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A framework to include socio-demographic characteristics in potential job accessibility levels in low-car and car-free development areas in the Netherlands

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Abstract: Car-free development has become popular in recent years due to concerns regarding transport-related health issues in urban areas as well as a growing trend toward sustainability and environmentally friendly living. Although car-free development is regarded as progress to promote active transport modes and healthier cities, the accessibility impacts for its residents remain unclear. To address this knowledge gap, this paper proposes a job accessibility assessment framework that integrates individual and household socio-demographic characteristics into a job accessibility assessment, making it possible to account for commuting preferences of different population groups in accessibility analyses. For this purpose, a stated choice survey was conducted in existing low-car areas in the Netherlands to determine transport use and perception of public transport trip characteristics. Then, the influence of socio-demographic characteristics on trip perceptions was analyzed using a Latent Class Logit (LCL) regression model and Monte Carlo simulations. Finally, a multi-modal transport network combining walking and public transport trips was used to assess potential job accessibility levels of different population groups in a car-free development area. The proposed framework was implemented in a case study in the province of Utrecht (the Netherlands). Results show notable differences between the job accessibility levels within different population groups, reflecting distinct perceptions toward commuting trip characteristics based on socio-demographic characteristics and demonstrating the suitability of the applied approach to assess accessibility levels in car-free development areas. Compared to the sample average distribution, more than 15% lower accessibility levels were observed for starters (age 18-35) in some urban areas, indicating the aversion to longer and more expensive commuting trips. Contrarily, increased accessibility levels for families (>2 persons in household) were observed, demonstrating the acceptance to experience longer commuting travel times and additional costs. No differences were observed between accessibility levels of the sample average and senior adults (age >50).

Keywords: Car-free development, utility-based accessibility, latent-class logit model, potential job accessibility

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1 Introduction

Over the last decades, cities have been trying to reduce the number of motorized vehicles that started floating the urban roadways. Eliminating car traffic from dense urban city centers is an ongoing trend in many European cities. For this purpose, restrictions on motorized vehicles entering the urban centers are imposed (Melia, 2014; Nobis, 2003; Parkhurst, 2003) and measures to reduce car ownership of inhabitants are being taken (Clark, Lyons, et al., 2016; Nijland & van Meerkerk, 2017; Ornetzeder et al., 2008). Similarly in the Netherlands, municipalities are establishing low-car areas in which individual car use is discouraged and instead more sustainable transport modes are promoted among the inhabitants. These kinds of developments are relatively new in the Netherlands. Although such plans are favorable for sustainability and overall public health due to the use of active modes and reduced emission, the effects of low-car and car-free development on accessibility to jobs and other opportunities for residents in these areas remain unclear. This is especially relevant for commuting trips, as commuting distances are often beyond a walkable or cyclable distance and commuters are therefore obliged to use public transportation when car transport is not available. Furthermore, it can be expected that these effects are not consistent throughout the population due to varying perceptions of different demographic groups.

A majority of accessibility studies often emphasize aggregate numbers about the accessibility levels of a particular area. A disadvantage of this approach is the assumption that every individual values all trip characteristics to be similar, while in reality trip characteristics are perceived differently from person to person. Although previous research evaluated the accessibility concerning individual time-space limitations (Delafontaine et al., 2012; Fransen et al., 2015; Kwan, 1998; Patterson & Farber, 2015), there is only limited research that includes transport perceptions when determining accessibility (Cascetta et al., 2013, 2016). To the authors knowledge, none of the studies in the literature address differences in transport perceptions when determining accessibility in car-free development. To address this gap, this study aims to assess the job accessibility levels of car-free development areas, while taking individual characteristics into account. For this purpose, this paper proposes a methodological framework that can be employed to model job accessibility through utilizing detailed transport impedance depending on different socioeconomic characteristics. This framework consists of four components. First, a survey is conducted to identify individual preferences on transport trip characteristics. Second, different impedance functions are developed using Latent Class Logit (LCL) regression. Third, a Monte Carlo simulation analysis is performed to simulate individuals in a population group with different socioeconomic characteristics. Fourth, an accessibility model determining the likelihood of making a trip for these population groups is developed using the found impedance functions. Together, the components comprise a framework that determines the suitability of an area to be developed as car-free. By analyzing accessibility levels of different socio-demographic population groups and evaluating the implications of alternative sustainable transport solutions.

