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Spatio-temporal accessibility modelling with mobile and GTFS data: Insights from Helsinki

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Abstract: This paper presents a spatially explicit method for evaluating urban accessibility using anonymised mobile phone origin-destination data combined with GTFS-based public transport travel times. Focusing on the Helsinki Capital Region, we apply cumulative and potential accessibility metrics across multiple transport modes to assess spatial and temporal variation in mobility patterns. The integration of mobile phone data with high-resolution transport networks enables the identification of areas with poor public transport accessibility and high car dependency, particularly among affluent populations. By leveraging geospatial methods and time-specific data, this study provides a replicable analytical framework for urban transport planning and supports evidence-based strategies to promote sustainable, multimodal mobility in metropolitan regions.

Keywords: spatiotemporal accessibility; mobile phone data; GTFS; transport modelling; public transport; GIS

1. Introduction

The increase in the number of cars in use significantly contributes to greenhouse gas emissions and air pollution (Gärling and Schuitema, 2007; Newman and Kenworthy, 1999). According to the IPCC 2021 report, the share of transport in global CO2 production is strongly correlated with the increase in the number of cars (González et al., 2019). The transport sector is still responsible for a large proportion of CO2 emissions (“IPCC,” 2021). To reduce excessive CO_2 emissions from transportation, it is essential to decrease the number of individual car trips in favour of public transport (PT) (Graham-Rowe et al., 2011). Many different charges have been introduced to reduce traffic (Nakamoto et al., 2019). Many measures have been introduced to promote public transport and support sustainable transport strategies in different cities (Goliszek, 2024). Several, such as a free PT service for drivers who opt out of car travel or free PT for city residents, have helped to reduce car travel (Friman et al., 2013; Meyer, 1999; Silva Cruz and Katz-Gerro, 2016). Researchers are increasingly delineating areas where one mode of transportation predominates (Söderström, P., Schulman, H., Ristimäki, 2015; Zhang et al., 2022).

The potential accessibility measured by the potential-gravity method determines the possibility of interaction between two regions in time and space. An early description of the concept of potential, or opportunity for interaction was in Carey's Principles of Social Science (Carey, 1867). Methods of potential accessibility were developed by Harris (Harris, 1954) and Hansen (Hansen, 1959); the persons who first used potential accessibility to assess the impact of transport investments. Although the index was developed several decades ago, the potential availability measure is today increasingly finding its

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way into transport-related work, including PT. The GTFS data format has also been of increasing importance in recent years and has found its way into many analyses (García-Albertos et al., 2019; Hadas, 2013; Stępniak et al., 2019).

Potential accessibility is a key concept and a parameter used in transportation research. It is used to determine the operating ranges of different transport modes and their impact on their surroundings. The theory of potential accessibility is based on the location of travel sources and destinations that can be reached using different modes of transport (Hansen, 1959; Harris, 1954; Vickerman, 1974). The simplest way to explain this method is to state that the demand for transportation services naturally arises in densely populated areas, with people generating this demand on a daily basis. People travel to satisfy their daily needs using various modes of transport. However, work (Merchant and Nemhauser, 1978; Niedzielski et al., 2024) and shopping (Fransen et al., 2015; Widener et al., 2015) remain the two main motivations for daily commuting. Commuting to work is obligatory and has a significant impact on people's daily lives, and most people commute to work every weekday (Goliszek et al., 2020; O'Kelly et al., 2012; O'Kelly and Niedzielski, 2009). Daily commuting is a popular topic studied by many researchers (Boussauw et al., 2011). As noted by Goliszek (2022), "*As a result, more and more data is available, which can be used to improve the operation of both public and private transport systems during the morning rush hour*" (p. 31). Increasingly, mobile phone data is being used to study trips at different times of the day in cities (Huang et al., 2019; Tsumura et al., 2022; Zhao et al., 2020). Observations of daily commuting patterns allow one to identify factors that directly reduce the accessibility of particular locations and formulate recommendations for the future (Niedzielski, 2006; Niedzielski and Boschmann, 2014; O'Kelly and Lee, 2005; Owen and Levinson, 2015; Shearmur, 2006). A study was carried out in selected cities that investigated differences in attitudes towards different modes of transport depending on the efficiency of the transport system and the transport alternatives available (Van et al., 2014). In recent years, there has been increasing research that utilises mobile phone data to study commuting to work. (Liu et al., 2024) Mobile phone data illustrates users' daily travel trajectories (Li et al., 2019; Yuan et al., 2012).

Currently, mobile phone data is an interesting support for sustainable PT planning. Mobile phones have increasingly become effective sensors of human activity throughout the day (Bassolas et al., 2019; Lane et al., 2010). Despite the many advantages of mobile phone data, mobile phone data does not contain detailed personal data, such as that obtained via detailed travel surveys. We need more information regarding the modes of transportation individuals use, which are included in cellular data records. Conversely, detailed traffic studies provide extensive granularity but need more overall population counts. Data on PT users (age, gender or income) and the journey itself (purpose and mode) are usually essential in this type of research (Alexander et al., 2015; Stopher and Greaves, 2007). Mobile phone data contains footprints left in approximate locations by the user when their phone communicates with a mobile phone tower, which gives an inaccurate and incomplete picture of daily travel (Ahas et al., 2010). Because of this, many researchers have only focused on developing methods to extract meaningful information about human mobility based on mobile phone data while maintaining knowledge of their limitations (Ahas et al., 2010; Calabrese et al., 2013; Järv et al., 2014). Mobile phone data can be used to infer the origin-destination (OD) of trips if, for example, there is a lack of good traffic volume data at a given time of day. (Iqbal et al., 2014) Daily trips based on mobile phone data are consistent with household surveys (Jiang et al., 2013; Tu et al., 2018).

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Regardless of the available matrixed mobile phone data, what is needed is to compare these data with GTFS data for PT,47, thus obtaining information on where and at what time of day PT may be sufficient to meet the travel demands of residents. As a step towards finding such places, this research proposes a methodology to extract Origin-Destination (O-D) trips by destination and time of day from mobile data. These results will capture different travel-taking patterns relevant to transport planning. The study will be based on the mobile phone data available and the publicly available GTFS data for Helsinki. This approach allows similar calculations to be applied in other large cities and conurbations.

In recent years, mobile phone data have emerged as a powerful tool for capturing real-world human mobility with high temporal granularity and extensive spatial coverage (Calabrese et al., 2013; Jiang et al., 2012). When integrated with Geographic Information Systems (GIS) and transport network models—such as those based on General Transit Feed Specification (GTFS)—these datasets enable a more accurate and dynamic representation of travel behaviour across urban regions (Anda et al., 2021). Unlike traditional travel surveys, which are often limited in sample size and frequency, mobile phone records provide continuous, large-scale information on population flows and activity patterns. Their integration into accessibility modelling enhances the ability to identify transport service gaps, analyse modal shifts, and design targeted interventions for sustainable urban mobility (Allen & Farber, 2019; Bassolas et al., 2019). This convergence of geospatial analytics and mobile data is increasingly shaping the future of evidence-based transport planning and urban systems research (Yabe et al., 2020).

In this study, the author utilised mobile phone data as an Origin-Destination (O-D) matrix for the Helsinki Capital Region, which was compared with O-D travel time data for PT (GTFS). On the other hand, information on average distance and travel time by selected mode of transport proved useful for illustrating differences throughout the day and broken down by weekends and weekdays. The average travel time within the HCR was sourced from mobility studies (Brandt E., Kantele S., 2019). The empirical results of this study may be helpful for transportation planning agencies aiming to meet the transportation needs of residents. The study aims to address the following questions:

1. What are the magnitudes of person flows generated using mobile phone data disaggregated by modes of transportation, weekdays and weekends, and throughout the day?
2. Do areas inhabited by the wealthier segments of society exhibit good PT accessibility when analysing mobile phone data?

1.1 Research area

For this study, the Helsinki Capital Region, the largest metropolitan area in Finland, is referred to as the HCR. HCR consists of four municipalities (Helsinki, Espoo, Vantaa, Kaumiainen) with over 1 million inhabitants in 2019. The breakdown of population by the municipality was as follows. Helsinki municipality had 55 per cent of all HCR residents. The municipality of Espoo contained 24.5 per cent of HCR's population, and the municipality of Vantaa, 19.7 per cent. The smallest number resided in the small town of Kaumiainen, which lived 0.9 per cent of all HCR residents. The HCR area is served by the Helsinki Regional Transport Authority (HRT). Helsinki's city centre is well connected to the rest of the HCR area, as reflected in some exciting studies on areas (Albacete et al., 2017; Hasanzadeh et al., 2021; Jäppinen et al., 2013; Kujala et al., 2018; Salonen and Toivonen, 2013a; Weckström et al., 2019).

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The entire transportation system of the HCR area has a radial pattern and is based on an extensive network of bus services and several railway lines. The PT network is supported by trams and two metro lines operating in the centre of Helsinki municipality and in Espoo. The region has about 600 transit lines (excluding service lines and night buses). In the HCR, the whole system is focused on getting residents to the city centre. For the harmonious development of the whole HCR area, it is essential to develop connections between all crucial locations within the HCR, reducing road congestion and supporting sustainable transport in the city (Fig. 1.).

According to the report "Travel Habits in the Helsinki Region 2018," 34% of daily trips in the Helsinki Capital Region (HCR) were made by car, while 25% of residents used PT. Over the years, interest in travelling by car and PT has declined, with a growing preference for walking. Pedestrian walkways saw a 3% increase compared to the 2012 study (Brandt E., Kantele S., 2019). Among the four HCR municipalities analysed, Helsinki Municipality has the highest share of PT usage at 31%, followed by Vantaa at 20%, and Espoo and Kauniainen at 18% and 17% of trips, respectively (Brandt E., Kantele S., 2019). In less populated municipalities, interest in PT is lower due to various factors such as the distance to bus stops and the travel time by PT to work, shopping, or school.

