Appendix to *Developing a composite indicator for the 15-minute city concept based on accessibility measures and assessment of spatial inequalities of different socio-demographic groups*

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Contents

A. Extended version of literature review

A.1 The 15-minute city

In a 15-minute city, residents should be able to access all of their essential needs within 15 minutes of travelling by active mode (walking or cycling), and thus the need for travel and specifically car travel will be reduced. The goal of 15-minute cities is to retain local population locally (Graells-Garrido et al., 2021). The 15-minute city has been adapted to fit different regional needs, such as 20-minute neighbourhoods in Melbourne (Victoria State Government, 2017) and Portland (City of Portland, 2010), the 15-minute city in Paris (Paris en commun, 2020), and now the ambition of Utrecht for the 10-minute city (Gemeente Utrecht, 2021b). Thus, despite the seemingly straightforward and quantitative nature of the name of the concept, there are many variations with different threshold travel times, and different modes included, such as public transit. Likewise, the types of amenities or services included that should be accessible within the specified travel time differ drastically between plans and in the literature (Carpio-Pinedo et al., 2021; Gaxiola-Beltrán et al., 2021; Graells-Garrido et al., 2021; Moreno et al., 2021; Pozoukidou & Chatziyiannaki, 2021; Weng et al., 2019).

The Congress for New Urbanism (CNU) has defined different sheds within the 15-minute city for 5-minute walks, 15-minute walks, 5-minute bike rides, and 15-minute bike rides. According to the CNU, a radius of 0.4 km (5 minutes walking) is the size of a neighbourhood and should contain services essential for daily needs such as groceries. A radius of between 1.2 km (15 minutes walking) and 1.6 km (5 minutes cycling) is defined as an appropriate size of the 15-minute shed, labelled the 'range of the 15-minute city'. Within this area the most essential services should be located such as schools, parks, and commerce. Outside of this area, within a 4.8 km radius (15 minutes cycling), larger companies and employment centres, cultural institutions, entertainment services, higher education opportunities, large parks, and major medical facilities should be located (Duany & Steuteville, 2021).

Thus, multiple neighbourhoods that can be covered by a 5-minute walk are present within a 15-minute city (15-minute walk or 5-minute bike ride). CNU seems to be the only organisation that has quantified any characteristics of the 15-minute city so far, providing some requirements that cities can work towards in their planning. Definitions of the 15-minute city differ across countries, and there are variations when it comes to services or modes of transport included. Thus, it is not a one-size-fits-all concept, but the goal is the same: reduce traffic.

As stated in the introduction, Utrecht is the first Dutch city with ambitions to become a 15-minute (or rather a 10-minute) city. In the Netherlands, most cities are medium-sized cities, and there are no cities with more than 1 million inhabitants. They range from 100.000 inhabitants to almost 1 million inhabitants (Amsterdam). However, some metropolitan areas consist of larger agglomerations, such as the Rotterdam-Den Haag area, Amsterdam with its suburbs, and Utrecht with its suburbs. Additionally, cycling is popular in the Netherlands and considered by many people as a main form of transportation. 28% of all trips in the Netherlands are by bicycle (CBS & RWS, 2020), more than other countries in Europe (Buehler & Pucher, 2012). Many trips already take place close to home, and people will most likely generally choose their bike over walking if something is a bit further away. Therefore, the concept of 15-minutes cities in the Dutch context becomes slightly different. Cycling is a more frequently chosen alternative to driving than walking, because of good bicycle infrastructure, convenience, and a greater distance can be covered in a shorter amount of time by biking than by walking. Not only is walking in the Netherlands not as important an alternative to driving as cycling but including walking in analysis requires a lot of data on infrastructure quality to properly assess walkability. Thus, walking will not be taken into account as a mode in this study, and the research will focus on cycling and cycling accessibility. However, that is not to say that walking should not be included in 15-minute cities.

It is worth noting that public transport should not be included as one of the modes used to define the 15-minute city because travel times on public transit depend on too many variables, such as delays and first- and last leg (Duany & Steuteville, 2021). Furthermore, 15 minutes is a relatively short amount of time. However, *access* to public transit hubs and stops is essential, for people unable to walk or bike, or to get out of the city every now and then.

A.1.1 Services in the 15-minute city

Within the 15-minute city, a number of different services should be located. Moreno et al. (2021) state that 6 main categories should be present: living, working, commerce, healthcare, education, and entertainment. In their analysis of Barcelona, Graells-Garrido et al. (2021) also consider access to healthy food, government facilities, green spaces, and public transit. While healthy food might be considered within the commerce category of Moreno, it may be beneficial to regard it separately, because access to healthy food has an influence on overall health. Food deserts are places where access to grocery stores is low, either because of boundaries such as busy roads or highways, distance, or affordability (Shaw, 2006). Although, a study in Amsterdam showed that there were no real food deserts (Helbich et al., 2017), access to healthy and affordable food is important to consider in order to promote a healthy lifestyle compliant with the 15-minute city available to everyone. Furthermore, green spaces are a very important asset in cities considering the effects of climate change and urban heat islands. While green spaces might be considered under the entertainment category, this is not specifically stated by Moreno.

Table 1 presents the amenities considered by papers that either define the 15-minute city concept or use it in analysis or assessment. The six main categories from Moreno seem to be present in some way in most of the other articles. The *living* category is captured by the origin points and spatial unit used in analysis, and the housing affordability category in Pozoukidou & Chatziyiannaki (2021). The *working* category is considered in Carpio-Pinedo et al. (2021) and Pozoukidou & Chatziyiannaki (2021) but no distinction is made between different types of jobs, or different types of workers. Gaxiola-Beltrán et al. (2021) include employment centres and make distinction in size (number of job positions). Employment is a very important characteristic of the 15-minute city because most people travel to work each day. For proper analysis of job accessibility, distinction between job types and education levels of workers could greatly influence results (Cervero et al., 1995; Geurs & Van Eck, 2003; Shen, 1998), and competition effects should be included (Geurs & van Wee, 2004). Furthermore, commuting trips still predominantly take place in the car in the Netherlands: in 2019, 50% of all trips to and from work were by car, and 26% by bike, and the average trip distance to and from work is 9.72 km (CBS & RWS, 2020). Many people have to travel further than what is considered a bikeable distance to work. Moreover, the commute to work is a trip that recurs daily for many people and thus determines a large part of their mobility pattern. However, in the 15-minute city, work should be accessible within 15 minutes of cycling or walking as well. It is therefore important to include work destinations in analysis.

The *commerce* category is included in all other articles, but in different ways. Gaxiola-Beltrán et al. (2021) only include supermarkets, which provide the most essential of daily needs. On the other hand, the other articles do not make distinctions between different types of commerce and do not analyse supermarkets separately. Graells-Garrido et al. (2021) consider supermarkets in their retail category together with other shops and malls. *Health* is also considered in all of the other articles. While some consider different types of healthcare, others consider all healthcare grouped and do not distinguish between types such as hospital, pharmacy, or general practitioner. However, these different health providers all have different amounts of people they need to service, and it is safe to assume that not every 15-minute neighbourhood needs regional services such as a hospital.

The *education* category is considered in 3 of the other articles. Gaxiola-Beltrán et al. (2021) and Weng et al. (2019) both distinguish different types and levels of education in their analysis, while Graells-Garrido et al. (2021) group all types together. Again, different types of schools have different catchment areas, and the presence of both an elementary school and high school in one neighbourhood provides more options for different types of families. Finally, there are some very distinctly different amenity types included in the *entertainment* category in all articles. Gaxiola-Beltrán et al. (2021) do not consider entertainment at all, while in other articles a distinction is made between entertainment and recreation Graells-Garrido et al. (2021). Carpio-Pinedo et al. (2021) and Weng et al. (2019) include parks, sports venues, cultural venues, restaurants, entertainment venues, and leisure and hospitality types in their analysis that may all be considered part of the *entertainment* category.

Table 1: *Amenity types in academic literature on 15-minute cities*

Source	Amenities	Use
Moreno et al. (2021)	Categories: *Living, Working, Commerce, Healthcare, Education, Entertainment*	Definition
Weng et al. (2019)	Amenities: *Education (School or Training institution), Medical care (Hospital or Pharmacy), Municipal administration (Public transport; Park and square; Sports venue; Cultural venue), Finance and telecommunication (finance and post office), Commercial service (restaurant, shopping, entertainment venue), Elderly care (nursing home or elderly education)*	Measuring walkable neighbourhoods
Pozoukidou & Chatziyiannaki (2021)	Categories: *Work, Basic healthcare, Cultural and recreational opportunities, "key resources"*	Assessing/evaluating transportation plans
Carpio-Pinedo et al. (2021)	Land-use types: *Industrial, Offices, Commercial, Sports, Show business, Leisure and hospitality, Health, Cultural, Religious*	Measuring walkability
Gaxiola-Beltrán et al. (2021)	Amenities: *Schools (Preschool, Primary school, Secondary school, Technical secondary school, High school), Hospitals (General hospital, Addiction and psychiatric hospitals, other hospitals), Other (Supermarkets and Employment centres)*	Assessing urban accessibility (walking and cycling)
Graells-Garrido et al. (2021)	Categories: *Education, Entertainment, Finance, Food, Government, Health, Professional, Recreation, Religion, Retail, Public transport*	Measuring 15-minute accessibility (walking)

A.1.2 Four dimensions

Moreno et al. (2021) define 4 dimensions for the 15-minute city: *density*, *proximity*, *diversity*, and *digitalization*. Density should be adequate to reduce sprawl and simultaneously promote proximity of services. However, too high density could lead to centralised development. The CNU defined several thresholds for residential density in their different sheds. The first shed of 5 minutes walking should contain about 2600 residents (around 5000/km2), and the 15-minute walking shed should contain around 23,500 residents (Duany & Steuteville, 2021). Diversity is applied two ways; diversity in land use in order to create mixed-use neighbourhoods, and diversity in culture and people. Mixed land use promotes walkability and proximity, while a multicultural society is beneficial for the economy and attractive for visitors. Diversity at the building level – multiple functions such as commerce and residential in one building – is important for optimal benefits and interaction. Finally, digitalization increases not only safety through e.g., sensors in traffic, but also efficiency of shopping, bike sharing facilities, and opportunities to work from home or any other location.

Accessibility (to services) is facilitated both through land use and transportation facilities, together with personal capabilities (Geurs & van Wee, 2004). However, considering the dimensions and distances that can be covered within 15 minutes of active transport, proximity to services is especially important to increase accessibility in the 15-minute city. Pozoukidou & Chatziyiannaki (2021) also argue for a shift in planning from accessibility of a neighbourhood in the context of the entire metropolitan region to planning for proximity of urban amenities within neighbourhoods. Thus, activities are brought to neighbourhoods instead of bringing people to the activities. In conclusion, land use mix and (optimal) density are some of the most important features of a 15-minute city. Furthermore, proximity to services has also been found to have a negative relationship with private car use in Melbourne (Boulange et al., 2017), meaning people are less likely to choose a private car if proximity increases.

Diversity could lead to more vibrant and connected communities. Mixed-use developments could address market demand for housing in an economically viable way and create sustainable spatial solutions (Delisle & Grissom, 2013), some of the key principles of the 15-minute city. Furthermore, together with density and pedestrian-oriented design, diversity could positively influence travel behaviour (Cervero & Kockelman, 1997). A diverse set of amenities in a single neighbourhood ensures that less traveling is necessary to reach all daily needs and makes for a more vibrant neighbourhood. A multicultural neighbourhood could promote tourism because of a more attractive environment to visitors, and ultimately create more job opportunities for locals and boost the economy. Diversity and land-use mix have been measured before using the Shannon entropy index (Shannon, 1948), first designed for measuring biodiversity. It has been used in Frank et al. (2005) and subsequently adapted in Mavoa et al. (2018) as Land Use Mix (LUM) to measure diversity in land-use spatially. Neighbourhoods with more diverse land-use gained a higher score (closer to 1) and were considered more walkable than neighbourhoods which were completely homogenic in land-use type (score close to 0). Thus, LUM index could be a proxy of some of the qualities of a 15-minute city in that it measures both diversity and proximity to some extent. However, it cannot be used to assess if all requirements of a 15-minute city have been met.

A 15-minute city could, through its dimensions such as proximity and diversity, create more lively and liveable neighbourhoods. Additionally, some other hypothesized benefits include economic boost of the area, more social cohesion and interaction, more sustainability (Moreno et al., 2021), and health benefits for the population due to an increase in active mode share (Weng et al., 2019). Furthermore, higher walkability, more density and mixed land-use all contribute to increased walking and cycling and reduced car traffic (Adhikari et al., 2020; Boulange et al., 2017; Forsyth et al., 2007; Gao et al., 2020; Lee & Moudon, 2004; Riggs & Sethi, 2020; Saelens & Handy, 2008; Saelens et al., 2003). Other potential long term benefits of the 15-minute city may include an overall higher quality of life due to less time spent in traffic and better health, a higher cultural output, and bridging social inequality in accessing services (Moreno et al., 2021). Furthermore, the pandemic and its travel restrictions have shown that emissions and pollutants reduce in cities as a consequence of less motorised traffic (Albayati et al., 2021; Wang & Li, 2021). Thus, a reduction in air pollution is another possible benefit of the 15-minute city. Furthermore, in a 15-minute city, resilience against threats such as covid-19 may be higher. A more tightly knit social network means people are more likely to have a support system if they get ill or cannot leave their house. In addition to this, proximity of essential services means that public transport might not be necessary to fulfil daily needs. If job allocation and residents' location match better, essential workers are also able to independently arrive at their work – by bike or on foot.

A.1.3 Other planning schemes

Aside from the 15-minute city, there are other urban planning schemes/concepts that promote sustainable transportation and aim to reduce motorised traffic. The smart city, Barcelona superblocks, and even the similarly named 20-minute neighbourhoods are some of these concepts.

The Smart City, in which the digital world takes prominence to make living more sustainable and efficient, is one of these concepts. Through the use of smart sensors that improve the flow of traffic, bike sharing schemes accessible anywhere in the city, and working at remote locations, the smart city makes life easier by connecting everyone and everything through the Internet of Things (Benevolo et al., 2016; Caragliu et al., 2011). In the smart city, one can access anything from anywhere, no matter location or built environment characteristics such as density, which disconnects it from the notion of proximity in the 15-minute city.

Barcelona's superblocks, already in implementation since the early 2010s, are cells surrounded by streets for through traffic, but with traffic calming measures and pedestrian traffic on the 'inner' streets, presented in Figure 1. Barcelona aims to have green space available for everyone within a 200 m walk from their home (Ajuntament de Barcelona, 2021). While other amenities are not specifically named, the concept is aimed at improving traffic safety, walkability, and bike ability for residents, and promotes activity in the streets.