The proposed framework is implemented in a case study area in the city of Utrecht, one of the fastest-growing cities in the Netherlands. In Utrecht, a combination of development areas at the outer edges and a compact renewal in the inner parts of the city has been proposed. The case study area is the Merwedekanaalzone district, located in one of these inner-city areas where the municipality is establishing a low-car area. The Merwedekanaalzone is the first low-car area in the Netherlands where in total over

10,000 dwellings will be realized, reducing car ownership throughout the entire area. Hence, it is the most suitable area for a case study implementation.

The remainder of this paper is structured as follows: Section 2 gives an overview of previous literature on existing car-free development, causes for a reduction in car ownership and accessibility using public transportation. An overview of methods used to design the survey, the decay functions for trip characteristics and the implementation of the accessibility model is provided in Section 3. In Section 4 the outcomes of the distributed survey and the job accessibility analysis are presented, after which a conclusion on the research is given in Section 5.

2 Literature review

2.1 Car-free development and factors influencing car ownership

The terms low-car and car-free development have been used in various contexts to refer to an area in which the number of car trips has been reduced or fully excluded. Over the last decades, several large-scale low-car and car-free residential areas have been constructed throughout Western Europe. Although differences can be observed between cases, mainly three different types of car-free development can be distinguished. First, the Vauban model restricts any form of parking places, both on-street as well as private parking spots, while car owners are obliged to buy a parking spot on the periphery of the area (Melia, 2014; Nobis, 2003). Second, the Limited Access model is often used in car-free development areas of smaller scale, preventing motorized traffic from entering the area and instead forcing inhabitants to park outside the area (Melia et al., 2010; Melia, 2014). Third, pedestrianized city centers can be seen as a form of low-car development, often significantly reducing the number of cars due to the proximity of activities and opportunities as well as their excellent public transport connections (Melia, 2014; Parkhurst, 2003). This study adopts the definition of Melia et al. (2010) in which low-car or car-free development is defined as a residential or mixed land-use development that:

1. includes a traffic-free or almost traffic-free direct environment;
2. offers limited to no parking opportunities other than facilities belonging to the residence; and
3. allows the residents to live without the need for car ownership.

According to this definition, residents in low-car and car-free development are discouraged to own a car and motorized vehicles are partly or fully excluded from the area. These two aspects are closely related to each other, as the exclusion of vehicles indirectly leads to a reduction in car ownership and vice versa (Melia, 2014). As a consequence, less land is needed for roads and parking places, the use of public transport is endorsed, more local services are established and an increase in active travel through cycling or walking compared to conventional areas can be noticed (Melia et al., 2013; Parkhurst, 2003). Advantages concerning the environmental improvement and quality of life depend on the type of exclusion of vehicles in the area (Melia et al., 2013; Ornetzeder et al., 2008). Melia et al. (2010) also found that the level of car ownership was reduced, even in areas where parking spots are available for residents. In many cases, households reduced the number of cars from multiple cars to only one. This suggests that a single car was enough to provide sufficient accessibility for households that used to own multiple cars.