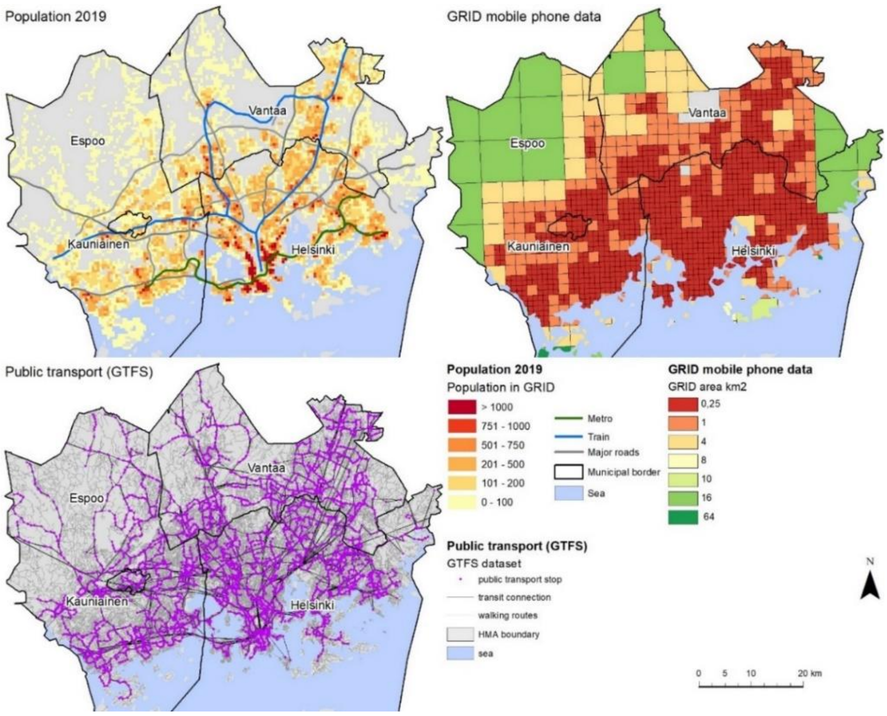

Fig. 1. Population 2019, GRID size of mobile data and PT model (own elaboration in ArcGIS based on (Finnish Environment Institute, 2020; "GTFS open data HSL Helsinki," 2019, "Traficom," 2020).

2. Methods

2.1 Data sources

This study used mobile phone data to measure cumulative accessibility to determine how many people choose each GRID area as a destination. These are actual changes of location and not hypothetical journeys to a destination, as in most studies. In particular, we calculated the cumulative accessibility of active individuals who changed their location between respective GRID areas or within a GRID if they changed their mobile phone tower coverage area. This calculated the cumulative and potential actual accessibility. In the study, using a percentage modal split allowed the analysis to break down the results into four transport modes.

Telia mobile data

This article used mobile data from one mobile data provider, Telia, which was anonymised and aggregated to the GRID cells. Telia Finland, through Telia Crowd, is one of Finland's three largest telecom companies, holding 32 per cent of the mobile market share in 2019 ("Traficom," 2020). Cellular data has not been made available to the public, but Telia has made its aggregated datasets available for research (Anda et al., 2021). Two datasets made available by Telia include (1) activity location data and (2) mobility data (O-D - origin-destination). This data identifies the mobility of Finnish residents between August 2018 and September 2019. Origin-destination mobility data from mobile phones indicate individual trips aggregated into daily mobility flows between GRID grids of different sizes. Each trip is a person's movement between two consecutive cellular antennas or GRID grids considered activity sites (time spent over 20 minutes) each day. In this case, one long-distance trip could be counted as several shorter trips if a trip contains longer (>20 min) intervals. Therefore, long-distance trips need to be more fully represented in the dataset and should be considered when explaining the results of the analysis. Furthermore, the dataset does not reveal the place of residence of these individuals, only the place of residence in the GRID grid (Willberg et al., 2021).

One of the biggest challenges in using mobile phone data has been their enormous volume (number of logins, size). In recent years, mobile network operators have begun to provide their own aggregated data products, which allow us to overcome some of these challenges. However, these products often introduce new challenges due to undisclosed methodologies, such as accurately understanding what the data represents and the consistency of terminology. Regardless of their characteristics, mobile phone data can be broadly divided into presence and mobility, depending on how they represent people. However, the definitions and measurements of these data vary depending on the products and providers. To illustrate the differences, we use the traditional geographical concept of the space-time path (Hägerstrand, 1970; Willberg et al., 2021).

Each space-time path indicates a so-called presence along an axis to determine people's whereabouts (Figure 2A). As noted by Willberg et. al (2021), "*Mobile phone data are generally processed from individual level space–time trajectories, thinking them as a series of location snapshots. In the raw, individual level mobile phone data, each location snapshot is recorded when a mobile phone continuously connects to a base station. Therefore, a snapshot of a space-time trajectory at a given location and a moment in time is seen as a measure of (physical) presence*" (p. 4). These snapshots do not necessarily imply that the phone is stationary, being in one location, but are simply momentary locations of the mobile phone user. These snapshots can be considered deviations of the space-time cone in space (Figure 2B) (Miller, 1991; Yu and Shaw, 2007). In aggregated mobile phone data, a measure of presence (also called activity) is created by aggregating data according to a specific time threshold within a spatial unit (GRID). The time threshold, which constitutes a measure of presence, is

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crucial as it influences which snapshots are identified as valid presence locations. Time thresholds that record activity vary between operators (Oliver et al., 2020). This study's time threshold for mobile phone data is 20 minutes. In other studies, it was one hour (Pepe et al., 2020) or even two hours (Jia et al., 2020).

In aggregated mobile phone datasets, various methods for defining mobility relate to different goals of presenting trips (also referred to as movements) or more general mobility (Figure 2C). As noted by Willberg et. al., (2021), "*When the aggregated dataset strives to capture trips, a measure of trip can simply be defined as continuous sequence of valid presence locations in a space-time path. The aim of these datasets therefore is to capture all individual trips and the "origins" change according to the presence locations*" (p. 4). However, if the aim is to capture general mobility, the "origin" is usually constant for 24 hours, for example, the night (Yabe et al., 2020) or morning (Zhou et al., 2020) location. In this case, the "origin" provides a more realistic representation of people's home locations, enabling broader analyses of origin areas within a country. However, not all trips are recorded; daily trips to another city and back are not captured due to constant "origins" (Willberg et al., 2021).

Regardless of the definition of mobility, defining the time threshold to determine valid presence locations of people plays an important role. Defining the time threshold influences how "destination" locations appear in mobility datasets. A shorter time threshold causes more trips to be divided into multiple segments, complicating the identification of actual Origin-Destination (O-D) travel chains ("Traficom," 2020). This means a "destination" location can include a momentary presence in a given location but does not indicate whether it was the trip's final destination or a passing place, nor how long the person stayed there. These differences in definitions and aggregation practices present challenges for data validity assessments and comparisons between datasets provided by various mobile network operators. The 20-minute time threshold used for data from Telia Finland appears appropriate for capturing signals from mobile phones (Anda et al., 2021).

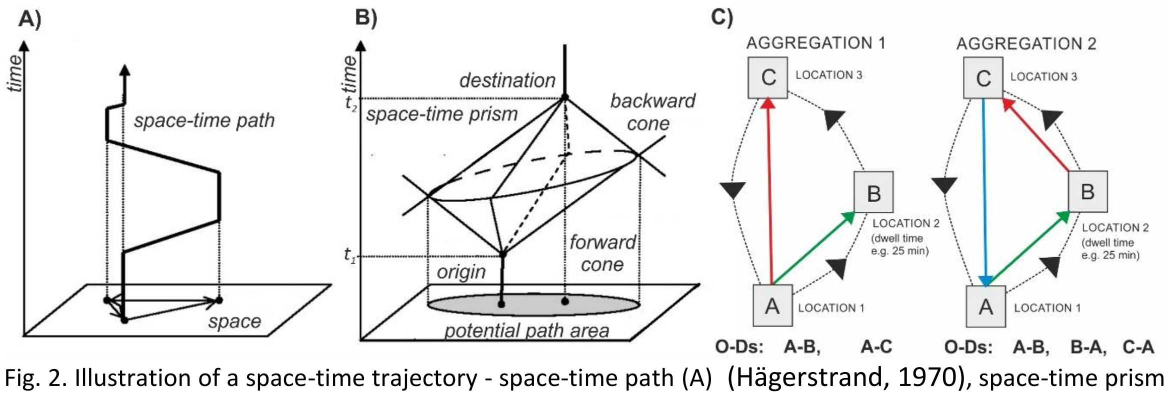

Fig. 2. Illustration of a space-time trajectory - space-time path (A) (Hägerstrand, 1970), space-time prism (2) (Miller, 1991; Yu and Shaw, 2007) and example aggregated into trip records in multiple ways in mobile phone datasets (Willberg et al., 2021).

Based on Telia's mobile data, the Finnish population's mobility profile was created and illustrated in Figure 3 (solid line). The mobility profile for working days (Monday-Thursday) exhibits two peaks that correspond to the commuting times both to and from work. A similar pattern is observed on Fridays, though the peaks are noticeably smaller, suggesting that many people work remotely or take time off to extend their weekends. Mobility patterns for Saturday and Sunday are pretty similar, marked by increased activity between 12 pm and 5 pm, indicating higher mobility during these non-working days.

The number of GRID grids used in this study to support sustainable PT is 1458. The size of the source and destination areas ranges from 0.25 km^2 to 64 km^2. With 64 km^2, two areas cover the far southeast and west islands of the HCR. Large GRID areas are mostly covered with forest and are inhabited by a small number of people. Of the 1458 areas noted above, 18 are approximately 16 km^2 in size, with one each of 14.5, 10 and 8 km^2. Also, there are 49 smaller areas with a size of 4 km^2 in the HCR region. Thus, there are 230 GRID grids of 1 km^2 in the HCR area, while 1156 of the most minor 0.25 km^2 areas in 2019 ("Traficom," 2020). This data includes traffic recorded at the mobile phone tower every hour for September 2019, broken down by Monday-Thursday, Friday, Saturday, and Sunday. This indicates overall mobility throughout the week—the number of activities recorded within the HCR averages about 70 per cent of all activities in Finland. This was the result of the size of the GRID and the high mobility rate of HCR residents.

The dashed line in Figure 3 represents the percentage of GRID cell data in the Helsinki Capital Region (HCR). In September 2019, the average percentage of movements within the HCR compared to all of Finland was just over 70 per cent. The highest percentage of mobile individuals relative to the total population occurs between 1 am and 3 am, followed by a drop to around 50 per cent. From 3 am to 5 am, there is an increase in the mobility of HCR residents, with the percentage remaining above 70 per cent for the rest of the day.

