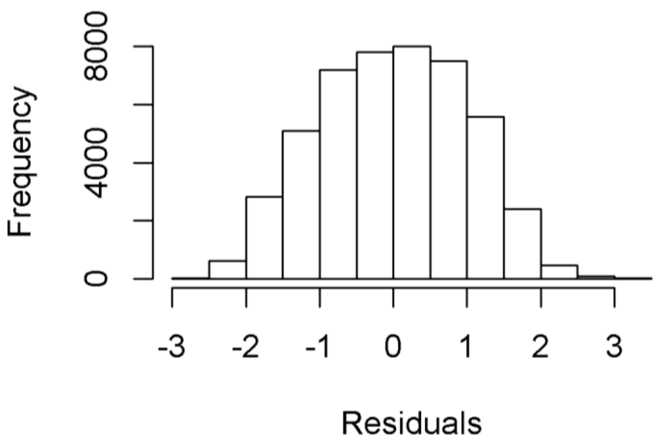

Figure A.7. Histogram of normalized residuals (logarithm of stop duration)

Annex 8. Duration of stops per domain

```
duration_domains <- lme(sqrt(durperdom) ~ tdow + new_dom + soc_role  + work_loc +
                        gend + dist_hw + children + cars,
                        random = ~1|user_id, data = domains, method = 'ML',
                        correlation = corAR1(~start_date|user_id, value=0.5))
```

Repeated measures ANOVA of duration of stops per domain

	numDF	**denDF**	**F-value**	**p-value**
(Intercept)	1	24074	975.7296	<.0001*
tdow	1	24074	143.3582	<.0001*
new_dom	4	24074	3083.7292	<.0001*
soc_role	1	64	0.4025	0.5281
work_loc	1	64	0.1975	0.6583
gend	1	64	0.0531	0.8185
dist_hw	1	24074	0.0059	0.9387
children	1	64	1.9421	0.1683
cars	2	64	0.9262	0.4013

* - statistically significant difference

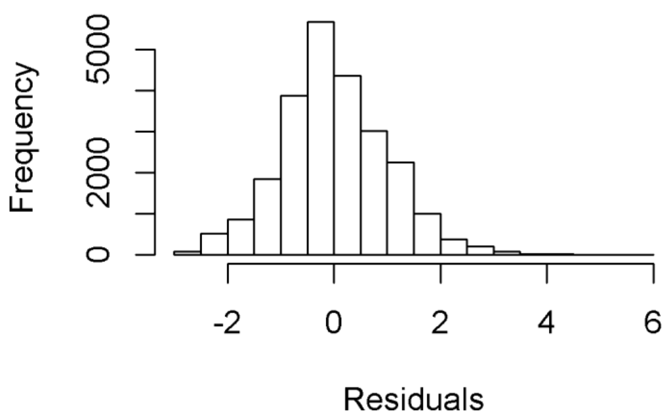

Figure A.8. Histogram of normalized residuals (square root of stop duration)

Annex 9. Duration of stops in work and studies domain

```
work_domain <- lme(sqrt(durperdom) ~ socworktdow + gend + dist_hw + children + cars,
                   random = ~1|user_id, data = work, method = 'ML',
                   correlation = corAR1(~start_date|user_id, value=0.5))
```

Repeated measures ANOVA of duration of stops in work and studies domain

	numDF	denDF	F-value	p-value
(Intercept)	1	4736	82.48148	<.0001*
socworktdow	7	4736	11.51151	<.0001*
gend	1	65	0.00352	0.9529
dist_hw	1	4736	0.38705	0.5339
children	1	65	0.89795	0.3468
cars	2	65	0.25973	0.7721

* - statistically significant difference

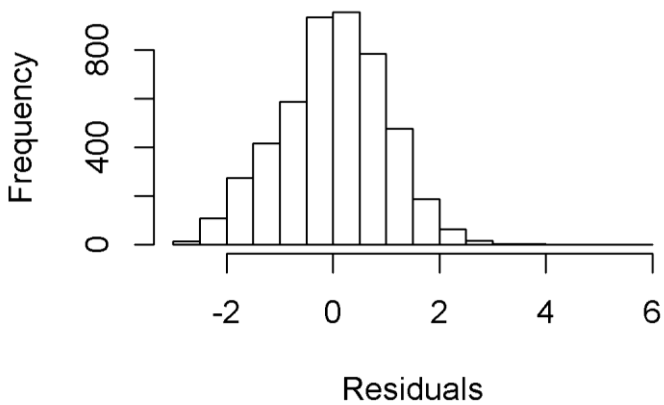

Figure A.9. Histogram of normalized residuals
(square root of stop duration within the domain “2. Work and studies”)

