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"The influence of socio-demographic factors and place of residence on people's activity space: a study based on GPS data in Tallinn, Estonia"

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Abstract

The influence of socio-demographic factors and place of residence on people's activity space: a study based on GPS data in Tallinn, Estonia

The aim of this study is to understand how social determinants and residential location impact individuals' mobility patterns. For the empirical part, GPS data from 186 individuals of two ethnically dominant neighborhoods Kalamaja and Priisle were collected between October 2020 and February 2021, along with pre-tracking interviews to gather socio-demographic information. Regression analysis and rasterization of aggregated activity spaces were applied to analyze the data. The results revealed that differences in activity spaces exist in Tallinn, with residency, ethnicity, occupation status, and car ownership shaping users' activity spaces. The analysis showed segregation trends between residents of different neighborhoods, with the central area of Tallinn serving as a common attraction. Regarding mobility and its connection to social factors, it was detected that Estonians and Russians from Kalamaja have a higher degree of spatial variations compared to Priisle residents; occupation status and car ownership contribute to more diverse mobility networks.

Keywords: activity space, social factors, residential segregation, spatial analysis, Tallinn

CERCS code: S230 – Social geography

Abstrakt

Sotsiaaldemograafiliste tegurite ja elukoha mõju inimeste tegevusruumile: GPS-andmetel põhinev uuring Tallinnas, Eestis

Eesmärk on mõista, kuidas mõjutavad sotsiaalsed tegurid ja elukoht inimeste liikumismustreid. Empiirilises osas on kasutatud GPS andmeid perioodist oktoober 2020 kuni veebruar 2021 186 inimese kohta, kes elavad kahes etniliselt domineerivas naabruskonnas Kalamajas ja Priisles. Lisaks viidi läbi intervjuud sotsiaaldemograafilise tausta teada saamiseks. Andmete analüüsimiseks kasutati regressioonanalüüsi ja agregeeritud tegevusruumide rasterdamist. Tulemused näitavad, et Tallinnas esinevad erinevused tegevusruumides ning neid erinevusi mõjutavad elukoht, rahvus, ametialane staatus ja auto omamine. Analüüs näitab segregatsioonitrende erinevate linnaosade elanike vahel; ühiseks tõmbekeskuseks on Tallinna kesklinn. Liikuvuse ja sotsiaalsete teguritega seoses leiti, et Kalamajas elavatel eestlastel ja venelastel on suuremad ruumilised erinevused võrreldes Priisle elanikega; ametialane staatus ja auto omamine aitavad kaasa mitmekesisematele liikumisvõrgustikele.

Märksõnad: tegevusruum, sotsiaalsed tegurid, eluasemesegregatsioon, ruumianalüüs, Tallinn

CERCS kood: S230 – Sotsiaalgeograafia

Table of contents

1. Introduction

Social background of people and their mobility are linked inextricably (Puura, Silm & Masso, 2022). They transform each other and change itself mutually throughout an individual's life. The analysis of spatial patterns reveals the nature of social inequalities and ongoing integration process in society. Although bidirectional relationships between mobility and background characteristics of population groups have been explored extensively especially in segregation studies the topic remains a prominent area of investigation for several reasons.

Firstly, there are fundamentals changes taking place in society which is resulted in increased diversity and scarcity in mobility patterns, as well as more possibilities for people to interact with one another (Sheller & Urry, 2006). With raised intensity and complexity of mobility it is of high importance to develop the tools capable of analyzing spatial movements. Secondly, uneven, and segregated mobility of population groups may cause problems such as social tensions and isolation, which can affect the efficiency and unity of society (Schönfelder & Axhausen, 2003). One of effective measures of preventing these problems would be early detection of mobility dissimilarities between people. Thirdly, technological advancement has given a new perspective on mobility analysis. A new level of computational resources and sophisticated software has increased the possibilities of data-rich research (Buliung & Kanaroglou, 2006). Moreover, the capabilities of tracking and storing spatial and temporal information among individuals in a cost-sufficient way broaden the potential of mobility analysis and its correlation to the social background (Müürisepp et al., 2022). Fourthly, and of significant importance, there has been a conceptual transformation in social science that shifted the focus of segregation analysis from a place-based to an activity space-based approach, focusing on individuals' unique socio-spatial segregation experiences beyond residential locations (Wong & Shaw, 2011).

Starting from the 2000s the activity space has been increasingly applied in spatial segregation studies which broaden its scope from residential neighborhoods to other socio-spatial contexts, giving a more precise picture. However, activity space segregation is a relatively young topic and needs more investigation. Moreover, there is a lack of studies deploying GPS tracking data sources for activity space analysis (the number of such works was equal to 5 in the Scopus database by 2022) (Müürisepp et al., 2022). Following the methodological advancements in analyzing spatial differences among population groups, this study implies the activity space method together with GPS data to better understand spatial segregation nature. The last notion about topic relevance is related to the specifics of the study area. Estonia has been facing a deep-rooted segregation between the Estonian-speaking majority and the Russian-speaking minority, which began during the Soviet era. Both ethnolinguistic groups with margin are the main populations in the country.

However, their separation marked by differences in the language remains over 60 years and manifests itself in occupation status, income, education access, and residency (Tammaru, Marcińczak, & Kukk, 2018). Furthermore, Tallinn city where data was collected has one of the highest growths of socioeconomic segregation among other European capitals (Musterd et al., 2017).

The mentioned points show the clear importance of continuing the research regarding the interconnection between spatial and social dimensions of people's lives. The aim of this study is to analyze the impact of social factors and place of residence on individuals' activity space. The work has the following research questions:

- To what extent do place of residence and socio-demographic factors impact the size of individuals' activity space?
- How does the place of residence contribute to spatial variations in people's activity spaces?
- How spatial mobility varies among different social groups?

2. Theoretical overview

2.1. The relationship between mobility and people's social background

Mobility and its connection to social background have attracted interest of academic community throughout years. Most commonly the connection is analyzed in terms of spatial differences among population groups which refers to the fundamental term of 'segregation'. Social segregation points to unjust social interactions among groups. In the case of spatial segregation, the focus is on the unequal distribution of social groups within a specific physical area and places where intergroup contact may be possible. Integrated social and spatial dimensions of segregation emphasize the physical and functional separation of spaces occupied by different social groups or ethnicities (Järv et al., 2020). Concrete aspects of this include the concentration of social groups in particular areas of the city and the creation of socially homogeneous spaces, as well as subjective aspects such as perceptions of this concentration and homogeneity (Massey, Rothwell, & Domina, 2009). The resulting interweaving of social and spatial structures is conceptualized as a two-way relationship in which spatial structures are influenced by social patterns, just as spatial structures reinforce and shape the evolution of social structures (Järv et al., 2015).

A major component of socio-spatial segregation is mobility. In general, mobility refers to embodied movements and the potential to realize such movements. However, different scientific approaches highlight different aspects of mobility. Time geography views society as a network of paths that are constantly intersecting and evolving over time and space. Intersections of trajectories provide opportunities for people to communicate and interact (McQuoid & Dijst, 2012). The approach emphasizes context as one of the factors in understanding mobility patterns. Another element that influences mobility is time, which is constantly changing, resulting in shifts in circumstances that affect an individual's actions (Bohman et al., 2021). A limitation of time geography is that it excludes emotional or subjective components, preventing a thorough understanding of mobility patterns.

The planned behavior approach introduced by Ajzen (1991) on the other hand takes norms, beliefs, and attitudes into consideration for analyzing mobility behavior. The main idea behind the theory is that behavioral achievement depends jointly on ability (actual control) and motivation (intention). The actual control is the availability of requisite opportunities and resources (e.g., time, money, skills, and cooperation of others). Intention consists of two components. The first is the degree to which a person has a favorable or unfavorable evaluation of the behavior in question. The second predictor is social pressure to perform or not the behavior. Two components are interrelated and influence each other (Ajzen, 1991).

Another approach is a life course that empathizes diversity and multiplicity of career paths happen in parallel and intertwine one another (Elder, 1985; Kulu & González-Ferrer, 2014). Different careers take place in various domains such as place of residence, workplace, school and etc. The life frameworks of others also impact the direction of an individual's careers. Together this multidimensional and interrelated process creates a specific political, institutional, social, and spatial environment in which a person makes their movement. Thus, the mobility should be analyzed in the context of the past events and their dependencies since the current careers are strongly dependent on this previous background.

Mentioned approaches give a comprehensive operationalization of mobility. This paper will use a combined approach considering both objective and subjective factors when understanding the nature and reasons behind mobility patterns. Based on this proposition, mobility is a complicated pattern of movements and social practices that happen in space and time (Jarv et al., 2015).

Mobility is the result of both internal (such as occupation status, income, age, personal values, etc.) and external aspects (proximity to public transport stations, cost of tickets, the density of activity locations in nearby areas, people living by, and others) (Van Ham & Tammaru, 2016). Consequently, mobility is an outcome of complex social processes and a person's perceptions of these actions. Moreover, through mobility, people shape their status, form networks, and gain knowledge regarding social structures. Thus, mobility acts as a driver and at the same time as a litmus paper of users' socialization and in particular social stratification and socio-spatial segregation. This conclusion is the foundation for analyzing differences among population groups in the scope of mobility patterns.

There are several theories that explain the dissimilarities of the spatial behavior of different groups. The ethnicity theory puts focus on common beliefs, values, and norms that connect people and make their movements related. Mobility is a tool to distinguish an ethnic group from others with special choices of locations and routes highly used only by that community. The marginality theory explains spatial segregation by socioeconomic factors. Minority groups being discriminated and processing lower status and income face limitations in their mobility and do not have access to some areas (Johnson et al., 1998). The barrier to mobility could also take the form of a lack of information and unavailability of transport. Finally, the social network and homophily theory (making ties with people similar to you) describe the mobility differences in regard to the formation of social bonds. The social network has significant power over person's movements since enhancing emotional closeness among individuals within a social network leads to an amplified level of interaction and spatial mobility among them (McPherson, Smith-Lovin, & Cook, 2001).

The analysis of the interaction of mobility and social background has a dominant factor that usually appears in every research which is a place of residence. In general, residential segregation refers to the extent of separation between multiple groups as they reside in distinct areas of the urban environment (Massey & Denton, 1988). The high interest regarding residential segregation is logical and understandable. The segregation among neighborhood is visible and vivid, signaling about potential accumulated problems of social tensions between extremely separated groups (Van Ham & Tammaru, 2016). Numerous research has demonstrated the influence of residential segregation on various aspects of individuals' lives. These effects encompass access to educational institutions, commercial establishments, and employment, as well as the facilitation of social interactions among neighbors. For example, it was detected that immigrants residing in ethnically homogenous districts have lower salaries and integration levels in the labor market compared to people living in non-ethnic neighborhoods (Galster et al., 2008). Moreover, residential segregation could impact leisure activities, resulting in more interethnic contacts in leisure locations for individuals who live in less segregated areas (van der Laan Bouma-Doff, 2007). Having such a profound effect on social life, residency consequently significantly shapes people's mobility. The power of place of residence could be explained by several reasons. Home remains the main anchor point where a person spends most of the time, socializing and interacting with others (Van Ham & Tammaru, 2016). The socialization process happening in a residential place has a considerable effect on other aspects of life, although the influence of residency depends on population groups. As an example, children, elderlies, women, and minorities are more bound to their home place thus the consequences are deeper (Silm & Ahas, 2014). Moreover, the residency reflects people's socioeconomic status usually they can afford housing and living conditions in accordance with their income thus it is extremely difficult to change the unfavorable segregated residential area because it requires a significant positive move in an individual's status (Wang, Li, & Chai 2012).

In the 90-s research on segregation mainly focused on residential space and differences between populations of predefined administrative units (e.g., districts). The source for such studies was census data aggregated on different geographical levels and did not really involve analysis of mobility patterns. While the impact of place of residence on segregation is undoubtedly profound, limiting the analysis only to one type of location although an important one was wrong and could have produced wrong conclusions (Chen & Akar, 2016). Residential segregation and its methodological advancement have led to making mobility and its connection to social background a rapidly developing and popular theme. The methodological development in short could be addressed as moving from place-based segregation to people-based. There are several reasons why people-based approach is gaining popularity over the place-based paradigm.

First of all, people's socio-geographical spaces are diverse and include not only home but other anchor points such as work, school, and entertainment facilities. Excluding such places cause biases in segregation analysis. Moreover, meaningful locations are connected to each other and may produce vicious circles of segregation. For instance, segregation in residential places might result in unequal and lower chances of high-quality education, which consequently leads to gloomy labor perspectives, worse socio-economic status, and limited mobility forming a vicious circle of segregation (Silm et al., 2021). The place-based approach can not catch these processes.

Secondly, census aggregations made in predefined spatial units fail to catch the variability of spatial patterns across neighborhoods and individuals of different social characteristics. Thus, scientists started including other types of places in the research scope. The results showed that the level of segregation varies in different locations: in schools, churches, and home places they are higher, while in leisure activities the isolation between groups drops (Athey et al., 2021). Increasing the number of locations for spatial segregation analysis was an effective step for a more detailed analysis. However, the "new mobilities" paradigm went further and suggested shifting from the trivial representation of mobility as systematic movements between home/work/leisure places towards people and how they interact with social and spatial environments. Instead of bounding segregation to some predetermined places, the authors advocate for using individuals' unique socio-spatial experiences to form the overall segregation picture. This is the revolutionary idea behind people-based segregation. Following the new methodological discourse, the study is aimed to contribute to people-based studies (Sheller & Urry, 2006).

Methodological shifts in segregation and mobility analysis are closely connected to modern trends in society. The main cause of social transformations is rapidly evolving technologies. In the 21st century, people's daily lives will be organized around machines (smartphones, smart bikes, wireless connections, 5G Internet, high-speed trains, etc.). These inventions and devices will expand and diversify social experience and make small-sized personalized networks 'on the go' prevailing in the world. Mobility will increase in both the physical and digital environments. In such circumstances, personal identity will no longer belong to one dominant community or place but will disperse among many social groups and locations (Greenberg & Shoval, 2014). Moreover, new technologies give new opportunities to collect detailed geospatial data which is essential for deriving insights into mobility and its correlation to social factors (Van Ham & Tammaru, 2016). The data could be gathered in many ways sometimes that even a person of interest could be unaware of being tracked: hotel bookings, GPS data, CCTV footage, call detail records, and others (Buliung & Kanaroglou, 2006). However, although technologies boost communications and movements, the rising dependence on machines may lead to sedentarism. People's mobility and

interactions might migrate from the real world to the cyberspace world which will be harder to track and analyze using general GIS software (Sheller & Urry, 2006).