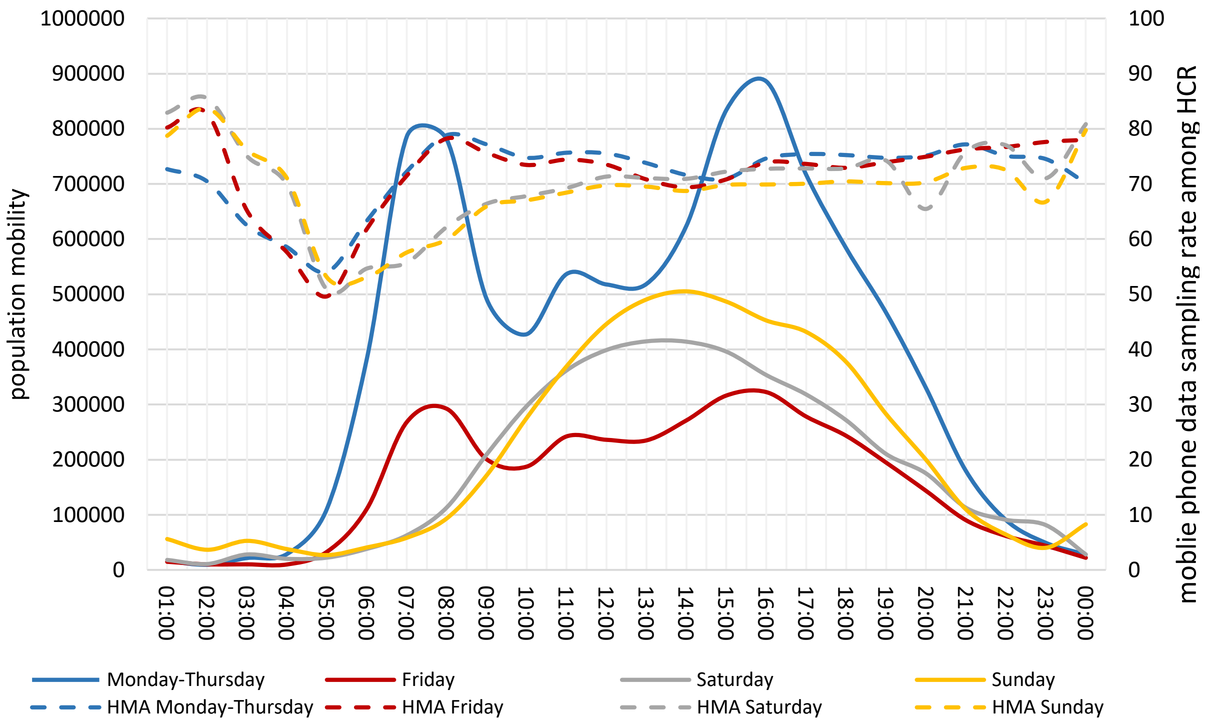

Fig. 3. Mobility in Finland and location data sampling rate among HCR is based on mobile data (own elaboration based on ("Traficom," 2020)).

2.2 GIS and network analysis implementation

ArcGIS software uses multiple steps to calculate public transport origin-destination (O-D) times. In the first step, the tool "Add GTFS to network dataset" is used to create a dataset based on General Transit Feed Specification (GTFS) data (Arias et al., 2021; Goliszek, 2021). The dataset in this analysis consists of text files for the HCR region for 12 September (weekday) 2019. First, the tool described above creates a network dataset (public transport stops and lines). Then, a dataset of pedestrian paths based on OSM is added to the network data, to which pedestrian speed is assigned depending on the parameters for the particular city concerned (Fig. 1). The pedestrian paths are connected to the stops with connectors so that the whole dataset works as a single PT model (Bok and Kwon, 2016). The network dataset includes all door-to-door travel segments such as in-vehicle travel time (Tahmasbi and Haghshenas, 2019), transfer time, waiting at a transit stop, and getting to the stop/entering a vehicle (Salonen and Toivonen, 2013b). The O-D locations in this paper are points corresponding to the cellular data shown in Figure 1. Then, ArcGIS Network Analyst calculates the O-D travel times for a selected hour during the day (Prommaharaj et al., 2020). The resulting O-D matrix includes pedestrian travel times if they are faster than transit. At each time point, the transit time inside the GRID (type of space mapping in geographic information system) surface is added to a calculation for each point corresponding to the diameter of the circle in which the GRID square is inscribed. The travel time matrix is calculated between 1,458 GRID centres ranging from 250 metres to 8 kilometres, arranged in a matrix, resulting in a total of 2,125,764 Origin-Destination relations for which PT travel times are recorded every hour throughout the day from 00:00 to 23:00 ("GTFS open data HSL Helsinki," 2019).

Road administrations and agencies responsible for the operation of PT in a particular area now increasingly use data on passenger movements from various sources to help them estimate changes in traffic over time and space. Transport agencies have to react quite quickly to changes in travel behaviour (Cheng et al., 2024). Sometimes, new routes appear where the potential passenger traffic changes due to dramatic increases or decreases in the traffic flow. In these situations, agencies need alternatives for their customers to meet their basic daily travel needs. This approach also fits into a sustainable urban transport policy. Change must also follow any change in the travel preferences of residents and the creation of new forms of PT (Wang et al., 2018). Matching routes with traffic flows increasingly requires new techniques and spatial information, such as mobile phone data, and mobile phone data provide ever increasing support to researchers and agents when improving PT performance.

2.3 Accessibility modelling framework

Cumulative accessibility was calculated using the following formulae:

$$A_i = \sum_{j=1}^{n} O_j f\,(C_{ij}) \qquad (1)$$

Where A_i represents the accessibility of location i, O_j represents the opportunities at location j, and C_{ij} represents the cost of travel from location i to location j, n represents the total number of locations, t_{ij} represents a threshold travel cost, and $f(C_{ij})$ is a function defined as:

$$f(C_{ij}) = \begin{cases} 1\ if\ C_{ij} \le t_{ij} \\ 0\ if\ C_{ij} > t_{ij} \end{cases} \qquad (2)$$

This function $f(C_{ij})$ assigns a value of 1 if the cost of travel C_{ij} is less than or equal to the threshold t_{ij} indicating accessibility and assigns a value of 0 otherwise (Michał A Niedzielski, 2021; Thompson et al., 2019). When calculating people's movements for cumulative accessibility, if the distance is greater than a certain threshold, the population reachable beyond this threshold is not considered in the results of the cumulative accessibility assessment according to formula (2) (Thompson et al., 2019). The trip length used is dependent on the mode choice. In the HCR area, more than 90 percent of trips are made in four modes: car, PT, bicycle, and walking (Figure 4). The average trip distances of the different modes are 11 km for car travel, 5.7 km for PT, 3.6 for cycling and 1.3 km for walking. These distances will serve as the distance of possible interaction in the HCR (Brandt E., Kantele S., 2019), based on the distances travelled by people recorded by a mobile phone provider in Finland.

The final results for cumulative accessibility for the different modes of transport will be compared with the number of people who make a trip to the selected area in the HCR. Trips on Monday-Thursday and Friday have been added together and appear as weekday trips. Furthermore, trips on Saturdays and Sundays were added together and classified as weekend trips. As a result, the travel split between car, PT, cycling and walking for weekdays and weekend days will be compared with each other on the map and the graph for the whole day.

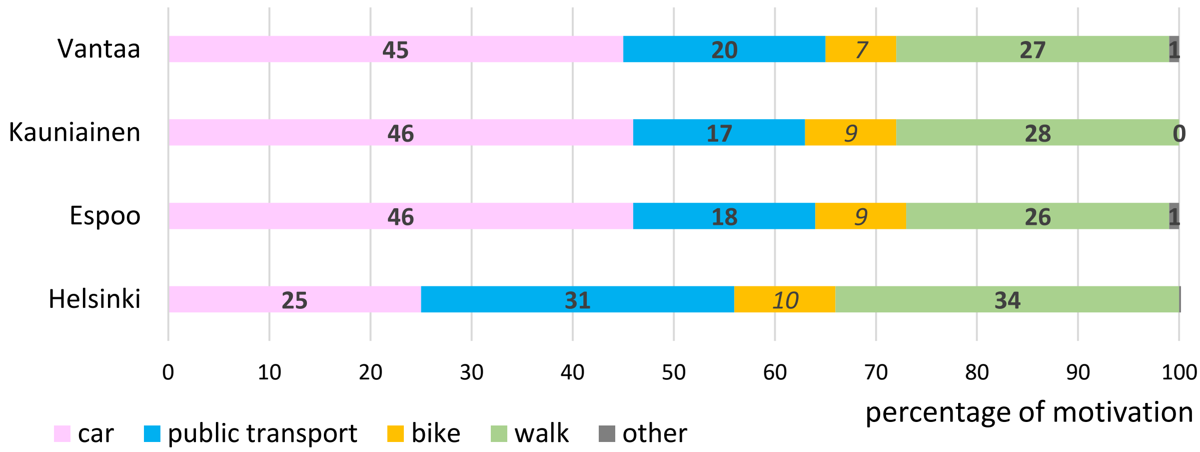

Fig. 4. The modal share of each mode of transport in the HCR is based on (Brandt E., Kantele S., 2019).

The accessibility level of a place is expressed by the accessibility index supported by cellular data for different modes of transport and different motivations, , and is expressed as $A(MP_{data)}{}_i$. This study expresses the travel time (distance) between two GRID areas by i and $j = t_{ij}$. Choosing a different transport mode will define the average travel time (distance) between i and $j = t_{ij}$ each time. The value of the spatial resistance function $f(t_{ij})$ reduces this parameter. The attractiveness of a given destination is expressed by the sum of all relations between GRID pairs using cellular data that give information on the change of location of the network users. The formula for the potential availability of mobile users is as follows:

$$A(MPdata)_i = \sum_{j=1}^{n} MPdata_j \, f(t_{ij}) \tag{3}$$

Coffey [90] was the first to apply the potential accessibility method to regional studies. In cities, the spatial resistance function significantly influences the results (Allen and Farber, 2020), which normalises the results according to time or distance. In this, the spatial resistance function depends on other transport modes. In contrast, the most commonly used function in potential accessibility studies is the exponential function (Beria et al., 2017). However, the choice of function depends on the characteristics of the study area and the choice of variables (Thompson et al., 2019). In this case, the exponential spatial resistance function takes the formula:

$$f(t_{ij}) = \exp(-\beta t_{ij}) \tag{4}$$

Where β differentiates the level of reduction in the attractiveness of a destination depending on the distance between the GRID pairs in order to determine the time (distance) for the spatial resistance function; the author used data published in the study "Travel Habits in the Helsinki Region 2018", where the average travel time by car in the HCR was 20 minutes. The same average time for a public transport journey was 37 minutes. In terms of average cycling time, on the other hand, it was 20 minutes and the pedestrian trip was 19 minutes. So the longest journeys on average are made by people using public transport, but when we check the average distances travelled, the furthest distances travelled were those travelled by car drivers who travelled 11 kilometres. Public transport users travel an average of 5.7 kilometres, and cycling averages 3.6 kilometres.