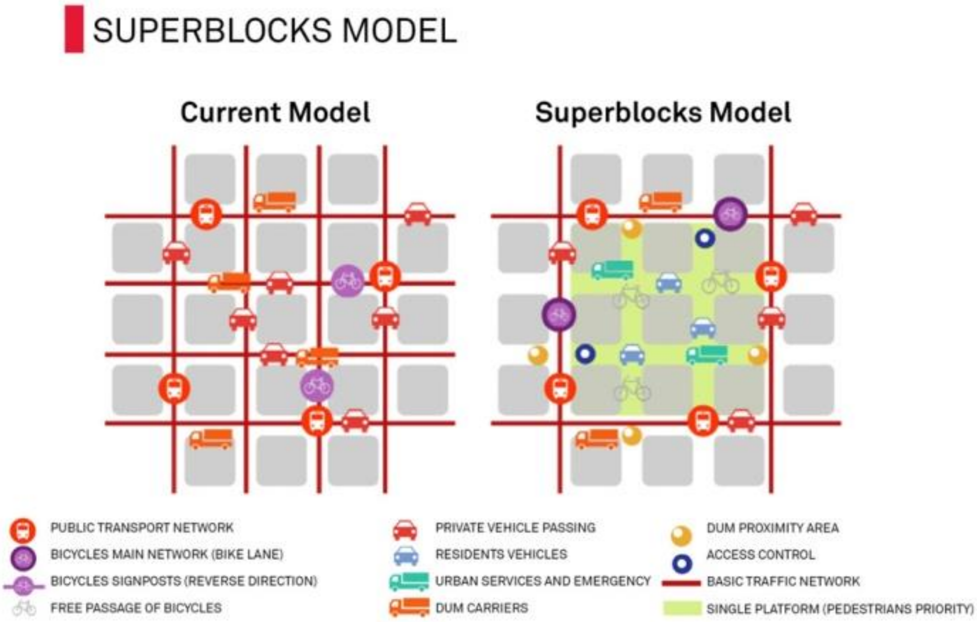


Figure 1: *Barcelona Superblocks (Ajuntament de Barcelona, 2014)*

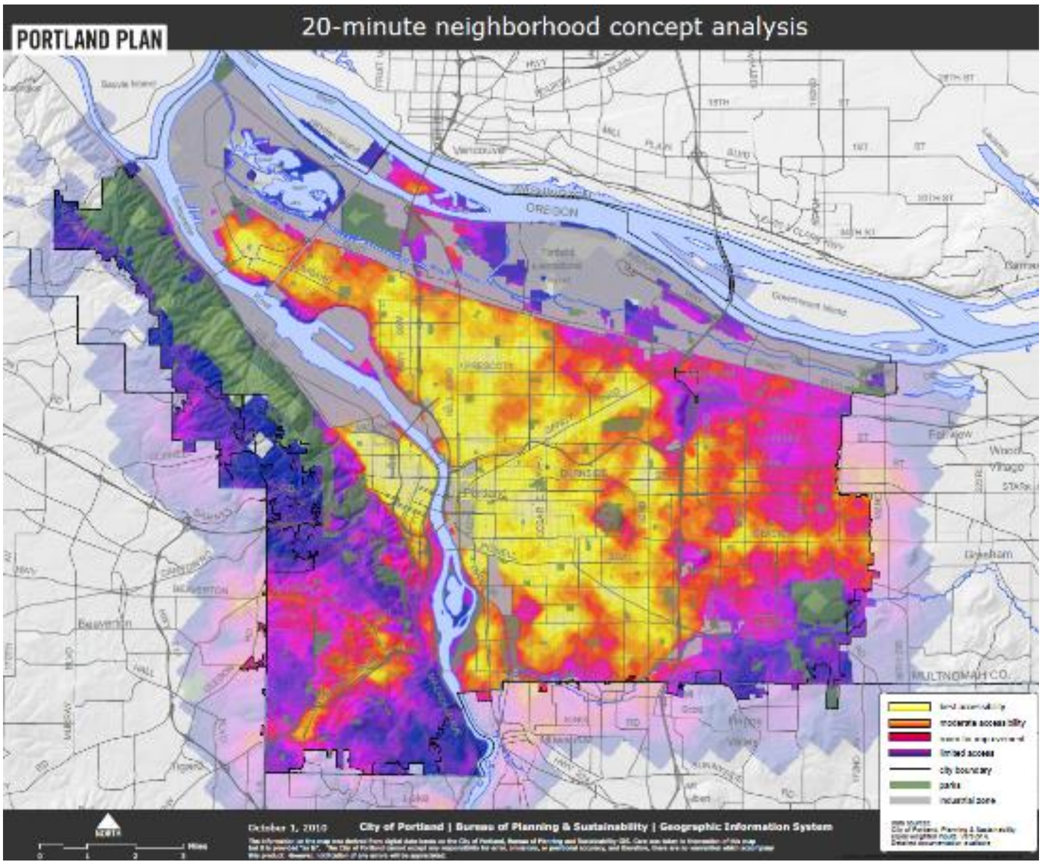


Figure 2: *Portland 20-minute neighbourhood index (City of Portland, 2010)*

In Portland, USA, the 20-minute neighbourhood has been a common term since before 2010. The 20-minute neighbourhood is aimed at walking and walkability. Amenities such as schools, grocery stores, public open spaces and recreational facilities should be accessible for all residents within a 20 minute walk (City of Portland, 2013). Figure 2 presents a map of the Portland 20-minute neighbourhood index showing best walkability in the city centre and lower in the suburbs. The index is combined from accessibility measures, percentage sidewalks in a neighbourhood, and slope (City of Portland, 2010).

The Town and Country Planning Association in the UK defined 20-minute neighbourhoods with the 15-minute city concept in mind. 20-minute neighbourhoods provide access to health facilities, schools, green space, and jobs within 20 minutes walking or cycling. They also promote the importance of local food production and affordable homes (TCPA, 2021).

These 20-minute neighbourhood concepts are thus very similar to the 15-minute city concept, and shows the adjustability of the concept. All of these aforementioned concepts touch upon or are similar to the idea of the 15-minute city, albeit with slightly different dimensions and priorities. A synergy of digitalization in the smart city, traffic safety and space for people in the Barcelona super blocks, and proximity of services in the 20-minute neighbourhoods come together in the 15-minute city concept as outlined in Moreno et al. (2021).

A.2 Travel behaviour

Through analysing travel behaviour and accessibility analysis, 15-minute cities have been measured before (Carpio-Pinedo et al., 2021; Gaxiola-Beltrán et al., 2021; Graells-Garrido et al., 2021). Graells-Garrido et al. (2021) analysed movement in and between neighbourhoods in the metropolitan area of Barcelona and discovered that people tend to travel to other neighbourhoods for services like retail and education. However, they could not account for bias in socio-economic and demographic groups because anonymised cell phone data was used. Gaxiola-Beltrán et al. (2021) assessed accessibility to essential services in the mega-city Monterrey using active modes and found that the district they analysed does not meet the requirements of a 15-minute city yet, because not everyone can reach schools or healthcare within a 15-minute walk. Finally, Carpio-Pinedo et al. (2021) measured the potential for walkable trips through looking at land use mix. If land use is mixed, origins and destinations appear at walking distances. The analysis concerned the metropolitan area of Madrid (including suburbs) and was based on individual building level spatial data.

Many studies have investigated which factors influence travel behaviour of individuals and to what extent. Verduzco Torres et al. (2021) considers 4 types of factors that could influence a decision on mode choice and travel distance. The theory of planned behaviour (Ajzen, 1991) states that psychological or reasoned factors consist of attitude, subjective norm (the norm in the location, culture), and perceived behavioural control. Unreasoned factors are constituted by habits. Socio-demographic factors such as gender, age, and income may have an influence on travel behaviour and have been studied in many cases, sometimes with contradicting results. Lastly, built environment factors such as land use and infrastructure quality influence travel behaviour.

Age has been found to have significant associations with the likeliness of cycling to work, but both negative and positive ones. Heinen et al. (2012) found through an internet survey with over 4000 respondents that older people (>60 years) are less likely to bike to work than younger people. However, Gao et al. (2019) found that this group is more likely to bike to work, using data from the 2014 mobility panel Netherlands (MPN). Different methods might explain the contradicting results. Another factor possibly influencing results is selection in Heinen et al. (2012), where only employees in 4 Dutch municipalities (Zwolle, Delft, and 2 municipalities adjacent to Delft) were invited for the survey, whereas the MPN contains respondents from a wider variety of residential locations.

Furthermore, having the habit of cycling seems to increase the likeliness of cycling for commuting. In this line, migrant status and time spent in the Netherlands also has an influence on choosing cycling as a mode. Native Dutch people are more likely to choose a bike, as well as people living in the Netherlands relatively longer (Verduzco Torres et al., 2021).

Built environment and residential location could also influence people’s mobility and activity pattern. The Dutch national travel survey in 2016 showed that people that live in less densely populated places travel more by car and less by bicycle, and also travel longer on average (CBS, 2019a). Thus, it is important to involve lower density suburbs (that are often connected to larger agglomerations) in 15-minute city analysis, since these are often the problem areas with lower density where people tend to travel more by car.

A.3 Accessibility

Many different methods for measuring accessibility by active transportation exist. Like other accessibility measures, they can be categorized into 4 groups; distance-based, gravity-based, infrastructure-based, and Walk Score types which consider multiple dimensions and are more like a composite measure of walkability or cyclability (Vale et al., 2016). Distance-based measures consider only the travel time or distance from an origin to destinations and could either count the destinations within a certain threshold, the closest destination(s), or the mean distance or travel time to the closest opportunities. These accessibility measures require origin points, places of interest, and a network data set that includes pedestrian and cycle paths and are relatively simple to compute. However, the distance threshold is arbitrarily chosen and could have a large influence on the number of opportunities that could be reached. Apparicio et al. (2008), Mavoa et al. (2012), and Yigitcanlar et al. (2007) use multiple thresholds in order to (somewhat) combat this problem. Methods for calculating distance vary from Euclidian or Manhattan distance to network distances. Apparicio et al. (2008) found that results from Euclidian and Manhattan distance correlate highly with results generated by using network distance. However, network distance is a more accurate measure and current technology, and data allows for relatively simple implementation.

Two-step Floating Catchment area (Luo & Wang, 2003) is a combination of two accessibility measures that takes into account the supply and demand of a service. It is often used to measure accessibility to healthcare (GP) or other service providers with capacity constraints. The measure can be cumulative and based on floating catchment areas, where a maximum travel time is set. Otherwise, the measure can be adapted to be gravity-based, using a cost-function. The measure could be interpreted as the ratio of supply of a service to demand of the population.

Gravity-based measures assign weights to opportunities/destinations based on their distance or travel time from the origin point, and possibly other factors such as floor space (Sun et al., 2012) or number of employees (Kockelman, 1997; Manaugh & El-Geneidy, 2012). These measures are more realistic because destinations further away are less attractive than ones closer. Furthermore, they do not have the problem of the arbitrarily chosen distance threshold but do require more computation and historical travel data to fit a decay or impedance function needed for calculating the accessibility.

Infrastructure-based accessibility measures do not take into account origins and destinations or opportunities in the area, but only consider the network itself. Characteristics such as type of cycle path, quality, sidewalk dimensions, and safety could be used to score the network. Many studies also use topology of the network such as connectivity, which is adequate to capture things in the network that could form an obstacle to pedestrians and cyclists, such as large roads that have to be crossed. However, this measure is not appropriate for the 15-minute city because travel time is not considered, while that is one of the main dimensions in the 15-minute city.

Lastly, some composite measures such as and its cyclability measure Bike Score (Winters et al., 2013), which is based on Walk Score (Walk Score, 2010), have been developed to capture both network qualities like the infrastructure-based measures, and travel time to opportunities much like the distance- or gravity-based measures. Bike Score uses a gravity-based approach and combines this with topological characteristics like connectivity and other aspects such as bike lane presence, hills, and destinations (Winters et al., 2013).

The spatial aggregation method in accessibility analysis could greatly influence the results of the analysis. Building level analysis has been shown to provide more accurate and smooth results, even when aggregating after calculation for the purpose of representation (Benenson et al., 2017). However, building level analysis requires a lot of data that might not be available everywhere. Census blocks, neighbourhoods, or grids provide other options for spatial aggregation, but a large block or cell could lead to inaccurate results because travel time from the edges differ greatly from those in the centre (usually taken as the origin point). Apparicio et al. (2008) found that population weighted centroid provided more accuracy in accessibility analysis than geometric centre of census blocks, meaning that this could pose a viable solution to deal with lack of data and computational power needed for building-level analysis. Furthermore, using census blocks indicates the impression that there are boundaries between them. However, political or institutional boundaries do not influence travel behaviour. Contrarily, physical boundaries such as large crossings or highways have a much larger influence on travel behaviour.

A.4 Composite indicators

Bike Score is an example of a composite indicator, consisting of multiple variables combined into one measure. Composite indicators provide a quick and easy way to compare things such as the cyclability of different neighbourhoods in a city, because they measure complex multidimensional concepts that cannot be captured by a single variable or indicator (OECD, 2008). However, if poorly constructed, composite indicators may send misleading information, or could hide shortcomings in one dimension leading to misinterpretation. Thus, a transparent (weighing) scheme and construction of a composite indicators is important. Weng et al. (2019) used a modified version of Walk Score, combining the indicators of walk score with walking accessibility to different types of amenities, and determined weight of the amenities based on a survey among 132 respondents stating importance of each amenity type. Thus, this indicator captured not only the quality of the pedestrian design, but also accessibility to different types of services. In order to construct a high quality composite indicator, the process needs to be transparent and start with a theoretical framework that links the different variables and sub-groups. To prevent from losing the nuance that the individual variables provide about a phenomenon, the composite indicator could be deconstructed into sub-groups or individual variables, showing their scores or values. This way, problems and good practice examples could be identified. Some methods for weighting the individual variables are equal weighting, analytical hierarchy process, or statistical methods such as factor analysis, which OECD recommends for economic composite indicators (OECD, 2008). However, in transportation, importance of different variables can be identified through either stated preference (Weng et al., 2019) or revealed preference in travel behaviour.

Automatically recorded travel behaviour such as in the Dutch mobility panel can provide data to determine the weighting through revealed preference.

Uncertainty analysis (UA) and Sensitivity Analysis (SA) can then provide insights into how each sub indicator contributes to the output of the composite indicator and its uncertainty or variance. In uncertainty analysis (UA), the way in which uncertainty in the sub indicators affects the value of the composite indicator under study is analysed. In Sensitivity analysis (SA), it is determined how much the uncertainty of each factor is represented in the variance of the metric output (Saisana et al., 2005). Uncertainties in composite indicators can stem from different steps or decisions in creating the composite indicator, such as (1) selection of sub indicators, (2) data selection, (3) data editing, (4) standardization method, (5) weighting method, (6) values of the weights, and (7) formula for the composite indicator (Saisana et al., 2005, p. 309). Through, SA, a composite indicator gains more transparency and represents not only an arbitrary value, but rather a distribution of outcomes (Saisana et al., 2005).

A.5 Research gap and contributions

Currently, the concept of a 15-minute city has been qualitatively defined in Moreno et al. (2021) and interpreted in other studies (Gaxiola-Beltrán et al., 2021; Graells-Garrido et al., 2021; Pozoukidou & Chatziyiannaki, 2021). (Abdelfattah et al., 2022) used Walk Score and density to map the potential for 15-minute city in Milan, and (Gaglione et al., 2022) carried out an analysis for walking destinations to health centres and grocery stores in different districts in Naples. Accessibility analysis in (Chabaud et al., 2022) to different urban services was focused on walking as well, and labelled Barcelona as a 15-minute city. (Caselli et al., 2022) also investigate walkability to different amenities in a single neighbourhood.

Thus, all current analyses focus on walking. As stated in section A.1, cycling is a very popular mode of transportation in the Netherlands that is accessible to many people. This study aims the analysis on cycling, although it recognizes the importance of walking in the 15-minute city, aimed at inclusion and social interaction.

While there are many analyses of places as 15-minute cities, there are still dissimilarities in the amenities included in analyses, although these and the need for them might differ per case or location. Dimensions such as density and land mix, the catchment area of different amenities, amount of people serviced by different amenities, and the distances people are comfortable biking have not yet been fully quantified and might differ between countries or cultures. This flexibility of the concept is also acknowledged in (Chen & Crooks, 2021), who map use an agent-based model to map walking communities in Queens, New York City.