Residential segregation gave an impulse to further development in the analysis of mobility among different groups, however, other social factors and their connection to spatial behavior are also being studied. For example, middle-aged people tend to have a more diverse and intense mobility pattern; being employed strengthens a person's mobility because of commuting between home and work and a number of travels they make given the specifics of their occupation (Aguil'era, & Proulha, 2015). Furthermore, higher education and economic status may result in higher mobility levels and a more diverse set of tools to perform such movements. The extensity of social networks impacts mobility in the way that people with geographically dispersed social connections move more frequently and cover bigger areas (Puura et al., 2022). Parenthood might reduce your mobility and limit it to your local neighborhood which happens due to time constraints when parents take care of their child they have fewer resources to maintain their social activities and bonds with people far away (Carrasco, Miller, & Wellman, 2008). Other empirical evidence of mobility and social background correlation will be given in the chapter devoted to activity space term where the practical results of implementing this approach are described. Nevertheless, it could be already seen that mobility is interconnected to various social characteristics.

In general, spatial segregation topic remains popular among the academic community. Recent methodological developments and social transformations opened new perspectives of its analysis and now are in the process of evaluation and adoption. Meanwhile, the foundation of such research is a two-way relationship of social and spatial structures that are interconnected and reflect the trends of each other. The key element of this relationship is mobility which spatially represents social inequality tendencies and at the same time shapes segregation. This dual role of mobility patterns gives way to investigating spatial differences between various population groups. The next question: what is a sufficient tool to describe individuals' mobility in the context of their social background? This issue is discussed in the next chapter.

2.2. Activity space approach

Spatial mobility affects our perception of social constructions and vice versa society influences our mobility patterns. The two-fold exchange between a person and society is happening through different spaces thus to capture the characteristics of this process there is a need to develop an approach that will describe a person's interaction with space (Järv et al, 2020). One of the most known and well-described concepts for analysing spatial mobility is an activity space. Among researchers, there is a consensus about defining an activity space. Usually, scientists refer to the common definition proposed by Holton and Reynolds which describes an activity space as a geographical space that combines locations visited during everyday activities by some individual(s) of a given period (Horton & Reynolds, 1971). Activity space is one of two essential parts of the cognitive map approach which is used to delineate someone's world and travel experience. Activity space presents the actual locations the actor had personal interactions with. However, there is another important component called knowledge space that defines indirect space a person knows through third-party sources such as friends, books, social media, family, etc (Shönfelder & Axhausen, 2003).

Activity spaces serve as a valuable tool for examining spatial variations among individuals from diverse social backgrounds. They delineate the extent to which a person can engage with the urban environment and interact with others, shedding light on areas of social experience and potential social exclusion (Shönfelder & Axhausen, 2003). As individuals traverse different spaces, they construct their perception of society and acquire a comprehension of moral values, social norms, and regulations. Furthermore, activity spaces provide insights into people's socioeconomic status and their utilization of urban spaces and resources (Wang et al., 2012). The activity space of a group is represented by the activity spaces of its members (Wong & Shaw, 2011). Based on the time geography framework, individuals' space-time path within their activity space can reveal the likelihood of social interaction and even suggest patterns of segregation (Järv et al., 2020). Overlapping areas of people's activity spaces indicate potential places for communication and a shared physical-social environment. The greater the overlap between groups, the more likely they are to have a higher level of communication.

Activity space is a useful tool for analyzing and representing spatial segregation patterns, however, it has its limitations. It is an approximate measure of a person's mental map, and it does not account for other forms of communication such as internet-based communication, letters, and face-to-face interactions that also shape a traveler's world (Shönfelder & Axhausen, 2003). In addition, activity space is influenced not only by social factors but also by personal characteristics which are hard to capture and analyze their impact on mobility (Wang et al., 2012).

While there is no contradiction between researchers regarding the general definition of activity space an agreeable universal method to operationalize and measure an activity space has not yet been designed (Wong & Shaw, 2011). One of the key components of an activity space which is widely implemented in most of the studies is a spatial extent. There are three ways to calculate special extent (Smith, Foley, & Panter, 2019):

- Using all movements
- Using key locations
- Using specific routes or activity types (e.g., commuting to work)

Since all types of activities are of particular concern in this research and input data is GPS points the author decided not to derive key locations or concentrate on specific routes but to use all movements to capture a broad picture of the spatial behavior of the respondents.

Regarding all movements approach there are several data-driven methods to define the spatial extent and visualize spatial patterns. Firstly, the minimum convex hull (MCH) is the smallest convex hull that encloses all points in the set. The main problem of this method is that it covers a big area of space where a user has never been (Chen & Akar, 2016). The next method, standard deviational ellipse (SDE), partially combats mentioned issue. It draws a two-dimensional ellipse around the centroid point usually an arithmetical mean so the true value of point coordinates will lie there with some predefined confidence (e.g., 95%). Although SDE proved its validity for mobile positioning data analysis (Järv et al., 2015) regarding GPS data this approach still produces rather a large area.

Another method is kernel densities. The overall idea behind it is converting point patterns to a smoothing area, which estimates the density in each location. Usually, the kernel density approach reorganizes the area of interest into a grid and calculates the estimated density for each centroid of the grid. One of the challenges of the method is finding an accurate bandwidth value. The greater it is the smoother area will be. The spatial extent of an activity space created by the kernel density approach could be measured as a number of cells whose value exceeds some threshold (e.g., > 0) (Shönfelder & Axhausen, 2003). Kernel density and its variation is a popular measurement technique, and it efficiently reduces the spatial extent of an activity space not losing much information. However, it stresses the popularity of often visited locations making them look like isolated islands on maps and ignoring the connection paths between places. Moreover, tuning a bandwidth parameter could be a problem. One more reason for denning the approach in this study concerns the MobilityLog application specification which was used to collect the data for this study. The app takes measurement not on a predefined frequency (e.g., each second), but depends

on a respondent's speed. When a user stands MobilityLog registers the record every 15 seconds while a respondent is moving, the app acts each second. This disproportion will cause an incorrect representation of activity space if applying kernel density.

One of conventional methods when dealing with GPS data remains the daily paths area (DPA) which buffers all points or tracks. The buffer radius could be ranged from 50 to 800 meters (Smith et al., 2019). The method is easy to implement, and it captures all mobility patterns of a population group. However, this approach also has a drawback because it depends on the quality of the data. The best results are gathered when GPS data is continuous and have few coordinate mistakes.

An activity space has also a temporal dimension. Three key elements are derived regarding the temporality of activity space. First is data accumulation. The data could be aggregated by a trip, a single day, or multiple days. Most studies focus on activity space by day by person, however, some also generate average daily activity space value. The minimum number of days for each respondent so they could be included in the analysis usually varies from one to four (Smith et al., 2019). The second temporal component that could be considered when studying activity space is the day of the week, although relatively few studies describe activity space differences between weekdays and weekends. Finally, time could be used as exposure weighting for an activity space. The main idea behind time weights lies in the assumption that the more time spent in some place the higher exposure to this location a person has. Time weighting is usually applied along with the kernel density method (Smith et al., 2019).

The last common dimension of activity space is the diversity that is represented by the number of unique meaningful locations visited by a user. However, the researchers might introduce their own characteristics of activity space. For example, Wang et al. (2012) use the term exclusivity – a level of isolation of activity space defined by the type of locations people visit, and the transport mode they use. A person with a private car and frequently appearing in fine dining restaurants and expensive fitness clubs has a high level of exclusivity.

The interest in the activity space approach for analyzing spatial differences among various populations appeared in the 2000s (Müürisepp et al., 2022). The first works used traditional sources of data – travel diaries and surveys to collect self-reported locations. Starting in 2010-s the opposite trend has taken place where the popularity of traditional sources has been significantly declining, and instead of them, big data has come (GPS tracking, social media, mobile positioning data, smart card). Big data-based studies are usually supplemented with additional information about the social background of people. Notably, the size of the respondents' group in this kind of study is either small (<100) or large (>10,000). Big data has an advantage over traditional sources allowing capturing activity space on bigger geographical levels like country or even transnational

scope. Usually, studies with big data analyze the whole individuals' activity space, however, it is possible to focus on some specific parts, for example, out-of-home non-employment movements (Silm & Ahas, 2014). In terms of activity space segregation, the researchers usually analyze spatial variations between socioeconomic, ethnic, racial, religious, and linguistic groups. Most works use one of mentioned social dimensions, although there are articles that form groups by intersecting different background characteristics, such as age and ethnicity (Silm, Ahas, & Nuga 2013), socioeconomic status and ethnicity (Järv et al., 2020), etc. Regarding activity space metrics the studies examine the number of locations visited, time spent in a place, and extent of movements although the last variable is of interest less often. A considerable amount of articles aggregated activity spaces to predefined spatial units, which is interesting, since the approach of representing people's spatial behavior is people-based but the segregation is investigated in place-based logic. In addition, some works used aggregation on activity spaces to depict the path network and its utilization intensity to analyze the spatial tendencies of a group (Müürisepp et al., 2022).

The published articles concerning activity space are mainly devoted to the topic of to what extent and how activity space is influenced by social factors. Chen & Akar (2016) found that elderlies, females, people with no car, and low income tend to have a smaller activity space. Race was also significantly important regarding activity space of non-work locations. The reason may be that non-whites have a lower income; therefore, they can only afford to live in areas that are far away from activity centers. Contrary to Chen & Akar (2016) results, Shönfelder & Axhausen (2003) did not see a strong correlation between socio-demographical characteristics and activity space in their work. The main conclusion was that there is no statistical evidence, that the population groups normally associated with social exclusion: the females, the elderly, and those with low incomes are significantly different from the rest of the sample in terms of the sparsity of activity space. Wang et al. (2012) found a correlation between activity space and social status (namely occupation, education, and income). The work compared people from three types of neighborhoods – institutionally privileged, economically privileged, and others. People from institutionally privileged areas had the most concentrated activity spaces which was explained by the proximity of all needed services to their home locations. Residents of economically privileged neighborhoods have the largest extensity of activity space but at the same time the least intensity. Both groups demonstrated a high level of exclusivity of activity space meaning that they regularly used private transport and held their leisure activities in "premium spaces" such as fitness clubs, restaurants, shopping malls, etc. In contrast, people from other units made use of public modes and urban spaces (parks, squares, and municipal centers). The main conclusion of the study is that

the affluent class having access to numerous privileged services in modern cities tends to isolate themselves from people of low status.

Mobility Lab at the University of Tartu, Estonia has conducted a series of studies utilizing the activity space approach with mobile positioning data. Their research focuses on the socio-spatial segregation primarily between the Estonian-speaking majority and the Russian-speaking minority, but there are some works regarding other types of segregation, for example, gender differences in spatial behavior. In one of the studies, Silm et al. (2013) revealed that males in Estonia exhibit longer commuting distances from home to work, with their workplaces dispersed throughout the city center. They engage in a greater number of activities and their occupations are more mobile. Women tend to have workplaces in closer proximity to their homes, with a concentration in the central business district (CBD). They spend more time at residences, resulting in a more limited daily travel range focused primarily on the home-work axis. Moreover, men demonstrate a higher frequency of car usage, whereas women show a greater preference for public transportation, bicycles, and walking.

Mobility Lab has reached several key conclusions regarding ethnic segregation. They have found that language is one of the most significant variables in explaining the differences in spatial behavior in Estonia. Russian speakers, compared to Estonian speakers, visit fewer activity locations, and these locations are also spatially concentrated (Järv et al., 2015). Moreover, in terms of out-of-home non-employment activities Russian-speaking citizens are inclined to visit areas predominantly populated by people of their group (Silm & Ahas, 2014). One of the works has detected a correlation between activity space and the social status of people among two ethnic groups. For example, people from lower and lower-middle classes tend to have fewer ethnic differences in spatial mobility because they lack the resources to extend their activity spaces. However, the Russian-speaking minority positioning themselves as middle class or higher have more limited activity spaces compared to Estonians of the same status group (Järv et al., 2020). Additionally, Estonian speakers tend to visit more places outside of their home administrative unit and these places are more evenly dispersed across the entire country. Moreover, the longer the study period, the stronger the observed differences in spatial behavior between the two ethnic groups (Järv et al., 2015).

Based on the findings of this chapter, activity space is a comprehensive concept that proves valuable in studying spatial differences between people of various social backgrounds. Activity space can function both as an exposure metric and as an outcome of social inequalities. There are numerous dimensions to the term, and within these dimensions, different measurement techniques

are available. Data availability and the research objectives determine which activity space dimension and technique to use.

3. Context: segregation and social differences in Estonia

The population of Estonia mainly consists of two biggest groups: the dominant, Estonians (roughly 69% of the whole population), and the minority represented by different nationalities from the former Soviet Union (about 24%) (Statistics Estonia, 2022). The migration of a minority group in Estonia started after Second World War and continued till 1991 when Estonia gained independence (Kulu, 2004). Russian-speaking population mainly resided in large cities (like Tallinn) and industrial areas (e.g., Ida-Viru County). Unlike in Western countries, the key marker of segregation in Estonian appears to be language. Language groups in Estonia share the same social beliefs, status, and historical background. The roots of segregation between the Estonian-speaking majority and the Russian-speaking minority lie back in the Soviet era and were mostly caused by three factors. Firstly, the housing policy resulted in the placement of Russian immigrant labor in residential areas that were geographically isolated from Estonians. (Kährik, & Tammaru, 2010). Secondly, coming immigrants were mostly deployed in the manufacturing, construction, and military sectors. This led to the situation that currently Russian-speaking minority works in blue-collar jobs while Estonian-speaking citizens occupy high-level positions, thus workplaces among the two groups have become spatially separated (Silm, Ahas, & Mooses, 2017). Finally, during the Soviet period, a linguistically segregated school system was imposed which also constrained contact between Russians and Estonians. Nowadays, the segregation between two ethnolinguistic groups is manifested in a low percentage of intermarriage, different places of residence at the administrative unit level, and income and occupational inequalities (Silm et al., 2021).