On the other hand, the average length of a pedestrian trip was 1.3 kilometres. In this study, we have used a distance that is the same for all modes of transport. It is from this parameter that the parameters of the spatial resistance function are adjusted. The use of different β-parameters for the different modes of transport reflects the actual impact ranges of the selected modes in the HCR. The assumed values of the spatial resistance function parameter for different distances range from -0.5332 for very short trips (walking) to -0.06301 for long trips like car travel. A parameter of -0.12159 was used for PT, while for cycling, the differential distance parameter was -0.19252. Researchers sometimes use the median travel time (distance) to measure passenger preference to calibrate the spatial resistance parameter to their models (Figure 5) (Merlin, 2020).

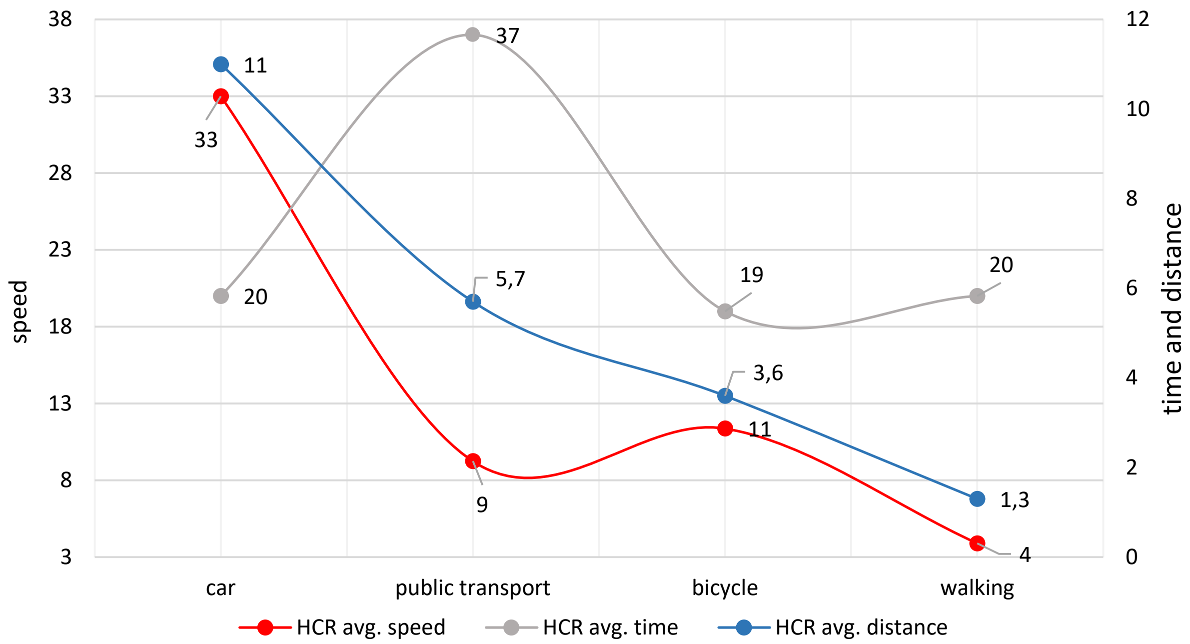

Fig. 5. Travel time and trip duration by mode in the HCR based on (Brandt E., Kantele S., 2019).

Comparison of the population flow matrix based on mobile data and PT travel times will make it possible to identify those places where people are likely to commute by car, such as workplaces during the morning peak. This is essential information for transport planners in the HCR. Formula (5) expresses the cumulative number of people who use private transport where A_i A_i is the accessibility of persons from zone i to all areas where people go j, O_i is the sum of persons in zone i, and (C_{ij}) a weighting function, where C_{ij} is the physical distance from i to j, and j is the distance travelled in time or distance (Widener, 2017).

$$A_i = \sum_{j=1}^{n} O_i \, f(C_{ij}) \tag{5}$$

The function $f\left(C_{ij}\right)$ is defined as follows:

$$f\left(C_{ij}\right) = \begin{cases} 1 \; if \; C_{ij} \leq t_{ij} \\ 0 \; if \; C_{ij} > t_{ij} \end{cases} \tag{6}$$

When calculating cumulative accessibility for people's movements, the population beyond a certain distance threshold is not considered in the results, as specified in Formula (5) (Thompson et al., 2019). The average travel time by PT in the HCR is 37 minutes, which will be used to select people's movements through mobile phone information, aggregated by point of departure (Brandt E., Kantele S., 2019). The analysis will reveal locations where high volumes of people travelling longer distances are likely to use private transport. Comparing the trip results for GRID squares and the locations where people earn above the median and third quartile of average earnings in the HCR will tell PT planners which areas need to be strengthened to achieve better sustainable development of PT in the HCR.

3. Results

The methodology of this study is based on the use of mobile phone data and the application of accessibility indicators to determine the catchment area and human activity in the HCR. The contribution of the study is significant because while most of existing accessibility studies only consider numbers of inhabitants, the mobile phone data in this one reflect actual movements. In the methods section, the author presents selected research methods using GTFS data ("GTFS open data HSL Helsinki," 2019) and Telia mobile data ("Traficom," 2020) to better understand the mobility of HCR residents and support sustainable transport planning in the area. Three research methods were used for this purpose.

The first method used in the results section is cumulative accessibility (Thompson et al., 2019). In this method, chosen destinations were indicated, considering different distances depending on the transport mode. The results for people's destinations were divided into weekdays and weekends. The next step was to compare the results illustrated in the GRID data figure (Fig. 6) and the graph during the day (Fig. 7). Supporting this method with cellular data allows the area of influence of displacements in the HCR area to be determined. The second method used in the study was potential-based accessibility (Goliszek, 2022; Rosik et al., 2021; Goliszek, 2017). With this method, accessibility was indicated based on the distance parameter and the share of people living in each municipality who declared that they travelled by car, PT, bicycle, or on foot in the 2018 traffic survey (Brandt E., Kantele S., 2019). The use of cellular data in this method and the taking into account different travel times and the share of residents in a given mode of transport will allow us to show the range of potential accessibility by different modes of transport. The results of potential accessibility were presented in a figure for GRID data (Fig. 8) and an hourly graph for the whole day (Fig. 9).

The last method was divided into two stages. In the first stage, the number of trips at a given location was compared to the number of people who live in that area for selected days of the week, such as Monday-Thursday, Friday, Saturday, and Sunday (Fig. 10). In the second step, for all trip sources for which the travel time by PT based on GTFS data is more than 37 minutes, the selected trips and the remaining trips were indicated and presented as a percentage of all trips on a graph (Fig. 11). Later, the author checked how the percentage of the population that potentially uses a car (times longer than 37 minutes by PT) changes if the PT time is between 25-55 minutes (Fig. 12). In this method the time between logins in the GRID area is significant because that is the basis for presenting areas from where people potentially make more frequent use of cars. As a final phase, for the morning peak hours between 6 and 8 am, when the variation in the number of long trips is the highest, the number of people who travel during the peak hours was compared to the remaining trips during the day. These results are illustrated in Figure 10, overlaid with a GRID grid showing the average values of residents above the median and third quartile of average earnings in the HCR. All results are shown in summed form for the whole day for the selected site and for the whole area for the selected hours during the day. Finally, the results of people moving more than 37 minutes by PT are compared with another map created by Söderström et al. (Söderström et al., 2015) which shows the main transport modes that residents use in the HCR area.