Furthermore, needs for different socio-demographic groups within the 15-minute city have not yet been investigated, and if these are different at all. Additional exploration is needed to determine if and how the concept fits in the Dutch lifestyle of being used to cycling and often biking further than 15 minutes without problem, or to what extent travel behaviour in the Netherlands already takes place within 15 minutes from home by bike. Therefore, in this thesis recorded travel data of people in the Netherlands will be used to explore the 15-minute city concept in a Dutch setting, and to operationalise the concept

Lastly, many accessibility studies including cycling already exist, but often also include public transport (Mavoa et al., 2012; Yigitcanlar et al., 2007), or only consider one type of amenity (Apparicio et al., 2008; Apparicio et al., 2007; Páez et al., 2012). The 15-minute city is a holistic concept and cannot be properly captured by only considering one type of amenity. To conclude, a city (Utrecht) in the Netherlands will be assessed with regard to the established requirements and dimension of the 15-minute city. Additionally, through spatial analysis and regression, factors relating to the 15-minute city and its population will be investigated to find spatial inequalities.

B. Extended description of study area

Utrecht is the first city in the Netherlands with ambitions to become a 10-minute city, based on the 15-minute city concept. Their strategy for achieving this is based on creating multiple centres and thus transitioning from a monocentric city to a polycentric one. Growth should be within the city limits through increasing density, first in the inner city centres, and then at the edges. A mixed use of space also contributes to this vision, and serves to create more interaction between people, groups, and to make the city 'more interesting' (Gemeente Utrecht, 2021b). All of this is in line with the 15-minute city concept and has as goal to reduce (necessary) longer trips.

In the Netherlands, most cities are medium-sized cities, and there are no cities with more than one million inhabitants. They range from 100.000 inhabitants to almost one million inhabitants (Amsterdam). However, some metropolitan areas consist of larger agglomerations, such as the Rotterdam-Den Haag area, Amsterdam with its suburbs, and Utrecht with its suburbs.

Figure 3 shows Utrecht's vision with regards to which services should be accessible within 10 minutes walking or biking. Some of these functions could be fulfilled in one space, such as playing, nature, resting and cooling down can all be done in a park. In addition to the six categories as defined by Moreno et al. (2021), energy production and access to public transit are included. Some strategies that are proposed to further this vision are investing more in small scale economy, shared workspaces, multifunctional use of space (spatial as well as temporal). Their goal is a more vibrant and inclusive city. Even though they mention that workspaces should be available in every neighbourhood, they also recognize that some forms of industry have to be separated from other functions in the city, such as manufacturing industry. The polycentric structure would ideally have mixed use centres located in Leidsche Rijn, Papendorp, Westraven, Lunetten Koningsweg, Utrecht Science Park, and Overvecht. These can be seen in Figure 4.

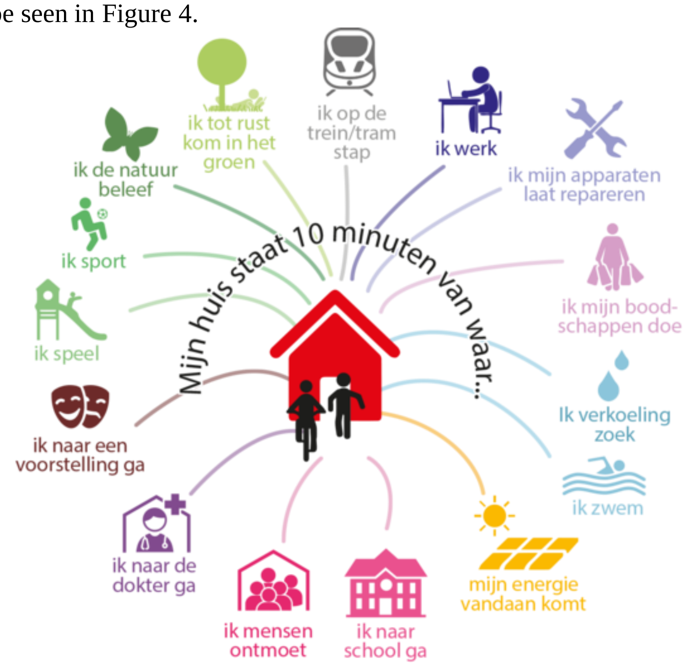


Figure 3: *Utrecht 10-minute city strategy* (Gemeente Utrecht, 2021b)

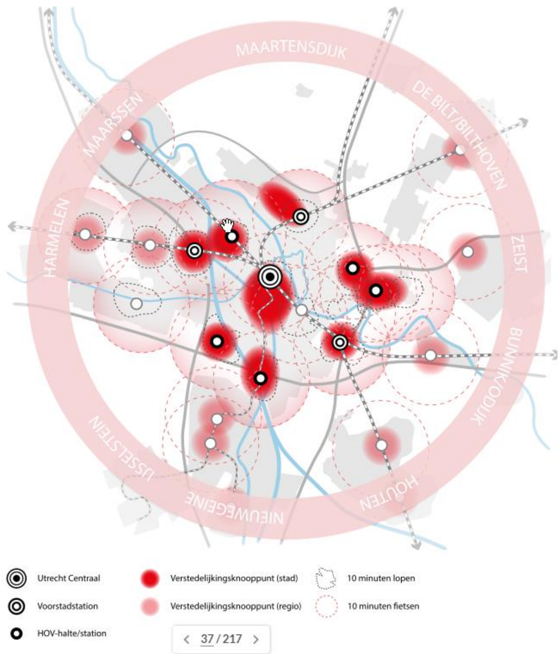


Figure 4: *Polycentric Structure of Utrecht* (Gemeente Utrecht, 2021b)

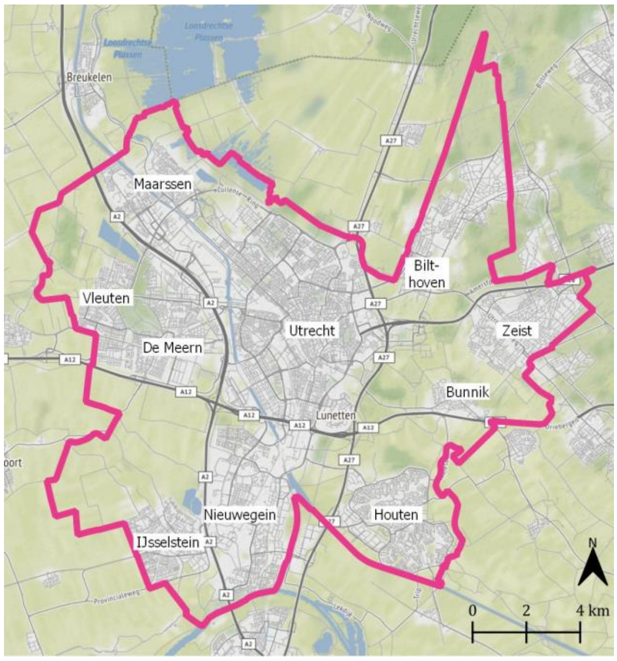


Figure 5: *Study area*

The case study in this research is an accessibility analysis in the metropolitan area of Utrecht. For this study, the metropolitan area of Utrecht includes the municipal area of Utrecht, and the towns Nieuwegein, Maarssen, Houten, Zeist, De Bilt, Bilthoven, and Bunnik. These towns were chosen because they are represented in the spatial strategy as new/existing centres for the polycentric structure. The study area consists of the neighbourhoods that have an urbanisation level of 1000 addresses/km^2 or higher, including the areas between these selected neighbourhoods, so as to not have gaps in the study area. The exact study area is shown in Figure 5.

The city of Utrecht is well-known as one where many people cycle due to the cycle-friendly infrastructure. 48.5% of all trips within the city of Utrecht are by bike, and 27.6% of all trips within, to, and from Utrecht are by bike. The percentage of trips by bike that take place within the city is exceptionally high in Utrecht, compared to Amsterdam (42.6%). 29.4% of all trips within, to, and from Amsterdam are by bike. In the whole country, 27.9% of all trips are by bike (CBS & RWS, 2020). Utrecht is much smaller than Amsterdam in area (99 km^2 vs. 219 km^2), which could explain the higher percentage of cycling trips within the city. A survey in 2019 showed that 87% of people in Utrecht is (very) satisfied with the accessibility of the city centre by bike, and that 58% chooses to cycle when they visit the city centre. Furthermore, 76% was (very) satisfied with guarded bike parking facilities in the city and 86% was (very) satisfied with the guarded bike parking facility at Utrecht Central station (Gemeente Utrecht, 2020).

Utrecht plans to increase the amount of cycling through smart investments in the current cycling network. Through these investments and increased capacity the cyclists will be distributed more appropriately over the available space. Main bicycle routes to and from the city centre will be improved or added, as well as main routes around the city centre to alleviate congestion in that area. Simultaneously, quiet bike routes in residential areas will provide safe and inclusive cycling opportunities for all ages and abilities (Gemeente Utrecht, 2021a).

Utrecht has 359370 inhabitants (CBS, 2021c), and 181775 households. A large number of households are one-person households (50%), compared to the whole of the Netherlands (38%), see also in Table 3. On average, a household in Utrecht has 0.58 cars. (105410 cars and 181775 households). 67% of Utrecht households has one or more cars. 50% has one car and 17% has more than one car (Gemeente Utrecht, 2020) (CBS, 2020b).

C. Extension of methodology

In addition to the methodology for the research described in the main report/text, in this section the methodology applied for response weighing of the survey data (NVP), linear regression and ANOVA, distance decay functions, sensitivity analysis, and spatial regression are explained.

C.1 Response weighing

When certain groups are over- or underrepresented in survey data such as with the subset of recorded trip data from the NVP used in this study, post-stratification or weighing the data is sometimes done to make the sample more representative. Thus, results from analyses will be more transferable to the entire population and conclusions drawn from these more grounded in reality. Furthermore, results and conclusions drawn from biased or unrepresentative response data could easily lead to faulty interpretations (J. Bethlehem, 2008). However, the precision of estimators can be less precise after weighting because variance and standard errors increase (Kalton, 1983; Vartivarian, 2004).

In this study, it was chosen to apply weighting of the data because in the NVP data, some age groups were not representative. Several methods of weighting were considered. A frequently used method is post-stratification, in which strata (combinations of variables) of the population are compared to those of the sample to calculate a weight for each stratum. However, this method requires that all present (in sample) combinations of variables are known for the *goal* population, but this is not the case. Linear or multiplicative weighting (or iterative proportional fitting) can be applied when post-stratification is not possible. Of these two, linear weighting is based on linear regression but could also lead to negative weights which is undesirable. Iterative proportional fitting only leads to positive weights, but can only be used with noncontinuous variables (J. Bethlehem, 2008). Since the subset of the NVP user data only contains noncontinuous data, it was chosen to apply iterative proportional fitting.

Using ideal values of the variables as obtained from CBS data, all users in the dataset get a weight, where underrepresented groups get a higher weight and overrepresented groups a lower weight. Starting with the age, in an iterative process the multiplication for each variable is determined to adjust the weights of the people with that variable/characteristic, where the weights are initialised at 1 (J. Bethlehem, 2002; Deville & Sarndal, 1992).

$$multiplier = \frac{ideal\ value}{w_s/w_{tot}} \tag{1}$$

The maximum multiplicator of the loop is saved and used to determine the margin between the multiplicator and the value 1, since when ideal values are reached, the multiplicator of each variable would be 1. Thus, a smaller margin is better. A while loop reiterates the process of calculating this margin and a maximum margin has been set at 0.1, as well as the maximum number of while loops at 30. This is sufficient because after 20 loops the margin hardly changes anymore. The final margin is 0.45.

$$margin = abs(1 - max(multiplier)) \quad (2)$$

When this margin is small enough and the loop stops, the weights of all users are saved and can be used to recalculate the demographic characteristics, and trip data. The sum of the weights equals the same sample size as originally.

C.2 Statistical analysis

Two techniques of statistical analysis are applied on the NVP data, to determine if cycling speed in the 15-minute city metric should differ across groups. Analysis of variance (ANOVA) is first carried out to investigate if there are significant differences in cycling speed between age groups, household types, or density of residential location. Then, linear regression is applied to determine to how strongly these different characteristics influence cycling speed, as well as gender.

C.2.1 ANOVA

As exploration of the data, ANOVA is applied first to investigate if there are significant differences in cycling speed between age groups, household types, and residential density. Since most variables in the dataset (except age and household size) are on a nominal or ordinal scale, simple bivariate correlation was not appropriate to determine if these independent variables had effect on the dependent variable (speed).

ANOVA tests if the means for two or more groups are significantly different, the null hypothesis is that all group means are equal. There are several assumptions that have to be met in order to carry out ANOVA:

1. The dependent variable (DV) should be metric, interval or ratio-scaled. The DV used in this study is speed, measured in km/h, which is a continuous metric variable.
2. The DV should be normally distributed. As shown in Figure 13, the cycling speed is normally distributed.
3. The variance among the groups should be approximately equal (homogeneity of variance). Levene's test is applied to determine homogeneity of variance in each case.
4. Observations are independent of each other. For ANOVA (and regression analysis) the average cycling speed per user was calculated, thus each observation is from a single user, and there are no repeat observations.

C.2.2 Linear regression

Regression analysis can be used to determine influence of characteristics or independent variables on a dependent variable. A multiple linear regression analysis with cycling speed as dependent variable is carried out to determine cycling speed of people with different characteristics. Independent variables consist of personal characteristics as well as residential location and household characteristics. Variables are listed in Table 2 below.

Table 2: *Variables in regression analysis*

Variable	Description	Type
Gender	Female = 0, Male = 1	Nominal (binary)
Age group	15-24; 25-44; 45-64; 65+	Ordinal
Density	Medium density: 1000 – 1500 addresses/km^2 High density: 1500 – 2500 addresses/km^2 Maximum density: > 2500 addresses/km^2	Ordinal
Household type	Households with children (under 18) Adult households Single person households	Nominal

For regression analysis, some assumptions have to be met:

1. The dependent variable should be measured on a continuous scale and measurements should be independent of each other. Speed in km/h is measured on a nonnegative continuous scale. Average user speeds are considered in this analysis together with the characteristics per user to ensure independence of measurements. Recorded trips are not independent measurements since one user makes a number of trips.
2. The sample size should be preferably 20 times the amount of variables. The sample used in regression analysis consists of 4719 users, and there are 8 variables, so this assumption is satisfied.
3. A linear relationships between the DV and independent variables. This is normally tested using scatter plots. However, since all independent variables are nominal or ordinal, scatter plots are not appropriate.

4. Residuals are normally distributed. This is tested with a residual plot after the construction of the model, see Figure 14.
5. No multicollinearity. The independent variables should not be highly correlated with each other. Correlations of >0.8 are considered high.

The model for a multiple linear regression is:

$$y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon \tag{3}$$

Where y = the prediction value of the DV. β_0 to β_n denotes the coefficient, with β_0 being the y-intercept. X_1 to X_n are the independent variables, and ε is the error term that is not explained by the variables. In the case of nominal variables, a dummy variable is used, where the dummy variable is 1 if true, or 0 if not true. For example, a coefficient for gender being male would be multiplied by 1 for males, but 0 if female.

One model with all variables from Table 2 is created.

C.3 Distance decay functions

The cost function is a unique distance decay function for each destination type. Since people are willing to cycle further for amenities such as theatres than for grocery stores, a function per destination category is warranted. The distance decay functions have been fitted using the recorded trip data, specifically the cycling trips. Outliers have been removed from the data. For example, some cycling trips were over 100 minutes long. These might be faulty measurements, or in the case of recreation trips, may be trips that are just cycling for the purpose of exercise or entertainment instead of visiting a specific destination. In order to fit the distance decay functions, the trips have been grouped by travel time (rounded to whole minutes), after which the probability of each travel time was calculated:

$$prob = \frac{sum(weight_i)}{sum(weight)} \tag{4}$$

Thus, the weights of each trip as determined through the survey response weighing has been incorporated as well. The results were ordered by trip duration and cumulative probabilities were calculated. The values used for fitting the distance decay function is 1 – cumulative probability, because the function starts at 1 and slopes down. It was chosen to fit 2 different functions and pick the best one based on visual results and AIC value, a log-logistic function (5) and an exponential function (6):

$$f(c_{ij}) = \frac{1}{1+e^{\beta_1 * c_{ij}^{\beta_2}}} \tag{5}$$

$$f(c_{ij}) = \beta_1 * e^{\beta_2 * c_{ij}} \tag{6}$$

Values for β_1 and β_2 were determined through optimization in python using the scipy package (Virtanen et al., 2020). In every case, the log-logistic function was a better fit.