In addition to the type of area, the success of low-car and car-free development also depends on attributes lowering the level of car ownership. The extent to which car ownership can be influenced relies on four attributes. First, having the opportunity to use public or shared transport modes is an important factor in lowering individual car ownership in low-car and car-free development areas (Clark, Chatterjee, et al., 2016). More opportunities to use these transport modes result in better levels of accessibility and lead to a reduction in car ownership (Cao et al., 2007; Rajamani et al., 2003; Van Acker & Witlox, 2010). Second, built environment attributes influence the preferred mode of transport through the so-called 6D aspects (Ewing & Cervero, 2010); An increasing urban density (Oakil et al., 2016), a diverse number of land-use types (Ewing et al., 1994; Kockelman, 1997), an attractive and safe design focused on non-car modes (Cao et al., 2007; Van Acker & Witlox, 2010), destination accessibility defined by spatial distribution of activities and the extent to which transport systems enable (groups) of individuals to reach these activities (Geurs & van Wee, 2004; Páez et al., 2012; Straatemeier & Bertolini, 2008), a short access and egress distance to public transport stations (Chatman, 2013; De Gruyter et al., 2020) and demand management in terms of price and availability of parking opportunities (Litman, 2010; Weinberger et al., 2009). Third, socio-demographic characteristics influence car ownership, with relatively fewer cars owned among younger (<30 years) and older (>75 years) persons (Kampert et al., 2017) and more cars owned when in presence of driving license availability, children or two-parent families (Clark, Chatterjee, et al., 2016; Oakil et al., 2016; Potoglou & Kanaroglou, 2008). Among young adults, both negative and positive changes in car ownership are caused by factors like a change in lifestyle, economic insecurity and the increase in e-communication (Goodwin & van Dender, 2013; Oakil et al., 2016). Fourth, individual perspective towards car transport in the form of habitual car use (Gärling & Axhausen, 2003; Nolan, 2010; Tao et al., 2019), status and affection (Bamberg et al., 2003; He & Thøgersen, 2017) and previous car ownership (Liao et al., 2020) results in higher car usage.

In summary, from the literature, it can be concluded that built environment attributes, the availability of alternatives to the car (shared and public transport) and socio-demographic characteristics of residents co-determine car ownership levels. More specifically, socio-demographic characteristics that are commonly found to have an impact on car ownership are gender, income or occupation and age (Chen & Akar, 2017; Dixit & Sivakumar, 2020; Mercier, 2016; Tseng & Wu, 2021). It is expected that within this study, similar influential socio-demographic characteristics can be identified to have an influence on (job) accessibility of residents of car-free areas. Therefore, it is key to further specify the definition of accessibility and its components in more detail.

2.2 Accessibility

The concept of accessibility can be considered as the combination between the transportation system and the spatial distribution of activities (Páez et al., 2012; Straatemeier & Bertolini, 2008), with other sources also including time and individual characteristics within this definition (Fransen et al., 2015; Geurs & van Wee, 2004; Stępniak et al., 2019). Thus, accessibility changes based on:

- the transportation component, defined by the transport network and its trip characteristics between origins and destinations;
- the land use component, represented by the number of spatial activities and its competitors within a reachable range;
- the temporal component, depicted by the trip characteristics in different time frames that are taken into account or the time frame budget of an individual in relation to timetables; or
- the individual component, including preferences of individuals or households and their acceptance of trip characteristics within the trip.

The first three components can be incorporated using standard potential accessibility measures originally presented by Hansen (1959) using a gravitational function. This function describes the influence of opportunities further away from an origin to be exponentially less important, while also other impedance functions can be used (Vale & Pereira, 2017). To better illustrate supply and demand for opportunities, various competition effects that are based on the share of the population with access to the opportunity can be incorporated within the accessibility analysis (Geurs & Ritsema van Eck, 2003; Joseph & Bantock, 1982; Shen, 1998). The fourth (individual) component is more difficult to include in a standard potential accessibility analysis, as within literature generally a decay function is considered that is based on conventional expectations (Páez et al., 2012). Recent literature tries to distinguish objective and perceived accessibility, with objective accessibility mostly relating to the aspects of the built environment and perceived accessibility capturing the subjective aspect of accessibility (Cascetta et al., 2013; Lättman et al., 2018). A major challenge has however been identified when considering perceptions in location-based accessibility measures, as decay parameters that correspond with perceptions need to be established (Pot et al., 2021).

In the case of accessibility in a car-free development area, Nobis (2003) identify the need for a robust public transport system immediately at the time of residents moving to the area. This guarantees accessibility by car-free modes and minimizes the need for inhabitants to rely on car ownership. Within these categories, attributes that have been found to be most critical in customer satisfaction are either physical attributes in terms of price, travel time, reliability and operating frequency or perceived attributes such as comfort, safety, convenience or attractiveness (Andreassen, 1995; Eboli & Mazzulla, 2008; Hensher et al., 2003; Redman et al., 2013). Besides, accessibility by active travel modes being walking and cycling needs to be encouraged in car-free development areas (Melia et al., 2010). This can often be realized by modifying the existing road network to exclude car traffic and instead providing more space for walking and cycling, making it more likely for people to walk or bike if destinations are more easily accessible using these modes (Rajamani et al., 2003).