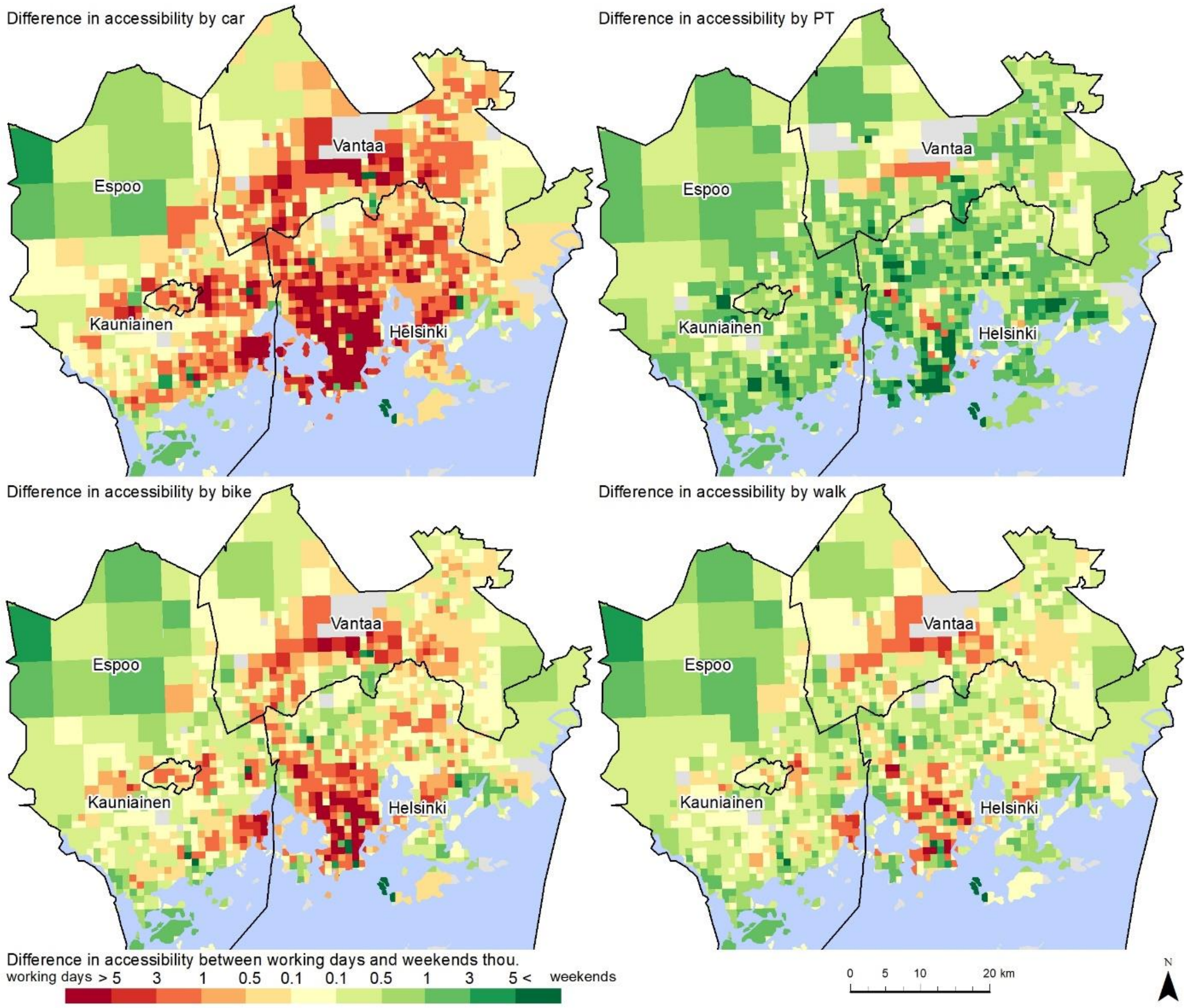

Fig. 6. Difference between weekday and weekend transport modes in HCR (own elaboration in ArcGIS based on *Traficom* [52]).

Difference between travel modes

The results for each trip length were determined by weekday, with Monday to Thursday and Friday each accounting for one-fifth of the total. On weekends, the results from Saturday and Sunday were combined and divided by two. All results were compared by mode of transport and for both weekdays and weekends, indicating the prevalence of each mode of transport. For example, the prevalence of car trips on weekdays indicates the primary mode of transport for residents commuting to work.

When considering longer distances, there is a significant predominance of weekend trips in the north-western part of Espoo Municipality as well as in the parts of Vantaa Municipality located to the north and in parts bordering Helsinki and Vantaa Municipalities in the north-eastern part of the HCR. By contrast, for the average distance travelled by PT, there was a noticeable predominance of weekend trips over weekdays, except for locations near the airport and Pasila train station and metro stations in the eastern part of Helsinki.

Comparing the prevalence of weekend trips by public and private transport shows that long-distance trips are more common on weekdays, while shorter-distance trips are more prevalent on weekends. The most significant differences in favour of weekend trips were recorded in the centre of Helsinki and point-to-point in the other municipalities in the HCR area. On the other hand, the average distance for bicycle trips shows a predominance of weekday trips along the metro line in Helsinki and near the railway route in the HCR area. The predominance of weekend trips for average cycling distances was recorded in the northwestern part of Espoo Municipality.

The shortest pedestrian journeys recorded a predominance of weekday journeys in the centre of Helsinki. Also, short trips were more common near the metro stations closer to the centre of Helsinki and the airport located in Vantaa Municipality, with a noticeable prevalence of weekday trips. The rest of the area has a predominance of travel counts at the weekend for short journeys of 1.3 km (Fig. 3).

Comparing the number of movements during a weekday with the weekend allows the time distribution and identification of the hours when HCR residents were most mobile to be tracked. The data shows that the most significant percentage differences in mobility for all modes of transport occur on weekdays in the morning, between 6:00 and 9:00 am. The most significant differences were observed for car journeys, followed by public transport, cycling, and walking. A comparison between weekend and weekday data always favours the latter for every mode of transport. Over 24 hours, this results in an average of 73 percentage more people per hour travelling by car on weekdays than on weekends. For public transport, there are 43 percentage more people per hour, 27 percentage more people per hour by bike, and 10 percentage more people per hour walking on weekdays compared to weekends (Fig. 7).

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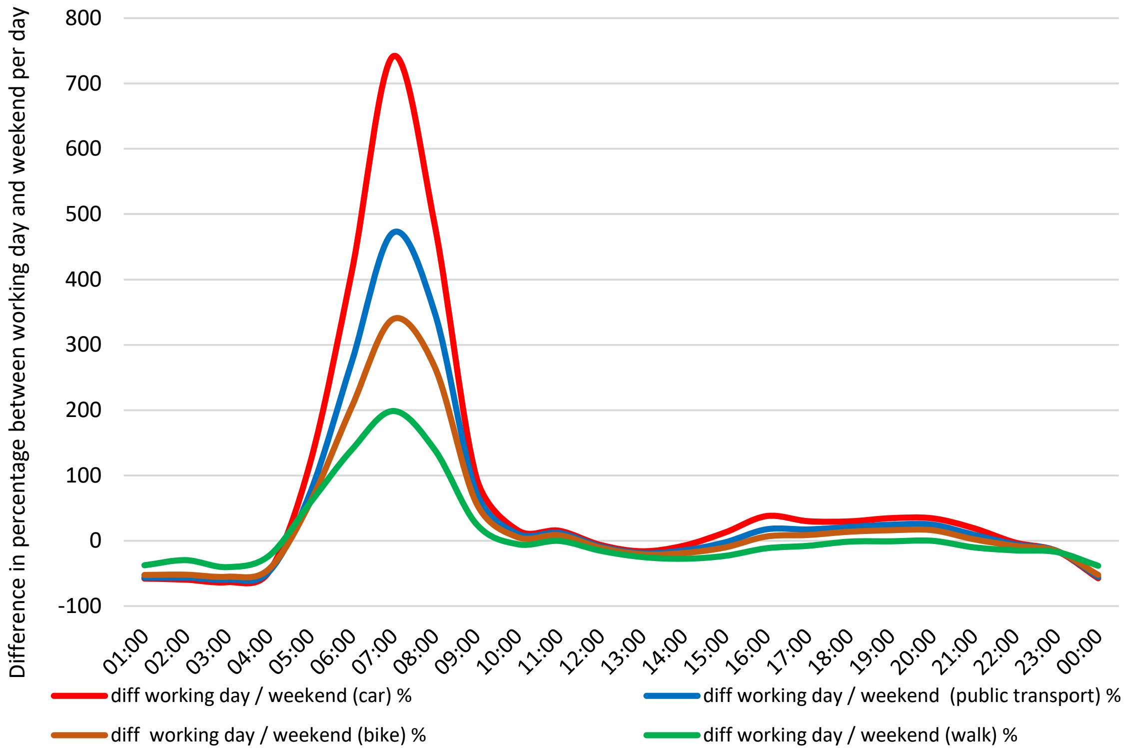

Fig. 7. Difference in percentage between working day and weekend per day by different transport modes in HCR (own elaboration based on *Traficom* [52]).

The values of average potential accessibility for the selected transport mode indicate in which locations the potential of the selected transport modes predominates. These results are presented as an average for each transport mode. Each time, the accessibility potential in the HCR was assumed to derive from the number of people agreeing to travel who use the selected mode of transport in relation to the average distance and the distance parameter to the selected destination, both of which were applied to the source of the trip. The potential accessibility score itself illustrates the sum for the destination.

The potential accessibility by car in the HCR is illustrated by the above-average score in the city centre and near the metro station. Relatively high scores are noticeable on the map near the airport and in the HCR. The lowest possible accessibility scores by car are in the northeastern part of Espoo Municipality, the northern and eastern parts of Vantaa Municipality, and the eastern part of Helsinki Municipality.

Areas of high average PT accessibility are visible in the centre of Helsinki, on the island located west of the centre and east near the metro station. The remaining areas of high average PT accessibility are distributed in a mosaic in the HCR area. The worst average accessibility is seen in similar locations as for car trips, namely the northeastern part of Espoo Municipality, the northern and eastern part of Vantaa Municipality, and the eastern part of Helsinki Municipality.

The results for average potential accessibility by bike and pedestrian travel are very similar, so they will be discussed together. The highest average values are visible in the central part of Helsinki and on the island to the west of the centre. The rest of the area, both above and below the average, is very much a mosaic, and it is difficult to point out areas of better or worse accessibility, as was the case for car and PT trips (Fig. 8).