Including a threshold for a maximum travel time d_0 in the city (e.g., 15 minutes) leads to the following cost-function/distance decay function:

$$f(c_{ij}) = \begin{cases} \frac{1}{1+e^{\beta_1 * c_{ij}^{\beta_2}}}, & if\ tt \leq d_0 \\ 0 & otherwise \end{cases} \tag{7}$$

This way, the method can simply be adapted to fit different cases; for 15-minute cities, 10-minute cities, or any other threshold.

D. Extension of Results

D.1 Descriptive statistics

Descriptive statistics of the panel users and recorded trips provide an overview of the demographics and trip characteristics used in this study. Table 3 shows the demographic characteristics of the NVP dataset, as well as of the whole Netherlands, the selected study area, and all regions with urbanisation level 1,2, and 3.

Table 3: *Demographic characteristics of all of the Netherlands, urbanisation level 1, 2, and 3, and NVP dataset (N=8,214)*

	NL - % (n) a,b,c	Urb. 1,2,3 - % (n) d	NVP dataset (after weighting) - %
Age group			
0-14	10.5 (1,815,614)	15.8 (1,781,040)	0
15-24	11.8 (2,031,881)	12.6 (1,415,890)	13.7
25-44	25.7 (4,443,850)	26.5 (2,981,990)	30.0
45-64	29.8 (5,141,541)	26.8 (3,019,890)	34.5
65+	19.8 (3,457,535)	18.3 (2,063,265)	21.8
Household types			
Single person	38 (3,097,117)	43.1 (2,322,740)	43.1
Multi without children	28.9 (2,331,454)	26.1 (1404035)	26.1
Multi with children	32.5 (2,614,872)	30.8 (1,660,470)	30.8
Unknown			0.03
Gender			
Male	49.7 (8,686,536)	49.2 (5,541,860)	49.2
Female	50.3 (8,788,879)	50.8 (5,721,705)	50.8
Density			
Max	24.6 (4,298,952)	34.8	34.8
High	30.4 (5,312,526)	43.1	43.1
Medium	15.6 (2,726,165)	22.1	22.1
Occupation			
Employed	33.4 (5,835,788)		53.3
Retired	18.0 (3,145,575)		17.7
Governmental	5.2 (908,722)		7.4
Incapacitated	3.2 (559,213)		5.8
Entrepreneur	6.3 (1,100,951)		5.7
At home	23.9 (4,176,624)		4.6
Unemployed	3.8 (664,066)		3.2
Studying	6.2 (1,083,475)		2.1
Unknown	-		0.2

a (CBS, 2021a), b (CBS, 2021b), c (CBS, 2020a), d (CBS, 2019b)

Response weighing is applied to approach a more representative sample, as described in C.1. The distributions of the NVP dataset after weighing are included in the last column. Note that the ‘at home’ category under occupation also includes children under 18 that do not have a job.

After weighing, the distribution of the sample in the dataset is quite representative of the people living in urbanisation levels 1,2, and 3 in the Netherlands. There are no children under 15 in the Netherlands mobility panel, and people aged 45 to 64 are somewhat overrepresented. Furthermore, occupation data specific for these urbanisation levels is not available, but compared to the occupation of everyone in the Netherlands, employed people are overrepresented in the NVP dataset, but this is also due to the exclusion of children under 15.

The modal split in the NVP data is compared to modal split of the Netherlands and of the Utrecht municipality, shown in Figure 6. It should be noted that while OViN and ODiN are each based on one whole year, the modal split of the NVP dataset is based only on a number of months, some of which were during the corona pandemic. Furthermore, the NVP dataset did not contain any trips by train and a very limited amount of trips by other public transit, because only trips starting at home were included in the dataset. Mode ‘other’ containing boat and plane trips are also not present because of this reason. Other than this, the rest of the distribution is somewhat similar to those of the Netherlands and Utrecht, with most trips by car, the second largest share by bike and 12% by foot.

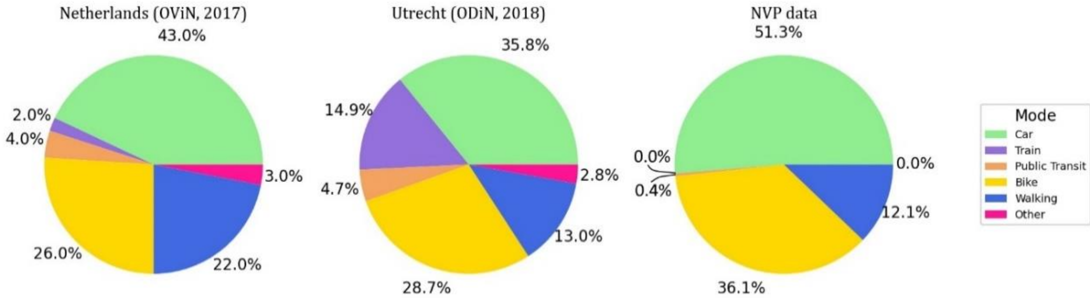


Figure 6: *Modal split*

Figure 7 shows the distribution of trips to different destination types. In this figure, trips from all modes are included to see what destinations people visit most often regardless of mode. Weights for the metric are determined based on this distribution of visits to destination types. and Figure 8 and Figure 9 show trip distributions of different household types and different age groups respectively.

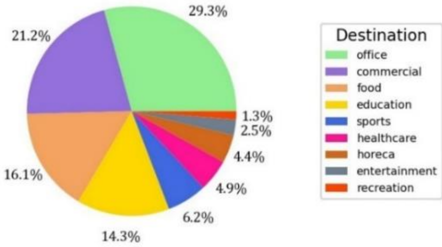


Figure 7: *Percentage of trips per destination type*

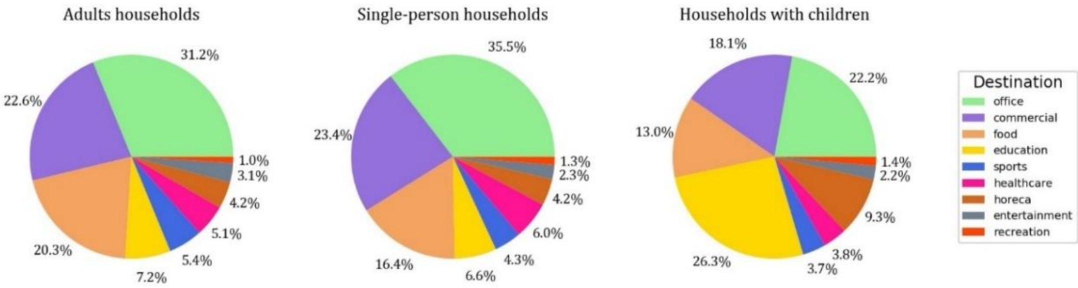


Figure 8: *Percentage of trips per destination type, by household type*

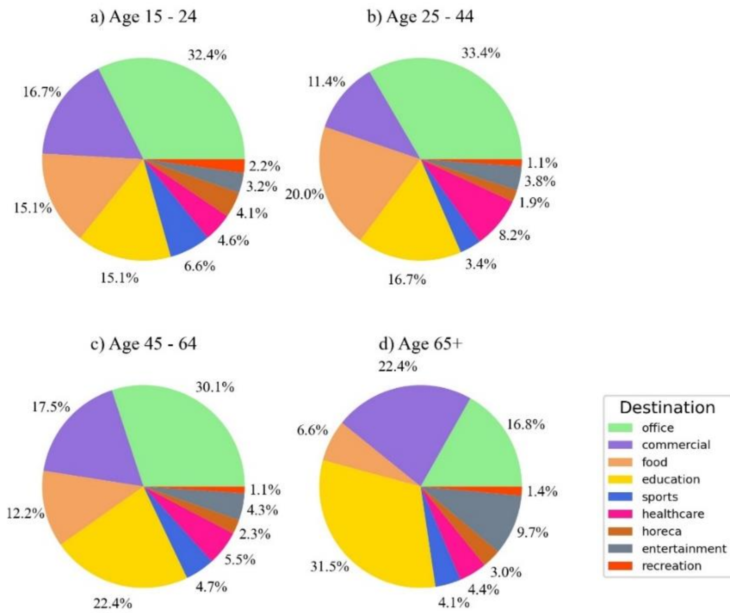


Figure 9: *Percentage of trips per destination type, by age*

Overall, most trips were made to the office or work. The relatively high number of trips to the office can be explained by the fact that employed people were overrepresented in the sample, even though some of the data is from during the corona pandemic. It is clear that people aged over 65 travel to the office less. 21% of all trips go to commercial destination types, and 16%, slightly less, to commercial type food, such as grocery stores and deli shops. 14% of all trips went to educational institutions and include those of caretakers bringing children to school. Finally, the number of recreation (1.3%) and entertainment (2.5%) trips seem especially low. While the low number of entertainment trips could be explained by the pandemic, the number of recreational trips is due to the difficult nature of classifying these trips. Since trips in the NVP data were selected based on their destination as explained in section 3.2.1, recreational walks or bike rides may have been omitted due to their not always having a specific destination, i.e. a round trip from home to home. Furthermore, Figure 9 shows that while the first three age groups have similar travel patterns, the 65+ has a more distinctive pattern, with very few trips to grocery and other food stores, and many to educational destinations. Perhaps, many grandparents in the Netherlands pick up their grandchild from school. People aged 65 and over also make more trips to entertainment destinations, most likely because they have more time for this during retirement.

Finally, in Figure 8 a distinctive pattern for households with children can be seen. These people travel more to education, and less to the office, commercial, and food destinations than the other household types.

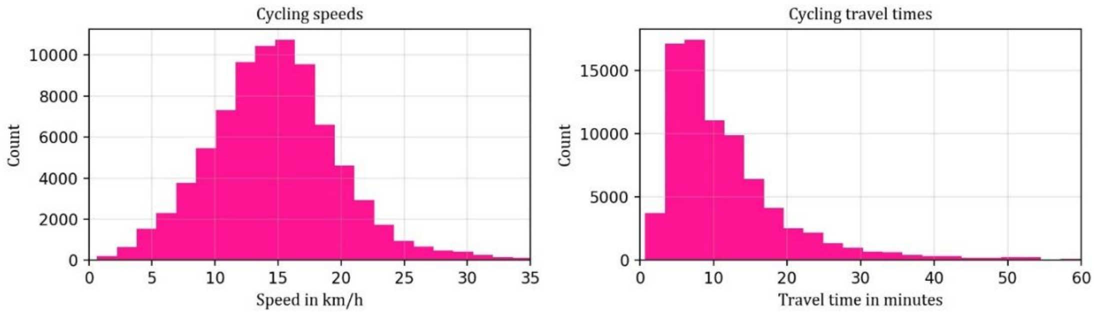


Figure 10: *Cycling speed and cycling travel times*

Figure 10 shows all recorded cycling speeds and travel times in the dataset. The distribution of speeds is a normal distribution with mode at 15 km/h. There are some outliers in the dataset with speeds over 30 km/h, which could be a faulty measurement or a speed pedelec (not recognized as a separate mode of transportation in the NVP data). There are also outliers at the lower boundary with speeds close to 0. A possibility is that these were walking trips, or very short trips for which measurement is hard to make. Furthermore, travel time is skewed to the left as expected. Mode is around 7 minutes, and the mean cycling travel time for all trips is 12 minutes.

Table 4: *Summaries of recorded cycling trips*

Destination	All	Jobs	Commercial	Food	Education	Sports	Healthcare	Restaurants, bars	Entertainment	Recreation
Trip duration (min)										
mean	12.08	15.71	10.32	8.78	10.14	10.93	11.79	15.91	13.65	19.63
std	10.38	11.46	8.94	7.91	7.86	8.30	8.42	16.35	11.56	22.38
min	0.72	1.22	1.18	0.90	0.75	0.98	0.72	1.38	1.48	1.90
max	215.83	215.83	173.08	197.05	136.53	146.75	95.15	193.62	116.52	196.18

Table 4 shows summary statistics of trip durations by bike in the dataset. There are very high outliers in every category. These might be errors in the recording such as wrong mode, or a faulty determination of start and/or stop time. The categories job, bars and restaurants, and recreation have an average travel time of more than 15 minutes. These also have a higher standard deviation, especially recreation since it can be conceived that some recreation cycling trips are purposefully a bit further. The standard deviation in travel time to bars and restaurants is also relatively high; some people have to travel further to go out for food, while others do not have to travel far at all. Trips to buy food are on average the shortest at an average travel time of almost 9 minutes, and a relatively low standard deviation which indicates most people are able to and also choose to do their groceries within 15 minutes cycling of their home.

Table 5 presents the cycling trip rates from the NVP dataset. It should be noted that these are only cycling trips that start at home and go to one of the destinations included in the data (see section 3.2.1 in main text). It is most likely not an accurate absolute number of cycling trips per day. However, the different groups can be compared to each other. Overall average trip rate was 0.083 trips/person/day.

Differences between income groups are quite small, although higher incomes have a slightly higher trip rate. A larger difference can be found between the households with children (young or adolescent) and without children. Households with children cycle much more in the Netherlands. Furthermore, a large difference can be observed between people aged over 65 and under 65. Older people cycle less. Residential density does not seem to matter much in terms of cycling trip rates.

Table 5: *Trip rates for different groups*

Variable	Trip rate (cycling trips/person/day)
Income	
Minimum	*0.07*
Lower than modal	*0.08*
Modal	*0.07*
One to two times modal	*0.08*
Two times modal	*0.09*
Higher than two times modal	*0.09*
Household type	
With young children	*0.11*
With adolescent children	*0.10*
Single	*0.07*
Adult household	*0.07*
Age	
< 65 years	*0.09*
> 65 years	*0.06*
Residential density	
Medium density	*0.08*
High density	*0.09*
Maximum density	*0.07*

D.2 ANOVA on cycling speed

ANOVA analysis was carried out to determine if there were significant differences in cycling speed between age groups, household types, and urban density. The ANOVA was carried out after weighting the users in the dataset as explained in C.1.

Age groups and cycling speed

While the first two and the last assumption are met, the third assumption on equal variance is not met (see section C.2.1). Table 6 shows the age groups, average cycling speed in km/h and the sample size of each group. Because the group sizes are very different, Levene's test was applied to test for equal variance. The null hypothesis that variance is equal across all groups is tested.

Table 6: *Descriptive statistics of age groups and speed*

Group	Mean speed (km/h)	Group size
15-24	14.99	720
25-44	14.43	1292
45-64	14.87	1615
65+	14.14	986

Levene's test indicated unequal variances ($F = 5.66$, $p<0.001$). Thus, the assumption is violated and results from one-way ANOVA cannot be interpreted.

Household types and speed

Table 7 presents the mean cycling speed of different household types and their group sizes. Because group sizes are very different, Levene's test is applied again to test for homogeneity of the variance.

__Table 7:__ Descriptive statistics of household types and speed

Group	Mean speed (km/h)	Group size
Adults	14.814	1246
Single	14.273	1790
With children	14.353	1578

The null hypothesis of equal variance could not be rejected (F=2.57, p =0.077). This means that all assumptions are met and ANOVA results can be interpreted.