Regarding the Tallinn population, the discrepancy between the number of Estonian-speaking people and the Russian-speaking people is smaller than on the country level: 49.5% and 44%. However, segregation in Tallinn is still vivid and serious. Moreover, after the fall of the Soviet Union, the situation only worsened leading Tallinn to be one of the most segregated cities in Europe (Musterd et al., 2017). The core explanation of this is the transformation of a centralized Soviet economy to the post-socialist liberal welfare regime and capital-driven housing market. Notably, rising socioeconomic segregation did not happen immediately but had a time gap. The reason was that at the begging the housing supply was undeveloped, and the vast privatization of real estate only strengthened the socio-spatial structures. However, with growing suburbanization and gentrification the housing stock met the need of the affluent class (which predominantly are Estonians) and spatial segregation took place (Tammaru et al., 2016). Another reason for rising socioeconomic and spatial differences between the two groups is changes in the political system. In the Soviet era, professions like qualified workers and soldiers due to ideological agenda were

prestigious and treated better. However, with gaining independence, the focus shifted to white-collar jobs, Russian-speaking citizens having occupations similar to their ancestors have found that their status dropped. Moreover, when the Soviet Union collapsed some Russians emigrated. It could be assumed that these were the most socially and economically active people, while more passive stayed in Estonia.

The empirical study has shown that younger generation of Estonian spikers and Russians spikers have deeper spatial differences compared to older generation of the same two groups (Silm et al., 2017). This dissimilarities manifests in higher discrepancy in area of activity spaces and number of visited districts of Tallinn. The socio-demographic characteristics of Tallinn population and their distribution over districts also indicate the segregation problem in the city. Two groups unevenly presented in Tallinn regions with highest percentage difference in Kesklinn (67% Estonians vs 18% Russians), Kristiine (70% Estonians vs 20% Russians), Nõmme (86% Estonians vs 10% Russians), Pirita (72% Estonians vs 20% Russians), and Lasnamäe (60% Estonians vs 26% Russians) (Statistical Yearbook of Tallinn, 2021). Some districts are highly differentiated economically. For example, Kesklinn (which borders with Kalamaja neighborhood - one of the areas of interest in this work) has the lowest unemployment rate in Tallinn and its monthly gross salary varies in the range of 1400-2000 euros (for Kalmaja it is 1904 €), while in Lasnamäe (where Priisle, another study area, is located) registered unemployed population is the highest and their wages fluctuate between 1000-1400 euros (in Priisle it equals 1273 €). This evidence of existing disparities in specific locations highlights the high possibility of people being separated based on various social backgrounds in Tallinn. This aspect will be thoroughly examined and evaluated in detail in the empirical part of the study.

4. Data and Methods

4.1. Data

There are two objectives of the empirical research. The first is to identify a correlation between various socio-demographic factors and the area of activity space. Once crucial socio-economic variables are determined, the second objective is to examine the spatial distribution of activity spaces among individuals from diverse backgrounds.

Two primary sources of data are used in the research - GPS data and socio-demographical characteristics of the users. Both data repositories were collected in the scope of the 4-year-long project "Understanding the Vicious Circles of Segregation. A Geographic Perspective" (Estonian Research Information System, 2023). All users gave formal consent to participate in the survey. During the process of data collection, particular emphasis was placed on recruiting participants from two distinct neighborhoods of Tallinn, namely Kalamaja and Priisle. The reason behind this selection was rooted in the hypothesis that people of these areas exhibit a pronounced degree of dissimilarities in spatial behavior, both within the community and between the residencies. As a result, the residential location plays a crucial role in this study.

The GPS data was obtained using a smartphone application Mobility Log, which is developed and designed by Mattias Linnap and the Mobility Lab of Tartu University. The application is set for long-term mobility tracing and provides users' GPS coordinates and metadata about call activities (Puura et al, 2022).

In Table 1 the description of variables derived from GPS data is shown:

Table 1. Variables of GPS data used in the study.

Variable	Description	Data type
User ID	a unique id of a respondent	Integer
Date and time	a time when a record is taken in date format (%Y-%m-%d %H:%M:%S)	Object
GPS point coordinates	coordinates of a GPS point	Object

The GPS data had 10693735 records and included 186 unique users. The start date of data collection varies between October and December, but most users started the survey in November. Overall, the period of measurement is from the 5th of October 2020 to the 1st of February 2021. Another source of data is quantitative pre-tracking face-to-face interviews. From the interviews, two main parts of the information were derived. Firstly, the survey provided addresses of

meaningful locations such as home, workplace, school, etc. Secondly, participants gave information about their socio-demographic characteristics, including variables such as mother tongue, occupation status, and income range, among others. Finally, the research uses the borders of local administrative units at different levels: Tallinn districts, Harju County, and Estonian borders.

Before the data analysis cleaning and preprocessing stages were performed. 163 unique users were left in the study after cleaning GPS data. Preprocessing steps were done both in Python and PostgreSQL and included the following:

- Delete the users from the dataset who have less than 7 days of data presented, 16 people were excluded. The imposition of a seven-day condition was intended to ensure we obtained a reliable representation of the users' movements and their extent.
- Create a bounding box of the continental part of Tallinn including Tallinna Ringtee road (see Figure 1). The bounding box was created to limit the movements to the study area. The bounding box includes Tallinna Ringtee road since some respondents use this road to travel between the western and eastern parts of Tallinn. The next step was to calculate how many unique days the users moved within this defined bounding box, if the number of days was less than 7 a user was excluded from the dataset. After this preprocessing stage, 7 people were deleted.

Preparing survey data for the analysis mainly required categorizing variables values. The main purpose of categorization is to form relatively big and logical groups of respondents that will be used in regression analysis. The description of socio-demographical characteristics and their distribution is provided in Table 2.

Table 2. Socio-demographic characteristics of the study subjects (N = 163).

Variable	**Values**	**Categorization**	**Percentage**
gender	Male	Male	43%
	Female	Female	57%
residency	Priisle	Priisle	51.5%
	Other Lasnamae		
	Kalamaja	Kalamaja	48.5%
	Other North Tallinn		
mother tongue	Estonian	Estonian	53.4%
	Russian	Russian	46.6%
occupational status	Senior manager		33.1%

	Middle manager	High (level 3 occupations based on ISCO labor standard)	
	Top specialist		
	Mid-level specialist	Middle-Low (level 2 and 1 occupations based on ISCO labor standard (ILO, 2015))	45.5%
	Official		
	Service and sales staff		
	Skilled worker		
	Assembler		
	Manual labor		
	Other	Other	0.05%
	NA	Don't work	15.9%
education level	General basic education	Lower education	36.8%
	Basic education and vocational education		
	General secondary education		
	Secondary education and vocational education		
	Professional higher education	Higher education	63.2%
	Higher education		
	PhD/Candidate of Sciences		
income class	< 1000 EUR	Low	15.3%
	EUR 1001-1500	Middle low	19.6%
	EUR 1501-2000	Middle	17.1%
	> 2001 EUR	High	24%
	Do not wish to answer	Do not wish to answer	24%

car ownership	Yes	Yes	70.5%
	No	No	29.5%
having a child/children	No children	Has no children to parent	55.8%
	No children to parent (they left the home)		
	Has child/children to parent	Has child/children to parent	44.2%
age	Numerical variable	25-35	42.3%
		36-50	33.1%
		51-65	24.6%

Males are less presented in the study than females, the difference in percentage is less than 15%. According to Tallinn City Government statistics, in 2021 the ratio of females and males in the city was approximately 55% and 45% respectively. The number of people among categories for both residency and mother tongue variables is almost equal. Regarding the mother tongue characteristic Statistical Yearbook of Tallinn provides the following information: 49.5% of people in Tallinn speak Estonian, while 44.1% speak Russian. Most respondents have non-managerial job positions however highest occupation status is also presented in the distribution. In 2020 among employed Tallinn residents about 60% occupied white color jobs, whereas the other 40% were blue-collar (Statistical Yearbook of Tallinn, 2021). The mismatching between survey distribution and official statistics could be explained by different categorization basses.

Higher education prevails among people taking part in the study (about 60%). In 2020 approximately 45% of people living in Tallinn acquired higher education. It should be kept in mind that Tallinn's official statistics concern all age groups (including teenagers), while in the survey the youngest participant is 25 years old. The age limitation of the study affects the distribution of education since older people are more likely to have a higher degree than youngsters. Thus the share of higher education among all other degrees is higher in the survey compared to official statistics. Income class variance is mostly equally presented in categories (each group has about 20% ± 5% of the total distribution). A lot of people refused to reveal their income, among those predominantly Estonians. The income borders for the category "middle" were chosen based on employees' monthly monetary gross income in 2019 which equals to 1533,70 EUR. Car ownership

in the study has the highest discrepancy between the number of people in each category (70% vs 30%). Both types of users with children and without children are presented in the study, the latter is the dominant type which corresponds to the official trend in Tallinn, where 75% of households are without children. Regarding age distribution, young people are the main group (42%), although middle-aged respondents and elderlies also participated in the survey, 33% and 25% respectively. This is not fully correlated with Tallinn's statistics where the 25-34 age group has 16% of the city's population, the 35-49 age group – 23%, and the 50-64 group – 18%. In general variables' distribution presented in the survey is mostly similar to the overall trends of a socio-demographical situation in Tallinn.

The final source of data is local administrative units. Below, in Figure 1 the study area is shown. Only the continental part of Tallinn is used for analysis. All islands belonging to Tallinn city along with the biggest one Aegna were excluded. Two neighbourhoods of research interest Priisle and Kalamaja are also presented on the map. Red-colored rectangle displays the bounding box border which was applied when filtering GPS data.

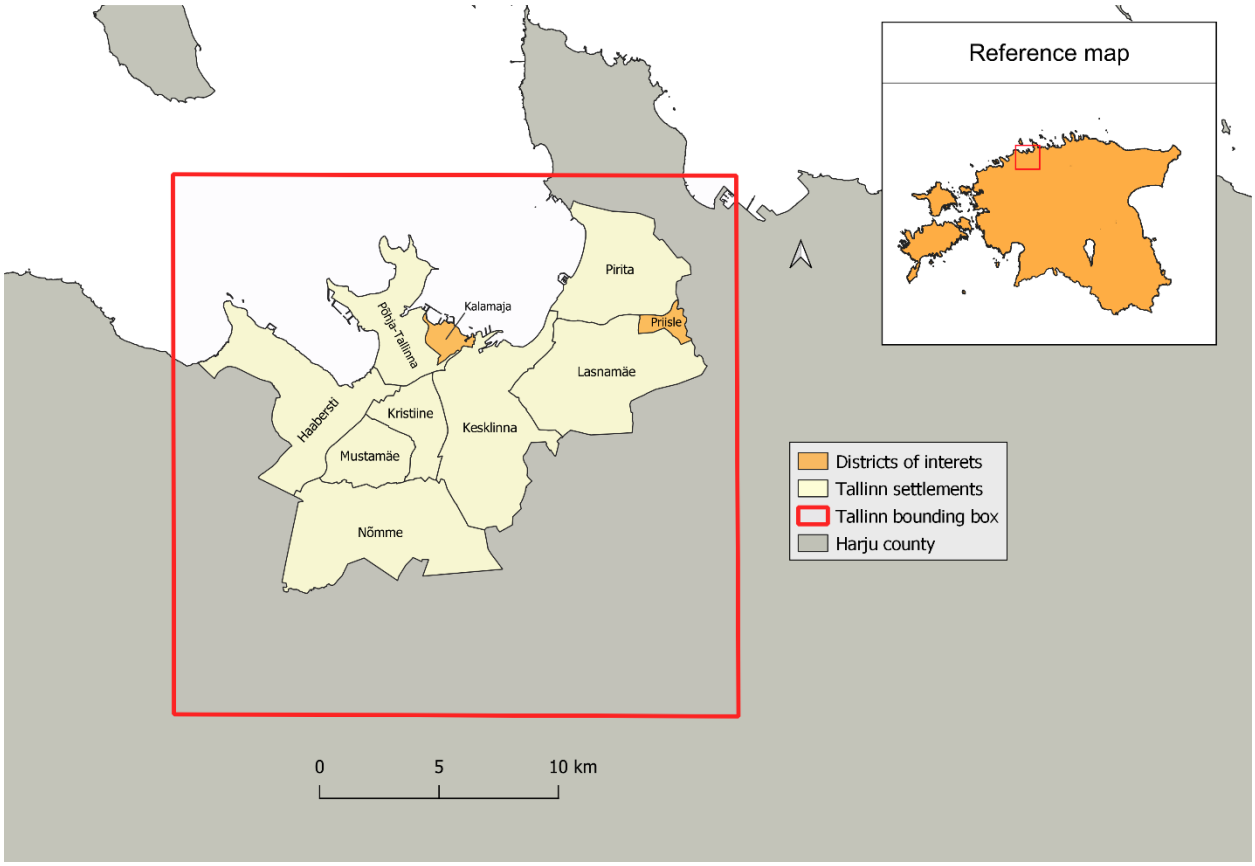

Figure 1. Study area of Tallinn

4.2. Analysis Methods

Two main indicators were calculated during the research – **overall activity space and daily activity spaces**. One method was applied to derive both indicators, namely daily paths area which creates a buffer around GPS points. The radius of the buffer can vary from 100 to 800 meters (Smith et al., 2019). In the study, the chosen radius of buffers is 100 meters since the area of interest has a small geographical extent.

The difference between the two variables is the level of aggregation: for overall activity space, a buffer is generated based on GPS data of the whole measurement period, while for daily activity spaces, a buffer is constructed using GPS points of each date. Every user has their own unique overall activity space and daily activity spaces. As an example, if a user has GPS data for 30 days, they will get one overall activity space and 30 daily activity spaces. From the resulting activity spaces, two features were derived to be then used in the analysis part – geometry (MultiPolygons/Polygons) and area. The process of creating activity spaces was performed in PostgreSQL.