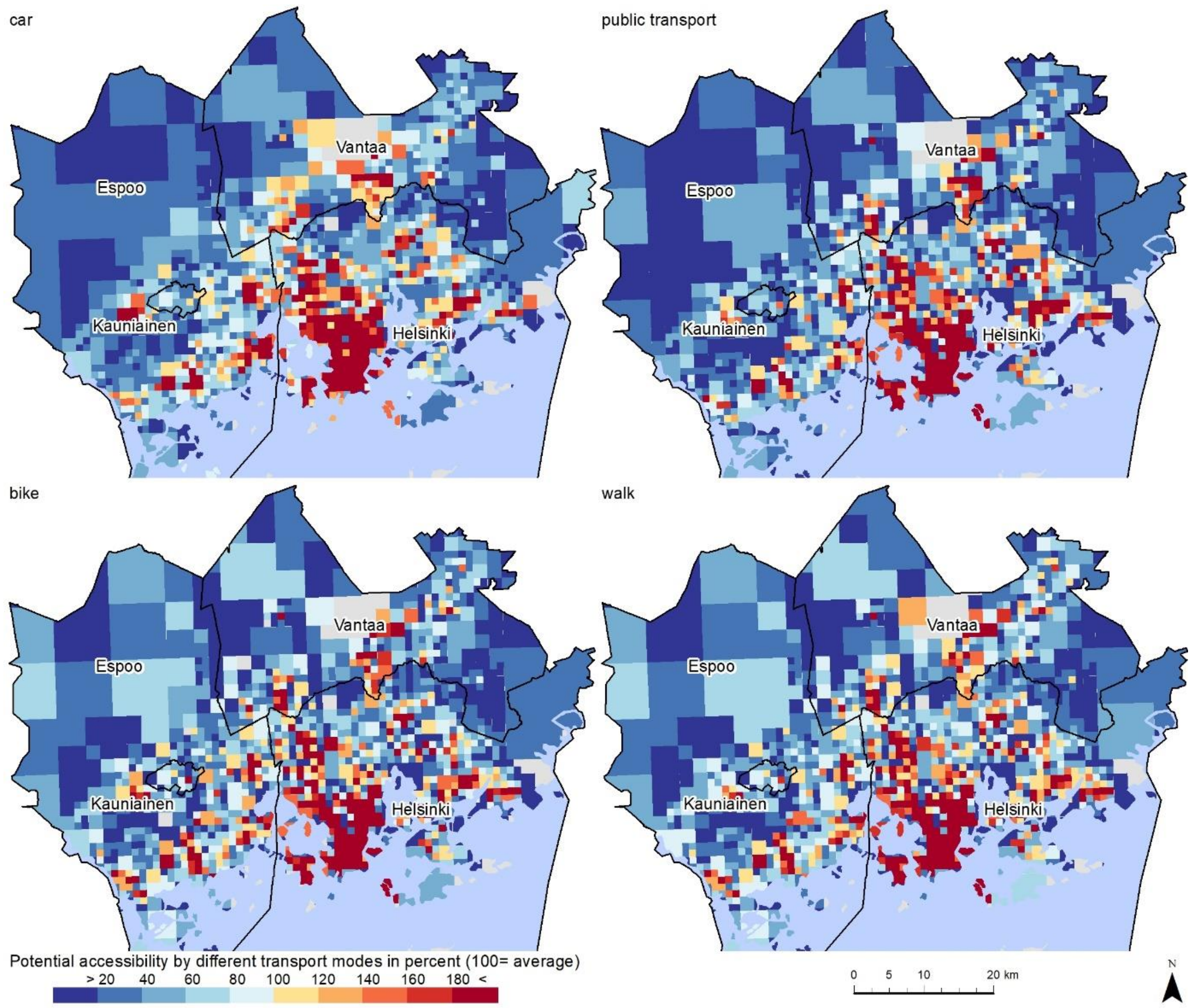

Fig. 8. The difference in potential accessibility by different transport modes in HCR (own elaboration in ArcGIS based on *Traficom* [52]).

Each accessibility indicator for the selected transport mode was based on percentages of people, allowing all the potential accessibility results to be combined. These results are presented as a graph for the whole day, with the share of each transport mode shown for selected hours.

The percentage share of potential daily accessibility by different modes of transport in the HCR shows how other forms of transport are declining in comparison with commuting by car. During the morning peak hours, the percentage share of cars among all modes of transport reaches up to 70 per cent. In the off-peak hours, the share of cars drops below 60 per cent, then slightly increases above 60 per cent during the afternoon peak hours. The opposite, almost a mirror image of the car's percentage share, is observed for other modes of transport, such as public transport, cycling, and walking (Fig. 9).

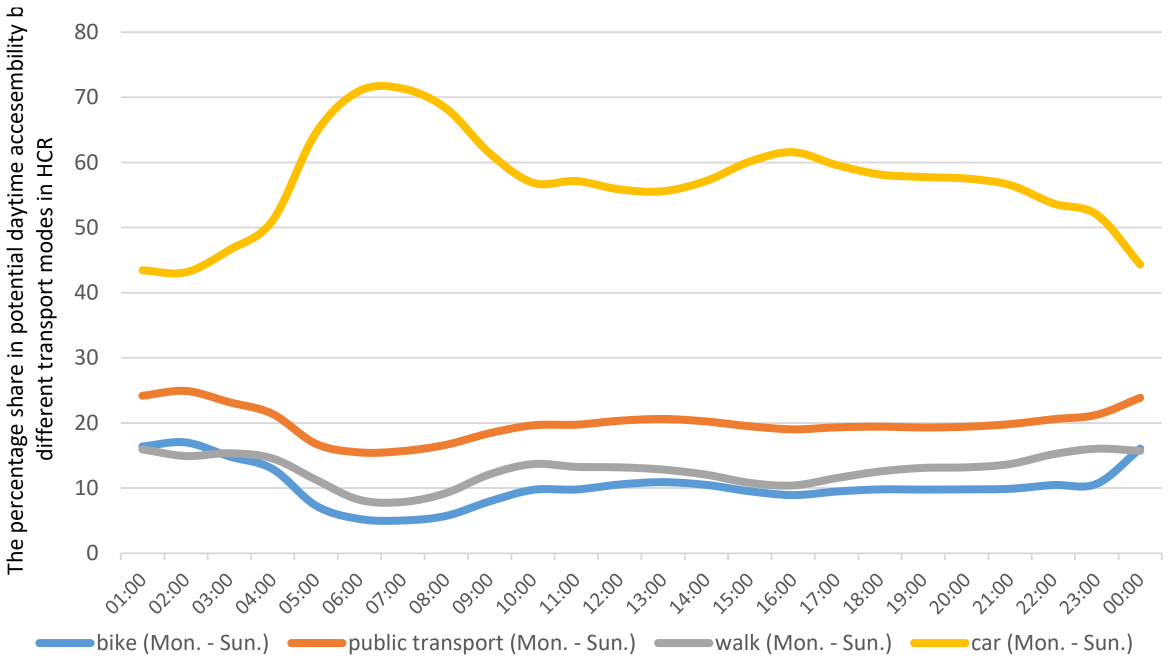

Fig. 9. The percentage share in potential daytime accessibility by different transport modes in HCR (own elaboration based on *Traficom* [52]).

Comparing the number of trips made to a destination and dividing this information by the number of people living in that area provides valuable insights into where people spend their time on selected days of the week. The highest values are recorded in places where workplaces are located, in uninhabited areas, or in areas with low population density.

The information on people's change of location is based on mobile data, and the breakdown of this information for weekdays between Monday and Thursday shows large concentrations of people who change their location due to their work. Many of these areas are visible in various parts of the HCR and coincide with large concentrations of workplaces. On the map, the large values apparent for large areas were due to the number of people who resided in these areas in 2019 and the relatively large number of recorded movements into the area. Large areas recording large values are visible on the map in Espoo Municipality, Vantaa, and the eastern parts of Helsinki Municipality. In Kauniainen municipality, these values are average compared to the rest.

On Friday, a different day of the week, high displacement values compared to the population are evident in areas with concentrations of large numbers of jobs and areas with no one living there. The distribution of high values is a complete mosaic across the HCR. In contrast, areas outside the high values are low compared to other days of the week (Monday-Thursday), which means that on Thursday, some people travel outside the HCR or stay at home and, for example, work remotely.

On the weekends, Saturdays and Sundays, uninhabited or sparsely inhabited areas also recorded high index values. However, compared to Thursday, significant increases were recorded in large, less frequently inhabited, areas in the municipality of Espoo, which were more frequently visited on these days because these areas are green and essentially have a recreational role for the residents of the HCR. Also, the areas around the airport, where people travel to work during the week and at weekends, are often leisure-related or people are simply travelling by air to/from elsewhere. High values here occur because these areas are uninhabited or inhabited by few people (Fig. 10.).

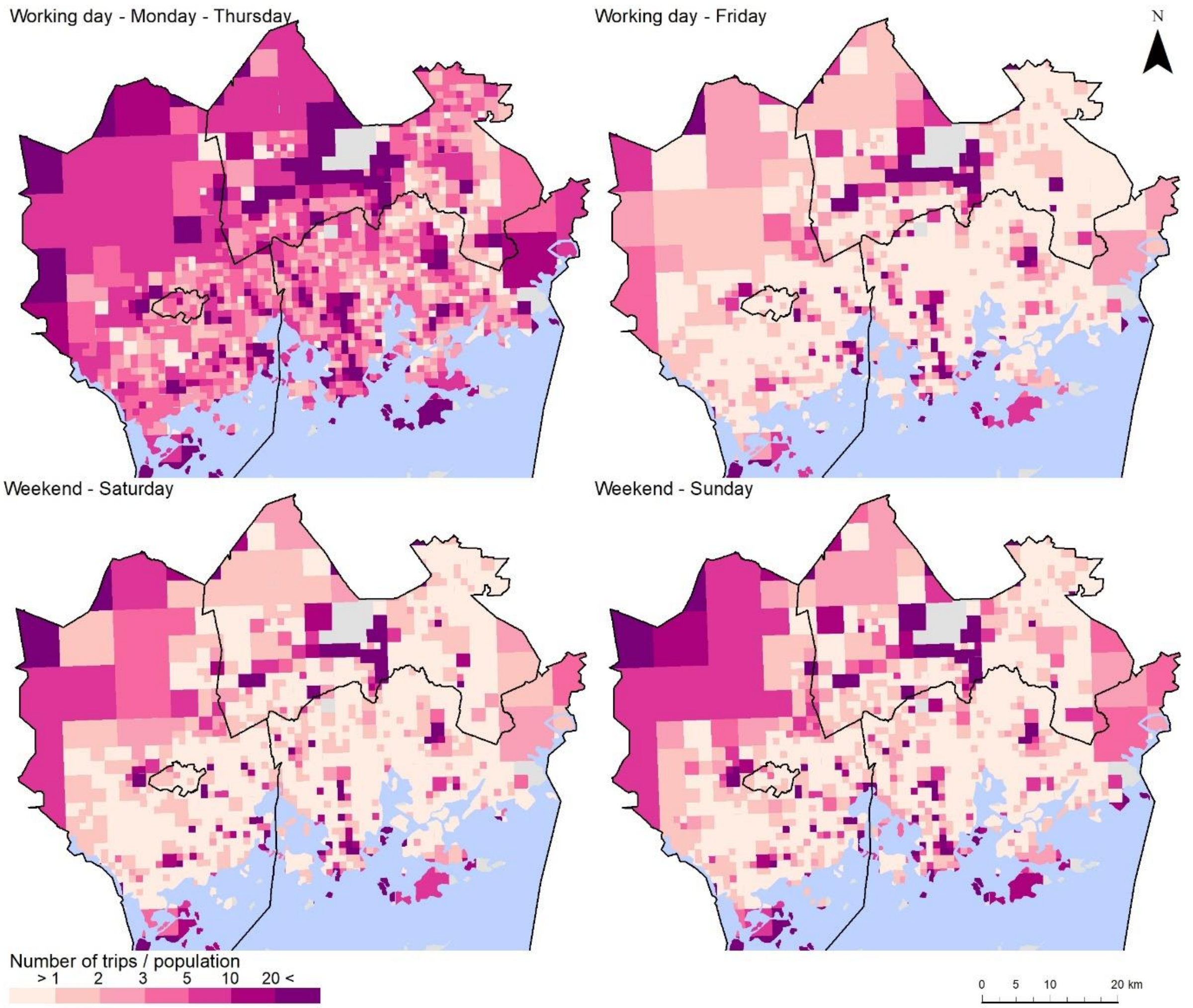

Fig. 10. Number of trips based on mobile data compared to the population in GRID in HCR (own elaboration in ArcGIS based on *Traficom* [52] and Finnish Environment Institute [58])

The following result shows the number of people who live in areas where the PT journey time to their destination is greater than the average PT journey time in the HCR, which is 37 minutes.