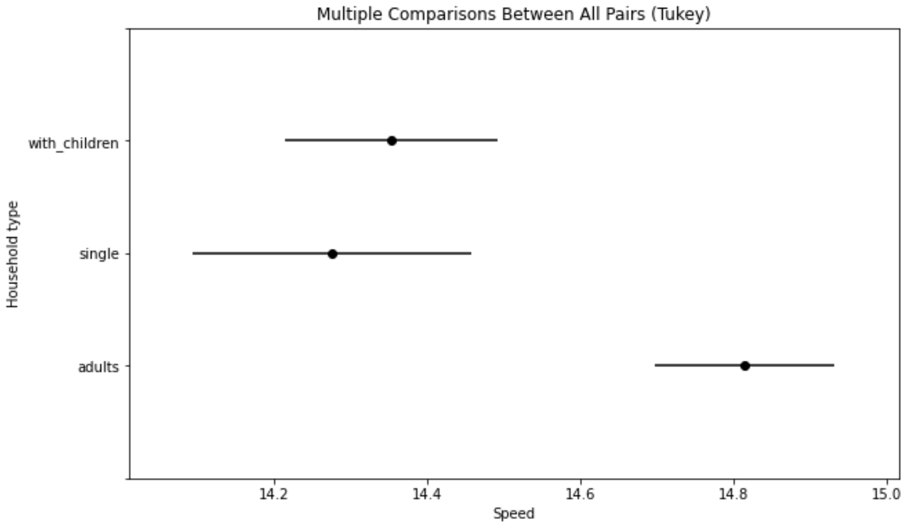


***Figure 11:** ANOVA cycling speed and household types: multiple comparisons between all pairs (Tukey)*

__Table 8:__ Multiple Comparison of Means - Tukey HSD, FWER=0.05. Cycling speed and household types

				95% Confidence Interval	
Group 1	Group 2	Mean difference	Significance	Lower bound	Upper bound
Adults	Single	-0.539	0.001	-0.838	-0.240
	With children	-0.461	0.001	-0.717	-0.205
Single	With children	0.077	0.818	-0.242	0.398

A one-way ANOVA was performed to compare the effect of household type on cycling speed in km/h. It revealed that there is a statistically significant difference in cycling speed between at least two groups ($F(2, 4716) = 13.25$, $p < 0.001$). Tukey's HSD Test for multiple comparisons found that the mean value of cycling speed was significantly different between adult households and households with children, as well as between adult households and single person households, see Figure 11 and Table 8.

The biggest difference is between adult household and single person households, at 0.4 km/h. This constitutes a 100 m difference on a 15 min travel time, which is negligible. Single people might be living more in crowded areas in the city and thus bike slower because of traffic. It could also be that many single households are older people.

Urban density and cycling speed

Table 9 presents the descriptive statistics of people living in different urban densities and their cycling speed.

__Table 9:__ Descriptive statistics of urban density and cycling speed

Group	Mean speed (km/h)	Group size
Medium density	14.617	948
High density	14.699	2027
Maximum density	14.239	1637

Levene's test indicated unequal variances ($F = 5.65$, $p = 0.004$). Thus, the assumption is violated and results from one-way ANOVA cannot be interpreted.

Overall, while ANOVA found some significant differences in cycling speed between household types, the difference is a marginal 0.4 km/hOn a 15-minute travel time, the difference this makes in distance is negligible.

D.3 Regression analysis on cycling speed

In order to carry out linear regression analysis some assumptions have to be met regarding the data. These assumptions are listed below.

The relationship between age and speed is depicted in Figure 12. Correlation is -0.167, p<0.001 and N=4719. Furthermore, Figure 13 shows that the distribution of the DV is normal. Because outliers can have considerable effects on the outcome of regression analysis, they should be removed if warranted. For this reason, outliers of average user speeds higher than 35 km/h and lower than 5 km/h have been removed from the dataset.

To test for multicollinearity, correlations between variables were calculated. There are moderate correlations between household size and age (-0.332). Since these correlations are moderate and not high (>0.8), the assumption of no or little multicollinearity is not violated. Correlation matrix of the variables is also presented in Appendix E.1.

Residuals should be random and independent from each other. After regression analysis, the residuals are equal across the regression line. Figure 14 shows residuals vs. the predicted values. It can be seen that the residuals are scattered fairly equally across the regression line.

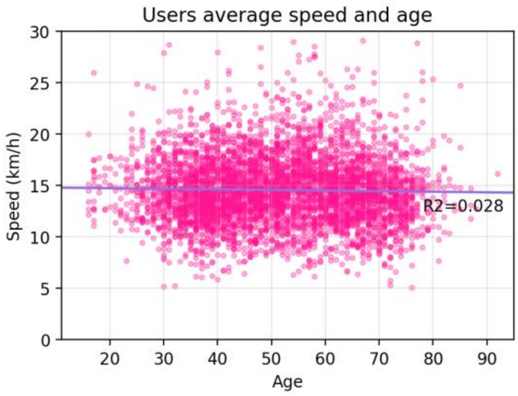


***Figure 12**: Relationship between age and average cycling speed (km/h).*

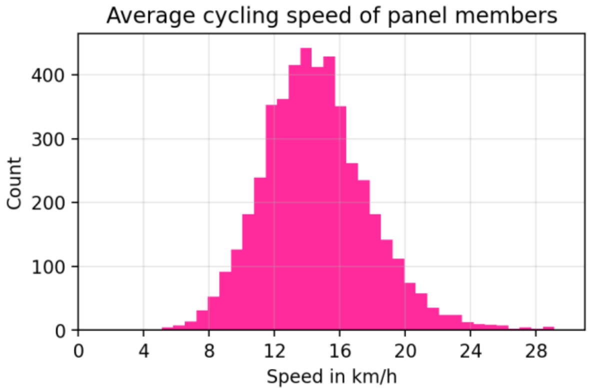


***Figure 13:** Average cycling speed distribution*

***Table 10:** model output*

Variable	B (coefficient)	Std. error	p-value
Constant	15.1048	0.361	0.000
Gender	0.7435	0.098	0.000
25-44	-0.4491	0.363	0.216
45-64	-0.3331	0.361	0.356
65+	-1.3507	0.370	0.000
Density max	0.4559	0.115	0.000
Density high	-0.0586	0.118	0.620
Hh type single	-0.4742	0.129	0.000
Hh type with children	-0.6673	0.125	0.000

The results of the model are presented in Table 10 and Figure 14. The model fit is very poor ($R^2 = 0.033$). Several variables are strongly significant. Gender has a significant relationship with the cycling speed, where being male leads to a higher cycling speed. Age group 65+ has a strongly significant negative relationship with the speed. Furthermore, people living in maximum density cycle faster than other densities, while ANOVA showed that the average speed of this group is lower than the other two groups. Finally, household types single person and with children cycle slower than adult households, which was also shown in ANOVA.

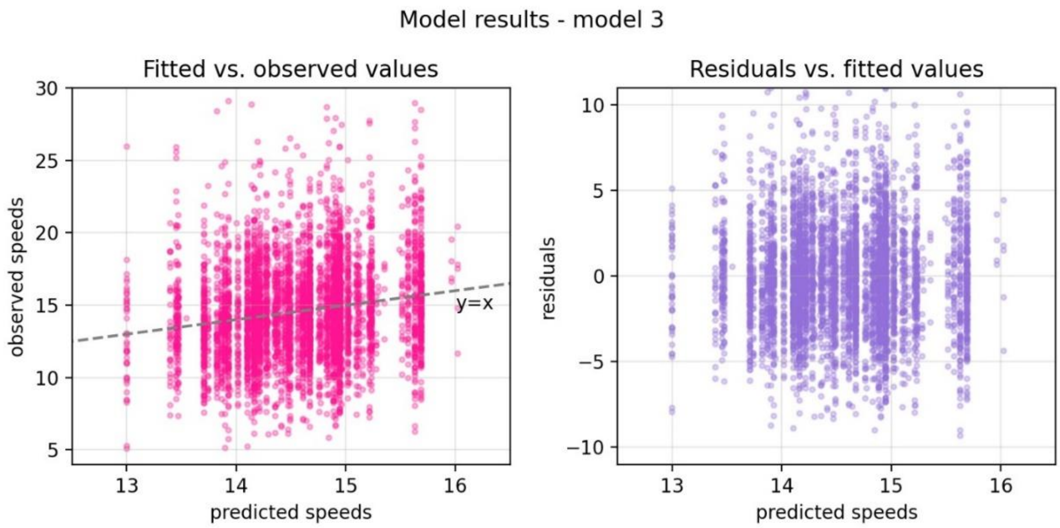


Figure 14: *(left) Actual vs. predicted speeds and (right) residuals vs. predicted speeds*

While the model itself was significant, and 5 of 8 variables were significant, the final cycling speeds range from 13 to 16 km/h. On a 15-minute travel time, this constitutes a difference of 500 m, more substantial than the differences found between groups in ANOVA. However, the fit of the model is very poor, with an R^2 value of 0.033. Because of this poor fit, and the small differences found in ANOVA, it was decided to use a single average cycling speed of 15 km/h. This is slightly higher than the average speed found in the data (13.8 km/h), but will be used in combination with network characteristics in the intersections, where wait times are added (see section 3.2.2 in the paper). This is assumed to be a more realistic approximation of cycling speed.

D.4 Distance decay functions

Figure 15 depicts the distance decay function for each destination type, taken from the entire sample of the NVP data cycling trips. The steepest lines are those of the category food (grocery and other food stores) and education, which means people are traveling the shortest distance to these destinations by bike. The latter of the two differs a lot per age group, as shown in Figure 16. Recreation is the least steepest line, so people are willing to travel the furthest for this category, although it should be noted that the function for recreation was fitted based on the smallest amount of data points out of all categories. Finally, it can be seen that the lines for most destination categories are at a relatively low probability at 15 minutes.

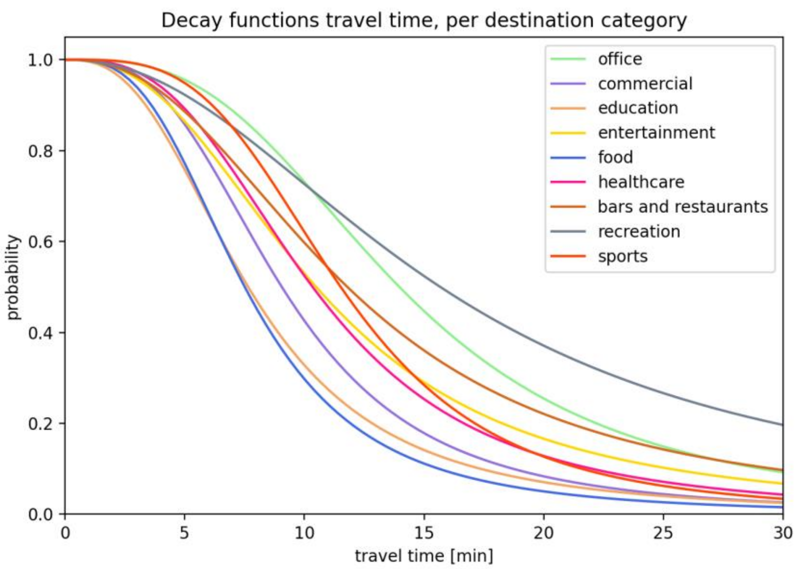


Figure 15: *Distance decay functions for all destination types*

Figure 16 shows that in most of the destination categories the distance decay functions differ per age group. The exception is the commercial category, where all lines are almost the same. It also shows that for education, as expected, people aged 15 to 24 cycle further. Furthermore, the differences in probability of travelling a certain travel time are largest in the entertainment, healthcare, bars and restaurants, and recreation categories. It should be noted that for recreation age group 15-24, only 14 data points were available, so this function may not be the most accurate. The younger age group travels shorter distances for entertainment and healthcare purposes. For the first, they might generally live closer to entertainment venues in the city. For the second, younger people travel less frequent to health care amenities than older people (in general). Finally, the age group 65+ travels much further to bars and restaurants, suggesting that they might try to find specific establishments to visit rather than going close to home, or that they generally live further away from these amenities.

Lastly, since only cycling trips are incorporated in this analysis, some of the differences may be explained by mode choice. While older people might cycle relatively far to bars and restaurants, younger people may choose to take public transit or the car instead. Likewise, younger people often cycle to education locations, either because they have no other means or because it is cheaper. However, since this analysis does not include other modes, conclusions on mode choice and willingness to cycle instead of other modes cannot be drawn. Only the willingness or probability to cycle certain distances.

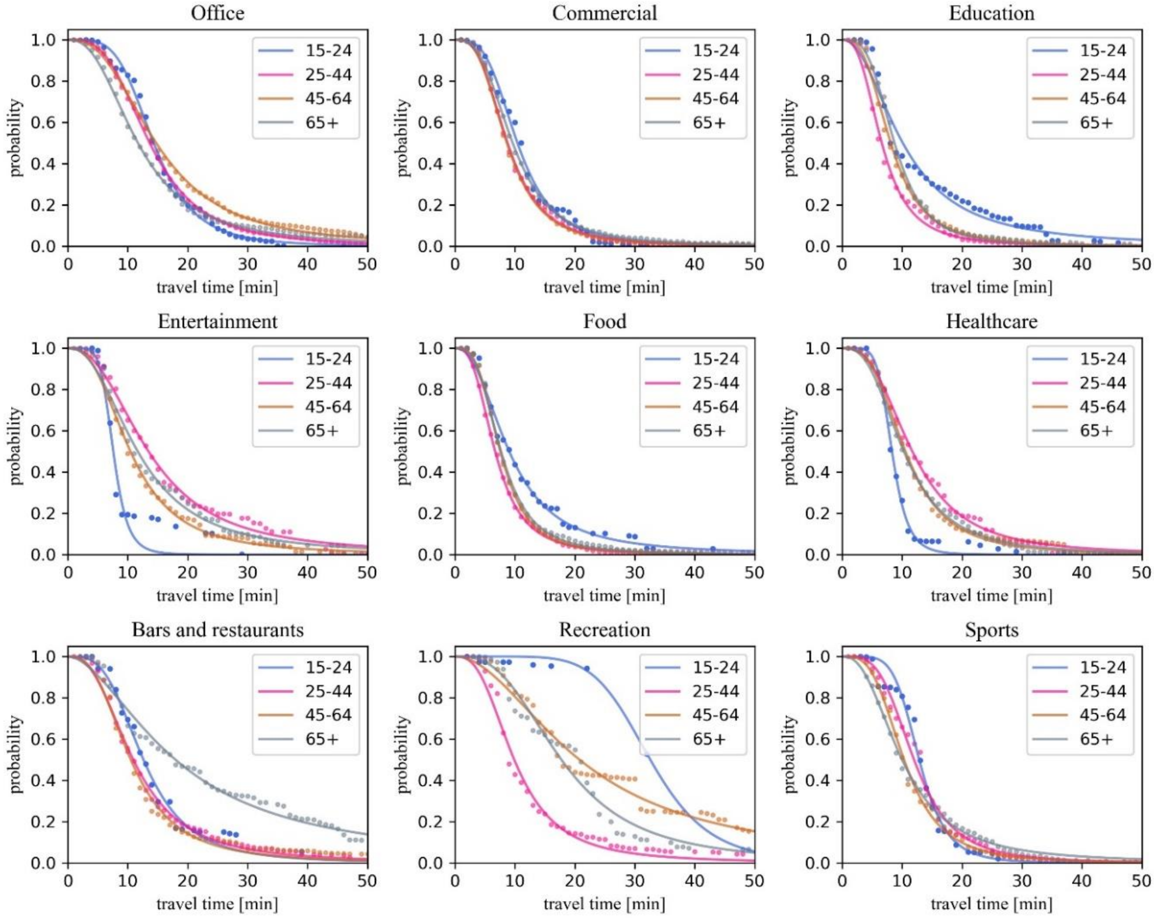


Figure 16: *Distance decay functions by age group*

D.5 Sensitivity analysis

UA and SA were run on the CS_{15} as well as on the CS_{10}. The UA output in Figure 17a shows the CS_{15} calculated with the original weights, as well as the median value of the CS_{15} generated by the 11,264 combinations of weights and the range of these simulated values. Generally, range (and thus uncertainty) is higher for the higher scoring grid cells in the study area, but some spikes can be observed for lower scoring cells as well. This is also true for the analysis on the CS_{10}, shown in Figure 17b.