The analysis methods are divided into two groups. The first class of methods implements the average area of activity spaces (both types) and identifies relationships between these variables and socio-demographical characteristics. The second group of methods uses the geometries of activity spaces as the main input and detects the similarities/differences in mobility patterns between population groups.

To perform regression analysis two dependent variables were calculated. The first one is the **average area of overall activity space**. The feature is computed as the overall activity space area of a user divided by the number of days of measurement. This normalization is necessary since users have different durations of measurement period. By dividing the overall activity space area by the number of days of measurement, we obtain a comparable measure of the average area covered by a user's activity space. The second dependent variable is **the average area of daily activity spaces**, which is calculated as the mean of the areas of the daily activity spaces. This measure represents the average size of a user's activity space on a daily basis. The difference between the two dependent variables is that the average size of the overall activity space is aggregated representation of the general mobility of respondents, and the average daily activity space area focuses on the daily extent of mobility patterns. These features are not the same, e.g., a user can have a large overall activity space, but their daily activity spaces could be scoped to small areas. The independent variable for the regression analysis was chosen to be the social and demographical background of users, namely residency, gender, mother tongue, occupation status, income class, educational level, car ownership, categorical age, and if a user has children to take

care of (for a more detailed description of independent variables please refer to Table 2). Regression analysis was done by implementing the Statsmodel Python library.

The leading approach in the second block of analysis methods is a raster representation of activity spaces. Raster files were created on mentioned above Tallinn bounding box with cell resolution 100 x 100 meters. Regarding rasters of overall activity spaces, each cell in the file was assigned a value based on the percentage of people in each population group that have been in that cell. First, the cell is checked on how many overall activity spaces intersect this cell, then the value is divided by the total number of social group respondents. Rasterization was also performed on daily activity spaces. The process is similar to creating rasters for overall activity space but in that case, the band value is divided by the total number of days combined among all people of the same social group. As an example, if a population group consists of 50 people and each of them has data for 7 days period the value will be divided by 350. The resulting value in the research is called the percentage of users-days. While the first type of raster files illustrates in general the most and the least popular areas among groups, the rasterization of daily activity spaces shows daily spatial patterns. All rasterization processes were done mainly using the Rasterio Python library.

The mobility patterns were also scoped to Tallinn districts which are shown in Figure 1. The goal is to calculate the percentage of each group who have visited the districts to analyze the most and the least visited units among different communities. Although the authors of the research are against bounding spatial patterns to predefined administrative units, to derive these results people-based approach was used which makes the outcome not biased to predetermined geographical borders and considers the individuals' mobility. The method applied for this purpose was a spatial join between overall activity spaces and districts performed using the Geopandas Python library.

5. Results

5.1. Relationship between activity space and socio-demographic characteristics

Two regression models were run with two dependent variables – the average size of overall activity space and the average size of daily activity spaces. The results are shown in Table 3.

Table 3. Regression results between activity spaces' average area and socio-demographical factors

	The average area of overall activity space (km^2)	**The average area of daily activity spaces (km^2)**
R – squared	**0.207**	**0.216**
Age (ref: 25-36)		
36-50	-0.0313	0.1177
51-65	-0.1688	-0.4474
Gender (ref: Female)		
Male	0.1086	0.3298
Residency (ref: Kalamaja)		
Priisle	0.1366*	0.5676**
Mother tongue (ref: Estonian)		
Russian	-0.1473	-0.3802
Occupation status (ref: Doesn't work)		
Middle-Low	0.1137	0.0668
High	0.2587*	0.6061**
Income class (ref: Do not wish to respond)		
Low	0.0867	0.3490
Middle-Low	0.0835	0.2019
Middle	-0.0208	-0.0317
High	0.0440	0.0034
Education level (ref: Higher)		
Pre-higher education	0.0015	0.1290

Car ownership (ref: No)		
Yes	0.2663***	0,7071**
Has no children to parent (ref: No)		
Yes	-0.0498	0.1380

Notes: OLS regression model; significance: *p < 0.1; **p < 0.05; ***p < 0.01

The first model was run with the average size of the overall activity space. Three variables were detected as significantly important: residency, car ownership, and occupation status. Priisle residents with mean value of the first dependent variable equals to 0.53 km^2 tend to have a bigger overall activity space compared to Kalamaja respondents who have on average a size of 0.41 km^2. The finding proves the assumption made before data collection that Priisle and Kalamaja residents have variations in their mobility characteristics. Thus the focus on the residency variable in this research is justified. The reasons behind the residency effect would be a matter of more detailed research in next chapters. The importance of car ownership is logical and proves the hypothesis that people with a car have larger mobility patterns. On average the overall activity of people with cars is 2 times bigger than those who do not have a vehicle (0.55 km^2 vs 0.28 km^2) The correlation between a greater activity space and a higher status could be explained by many reasons: people with high job positions have more diverse social networks, more options to travel, etc. The current data can not give a clear answer as to which reason is the main. The average value of the dependent variable among occupation categories «Doesn't work», «Middle-Low», and «High» are 0.30 km^2, 0.42 km^2, and 0.58 km^2 respectively.

The second model has found the same significantly important features as the first model. On average, Priisle users have a 1.5 times bigger daily activity space compared to Kalamaja respondents (1.5 km^2 vs 1.05 km^2), while car ownership has an even greater effect resulting in an almost 2 times increase (0.8 km^2 vs 1.48 km^2). The occupation categories «Doesn't work» and «Middle-Low» have smaller discrepancies between each other (0.91 km^2 vs 1.04 km^2) but their mean sizes are considerably lower compared to the «High» class (1.54 km^2).

The two models have identified common significant variables. However, the influence of residency and occupation status appears to have a more pronounced effect on the area of daily activity space, whereas car ownership is more impactful for the size of the overall activity space. Neither of the models demonstrated a strong correlation between users' social background and their activity space area, as indicated by the modest R-squared values of around 0.20. Among the independent variables which were found insignificant in models, mother tongue or ethnicity stood out as particularly unexpected. Given the context of segregation in Estonia and previous studies, where ethnicity has been shown to have a considerable impact on spatial behavior (Järv et al., 2015; Järv et al., 2020; Silm & Ahas, 2014; Silm et al., 2018), it was surprising to find that it did not have a strong effect in this dataset. However, the coefficients of the two models suggested that the Russian-speaking group tends to have a smaller activity space compared to Estonian-speaking individuals, which aligns with findings from other research. Despite its lack of impact on the area of activity space, ethnicity is still considered in the subsequent chapter to examine differences and

similarities in spatial patterns among its categories. Although ethnicity may not directly influence the size of the activity space, it could still be significant in terms of spatial variations. Therefore, the author of this study decided to include it in the analysis.

In conclusion, four social factors were chosen for the next iteration of the empirical study: residency, ethnicity, occupation status, and car ownership. These derived indicators are used to describe the spatial distribution of users' activity spaces among various population groups. The spatial segregation movements are analyzed through the prism of the residency because of data collection specifics which made focus on people from two residential places – Kalamaja and Priisle.

5.2. Spatial patterns among population groups

In the second part of the empirical research, groups of interest are examined for their mobility patterns, analyzing how their movements intersect or diverge. The first set of social communities is formed based on residency and mother tongue categories.

5.2.1. Residency and Ethnicity

There are four groups: Estonians and Russians living in Kalamaja and Estonians and Russians in Priisle. While both ethnicities are presented in two neighborhoods, Kalamaja is predominantly populated with Estonians and Priisle with Russians. This disproportion should be kept in mind when analyzing the rasterization results however it does not misrepresent the trends of mobility through the groups. The number of users in each group is illustrated in Figure 2.

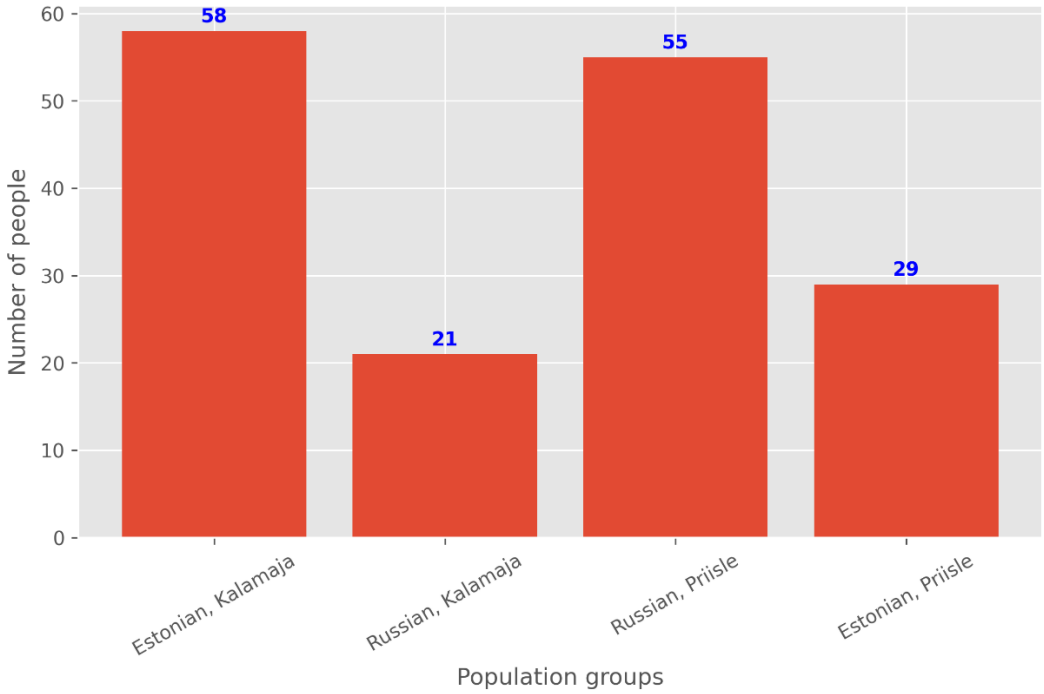

Figure 2. Number of people in each reference group (residency and mother tongue)

The analysis starts with the spatial distribution of people's movements in the scope of Tallinn districts. Figure 3 shows a graph with the percentage of users in each group who visited Tallinn districts.

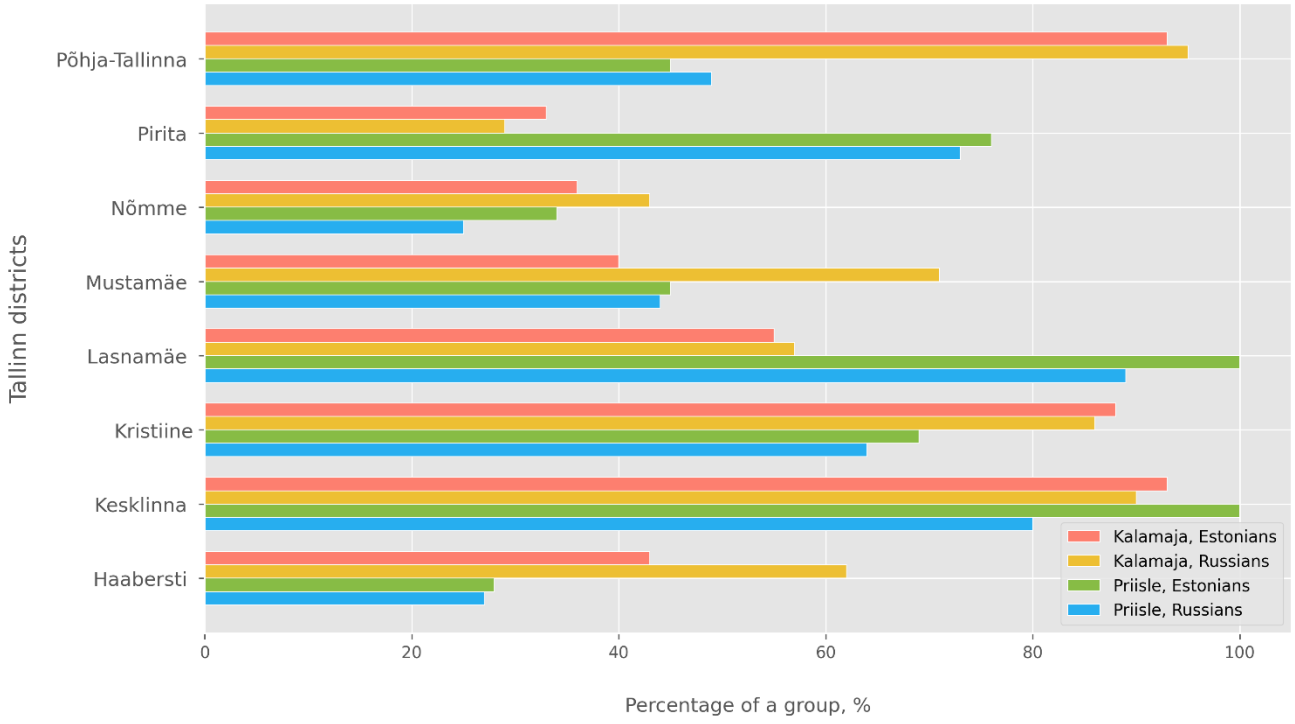

Figure 3. Percentage of reference groups visited Tallinn settlements, differentiated by residency and mother tongue

The first comparison is done between groups with the same ethnicity but different residency. Regarding Estonians in Kalamaja and Priisle, both groups have the same most visited Tallinn district Kesklinn (97% and 100% respectively). While for Estonian Kalamaja residents the popularity of Kesklinn is anticipated since its proximity to their home place, the fact that all Estonians from Priisle have visited this district is surprising. The same trend is seen for Russians from Kalamaja and Priisle where more than 90% of each group has been in the area. The results illustrate that Kesklinn is a place of attraction for all residents. Besides that, Estonians from both residency places share the same not often visited districts – Nõmme and Mustamäe (less than 50%). Concerning Russians in Kalamaja and Priisle, the discrepancy in visiting level among the rest of Tallinn districts remains high which concludes the fact that Russians from two different residencies tend to have a higher degree of spatial variations compared to Estonians.