The most important difference between accessibility by private cars and by public or shared transport modes is the trip approach. Although from an in-vehicle perspective (i.e., time in the transport mode) not many differences between these modes are noticeable, private car ownership is highly advantageous from a door-to-door approach due to the number of steps that need to be considered at the access and egress part of a trip when using a public or shared mode (Pritchard et al., 2019; Salonen & Toivonen, 2013). To minimize the difference in the levels of accessibility by private car and by public transport, the integration between public transport or car sharing with walking and cycling has the utmost importance. Three types of indicator measures are key within this integration, being system accessibility in terms of travel resistance at the access and egress part of a trip, system facilitated accessibility in terms of travel resistance within the transport system itself and service level accessibility by for example higher frequencies and sufficient (bike) parking facilities (Fransen et al., 2015; Lei & Church, 2010; Shelat et al., 2018).

Although car-free development is regarded as a progression to promote active transport modes and healthier cities, the effects of these developments on accessibility levels of different population groups have not been fully understood. Literature has focused primarily on the impacts of low-car and car-free areas on mobility patterns and car ownership, but individual preferences and the perception of trip characteristics within a trip are rarely included in potential accessibility analyses within the literature. To address this gap, this paper proposes an accessibility assessment framework that integrates socio-demographic characteristics at an individual and a household level into an accessibility assessment.

3 Methodology

This section provides an overview of the method followed within this research. A schematic overview of this method is depicted in Figure 1. A survey has been conducted in existing car-free development areas in the Netherlands (subsection 3.1), which feeds into a Latent Class Logit (LCL) model to determine trip characteristic utilities for public transport trips (subsection 3.2). A Monte Carlo simulation is used to establish average trip characteristic utilities for different socio-demographic groups (subsection 3.3), after which car-free job accessibility for these groups is evaluated in the Province of Utrecht (subsection 3.4).

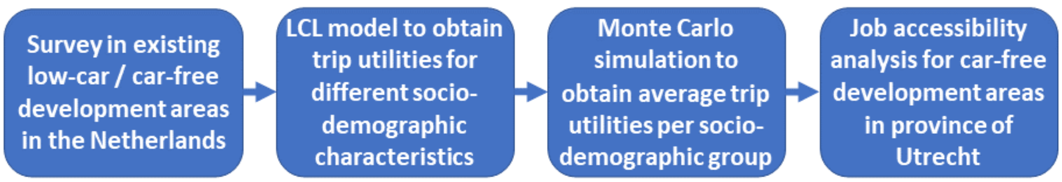


Figure 1. Schematic overview of the method followed in this research

3.1 Case study and survey

The job accessibility analysis in this study was conducted in the province of Utrecht, the Netherlands. As one the first low-car development areas in Utrecht, the Merwedekanaalzone, is not fully developed yet, inhabitants in similar car-free or low-car development areas were needed to collect data. To do so, a random survey sample of inhabitants in three different low-car areas in the Netherlands (Merwedekaalzone in Utrecht, GWL Terrein in Amsterdam and Ebbingekwartier in Groningen) was collected via door-to-door flyers. The selected areas have approximately the same size (500-1000 households), are located in urban to very-urban zones close to the city center, and accommodate around 20 to 25% of the number of parking places that a regular urban area would provide. An overview of the survey areas can be found in Figure 2.

There are also differences within the three areas: the Merwedekanaalzone is characterized by high-rise apartment households, while the GWL Terrein has low-rise apartments and Ebbingekwartier has terraced residences. This results in different population densities of respectively 3310 (Merwedekanaalzone, 10.000 when fully developed), 8916 (GWL Terrein) and 6503 (Ebbingekwartier) addresses per km^2. The collected data from the survey was employed to construct a general model representing the values attributed to certain trip characteristics by the inhabitants in low-car and car-free development areas.