Figure 18 shows the output uncertainty plotted in the study area. It can be observed that while the higher scoring cells have a high level of uncertainty (as is clear from Figure 17), cells in Houten and in Bilthoven have a relatively high level of uncertainty but a low CS_{15} (see figure 7 in main text). Houten scores very high on recreation (playgrounds), as can be seen in figure 6 in the main text, and this factor explains a lot of uncertainty in the output. On the other hand, Bilthoven scores relatively low on entertainment, and a 25% of uncertainty in the output is explained by the weight for this factor. For the $CS_{10,}$ there are some outliers with high uncertainty in Bilthoven and Zeist. These cells originally score high on healthcare (see Appendix E.2), the weight for which contributes to 9.2% of the uncertainty in the output.

Furthermore, Figure 17 shows that most of the original scores are lower than the median of the simulated scores.

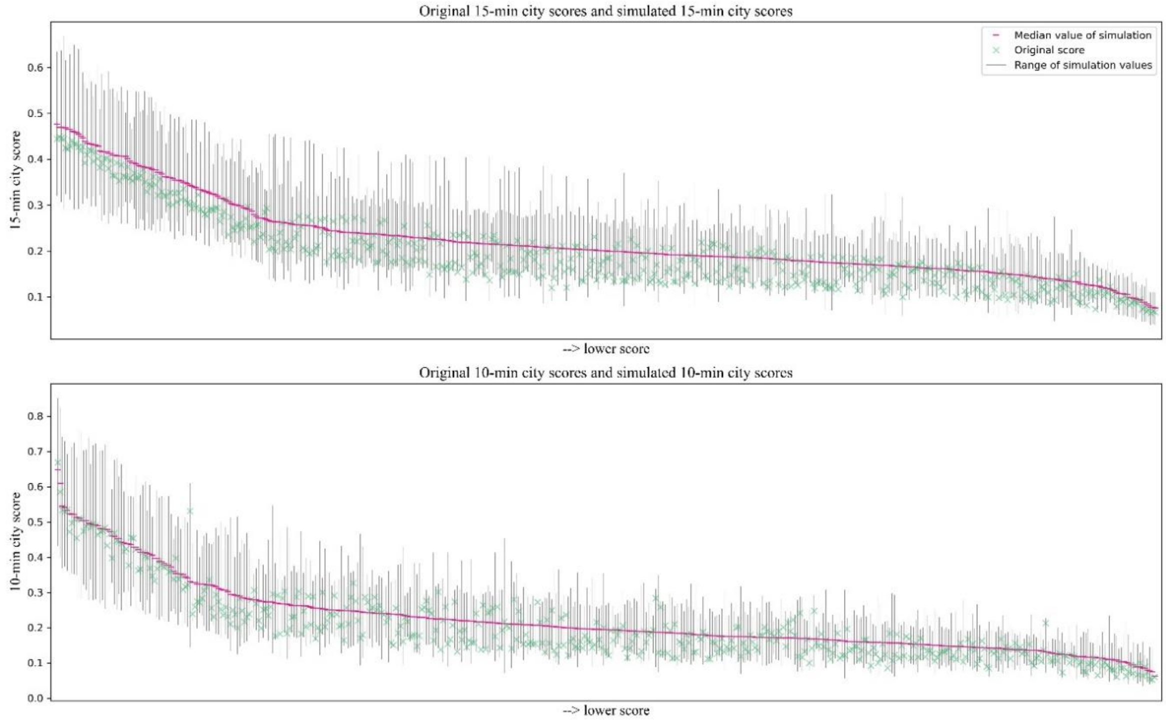


Figure 17: *Uncertainty analysis output*

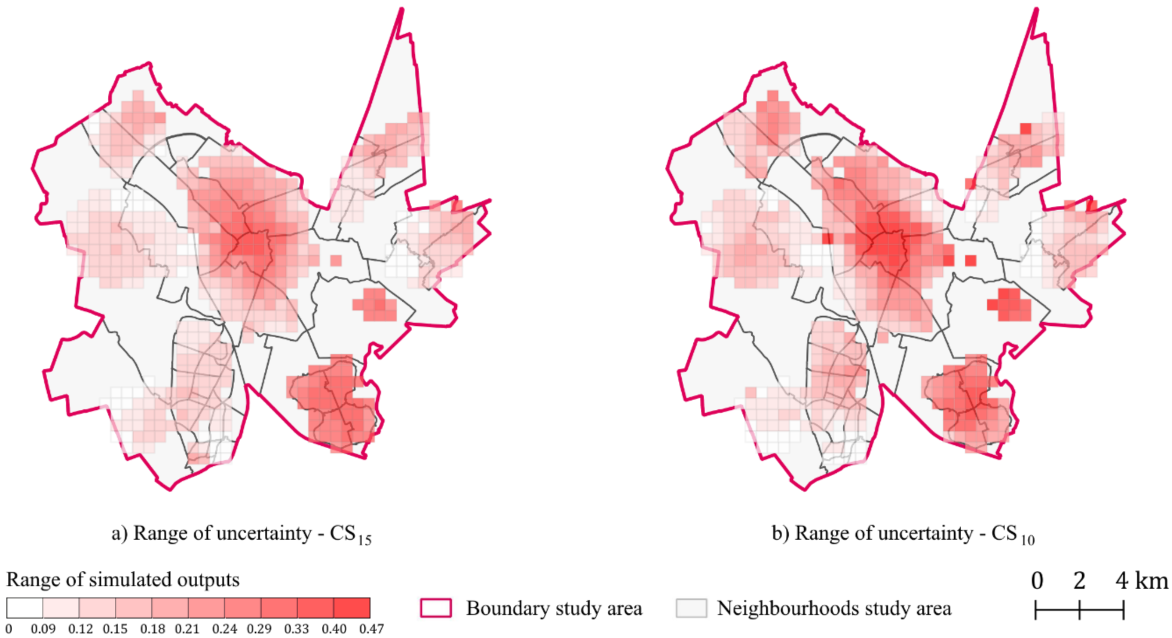


Figure 18: *Uncertainty in output*

Table 11 presents the mean sensitivity indices across all cells for each input weight, and Figure 19 shows the shows the distribution of the sensitivity indices across all cells for each variable. All input weights without interaction explain on average 96% of the output variance in both the CS_{15} and the CS_{10}, while the interaction effects explain only a marginal 4% of the uncertainty.

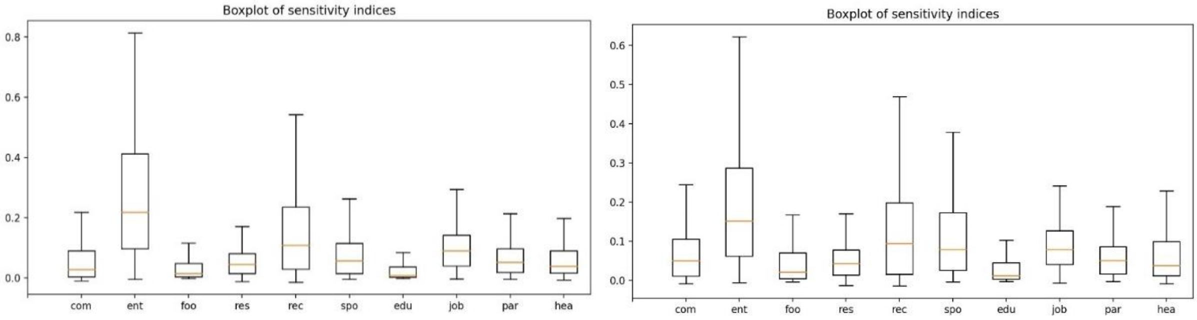


Figure 19: *Boxplot of sensitivity indices (left) 15-minutes and (right) 10-minutes.*

Table 11: *Sobol Sensitivity indices for first and total order effect*

	CS15			CS10		
	S_i	S_{Ti}	$S_{Ti} - S_i$	S_i	S_{Ti}	$S_{Ti} - S_i$
Commercial	0.054	0.062	0.008	0.068	0.076	0.008
Entertainment	0.258	0.271	0.013	0.197	0.208	0.011
Food	0.046	0.050	0.004	0.056	0.060	0.004
Restaurants	0.053	0.059	0.007	0.062	0.069	0.007
Recreation	0.182	0.191	0.008	0.162	0.172	0.009
Sports	0.086	0.092	0.006	0.129	0.135	0.006
Education	0.030	0.035	0.005	0.037	0.041	0.005
Jobs	0.102	0.107	0.005	0.098	0.102	0.004
Park	0.060	0.065	0.004	0.062	0.068	0.006
Healthcare	0.092	0.096	0.005	0.092	0.097	0.005
Sum	0.964	1.028	0.064	0.964	1.03	0.064

Most of the output variance in the CS_{15} is explained by the weight for entertainment, recreation, and jobs; 54%. In the CS_{10}, most of the output variance is explained by the weights for entertainment, recreation, and sports; 49%. Entertainment has some very high outlier values in the study area, but also some low outliers. To a lesser extent, this is also true for recreation. The job category however mostly has relatively low values in the study area, with only some outliers in Nieuwegein. Sports in the CS_{10} has 0 values in some areas (see Appendix E.2). Figure 19 shows that while the weights of these three indicators have on average the highest uncertainty, the distribution of uncertainty across the cells is also the largest for these factors. On the other hand, it can be said that the weights for food and education do not contribute substantially to the uncertainty in the output.

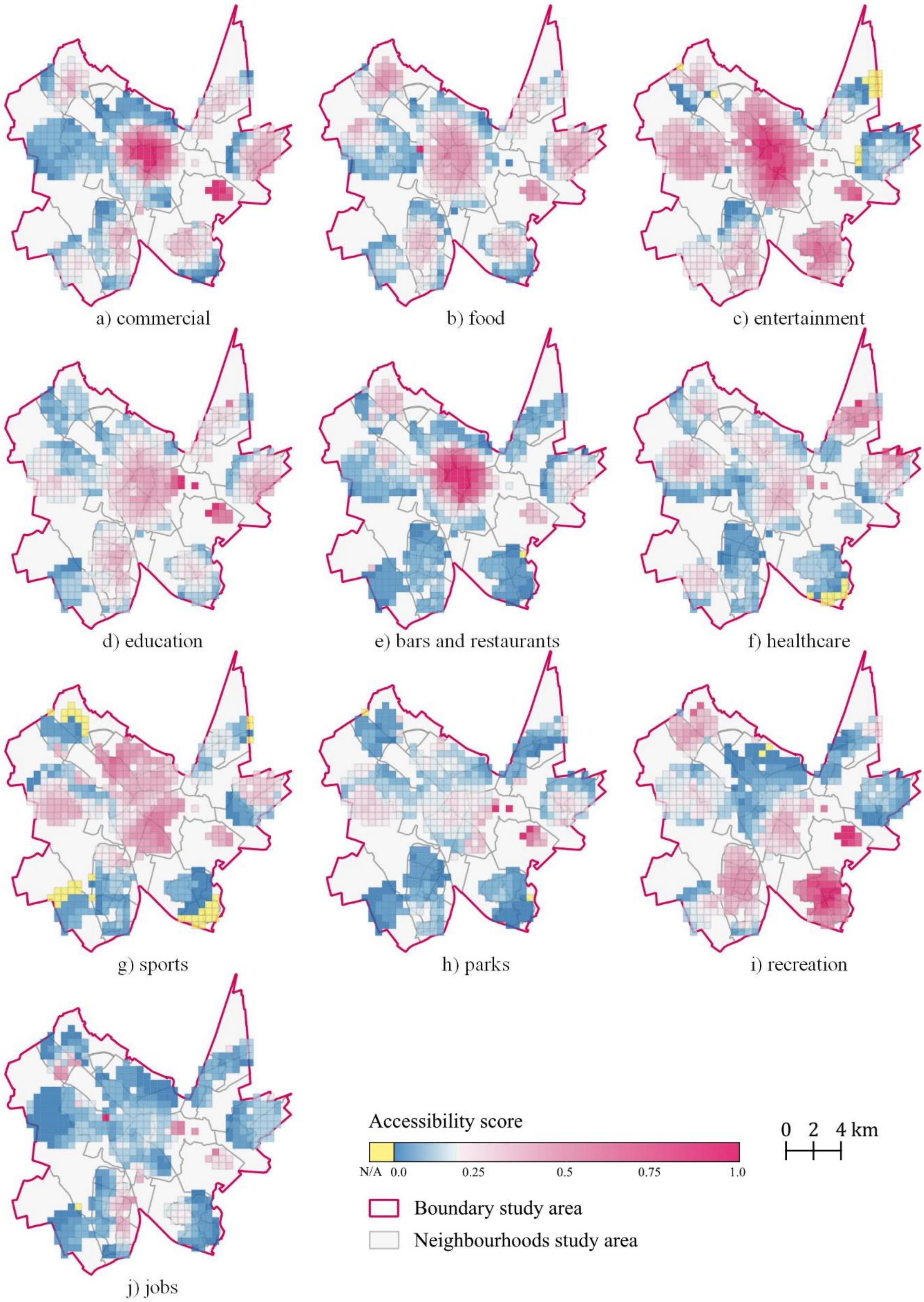
Compared to the sensitivity analysis of the 15-minute city scores, the uncertainty in the 10-minute city scores can be attributed to more different variables, while in the 15-minute city scores the uncertainty could mostly be attributed to the weight for entertainment.

E. Figures and tables

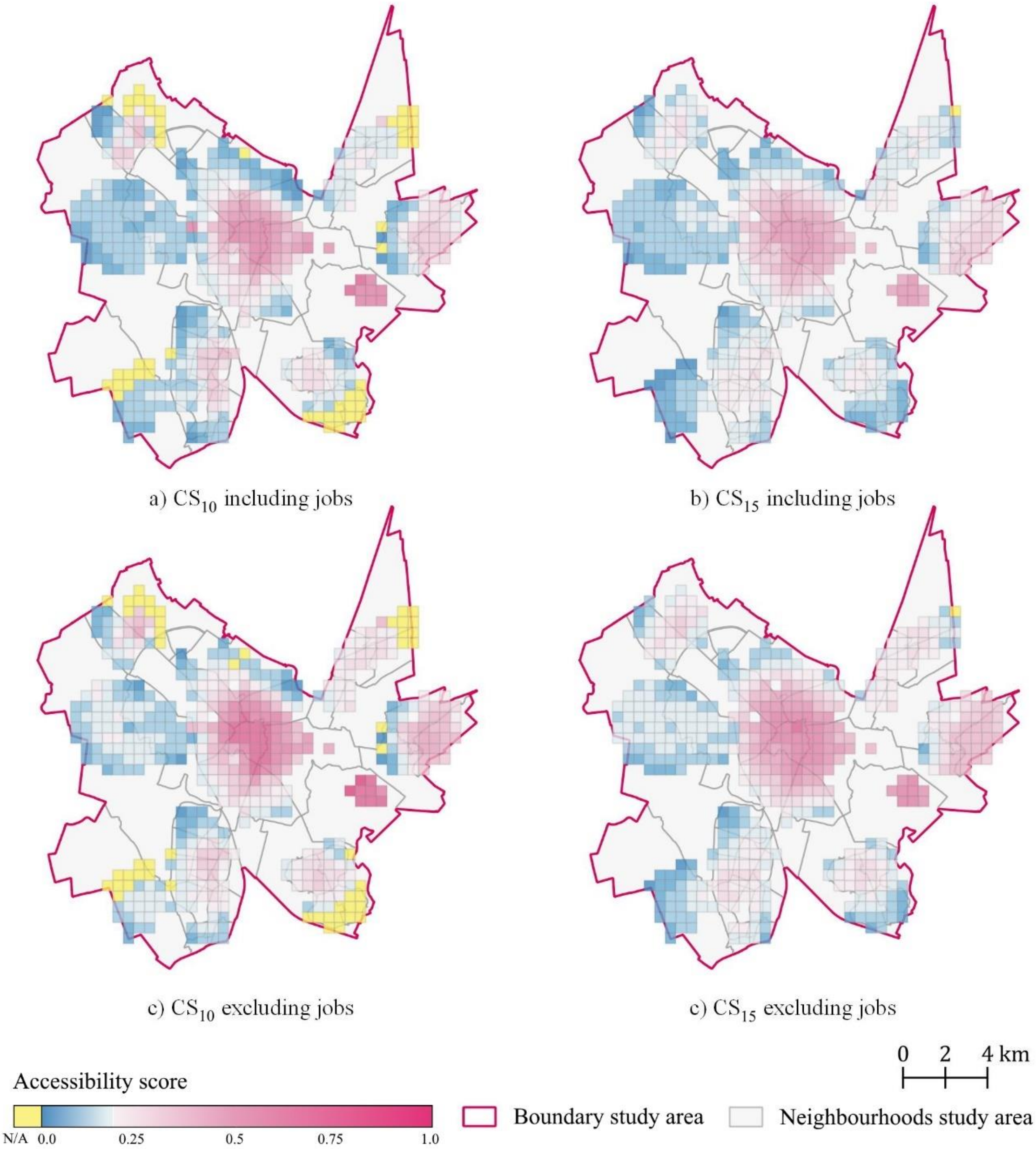
E.1 Correlation matrix linear regression cycling speed