The morning peak period between Monday and Thursday recorded the highest proportion of people travelling to destinations taking more than 37 minutes of travel time, accumulating almost 60% of the traffic during those hours. This result is primarily derived from long journeys to schools and workplaces in the morning. The peak was also noticeable on Friday but lower than on other weekdays.

By contrast, the afternoon peak is less noticeable because many people return from work to pick up children from school, make purchases, or engage in other activities. Mobile data does not capture these types of trips, so the morning peak seems to reflect the peak of poor traffic circulation (Fig. 11.).

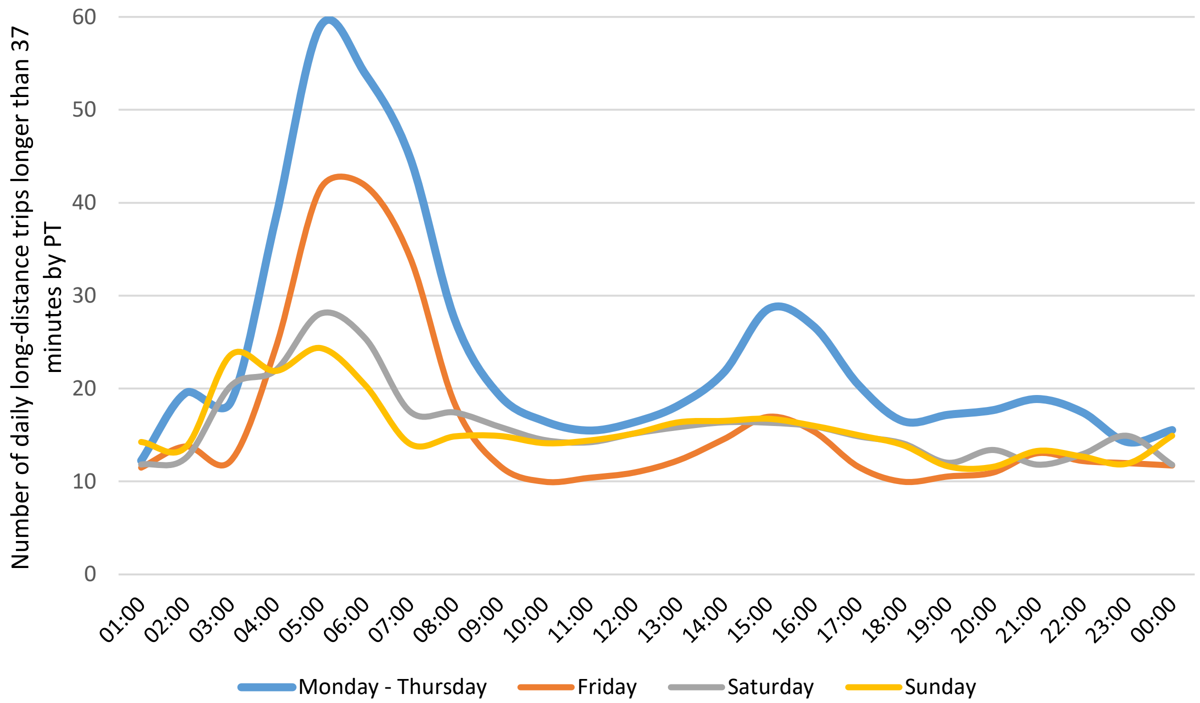

Fig. 11. The number of daily long-distance PT trips longer than 37 minutes (own elaboration based *GTFS Open Data HSL Helsinki* [38] and *Traficom* [52]).

The previous results prompted the author to compare different PT travel times throughout the day. The following graph illustrates the percentage of trips with PT travel times between 25 and 55 minutes at two-minute intervals relative to all recorded trips. The values obtained during the morning and afternoon traffic peaks leave no doubt about how long journeys take during these periods. In particular, during the afternoon traffic peak, more than 50 per cent of all recorded trips have a travel time exceeding 25 minutes by PT. Similarly, records show that more than 70 per cent of trips during the morning traffic peak had a PT travel time greater than 25 minutes.

As PT travel time increases by two minutes, there is a decrease of about 4 per cent in the percentage of people travelling within that period, with the sharpest drop occurring between 5 and 6 am. These results suggest that long journeys from areas with limited PT access dominate at this time. However, the percentage of trips over 25 minutes by PT reaches its highest value at 6 am. At that time observe declines rapidly and shifts to the earlier time between 5 and 6 am, where the highest values are recorded (Fig. 12.).

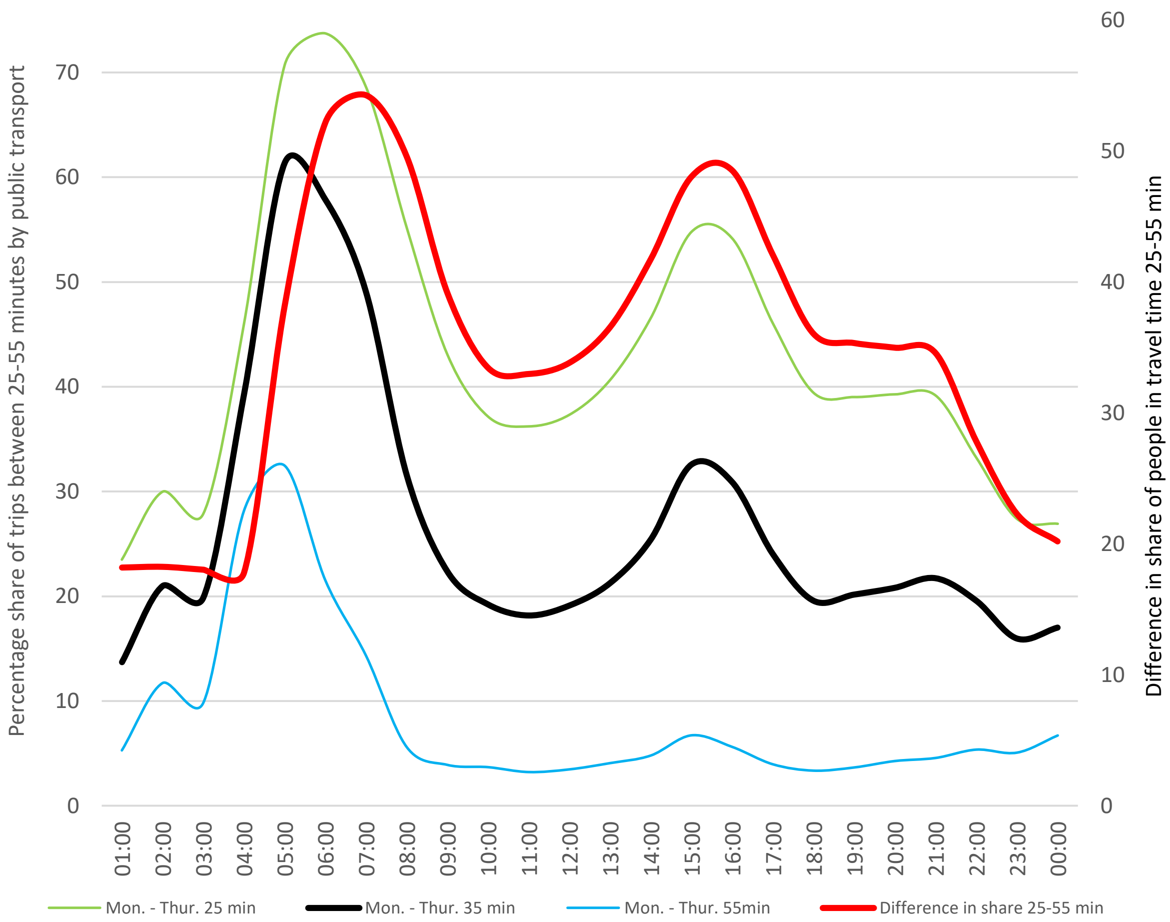

Fig. 12. Several long journeys per day longer than 25-55 minutes travel time by PT (own elaboration based *GTFS Open Data HSL Helsinki* [38] and *Traficom* [52]).

Based on mobile data, the final analysis results show the percentage of residents who travelled by PT between 6 and 8 am over distances greater than 37 minutes between origin and destination. The map compares this information with the spatial distribution of residents' income levels for 2018 above the median and third quartile.

The map shows that the smallest number of people travelling less than 37 minutes by PT is seen in trips from Helsinki city centre and nearby metro stations to locations located to the west and east of the centre. Due to their location and housing prices, these areas tend to be inhabited by wealthy people whose earnings are well above the average for the HCR. Also worth noting are the areas bordering the municipalities of Kauniainen and Espoo and the relatively large area near the airport in Vantaa municipality, which extends to the west along the railway line. The map also highlights smaller areas located near to railway stations. The area to the northwest in Espoo Municipality is a welcome surprise, an area from which relatively few people move in poorly connected destination served by public transport.

Conversely, there are areas from which more than 50% of the residents commute by PT for over 37 minutes, and these individuals likely opt to use private vehicles. The most extensive and prominent area is located southwest and northeast of Kauniainen Municipality in Espoo.

On the other hand, these areas are inhabited by people with earnings above the third quartile for all people living in the HCR, which means that rich people live there. A second reasonably extensive area has been recorded in Helsinki Municipality stretching along the border of the municipality. However, this area, especially in the northern part of the municipality, is also uninhabited. Individuals who undertake morning exercise in this city may contribute to the high volume of trips. On the other hand, in the municipality of Vantaa, the areas where it is more difficult to go by PT and where there have been significant movements of people in the morning are in the north-western part of the city. This area is primarily inhabited by residents with above-median income levels.

There is an apparent relationship on the map. The better the accessibility by PT during peak hours, the more likely it is that this area is densely built up, and people earning below the HCR region average live there. In contrast, less accessible areas with lower population density are more likely to be inhabited by wealthier people who use private cars for travel (Fig. 13.).