Annex 10. Duration of stops in maintenance domain

Model

maintenance_domain <- lme(log(durperdom) ~ socworktdow + gend + dist_hw + children + cars,

random = ~1|user_id, data = maint, method = 'ML',

correlation = corAR1(~start_date|user_id, value=0.5))

Repeated measures ANOVA of duration of stops in work and studies domain

	numDF	denDF	F-value	p-value
(Intercept)	1	4372	144.11725	<.0001*
socworktdow	7	4372	3.43972	0.0011*
gend	1	66	2.52108	0.1171
dist_hw	1	4372	0.34242	0.5585
children	1	66	0.18100	0.6719
cars	2	66	0.40154	0.6709

* - statistically significant difference

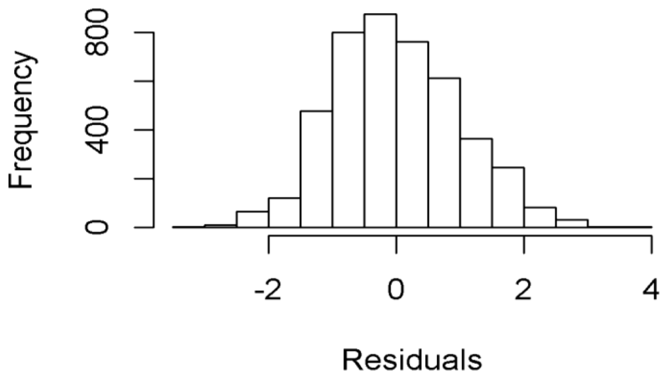

Figure A.10. Histogram of normalized residuals
(square root of stop duration within the domain “4. Maintenance”)

Annex 11. Duration of stops in domain “NA”

```
na_domain <- lme(log(durperdom) ~  socworktdow + gend + dist_hw + children + cars,
                 random = ~1|user_id, data = domna, method = 'ML',
                 correlation = corAR1(~start_date|user_id, value=0.5))
```

Repeated measures ANOVA of duration of stops in domain “NA”

	numDF	denDF	F-value	p-value
(Intercept)	1	3292	420.5070	<.0001*
socworktdow	7	3292	100.7130	<.0001*
gend	1	66	1.5292	0.2206
dist_hw	1	3292	3.6567	0.0559
children	1	66	5.8660	0.0182*
cars	2	66	0.8601	0.4278

* - statistically significant difference

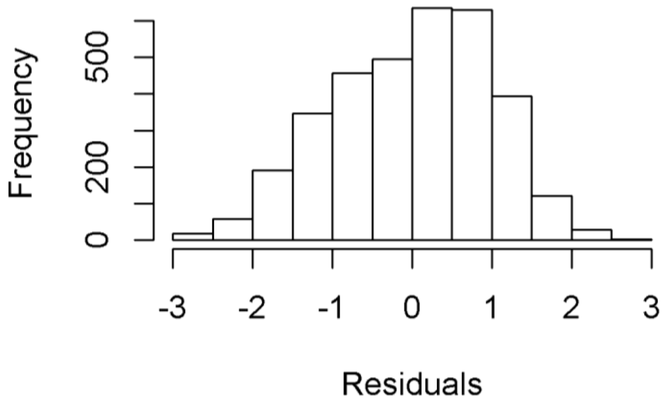

Figure A.11. Histogram of normalized residuals
(square root of stop duration within the domain “5. NA”)