	Mean cycling speed	Urban density	Age	Gender	Education	Household size	Income	Age group
Mean cycling speed	1.000	-0.034	-0.030	0.102	0.024	0.021	0.008	-0.026
Urban density	-0.034	1.000	0.009	-0.019	-0.006	-0.022	-0.005	0.004
Age	-0.030	0.009	1.000	0.221	0.201	-0.308	0.090	0.937
Gender	0.102	-0.019	0.221	1.000	-0.040	-0.037	-0.054	0.205
Education level	0.024	-0.006	0.201	-0.040	1.000	-0.070	0.220	0.186
Household size	0.021	-0.022	-0.308	-0.037	-0.070	1.000	-0.100	-0.305
Income	0.008	-0.005	0.090	-0.054	0.220	-0.100	1.000	0.094
Age group	-0.026	0.004	0.937	0.205	0.186	-0.305	0.094	1.000

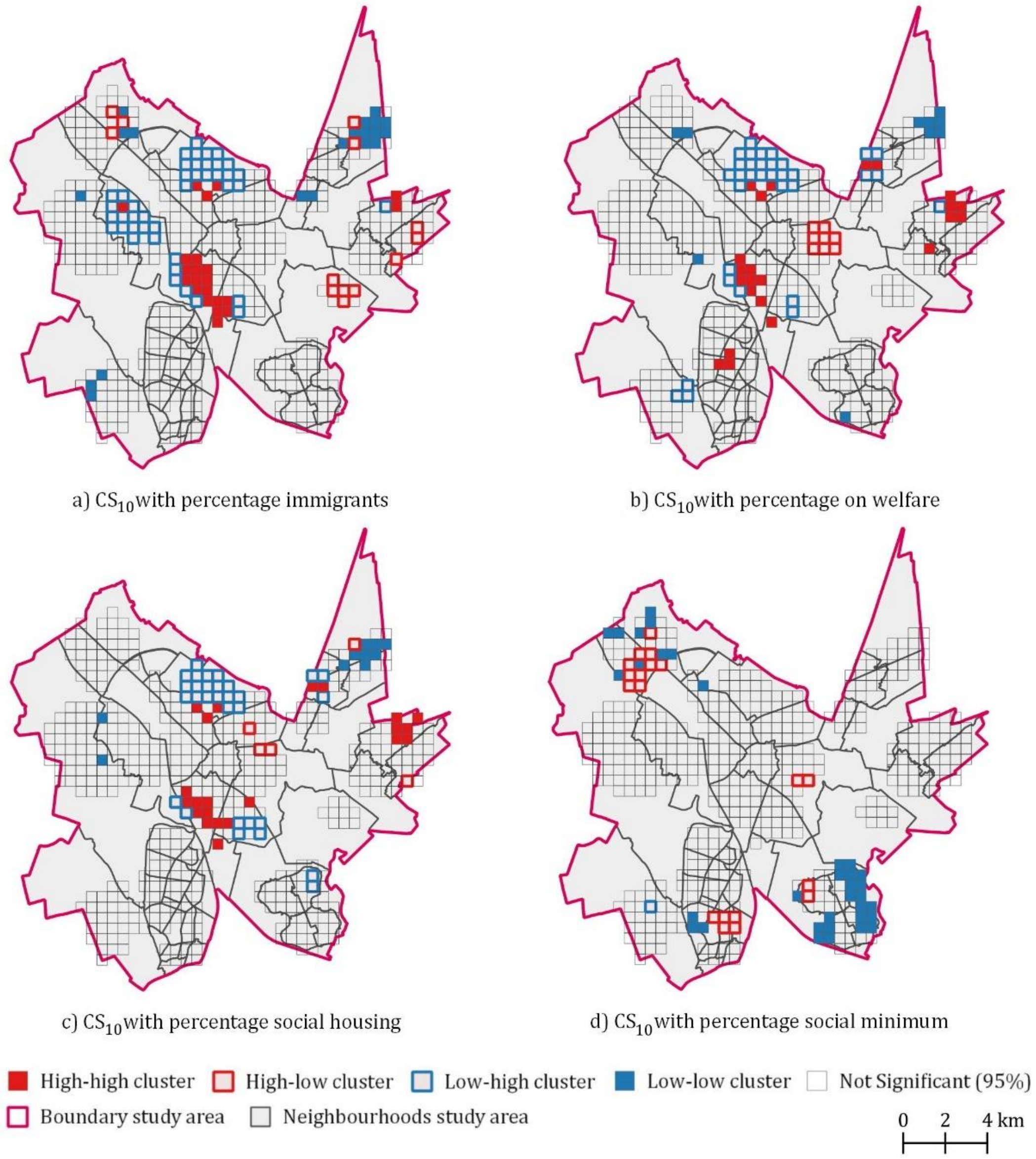
E.2 Standardized accessibility scores with a 10-minute cycling travel time



E.3 15-min city score results excluding jobs



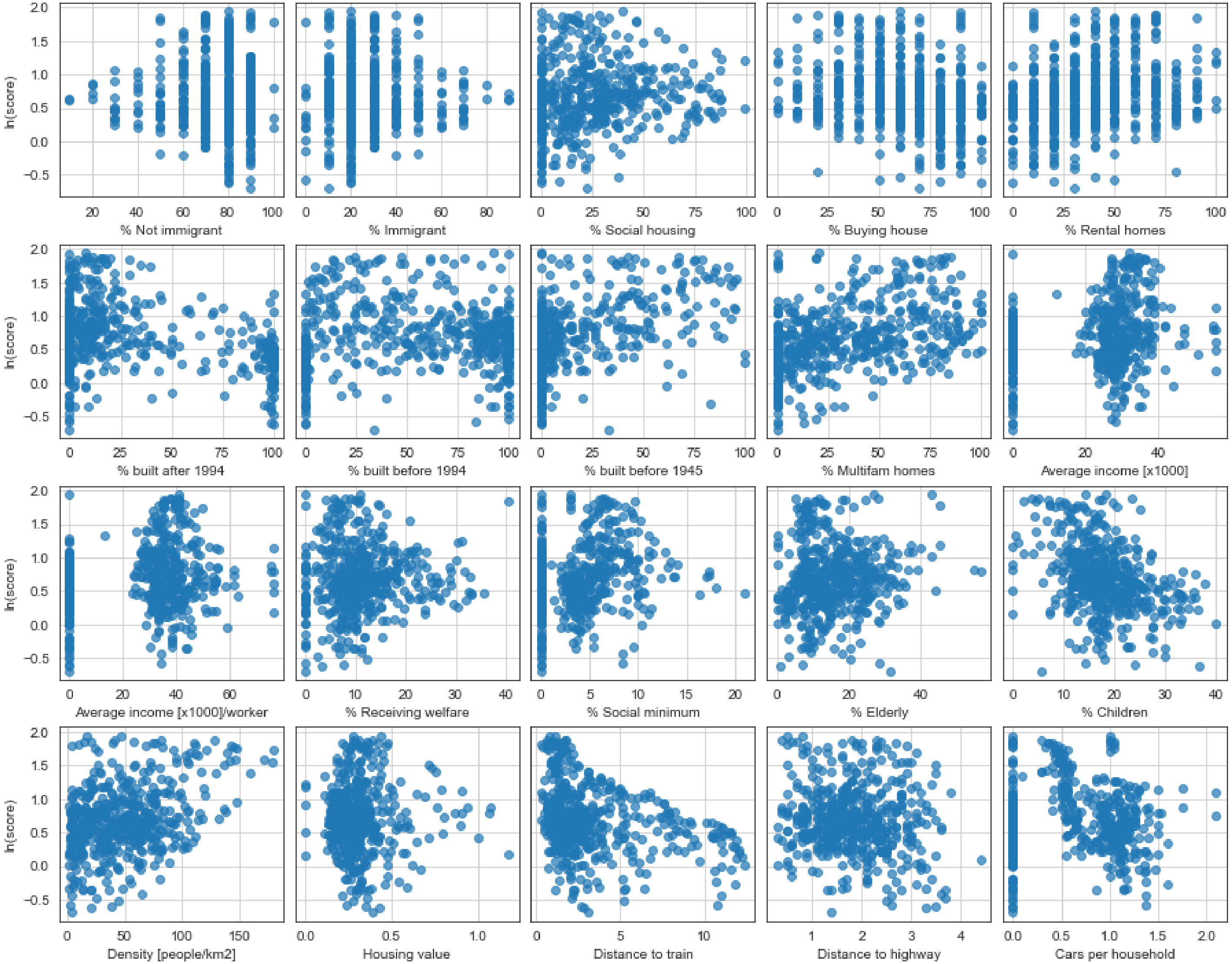
E.4 Bivariate maps CS_{10} and socio-demographic and neighbourhood factors



E.5 Correlation matrix used in spatial regression

	CS 10	CS 10 with jobs	% Western	% Nonwestern	% Not imm.	% Immigrant	% Social house	% Buying house	% Rental homes	% built after 94	% Built before 94	% Built before 45	% Apartments	Mean income	Mean income/w	% welfare	% Soc. Min.	% Elderly	% Children	Density	Housing value	Dist to train	Dist to highway	Cars per hh
CS 10	1.00	0.96	0.27	-0.08	-0.02	0.01	0.14	-0.29	0.29	-0.16	0.05	0.49	0.40	0.24	0.16	0.06	0.29	0.10	-0.38	0.27	0.01	-0.33	-0.08	-0.07
CS 10 with jobs	0.96	1.00	0.24	-0.06	-0.04	0.02	0.13	-0.27	0.26	-0.17	0.06	0.46	0.38	0.17	0.10	0.03	0.24	0.09	-0.38	0.23	-0.03	-0.28	-0.10	-0.15
% Western	0.27	0.24	1.00	0.04	-0.24	0.32	-0.03	-0.13	0.14	0.00	-0.01	0.12	0.19	0.15	0.11	0.00	0.19	-0.12	-0.19	0.23	0.03	-0.09	0.01	-0.02
% Nonwestern	-0.08	-0.06	0.04	1.00	-0.88	0.95	0.63	-0.60	0.60	0.16	0.04	-0.31	0.45	-0.26	-0.20	0.63	0.24	-0.40	0.13	0.42	-0.63	-0.03	0.07	-0.15
% Not imm.	-0.02	-0.04	-0.24	-0.88	1.00	-0.92	-0.57	0.63	-0.62	-0.11	-0.04	0.22	-0.51	0.19	0.14	-0.56	-0.29	0.38	-0.03	-0.39	0.58	0.09	-0.05	0.17
% Immigrant	0.01	0.02	0.32	0.95	-0.92	1.00	0.59	-0.62	0.61	0.15	0.04	-0.25	0.49	-0.20	-0.16	0.58	0.28	-0.41	0.06	0.44	-0.58	-0.05	0.06	-0.15
% Social house	0.14	0.13	-0.03	0.63	-0.57	0.59	1.00	-0.78	0.81	0.00	0.24	-0.16	0.53	-0.23	-0.21	0.79	0.20	-0.04	-0.08	0.46	-0.64	-0.06	-0.01	-0.14
% Buying house	-0.29	-0.27	-0.13	-0.60	0.63	-0.62	-0.78	1.00	-0.97	0.03	-0.17	0.00	-0.75	0.09	0.10	-0.64	-0.31	0.11	0.28	-0.45	0.67	0.12	-0.02	0.17
% Rental homes	0.29	0.26	0.14	0.60	-0.62	0.61	0.81	-0.97	1.00	-0.01	0.19	-0.01	0.74	-0.09	-0.10	0.66	0.32	-0.09	-0.27	0.48	-0.67	-0.14	0.03	-0.16
% built after 94	-0.16	-0.17	0.00	0.16	-0.11	0.15	0.00	0.03	-0.01	1.00	-0.74	-0.11	0.05	0.10	0.15	-0.09	-0.03	-0.32	0.29	0.11	0.19	-0.09	0.19	0.10
% Built before94	0.05	0.06	-0.01	0.04	-0.04	0.04	0.24	-0.17	0.19	-0.74	1.00	-0.30	0.11	-0.22	-0.27	0.36	0.01	0.38	-0.28	0.01	-0.46	0.16	-0.21	-0.09
% Built before45	0.49	0.46	0.12	-0.31	0.22	-0.25	-0.16	0.00	-0.01	-0.11	-0.30	1.00	0.06	0.41	0.34	-0.21	0.26	0.14	-0.20	0.10	0.35	-0.21	0.08	0.08
% Apartments	0.40	0.38	0.19	0.45	-0.51	0.49	0.53	-0.75	0.74	0.05	0.11	0.06	1.00	0.01	-0.03	0.46	0.33	-0.09	-0.36	0.48	-0.53	-0.15	0.02	-0.18
Mean income	0.24	0.17	0.15	-0.26	0.19	-0.20	-0.23	0.09	-0.09	0.10	-0.22	0.41	0.01	1.00	0.95	-0.22	0.31	0.13	-0.03	0.04	0.41	-0.14	0.06	0.64
Mean income/w	0.16	0.10	0.11	-0.20	0.14	-0.16	-0.21	0.10	-0.10	0.15	-0.27	0.34	-0.03	0.95	1.00	-0.21	0.33	0.08	0.08	0.04	0.41	-0.15	0.06	0.68
% Welfare	0.06	0.03	0.00	0.63	-0.56	0.58	0.79	-0.64	0.66	-0.09	0.36	-0.21	0.46	-0.22	-0.21	1.00	0.21	0.05	-0.06	0.39	-0.69	0.04	0.03	-0.06
% Soc. Min.	0.29	0.24	0.19	0.24	-0.29	0.28	0.20	-0.31	0.32	-0.03	0.01	0.26	0.33	0.31	0.33	0.21	1.00	-0.06	-0.19	0.40	-0.20	-0.05	0.14	0.33
% Elderly	0.10	0.09	-0.12	-0.40	0.38	-0.41	-0.04	0.11	-0.09	-0.32	0.38	0.14	-0.09	0.13	0.08	0.05	-0.06	1.00	-0.37	-0.20	0.05	0.19	-0.13	0.20
% Children	-0.38	-0.38	-0.19	0.13	-0.03	0.06	-0.08	0.28	-0.27	0.29	-0.28	-0.20	-0.36	-0.03	0.08	-0.06	-0.19	-0.37	1.00	-0.04	0.25	0.00	0.03	0.14
Density	0.27	0.23	0.23	0.42	-0.39	0.44	0.46	-0.45	0.48	0.11	0.01	0.10	0.48	0.04	0.04	0.39	0.40	-0.20	-0.04	1.00	-0.37	-0.17	0.13	-0.05
Housing value	0.01	-0.03	0.03	-0.63	0.58	-0.58	-0.64	0.67	-0.67	0.19	-0.46	0.35	-0.53	0.41	0.41	-0.69	-0.20	0.05	0.25	-0.37	1.00	-0.12	-0.01	0.22
Dist to train	-0.33	-0.28	-0.09	-0.03	0.09	-0.05	-0.06	0.12	-0.14	-0.09	0.16	-0.21	-0.15	-0.14	-0.15	0.04	-0.05	0.19	0.00	-0.17	-0.12	1.00	-0.21	0.13
Dist to highway	-0.08	-0.10	0.01	0.07	-0.05	0.06	-0.01	-0.02	0.03	0.19	-0.21	0.08	0.02	0.06	0.06	0.03	0.14	-0.13	0.03	0.13	-0.01	-0.21	1.00	-0.01
Cars per hh	-0.07	-0.15	-0.02	-0.15	0.17	-0.15	-0.14	0.17	-0.16	0.10	-0.09	0.08	-0.18	0.64	0.68	-0.06	0.33	0.20	0.14	-0.05	0.22	0.13	-0.01	1.00