The next iteration of analysis is performed among people of the same residency but varying mother languages. Regarding Estonians and Russians living in Kalamaja both of them have the same three most popular Tallinn units with the percentage of visitors exceeding 90% – Põhja-Tallinna, Kristiine, and Kesklinn. This result could be explained by the fact that users' home locations are placed in the city's central neighborhood Kalamaja. Concerning Russians and Estonians in Priisle their most visited districts are eastern ones – Lasnamae and Pirita which is also interpreted by the proximity of home anchors to these districts. The most notable disparity in percentage values between Estonians and Russians in Kalamaja is observed in two Western units, namely Mustamae and Haabersti. In both districts, the presence of Kalamaja Russians surpasses that of Estonians by a margin of 20%. The tendency although not so distinctly repeats for Russians and Estonians residing in Priisle. Unlike respondents living in Kalamaja ethnic groups of Priisle do not have such a high discrepancy of percentage values in visiting districts which proves the conclusion that mobility patterns are more similar between Russians and Estonians in Priisle than in Kalamaja. A more detailed picture of visiting Tallinn units by various population groups is presented in the Annexes section where the tables of the exact percentage values are stored.

Figure 4 illustrates the share of a population group that has been in some areas of Tallinn. Contrary to the previous Figure 3 the map below is not limited to predefined Tallinn districts but shows the most common general mobility patterns among people.

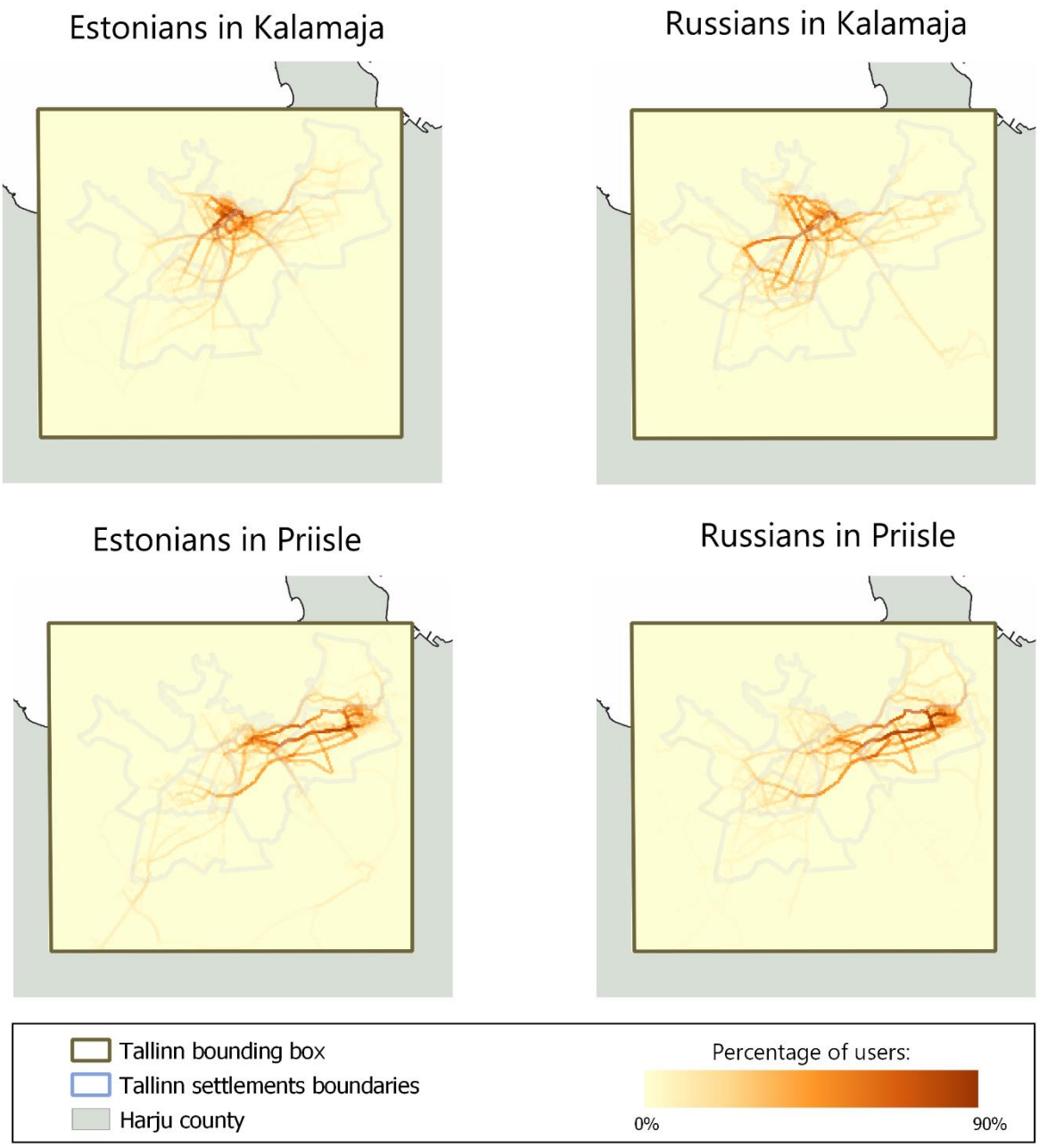

Figure 4. Percentage of users in each population group in rasterized Tallinn bounding box, differentiated by residency and mother tongue

First, the extent of activity spaces is investigated. Estonians from both residency areas have mostly the same extent of mobility exceeding the borders of Tallinn districts. However, the northern parts of the city are not covered by Estonians from Priisle contrary to Estonians from Kalamaja. Regarding Russians, the ones living in Kalamaja have a more scoped extent of activity space compared to Priisle residents. With respect to Estonians and Russians in Kalamaja. their spread of

movements looks mostly similar, although a Russian group mainly not cover the eastern part of the city. However, it should be kept in mind that the number of Russians from Kalamaja is considerably smaller than Estonians. Russians fewer in numbers covered almost the same areas as Estonians. The map for Priisle residents illustrates mostly the same extent of activity spaces among the two ethnic groups, however, Russians are more dominant in the western part of Tallinn.

The next step of analysis concerns a more detailed analysis of the paths, their directions and usage intensity. Comparing users of Priisle and Kalamaja demonstrates that Kalamaja users are concentrated in one place (which is the city center) and almost do not visit the eastern part of Tallinn, whereas Priisle residents have at least two vivid concentration areas (their home area and Tallinn's central part. Furthermore, the mobility patterns of Kalamaja residents have a more vertical orientation (North-South), whereas movements of Priisle people are more distributed between East and West. Nevertheless, the two groups are not totally isolated, the intersection of paths among Kalamaja and Priisle users happens mostly in central districts.

Regarding Estonians and Russians living in Kalamaja, the most vivid difference between them is that Estonians' overall activity spaces are more present in the central area than Russians'. While groups have some common paths that are highly used by them, the popularity of these paths is different: Kalamaja Russians more often move in the western part of Tallinn, whereas Estonians' mobility patterns are mostly equally sparse in all directions from their home locations. Another two comparison groups are Russians and Estonians living in Priisle. Trends seen among these communities show a high level of similarity between them: main mobility patterns between Priisle residents are quite identical with the three most used paths repeating each other, two of them lead to the center area of Tallinn, and one to the west.

Four population groups were analyzed in terms of their daily activity spaces, which were aggregated to show the percentage of users-days. The results are presented in Figure 5.

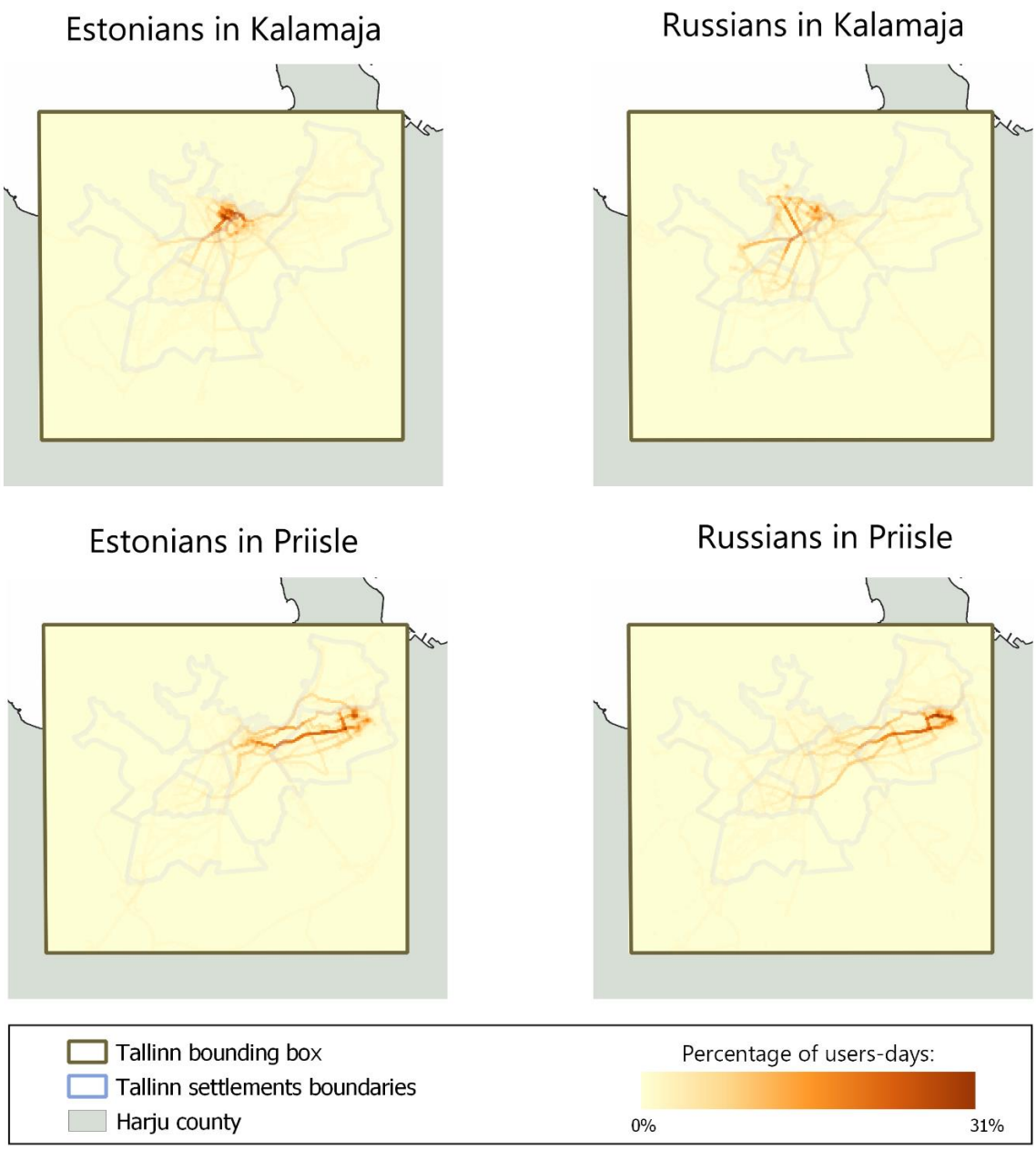

Figure 5. Percentage of users-days in each reference group in rasterized Tallinn bounding box, differentiated by residency and mother tongue

A comparison of Priisle and Kalamaja residents and their daily patterns has not revealed new trends already detected by overall activity space. In the case of Estonians and Russians in Kalamaja, the daily activity spaces have illustrated more vividly the concentration of Estonians in Kalamaja in one place and the more dispersed daily patterns of Russians covering not only the central part of Tallinn but also the western. Regarding Priisle users, two ethnic groups have one common daily path that they both use regularly. In addition, the Russian respondents in Priisle more often traverse the path leading to the western part of the city, whereas Estonians more frequently use the second trackway to the city center.

5.2.2. Residency and Occupation Status

The next groups for analysis are differentiated by residency and occupation variables. In Figure 6 the number of users of each reference group is shown. People with middle-low status are most popular in both districts. However, the Kalamaja area has a bigger number of high-status respondents and at the same time lower percentage of unemployed people compared to Priisle. In general, Kalamaja residents have a higher occupational level.

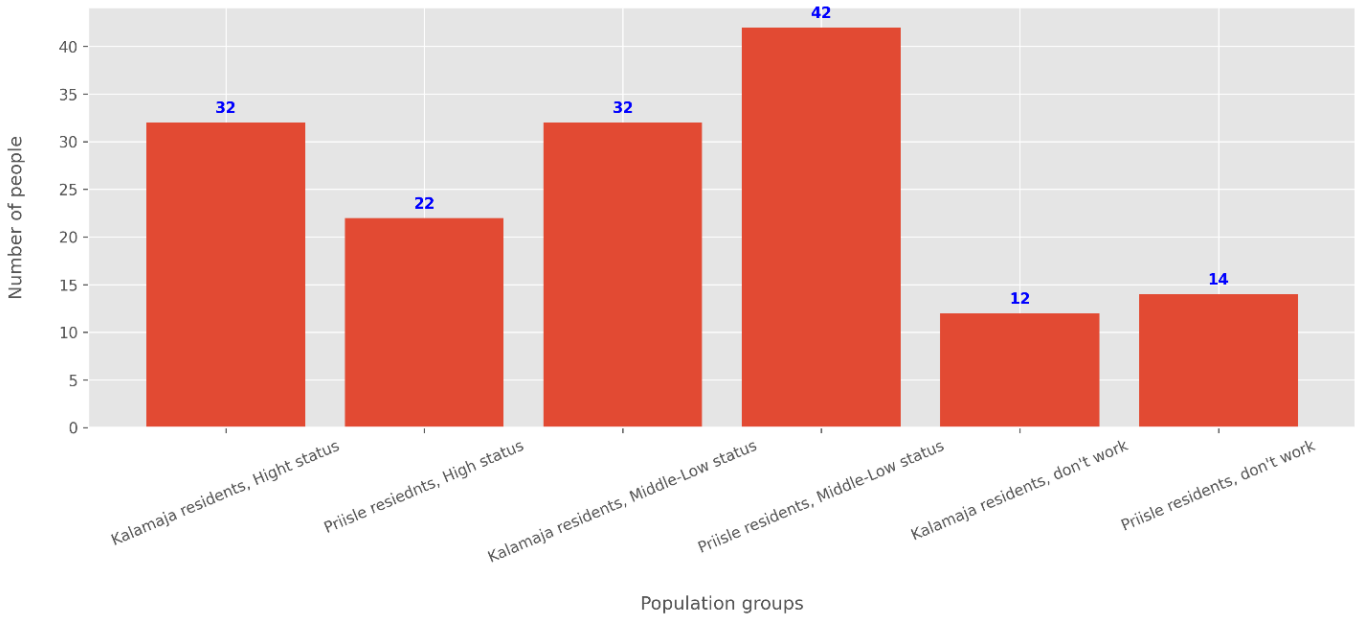

Figure 6. Number of people in each reference group (residency and mother tongue)

Figure 7 demonstrates the percentage of population groups visiting Tallinn districts. As in the case of Estonians and Russians, the Kesklinn is a place of attraction for all occupation statuses from both districts (the percentage of each group mostly is higher than 90%). In addition, the middle-low class of Kalamaja and Priisle approximately equally visit the Mustamäe (about 50%). Furthermore, in terms of the Haabertsi district Priisle and Kalamaja respondents share the same pattern: the higher the status, the more often people visit the place. On the other hand, the discrepancy in visiting percentage between the two groups of residents is profound in Pirita and Lasnamäe: users from Kalamaja of all statuses come to the areas in a much lower number than Priisle respondents (the percentage margin in some cases exceeds 50%). Another difference regards the high-status category: while white-collar workers in Kalamaja are mostly present in central Tallinn districts, the Priisle residents with high-level jobs apart from the city center regularly visit the eastern part where their home anchors are located.