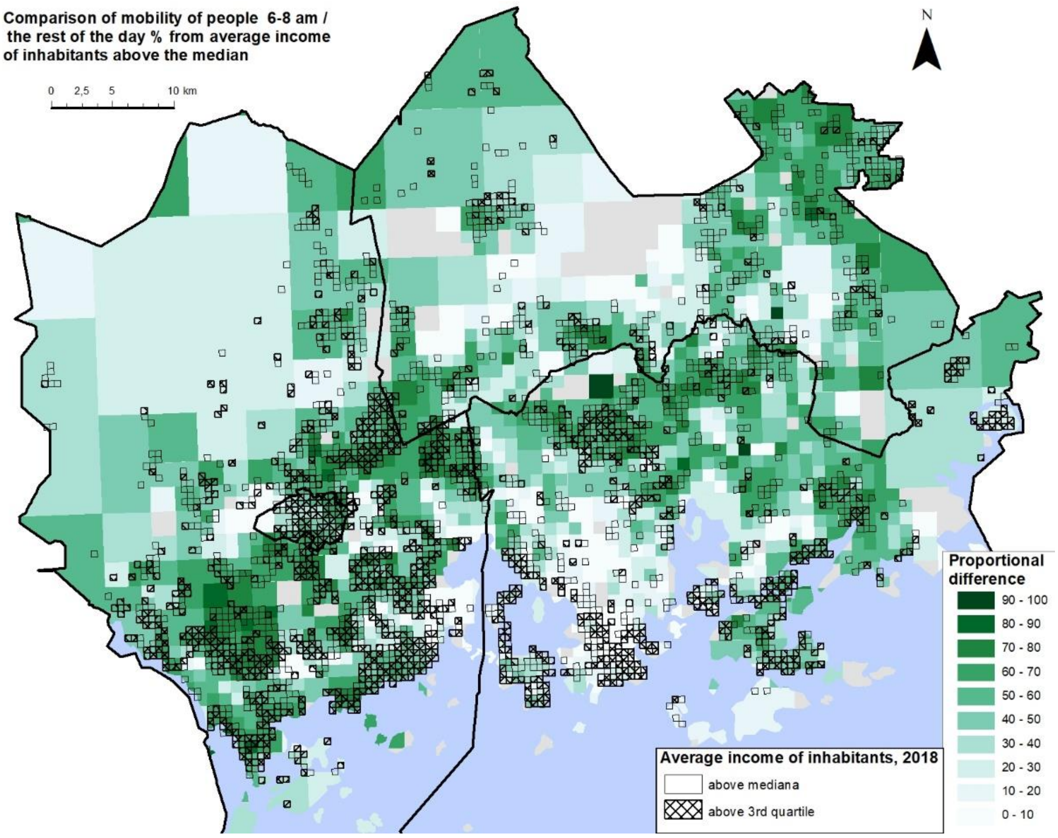

Fig. 13. Comparison of where people move from between 6 am and 8 am the percentage of remaining trips over 37 minutes by PT (own elaboration in ArcGIS based on Finnish Environment Institute [58]; *GTFS Open Data HSL Helsinki* [38]and 2019; *Traficom* [58]).

4. **Discussion**

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Using known methods for assessing spatial accessibility, GTFS data and mobile phone data were used to derive various parameters from mobile data for each location in the HCR area. Additionally, mobile data were aggregated for the entire HCR area and presented as charts throughout the day. How significant are the flow of individuals values that are generated from mobile phone data, broken down by mode of transport, weekdays, weekends, and throughout the day? Do areas inhabited by wealthier segments of society exhibit good public transport accessibility when using mobile phone data? The results suggest that in the HCR area, there are many correlations between travel time, travel distance, and number of people travelling throughout the day—the first correlations concern travel distance and weekdays versus weekends. Here, the results concerning car travel are concerning, showing significant areas where the car has the advantage on weekdays. Additionally, the hourly chart demonstrates that car travel is used for a significant share of long journeys on weekdays.

The study utilised results from the GTFS public transportation (Hadas, 2013; Wessel et al., 2017) and mobile phone origin-destination (O-D) data (Iqbal et al., 2014) to assess public transportation accessibility in the HCR (Helsinki Capital Region). Other studies have employed mobile phone data to create semi-open public transportation databases based on the GTFS (García-Albertos et al., 2019) in the municipality of Madrid (Spain). Other studies have employed mobile phone data to create semi-open public transportation data based on the GTFS (Williams et al., 2015). According to the author, this is the first work that combines the two datasets. O-D mobile phone-based passenger movement information and PT timetables are stored in a test format called GTFS.

Moreover, despite using a variety of methods for determining transport accessibility, namely switched accessibility, potential accessibility and matrix comparison, this paper makes a methodological contribution that relies heavily on cellular data and GTFS for HCR. Cellular and GTFS data have made it possible to indicate how large traffic flows are generated using mobile phone data. This enabled problem areas to be identified where residents will be most likely to use a private car.

The results support studies based on GTFS data. The standardised nature of this data has enabled the utilisation of plugins and programs developed for GTFS in measuring transport accessibility and traffic flows in other planning applications (Hadas, 2013; Wong, 2013). In addition, Origin and Destination data from mobile phones may contribute to sustainable transport planning (Alexander et al., 2015; Tsumura et al., 2022). Combining these two data sources allows problematic locations to be identified where residents are highly likely to commute by private car, a mode which has a significant environmental impact compared to other alternative modes of transport. In the HCR area, 44% of trips were made by respondents (residents) who chose the fastest mode of transport, which in most cases meant using a private car. Planners need to designate zones relevant to different groups of residents who use different modes of transport (Söderström, P., Schulman, H., Ristimäki, 2015) in order to be able to efficiently support areas that overuse the car in comparison with, for example, PT (Audouin and Finger, 2018). The results presented in this study differ somewhat from those found in other studies (Hasanzadeh et al., 2021). The author of this study mainly highlights differences in the area around the municipality of Kauniainen, designated as an area for PT use (Söderström, P., Schulman, H., Ristimäki, 2015; Zhang et al., 2022). From the results obtained in this study, it can be presumed that this is a zone where residents use private cars for travel. The centre of the HCR is primarily made up of walkable areas (Hasanzadeh et al., 2021). The HCR area contains many jobs and services that PT can access. Pedestrianised sub-centre zones are located around major railway stations and shopping centres (Hasanzadeh et al., 2019). These zones contain a range of housing, employment and services. Together with the intensive PT zone, they form corridors with good access to PT. In contrast, the PT and car zones are located further away from PT links, closer to the city's edge. These zones often have lower population density and poorer access to jobs and services.

The survey classified further potential accessibility scores by car use and other modes of travel, but have also showed a high percentage of trips made by car. The overall accessibility score on the hourly graph for the day shows a significant proportion of the traffic occurring in the afternoon. This result shows that long trips are made in peak morning hours and are commuting trips (Zhao et al., 2020) or trips taking children to school. The increase in trips in the afternoon is related to other activities, which are more numerous and, therefore, more trips are recorded. Therefore, this total share is higher. Comparing the number of trips with the number of people living in the area is also fascinating. It can be seen that on weekdays, the location of workplaces is visible as darker colours, while on weekends, large green areas located further away from the centre are more significant. This part of the study also shows the number of people who travel compared to the other PT matrix and selects those who travel longer than 37 minutes by PT. On this basis, the major proportion of people who travel long distances in the morning peak hour was extracted. Key results were obtained by comparing the O-D of cellular data with the O-D times for PT based on GTFS data. By determining the time threshold and the morning peak hour, it was possible to separate the population that travels in the morning peak between 6–8 am from the remaining trips during the other hours. These results have identified problem areas in the HCR that have yet to be directly defined in other studies and where there may be excessive car use by people living in the area. Areas of poorer accessibility by private transport and possible greater use of private cars are populated by wealthy people who live in areas poorly served by PT.

Previous studies have used surveys to determine the flows of people in selected spatial links and using which means of transport (Salonen et al., 2014). The final result consists of a limited number of answers from respondents. A drawback of mobile phone data is the lack of personal information about mobile phone users and the requirement that individuals registered by the mobile network must spend more than 20 minutes in a specific region. (Willberg et al., 2021) In future research, it is possible to combine the detailed data in the interviews that Carrier conducts in its research on the HCR (Brandt E., Kantele S., 2019) with mobile data (“Traficom,” 2020) and data from other sources (Tenkanen and Toivonen, 2020), including GTFS data (“GTFS open data HSL Helsinki,” 2019) for the HCR. This information can be used to estimate all movements within the HCR by transport mode selected, hours, and destination, which is of great interest to those involved in planning and implementing sustainable PT in cities and regions (Jurgilevich et al., 2021).

The study contributes to the literature on the sensitivity of GTFS and mobile phone data when obtaining the daily dynamics and diversity for selected locations. These results show areas that could be heavily used by one mode of transport with negative impacts, in this case, the car. These results can help transport planners, who can use the results to look at these areas in more detail and propose measures to reduce car use, with beneficial implications for the future. Practitioners can use the methodology developed and the results obtained to designate areas and a new strategy to support

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sustainable mobility in the HCR. This approach will reduce carbon emissions in the HCR, positively impacting the quality of life for all residents in the area.

Finally, sites in which high use levels of private cars are possible should be investigated further. We suggest that these sites should be placed under special surveillance. Furthermore, in the future, more detailed studies should be carried out at the urban level to investigate the links between the resident population, the number of car journeys, and the transport mode preferences of the residents (Huang et al., 2019). Unfortunately, the results of this study already show that these areas are inhabited by affluent residents who are unlikely to change their travel habits. In future research, it might be worthwhile to investigate what types of cars these people drive and their impact on the HCR's environment. An important issue is the inclusion of such areas in strategic urban planning for sustainable urban transport in the HCR, which is worthy of further investigation.

A limitation of this study is the use of average travel speed and distance values in the formulae for calculating accessibility. This may have some influence on the results; however, it should not compromise the overall interpretation of the study or the accessibility outcomes in the HCR area.

Data availability

The datasets generated and/or analysed during the current study are not publicly available due to the mobile data being owned by Thelia. I gained access to it by signing an agreement with the University of Helsinki for an internship at the Digital Geography lab.

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Author Contribution

Sławomir Goliszek: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Competing interests

The author(s) declare no competing interests.

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