E.6 Scatter plots of natural logarithm of the CS_{10} with variables



E.7 OLS model outputs

Variables	Model A DV = CS_{10} without jobs Coefficient	SE	Model A DV = CS_{10} with jobs Coefficient	SE	Model B DV = CS_{10} without jobs Coefficient	SE	Model B DV = CS_{10} with jobs Coefficient	SE
Constant	3.054***	0.099	2.468***	0.104	1.298***	0.108	1.121***	0.116
% soc. minimum	0.050***	0.01	0.033**	0.01	0.003	0.012	-0.002	0.013
% welfare	0.328	0.386	0.047	0.402	-0.114	0.359	-0.386	0.384
% > 65 years	-0.078	0.254	-0.118	0.264	0.027	0.234	-0.019	0.251
% < 15 years	-2.754***	0.307	-2.858***	0.32	-1.348***	0.328	-1.478***	0.352
% immigrants	-0.072	0.191	0.08	0.198	-0.173	0.178	-0.019	0.19
D train station	-0.242***	0.025	-0.211***	0.026	-0.153***	0.023	-0.130***	0.025
% < 1945					0.059***	0.007	0.059***	0.008
% > 1994					-0.014*	0.007	-0.013	0.007
% apartments					0.408***	0.083	0.416***	0.089
Income					0.178	0.173	0.002	0.185
Pop. density					0.240***	0.058	0.172**	0.063
Spatial dependency								
Moran's I, p(z(i))	0.70	0.000	0.71	0.000	0.64	0.000	0.658	0.000
LM test for lag	600.22	0.000	597.58	0.000	512.11	0.000	515.92	0.000
LM test for error	519.76	0.000	535.12	0.000	439.68	0.000	458.78	0.000
Robust LM lag	80.80	0.000	63.26	0.000	79.13	0.000	63.38	0.000
Robust LM error	0.341	0.559	0.8	0.371	6.69	0.010	6.25	0.012
Model fit								
LL	-272.01		-292.04		-205		-239.63	
AIC	558.02		598.08		433.99		503.26	
R2	0.307		0.255		0.465		0.39	

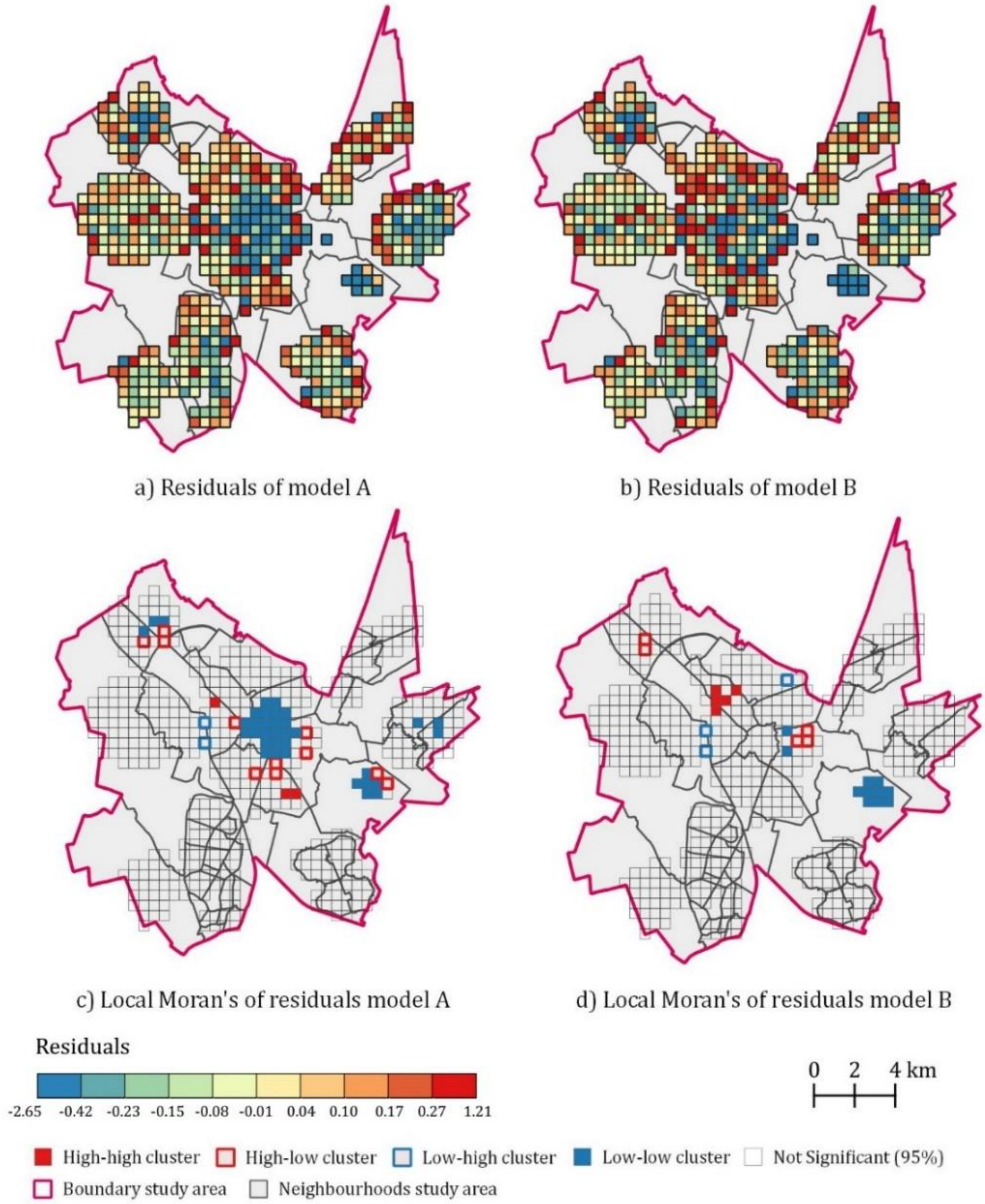
*** = P < 0.001; ** = P <0.01; * = P <0.05

E.8 Spatial model outputs

	Model A DV = CS_{10} without jobs		Model A DV = CS_{10} with jobs		Model B DV = CS_{10} without jobs				Model B DV = CS_{10} with jobs	
	Lag (w = Rook)		Lag (w=KNN, k =4)		Lag (w = Rook)		Combo (w=KNN, k=4)		Lag (w=KNN, k=4)	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Constant	0.201***	0.041	0.129**	0.042	0.096*	0.046	-0.079	0.055	0.044	0.05
% soc. minimum	0.014***	0.004	0.011**	0.004	0.005	0.005	0.004	0.005	0.002	0.006
% welfare	0.394**	0.148	0.436**	0.161	0.302*	0.151	0.435***	0.14	0.396*	0.167
% > 65 years	-0.034	0.097	0.021	0.106	0.045	0.099	0.177*	0.089	0.074	0.109
% < 15 years	-0.520***	0.121	-0.480***	0.131	-0.369**	0.14	-0.113	0.136	-0.395*	0.154
% immigrants	-0.112	0.073	-0.086	0.079	-0.157*	0.075	-0.115	0.067	-0.094	0.083
D train station	-0.043***	0.01	-0.042***	0.011	-0.028**	0.01	-0.016	0.01	-0.027*	0.011
% < 1945					0.010***	0.003	0.006	0.003	0.011**	0.003
% > 1994					0.006*	0.003	0.007*	0.003	0.005	0.003
% apartments					0.075*	0.036	0.007	0.036	0.031	0.039
Income					0.005	0.073	0.008	0.064	0.009	0.081
Pop. density					0.083***	0.025	0.089***	0.023	0.071**	0.027
Rho (lag)	1.446***	1.467	1.501***	1.31	1.384***	1.658	1.683***	4.018	1.458***	1.464
Lambda (error)							-0.157			
Spatial dependency residuals										
Moran's I z-value, p-value	1.323	0.186	0.640	0.522	1.201	0.23	-2.453	0.014	0.948	0.343
Model fit										
Log likelihood	113.9		81.94		135.69				95.87	
AIC	-211.79		-147.89		-245.38				-165.75	
Spatial R2	0.362		0.269		0.488		0.227		0.347	

*** = p < 0.001; ** = p <0.01; * = p <0.05

E.9 Residuals and local Moran's I of the spatial model



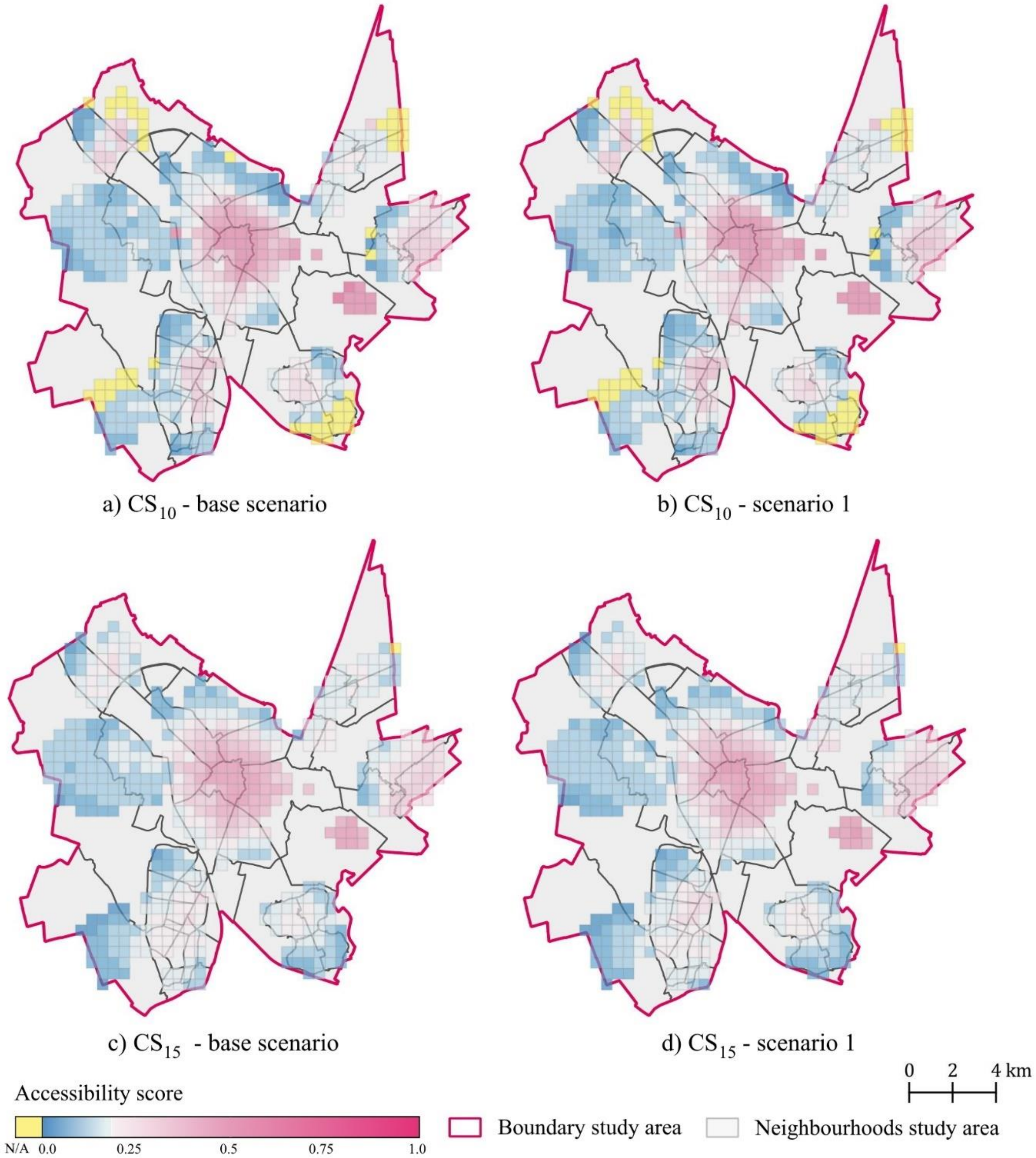
a) Residuals of model A

b) Residuals of model B

c) Local Moran's of residuals model A

d) Local Moran's of residuals model B

E.10 Scenario analysis results



F. Discussion with experts

A discussion with two experts from the field of mobility that are active in the study area, was held on march 8. Preliminary results of the accessibility scores and final metric were presented, as well as an example grid cell including its characteristics of inhabitants, density, types of buildings. Of the example grid cell, the accessibility scores per destination category were also presented and compared to average values in the study area.

Since the discussion session was held to validate the metric, the experts were asked if the results lined up with their expectations for Utrecht as a 10- and 15-minute city stemming from their knowledge of the area. Other questions were if they could use the metric in practice and what suggestions they had for improvements and practicality.

What follows is a description of results of the discussion, starting with the destinations and spatial unit that were selected, the weighing scheme, and ending with the results and suggestions.

The experts liked to know how destinations were selected and if everything was accurate in OpenStreetMap. They agreed that capacity of services should be included so that the interpretability of the metric would be improved, and that a measure for diversity of destinations such as restaurants may make a nice expansion on the metric.

The grid cells of 500 by 500 m are readable on the maps. Aggregation to neighbourhood or postal code level may distort the results too much because some zones or neighbourhoods are very large, while difference in accessibility within 10 minutes can change fast in a small area.

The experts agreed that the weighing scheme may not make the most sense right now, and that especially recreation and entertainment should be weighed higher in the metric, but it does show what is possible with the metric. There was a strong suggestion to improve the metric by basing weights on peoples preference through surveys.

The experts were very interested in the results. The use of 2SFCA made it clear why Bunnik scores high compared to other locations. Otherwise they would have expected the city centre to score high on every category, but this is not the case. In this sense, it lines up with real world expectations. They noticed that Leidse Rijn and Vleuten-De Meern area seem to be reliant on the city centre of Utrecht for many services and amenities, most notably commercial.

The experts wanted to know what a threshold value for the 15-minute city would be, but this is hard to determine. In the discussion session, the median value was taken as threshold value, but it is an arbitrary number. Instead, through looking more closely at the standard deviation maps, and the bivariate score and standard deviation maps, 'good' areas may be found as well as 'bad' ones. Then, to determine possible solutions, more detailed insights should be gathered from the individual accessibility scores.

The example grid cell with breakup of the destination categories were appreciated, as well as showing the isochrones of the 10- and 15-minute cycling time from the centre of the grid cell. Numbers are hard to interpret and instead it may be good to use a nominal scale from 'insufficient' to 'good'.

Practical application is mostly in testing additions or changes to the network, and thus it was also suggested to include network quality or even experienced travel time, and to make the impact of boundaries, unsafe situations, and crossings on the travel time larger.

Overall, the discussion session yielded many suggestions for improvements that are also discussed in section 6.4 in the main paper.

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