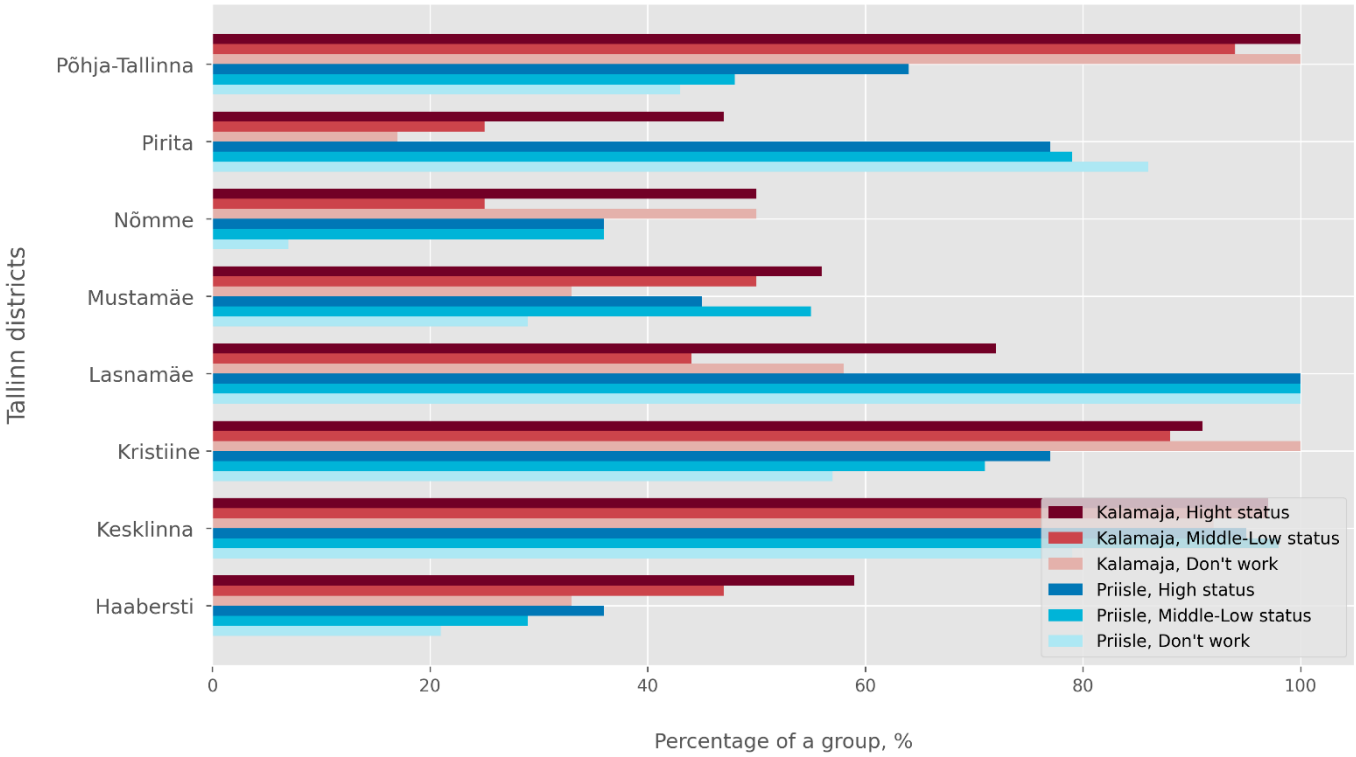

Figure 7. Percentage of reference groups visited Tallinn settlements, differentiated by residency and occupation status

A comparison of different occupation groups living in Kalamaja reveals their top three most visited neighborhoods – Põhja-Tallinna, Kesklinn, and Kristiine (about 90% among each group), which implies that the occupation status does not change the main mobility pattern of Kalamaja residents – they all concentrated in the city center, their home area. In general, among Kalamaja residents the Tallinn districts are visited more often by those with high occupation status. The same tendency is seen for white-collar workers from the Priisle neighborhood. This result accompanies by regression outcomes that show the users with higher status are more mobile.

Figure 8 displays the rasterized aggregated overall activity spaces of population groups which demonstrate the percentage of users been at least once in this area. Kalamaja and Priisle residents with high status exhibit a similar scale of mobility, while in the case of the middle-low class, coverage is slightly bigger among Priisle residents. In both districts, the mobility of unemployed individuals is restricted to their home locations. As observed among Kalamaja residents and Priisle respondents, the extent of mobility decreases with lower levels of occupation. However, for Kalamaja the difference between users of high and middle-low levels is more significant than for the same occupation classes for Priisle residents, where the extent is almost identical.

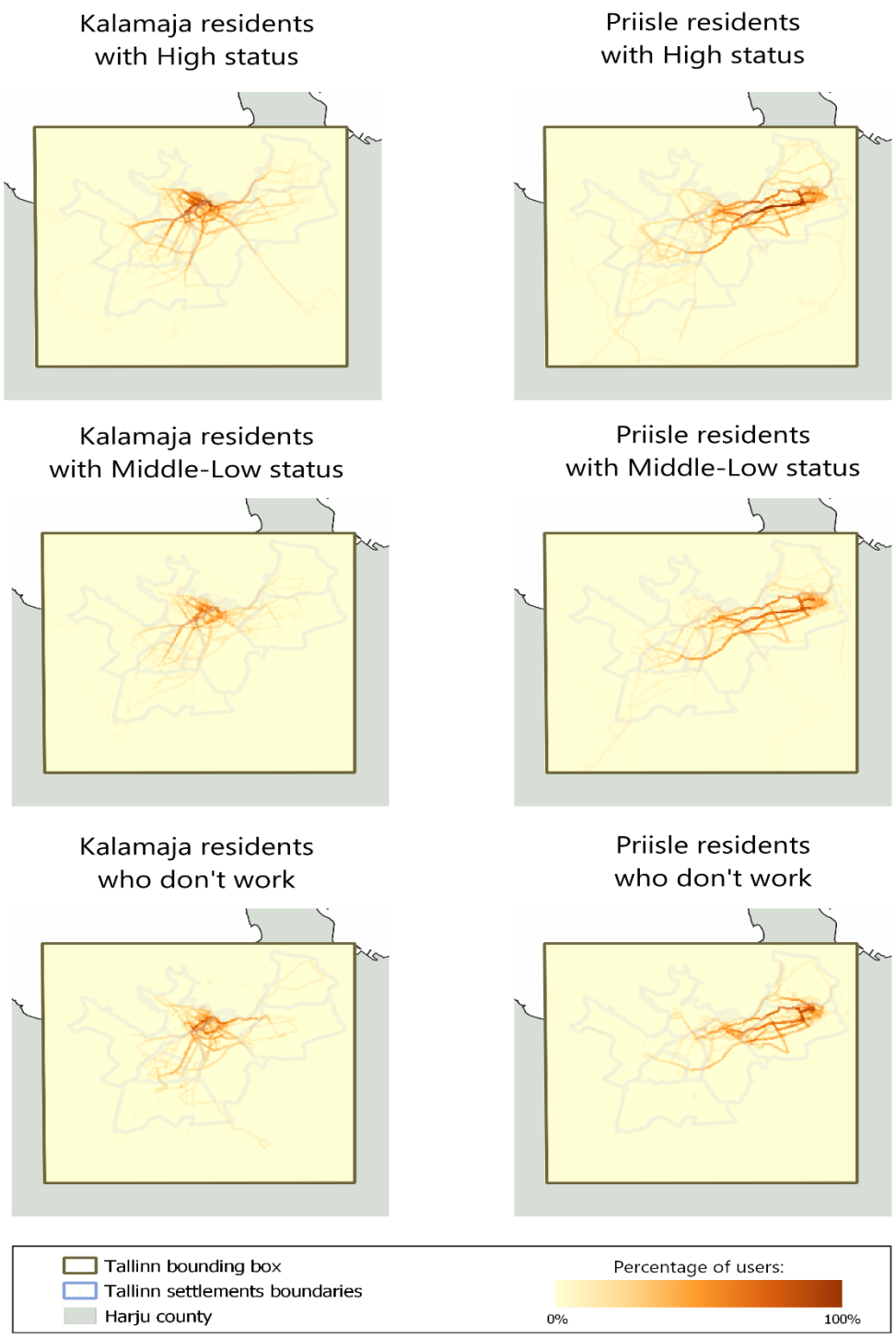

Figure 8. Percentage of users in each reference group in rasterized Tallinn bounding box, differentiated by residency and occupation status

Analysis of the path network reveals that individuals of high status residing in Kalamaja and Priisle frequently traverse all parts of Tallinn, but Priisle respondents exhibit a greater variety of paths and a higher percentage of path usage. The trend holds for middle-low class individuals in both neighborhoods, mirroring the pattern observed in white-collar workers. The study also shows that unemployed individuals in Kalamaja and Priisle tend to avoid each other's residential areas.

Specifically, respondents from Kalamaja do not traverse to Priisle, while those from Priisle infrequently intersect the Põhja-Talinna district, where Kalamaja is situated.

In general, the most common paths of occupation groups in Kalamaja are repeating each other. Nonetheless, the high class has more diverse and frequently used trajectories. The same tendency is observed for occupation classes in Priisle. Of particular note is the similarity in mobility patterns among individuals occupying the middle-low status bracket and non-working users across both residencies. This is a noteworthy observation considering that the sample size for unemployed groups is relatively small, yet their aggregate mobility patterns do not significantly diverge from the middle-low group.

Figure 9 depicts the distribution of user-days among various population groups. Consistent with the previous map, individuals with high social status exhibit a propensity to commute across the city on a daily basis, while unemployed residents of Kalamaja and Priisle display limited spatial interaction with each other. High occupation class individuals in Kalamaja demonstrate a balanced usage of daily paths, whereas respondents from Priisle tend to focus on a single route leading to the city center. Regarding middle-low status, residents from both neighborhoods do not exhibit a specific preference for daily movement. However, Kalamaja residents with middle-low status tend to avoid the southeastern part of Tallinn and exhibit more concentrated paths compared to their counterparts in Priisle. Analyzing different occupation classes in Kalamaja and Priisle reveals a consistent pattern observed in overall activity spaces: the high-level group displays a more diverse and frequently traversed daily path network compared to other occupation categories. However, daily activity spaces reveal that Kalamaja residents of different occupation levels tend to follow distinct paths when traveling to the western part of the city.

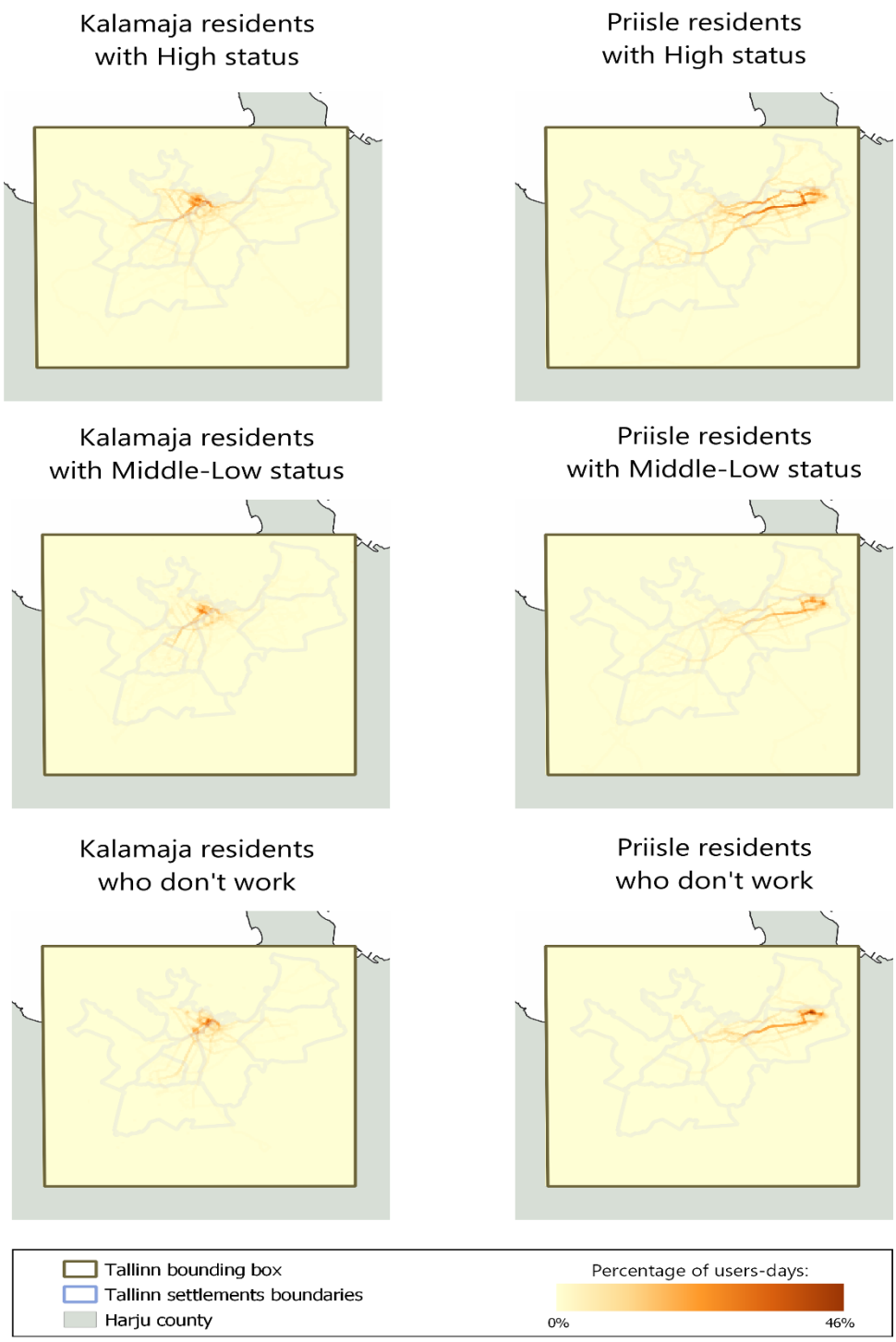

Figure 9. Percentage of users-days in each reference group in rasterized Tallinn bounding box, differentiated by residency and occupation status

5.2.1 Residency and Car Ownership

The final set of groups is formed using residency and car ownership variables. The distribution of categories is shown in Figure 10. In both districts, the majority of users own a vehicle, but the percentage of people with cars is a little higher in Priisle than in Kalamaja.