To determine the utility of the various trip characteristics and to account for individual and household characteristics in the job accessibility analysis, a web-based stated choice survey has been conducted that consists of three different sections:

1. Socio-demographic characteristics: Age, income, education, gender, household situation, employment, car ownership.
2. Commuting characteristics: Current travel time and travel mode, satisfaction with current travel time and mode, preferred travel time and travel mode, perception on travel modes.

3. Five discrete stated choice experiments consisting of two choices that vary in terms of walking time, waiting time, in-vehicle time and costs.

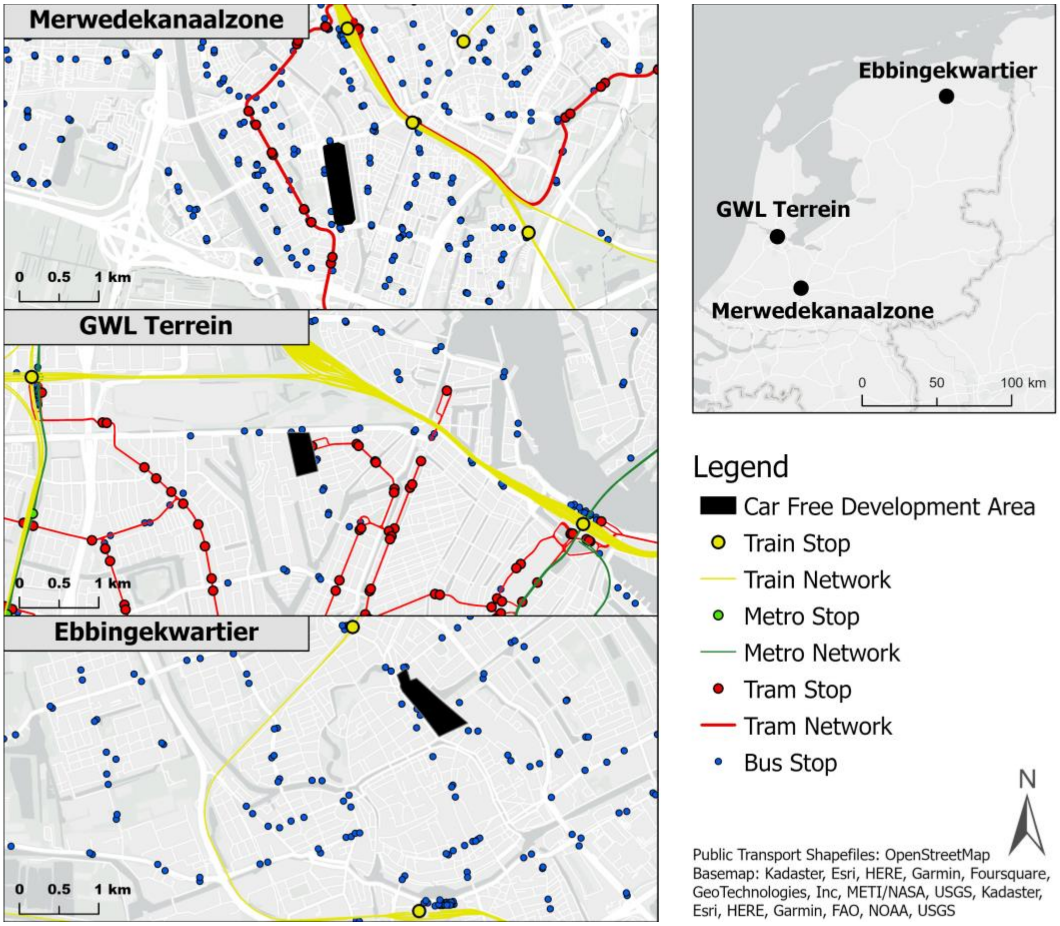


Figure 2. Overview of the case study areas in the Netherlands, the Merwedekanaalzone (Utrecht), GWL Terrein (Amsterdam), and Ebbingekwartier (Groningen)

To obtain a stated choice experiment that properly depicts the utility of the respondents, the concept of accessibility from a door-to-door perspective was used (Salonen & Toivonen, 2013). This concept states that accessibility by public transport is different from normal car transport in terms of access and egress time. Moreover, the time waiting at the public transport station is also needed to be taken into account. Therefore, not only travel costs and travel time are important, but also waiting time and access time are significant (Van Hagen, 2011). As a result, four different travel attributes as enumerated below were altered throughout the choice sets. In every attribute, three different attribute levels were presented, as listed below in Table 1.