Annex 12. Distance between home and work/study places

```
SELECT a.user_id, a.place_type_value, a.place_id, a.place_address, a.est_place_geom, a.res_per_start, a.res_per_end, b.user_id as buser_id, b.place_type_value as bplace_type_value, b.place_id as bplace_is, b.place_address as bplace_address, b.est_place_geom as best_place_geom, b.res_per_start as bres_per_start, b.res_per_end as bres_per_end, ST_Distance(a.est_place_geom, b.est_place_geom) as dist_hw

INTO home_work_distances

FROM public.home_work_study_places a

CROSS JOIN public.home_work_study_places b

    WHERE a.place_id > b.place_id

    AND a.user_id=b.user_id

    ORDER by a.*, b.*;
```

```
SELECT a.user_id, AVG(a.dist_hw) as dist_hw, b.place_type_value, b.place_id, b.place_address, b.est_place_geom, b.res_per_start, b.res_per_end

INTO home_work_avgdistance

FROM home_work_distances a

LEFT JOIN places_home b ON a.user_id=b.user_id

GROUP BY a.user_id,b.place_type_value, b.place_id, b.place_address, b.est_place_geom, b.res_per_start, b.res_per_end

ORDER BY a.user_id,b.place_type_value, b.place_id, b.place_address, b.est_place_geom, b.res_per_start, b.res_per_end
```

Annex 13. Code for aggregation of stops per hour

```
CREATE TABLE public.aggr_dom_hour (hourr int, group int, dom int, val int);

DO
$do$
BEGIN
        for i in 0..23 LOOP
        for d in 1..5 LOOP
        for g in 1..4 LOOP
                INSERT INTO aggr_dom_hour (hourr, dom, groupp) VALUES (i, d, g);

      END LOOP;
      END LOOP;
      END LOOP;
      END
      $do$;



DO
$do$
BEGIN
        for i in 0..23 LOOP
        for d in 1..5 LOOP
        for g in 1..4 LOOP
                UPDATE aggr_dom_hour
      SET val=
      (SELECT SUM(CASE WHEN end_hour>start_hour AND 23 BETWEEN start_hour
AND end_hour
        THEN 1
WHEN start_hour>end_hour AND ((i BETWEEN start_hour AND end_hour+24) or (i+24
BETWEEN start_hour AND end_hour+24))
        THEN 1
ELSE 0
        END ) from startend_hour where new_dom = d and comb_group =
(CASE WHEN g=1 THEN  ‘Student: Centre’
        WHEN g=2 THEN  ‘Student: Maarjamoisa’
        WHEN g=3 THEN  ‘Academic: Centre’
        WHEN g=4 THEN  ‘Academic: Maarjamoisa’
        END))
   where hourr=i and dom=d and groupp=g;
      END LOOP;
      END LOOP;
      END LOOP;
      END
      $do$;
```

Annex 14. Tukey's test: estimates of difference between groups

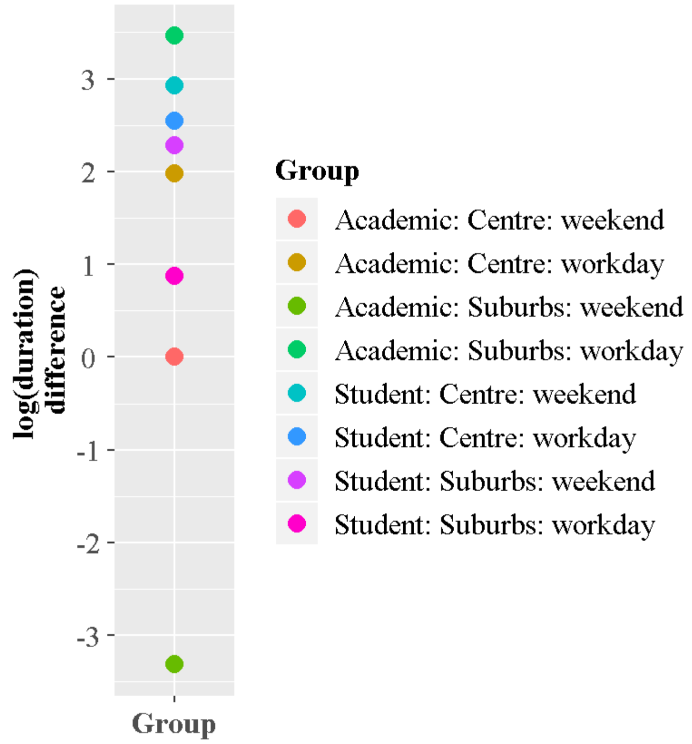

Figure A.14.1. Estimates of difference in duration of stops in domain "Work and studies" according to Tukey test ("Academic:Centre:weekend" = 0).