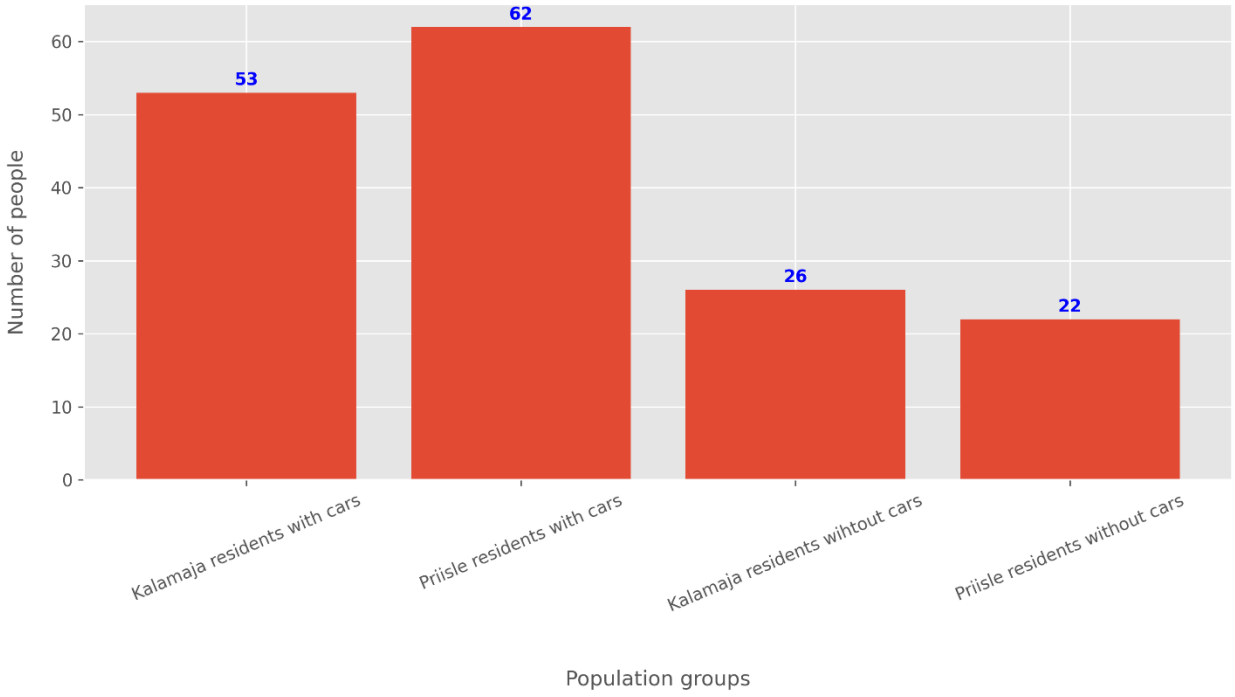

Figure 10. Number of people in each reference group (residency and car ownership)

In Figure 11, the percentage of users from each group who visited various districts in Tallinn is depicted. Similar to the previous observations, the district of Kesklinn attracts nearly all respondents, with percentages ranging from 92% to 100%. It is worth noting that Kesklinn is the only district commonly visited by both car-owning residents of Kalamaja and Priisle. The disparity between Kalamaja and Priisle residents without a car is less pronounced compared to those with car ownership, with one notable similarity being their avoidance of visiting the Nõmme and Mustamäe districts, with visitation percentages below 40%.

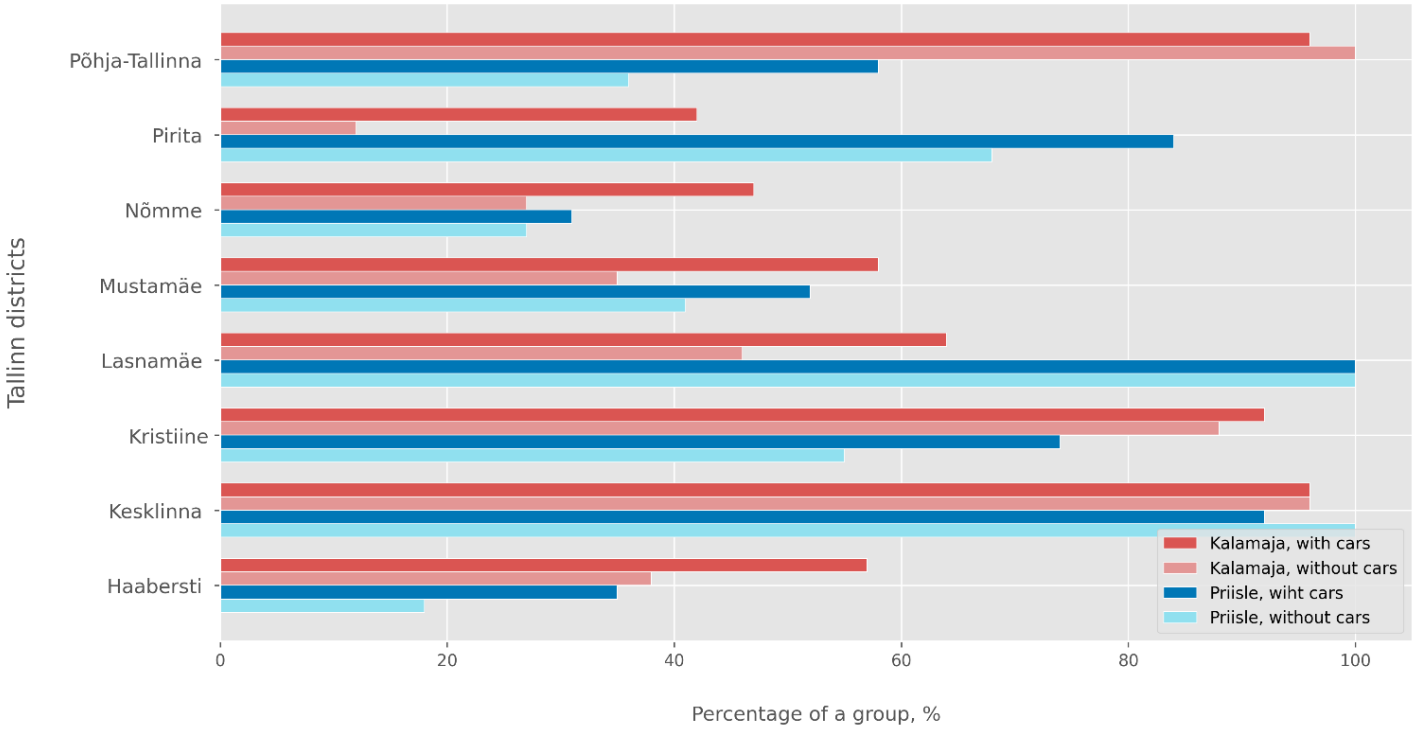

Figure 11. Percentage of reference groups visited Tallinn settlements, differentiated by residency and car ownership

Regarding respondents living in the same neighborhood with and without a vehicle, the trend is that the discrepancy in visiting percentage increases as the distance from the home district rises. Although, it is worth mentioning that the percentage of Priisle respondents with and without a car visiting Nõmme differs insignificantly (31% vs 27%), despite its distance from the neighborhood.

Figure 12 shows the percentage of users of four population groups in rasterized Tallinn box. Priisle users with cars have a slightly larger coverage compared to Kalamaja residents of the same group primarily due to a higher number of movements outside Tallinn city. The opposite situation is observed for people without cars: Kalamaja residents have a little greater extent than Priisle. As expected, in both Kalamaja and Priisle, the extent of movement for individuals with cars is significantly greater than for those without cars, which corresponds with regression results.

People with cars living in Kalamaja and Priisle have diverse and frequently used path networks that mostly cover the whole of Tallinn and nearby places outside cities. However, their most common paths are not intersecting which highlights spatial differences between users of the two neighborhoods. Notably, movements among respondents without cars from both residencies are not concentrated in one place. However, the Kalamaja residents almost don't visit the eastern part while Priisle users mainly ignore western Tallinn which makes the city center the only place for spatial interaction between the two groups. In terms of comparison among users who possess a car

and those who don't; Kalamaja and Priisle have a similar trend, users with cars have longer, more varying, and more traversed trajectories along the whole Tallinn area than people without cars.

Figure 12. Percentage of users in each reference group in rasterized Tallinn bounding box, differentiated by residency and car ownership

The percentage of users-days among Priisle and Kalamaja residents of various car ownership statuses is shown in Figure 13. On a daily basis, people with cars most often travel within a radius of their home place. Individuals without cars exhibit infrequent and limited daily mobility, with their trajectories failing to cover a significant portion of Tallinn, especially among Priisle residents.

For Kalamaja residents, the map reveals a high degree of similarity in daily path networks between those with and without cars, although individuals without cars show lower levels of path usage. The same tendency is seen in Priisle where individuals who have a car and who don't share two daily paths connecting the neighborhood with the city center.

Figure 13. Percentage of users-days in each reference group in rasterized Tallinn bounding box, differentiated by residency and occupation status

6. Discussion and conclusions

The study addresses the growing interest among researchers in understanding the relationship between mobility and background characteristics, which sheds light on the spatial behavioral variations among different population groups. Specifically, this research focuses on analyzing activity space patterns among residents of two ethnically dominant neighborhoods, namely Kalamaja and Priisle. The investigation identifies three significant variables associated with the size of the activity space: residency, occupation status, and car ownership. The regression findings indicate that individuals residing in Priisle, having a high-level job, and owning a car tend to exhibit larger activity spaces compared to other groups. The significance of residential segregation is logical since a home location is a place where a user spends most of the time socializing and creating social ties that then will determine their mobility in the future. The power of occupation status and car ownership could be explained by marginality theory which suggests that socioeconomic factors play a crucial role in the mobility of people (Johnson et al., 1998). Individuals with lower status and income have fewer opportunities to diversify and expand their spatial patterns. Other variables such as gender, age, gender, having a child, education level, and income, which were expected to have an impact based on theoretical considerations, did not demonstrate any influence in the model. The insignificance of certain features is not uncommon and has been observed in previous studies (Shönfelder & Axhausen, 2003), it suggests that the relationship between social background and spatial variation is not universally determined, but rather context specific.

However, no significant correlation between the size of activity space and ethnicity variable in both model runs was unexpected, considering numerous studies highlighting that the Estonian-speaking majority tends to have a considerably bigger extent of mobility compared to the Russian-speaking minority (Järv et al., 2015; Silm et al., 2018). Several reasons could explain this finding. Firstly, previous research utilized mobile positioning data and the standard deviational ellipse method, whereas this study employed GPS tracking and a daily path area approach, leading to potentially divergent results. Secondly, the dataset used in this study had a smaller sample size and a shorter time period compared to other research, potentially limiting the ability to detect ethnic differences in mobility. It is worth noting that larger sample sizes and longer observation periods provide more robust validation and enable clearer identification of spatial differences (Järv et al., 2015). Thirdly, the analysis of activity spaces was restricted to the Tallinn area and did not encompass a broader national or transnational level. Studies on ethnic segregation in Estonia have shown that spatial disparities become more pronounced at larger geographical scales, whereas differences in spatial behavior within cities tend to be less profound due to the relatively small

geographic distribution of urban opportunities (Silm & Ahas, 2014). Finally, it is worth considering that the specific characteristics of the respondents may have influenced the results. It is important to note that the profile of survey respondents from the two ethnically homogeneous neighborhoods did not demonstrate significant variations in socioeconomic status. Despite Kalamaja being primarily inhabited by Estonians and Priisle predominantly populated by Russians, there were minimal disparities observed in terms of occupation status between these two neighborhoods. Additionally, the examination of income distribution among the two groups of residents did not reveal significant discrepancies (although it is important to mention that nearly 25% of respondents chose not to answer that question). This portrayal of the survey participants contradicts previous studies that suggest language segregation in Estonia leads to greater socioeconomic segregation, with Russian-speaking minorities experiencing lower wages and occupying lower-level jobs (Musterd et al., 2017). Nevertheless, further analysis of spatial patterns of activity space has proved that ethnicity does influence the spatial behavior of Tallinn residents although not as significant as the other three variables mentioned above.

The analysis of mobility patterns among different groups gave valuable insights into spatial trends between residents of Kalamaja and Priisle. The Kesklinn district appears to be a place that attracts all users no matter what their socio-economic status is, at the same time there are two Tallinn districts that on the contrary are visited the least by any users – Nõmme and Mustamäe. Both Kalamaja and Priisle residents have concentrated their mobility around their home locations, however, Priisle users have an additional center of mobility in Kesklinn where mainly the spatial interaction of two kinds of residents happens. Notably, Kalamaja people do not often visit the residency area of Priisle respondents, thus, it could be concluded that the main communication takes place because of mobility specifics among Priisle users. Without them, the spatial differences between the two groups would have been worse.

The study also examined the trends among residents of Kalamaja and Priisle based on various social characteristics. In terms of ethnicity, it was observed that Russian residents from both neighborhoods have less common frequently visited Tallinn districts compared to Estonians. In addition, the findings suggest that there is a greater disparity in mobility patterns between Russians and Estonians residing in Kalamaja compared to those in Priisle. Regarding occupation status, it is noteworthy that there are no significant differences in the path networks of individuals belonging to the middle-low and unemployed classes in both neighborhoods. However, these two occupation levels exhibited less diverse trajectories and lower mobility intensity compared to white-collar workers. Spatial dissimilarities were evident for both resident types with and without cars, indicating a reduced degree of spatial interaction. However, the reasons for spatial dissimilarities

differed between individuals with cars and those without. Residents of Kalamaja and Priisle who owned vehicles traveled throughout the city, but their most popular overall and daily activity spaces had limited intersections. On the other hand, residents without cars in both neighborhoods exhibited limited mobility patterns, resulting in spatial isolation. In terms of the spatial differences between people of the same residency, individuals with cars and without cars had similar path networks, but the difference lay in the extent of path usage, with residents owning cars utilizing their paths more frequently. In addition, the daily activity spaces of residents with cars in Priisle and Kalamaja are more concentrated and limited compared to their overall activity spaces, indicating that although in general, these individuals covered most of the city, on a daily basis their travel distances from their home locations were relatively short.

In summary, the mobility patterns observed between the two neighborhoods are intricate and multifaceted, strongly influenced by the background characteristics identified through regression analysis. While residents of both neighborhoods share common paths and visit similar districts, there are still noticeable spatial variations. The relationship between social factors and the spatial behavior of residents within their respective neighborhoods is complex and ongoing: some trends are common between the two neighborhoods (for example, the higher the occupation status the bigger the extent), and at the same time each neighborhood also exhibits its own distinct set of spatial patterns (as an example, Kalamaja residents of all occupation statuses use the path network more equally compared to Priisle workers).

The study also is valuable in terms of conclusions regarding methodological approaches. A relatively young measurement approach activity space (Müürisepp et al., 2022) applied to GPS data proved to be effective in assessing and describing spatial processes. The resulting mobility patterns and features derived from GPS gave a more precise and detailed picture compared to other geospatial data (e.g., call detail records). By adopting a people-based approach to examine the spatial behavior of different population groups, the study was able to capture the nuanced and varied nature of spatial patterns. This approach resulted in more complex and balanced findings. Nevertheless, it is important to acknowledge the limitations of the study. GPS data have some constraints that are hard to overcome: one set of problems concerns the GPS device (e.g., lack of signal, inaccurate positioning, or loss of battery power) and another regards participants' handling (e.g., forgetting to wear or switch on the device) (Krenn et al., 2011). Moreover, the GPS data is not able to reveal the type of activities done in areas and the goals of users' movements which also limits the analysis of spatial differences depending on social factors. Finally, the data has a limitation regarding the number of representatives in some of the population groups, for example, the amount of unemployed people in Kalamaja and Priisle does not exceed 14. The small sample

of a group does not allow to fully describe the spatial specifics. The analysis with a bigger quantity of respondents and a longer time period could be a matter of future studies.

7. Summary

The influence of socio-demographic factors and place of residence on people's activity space: a study based on GPS data in Tallinn, Estonia

Nikolay Kozlovskiy

The social background of people and their mobility are interconnected and changes in one may impact the other (Jarv et al., 2015). With globalization, and more diverse and affordable options for traveling this connection between social determinants and mobility patterns is getting stronger (Sheller & Urry, 2006). The aim of the study was to analyze the influence of social factors and place of residence on the activity space of people. The location for empirical research was chosen to be Tallinn, Estonia, which is known for its deep-rooted and long-standing segregation between the Estonian-speaking majority and the Russian-speaking minority. The selection of the activity space method as the primary approach stemmed from its well-documented efficacy in examining unique individuals' mobility and capturing diverse facets of spatial movements, including the average area of activity spaces, the breadth of their spatial diversity, and the popularity of specific spatial patterns. The work investigated the following research questions:

- How do place of residence and socio-demographic factors impact the size of individuals' activity space?
- How does the place of residence impact spatial variations in people's activity spaces?
- How does spatial mobility differ among individuals residing in the same residential area but with varying socioeconomic statuses?

The methodological framework of this study comprised three primary components. Firstly, the study incorporated the concepts of time geography and planned behavior approaches to establish a comprehensive understanding of mobility, which is conceptualized as a multifaceted pattern of movements and social practices occurring in both spatial and temporal dimensions. Secondly, in line with the evolving methodological discourse on analyzing mobility differences, a people-based approach was employed, emphasizing the individual's distinct experience of interacting with social and spatial environments and avoiding confining their movements to predefined locations.

To conduct this research GPS data from 186 individuals in Tallinn were collected between October 2020 and February 2021. Emphasizing the importance of social factors and place of residence, participants were primarily recruited from two specific neighborhoods: Kalamaja, known for its Estonian-speaking majority ethnicity, and Priisle, characterized by a Russian-speaking minority. Apart from GPS data, pre-tracking interviews with participants were held to reveal their socio-demographic characteristics.

Two groups of methods were implemented in the survey. The first is regression analysis which examines the relationship between the average area of users' activity space and their social background. The second set of methods applies the rasterization of aggregated activity spaces to reveal the spatial patterns of different social groups.

The results showed that dissimilarities in people's activity spaces do exist in Tallinn, however, only part of the social-demographical variables has an influence on users' movements, among them are residency, ethnicity, occupation status, and car ownership. Notably, despite the results of other studies (Järv et al., 2015; Silm et al., 2018) the ethnicity factor did not have an influence on the area of activity space. The analysis of mobility patterns among different social groups gave valuable insights into segregation trends between residents of Kalamaja and Priisle. The Kesklinn district is a place of attraction for all users no matter what their socio-economic status is, however, it is the only Tallinn area where the spatial interaction between two groups is high. Moreover, it was detected that the activity spaces of Kalamaja residents are more concentrated compared to residents of Priisle. Additionally, Kalamaja people do not often visit the residency area of Priisle respondents, thus, the main communication between the two groups takes place because of mobility specifics among Priisle users who regularly traverse the central part of Tallinn where Kalamaja district is suited. Regarding socio-demographic factors affecting people's mobility, it has been observed that Russians in Tallinn exhibit a higher degree of separation among themselves compared to Estonians. This is evident from the visiting patterns of various districts within the city. Other factors – occupation status and car ownership have a big impact on residents from both Kalamaja and Priisle districts which appears in the trend that people of a higher occupation class and possessing a vehicle have more sparse and diverse mobility networks with greater path usage compared to others. In conclusion, the activity space approach applied with GPS data has proved effective in assessing and describing spatial differences in people's mobility.

Kokkuvõte

Sotsiaaldemograafiliste tegurite ja elukoha mõju inimeste tegevusruumile: GPS-andmetel põhinev uuring Tallinnas, Eestis

Nikolay Kozlovskiy

Inimeste sotsiaalne taust ja nende liikuvus on omavahel seotud ning muutused ühes võivad mõjutada teist (Jarv et al., 2015). Globaliseerumisest ning mitmekesisematest ja taskukohasematest reisimisvõimalustest tulenevalt on see seos sotsiaalsete tegurite ja liikumismustrite vahel tugevnenud (Sheller & Urry, 2006). Magistritöö eesmärk oli analüüsida sotsiaalsete tegurite ja elukoha mõju inimeste tegevusruumile. Empiirilise uurimistöö asukohaks valiti Tallinn, mis on tuntud oma sügavalt juurdunud ja pikaajalise segregatsiooni poolest kahe rühma, eestikeelse enamuse ja venekeelse vähemuse, vahel. Tegevusruumipõhine lähenemine valiti kuna see on varasemate uuringute põhjal efektiivne meetod inimeste liikuvuse ja ruumiliste aspektide kirjeldamisel, hõlmates keskmise tegevusruumi pindala, mitmekesisuse ja ruumimustrite populaarsust. Töös lähtuti järgmistest uurimisküsimustest:

- Mil määral mõjutavad elukoht ja sotsiaaldemograafilised tegurid inimeste tegevusruumi suurust?
- Kuidas aitab elukoht kaasa inimeste tegevusruumide ruumilistele erinevustele?
- Kuidas erineb ruumiline liikuvus inimeste vahel, kes elavad samas piirkonnas, kuid on erineva sotsiaalmajandusliku staatusega?

Käesoleva uuringu metoodiline raamistik koosnes kolmest põhikomponendist. Esiteks hõlmas uuring ajageograafia ja kavandatud käitumise käsitlusi, et luua terviklik arusaam liikuvusest, mida käsitatakse nii ruumilises kui ka ajalises mõõtmes esinevate liikumiste ja sotsiaalsete praktikate mitmetahulise mustrina. Teiseks, kooskõlas areneva metodoloogilise diskursusega liikuvuserinevuste analüüsimisel, kasutati inimestepõhist lähenemist, rõhutades indiviidi selget kogemust sotsiaalse ja ruumilise keskkonnaga suhtlemisel ning välditi nende liikumise piiramist ettemääratud asukohtadega.

Uuringu läbiviimiseks koguti ajavahemikus oktoober 2020 kuni veebruar 2021 GPS-andmeid 186-lt Tallinna inimeselt. Rõhutades sotsiaalsete tegurite ja elukoha olulisust, kaasati osalejaid kahest linnaosast: eestikeelse enamusrahvuse poolest tuntud Kalamajast ning Priislest, mida iseloomustab venekeelse vähemuse domineerimine. Lisaks GPS-andmetele viidi osalejatega läbi intervjuud, et selgitada välja nende sotsiaal-demograafilised tunnused.

Magistritöös kasutati kahte analüüsi meetodit. Esimene oli regressioonanalüüs, millega uuriti seost tegevusruumi keskmise pindala ja sotsiaalse tausta vahel. Teiseks meetodiks oli agregeeritud tegevusruumide rasterdamine, et selgitada välja erinevate sotsiaalsete rühmade ruumimustrid.

Tulemused näitasid, et Tallinnas esineb inimeste tegevusruumides erinevusi, kuid liikumisi mõjutavad vaid osad sotsiaaldemograafilistest tunnustest, nende hulgas elukoht, rahvus, ametialane staatus ja auto omamine. Hoolimata teiste uuringute tulemustest (Järv et al., 2015; Silm et al., 2018) ei ole etnilisusel mõju tegevusruumi ulatusele. Erinevate sotsiaalsete rühmade liikumismustrite analüüs andis väärtusliku ülevaate Kalamaja ja Priisle elanike segregatsioonitrendidest. Kesklinna piirkond on tõmbekoht kõigile inimestele sõltumata nende sotsiaalmajanduslikust staatusest, kuid see on ainus Tallinna piirkond, mida mõlema rahvusrühma inimesed tihedalt külastavad. Lisaks saadi teada, et Kalamaja elanike tegevusruumid on Priisle elanikega võrreldes kontsentreeritumad. Nimelt ei satu Kalamaja inimesed sageli Priisle piirkonda, seega toimub põhiline kokkusaamine kahe grupi vahel Priisle elanike liikuvuse eripära tõttu, kes käivad regulaarselt Tallinna kesklinna piirkonnas, mille lähedal on Kalamaja piirkond. Inimeste liikumist mõjutavate sotsiaaldemograafiliste tegurite analüüsist selgus, et Tallinna venelased eraldavad end rohkem võrreldes eestlastega. See ilmneb erinevate linnaosade külastamise mustritest. Muud tegurid nagu ametialane staatus ja auto omamine mõjutavad suurel määral nii Kalamaja kui ka Priisle linnaosa elanikke. See väljendub trendis, et kõrgema ametialase staatusega ja sõidukit omavatel inimestel on võrreldes teistega hõredam ja mitmekesisem liikumisvõrgustik ning suurem teekasutus. Kokkuvõtteks võib öelda, et tegevusruumi lähenemine GPS-andmetega on tõhus inimeste liikuvuse ruumiliste erinevuste hindamisel ja kirjeldamisel.

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Annexes

Table 1. Percentage of each population group visited Tallinn districts, differentiated by residency and mother tongue

	Haabersti	Kesklinna	Kristiine	Lasnamäe	Mustamäe	Nõmme	Pirita	Põhja-Tallinna
Kalamaja, Estonian	45	97	91	57	41	38	33	97
Kalamaja, Russian	67	95	90	62	76	48	29	100
Priisle, Estonian	28	100	69	100	45	34	76	45
Priisle, Russian	33	91	69	100	51	27	82	56

Table 2. Percentage of each population group visited Tallinn districts, differentiated by residency and occupation status

	Haabersti	Kesklinna	Kristiine	Lasnamäe	Mustamäe	Nõmme	Pirita	Põhja-Tallinna
Kalamaja, Hight status	59	97	91	72	56	50	47	100
Kalamaja, Middle-Low status	47	97	88	44	50	25	25	94
Kalamaja, Don't work	33	92	100	58	33	50	17	100
Priisle, High status	36	95	77	100	45	36	77	64
Priisle, Middle-Low status	29	98	71	100	55	36	79	48
Priisle, Don't work	21	79	57	100	29	7	86	43

Table 3. Percentage of each population group visited Tallinn districts, differentiated by residency and car ownership

	Haabersti	Kesklinna	Kristiine	Lasnamäe	Mustamäe	Nõmme	Pirita	Põhja-Tallinna
Kalamaja, with cars	57	96	92	64	58	47	42	96
Kalamaja, wihtout cars	38	96	88	46	35	27	12	100
Priisle, with cars	35	92	74	100	52	31	84	58
Priisle, without cars	18	100	55	100	41	27	68	36

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