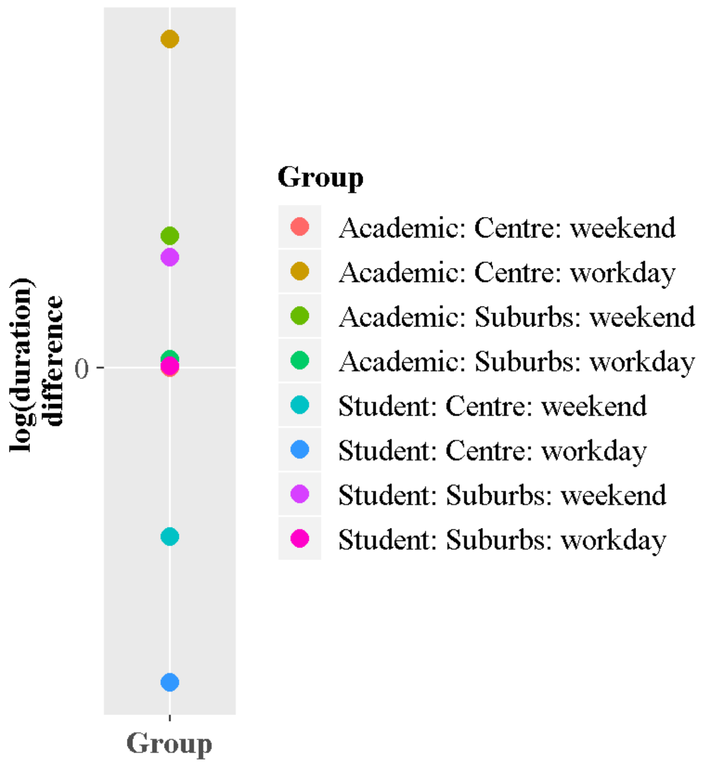

Figure A.14.2. Estimates of difference in duration of stops in domain "Maintenance" according to Tukey test ("Academic:Centre:weekend" = 0).

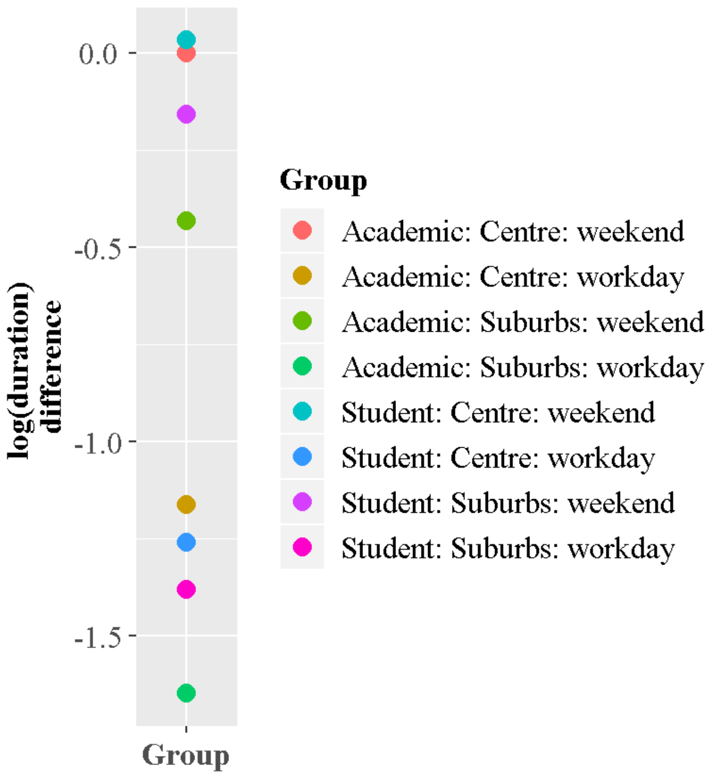

Figure A.14.3. Estimates of difference in duration of stops in domain “Maintenance” according to Tukey test (“Academic:Centre:weekend” = 0).

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