1. **In-vehicle time** spent actively on the public transport vehicle by a person.
2. **Access and egress time** for a person to travel to and from the nearest public transport station.
3. **Average waiting time** before departure at public transport or shared car station: Time between arrival at the public transport station and departure of the public transport vehicle.

4. **Usage cost** of a shared car for a fixed distance and time: As in one-way trips using a shared car is not an option due to the absence of handing in the vehicle, a large renting time for a predefined cost has been used within the analysis. Costs are the average price of car-sharing operators in the Netherlands.

Table 1. Attributes and attribute levels as used in stated choice experiment

Attribute	Level 0	Level 1	Level 2
In-vehicle time	20% faster	Same as current trip	20% slower
Access time	6 minutes walking	12 minutes walking	18 minutes walking
Average waiting time	5 minutes	10 minutes	15 minutes
Usage costs	€15 for 5h and 50km	€25 for 5h and 50km	€35 for 5h and 50km

The number of different choice sets that needed to be filled in by respondents was limited to minimize the chance of respondents quitting the survey or finishing the survey without making a thorough consideration between alternatives. Therefore, a maximum of five choice sets were given to the respondents. An example of a choice card has been provided in Table 2. In order for the design to be sufficiently efficient, respondents were evenly distributed among five different choice designs with no nearly identical options or alternatives that were objectively worse (Street et al., 2005). This resulted in a total of 25 different choice sets in which the alternatives were considered. A choice set was generated by making use of a pilot version to eliminate redundant choices which create an undesirable advantage for one of the alternatives in all attribute levels. A fractional factorial design was adopted to create the choice sets, giving the possibility of best describing the utility of the different attributes (Rose & Bliemer, 2009). Thus, the efficiency of the design needed to be evaluated. By using the created choice design, a D-efficiency of 95 was reached, indicating that the choice design is appropriate to use (Kuhfeld, 2012; Louviere et al., 2008).

Table 2. Example choice card as used within this research

Question:	Considering the following characteristics for your daily commuting trip, which car-free development area would have your preference		
	Neighborhood A		Neighborhood B
Usage costs	€25		€15
In-vehicle time	20% less than original		20% more than original
Walking time	6 minutes		12 minutes
Waiting time	On average 10 minutes		On average 5 minutes
Choice:	Neighborhood A	No preference	Neighborhood B

3.2 Analysis of the trip utilities based on the survey

The survey results were analyzed using a latent class logit model. Latent class logit modelling is part of the discrete choice models, adopted from the multinomial logit (MNL) regression model which is widely used in different applications as it is easily interpretable and considerations between mutually exclusive alternatives can be found (Aloulou, 2018; Train, 2003). Depending on the presented attributes and individual preferences, respondents will value one aspect of a low-car development area over another, resulting in an objective function that the individual tries to optimize. This objective function reflects the rational behavior of the individual, thus also being different for every individual. By using a multinomial logit model, the estimated probability of a certain alternative according to the given aspects can be determined.

Within this MNL regression model, an important assumption needs to be evaluated, as the MNL regression model considers the principle of Independence from Irrelevant Alternatives (IIA). The IIA assumption states that the ratio of the probabilities of choosing one choice alternative over another is unaffected by the presence of any additional alternatives in the choice set (Louviere et al., 2000). This assumption holds when every respondent within the analysis is making a single choice decision based on their preferences. In a discrete choice experiment as used within this research, however, individuals are making multiple decisions based on their individual preferences. As these decisions are based on the same decision process of the individual, the error terms are not independent anymore and the assumption is violated. This introduces the need for other models that focus on relaxing the strong assumptions with independent and identically distributed error terms (Louviere et al., 2000).

The Latent Class Logit (LCL) regression model in Equation (1) provides similar results in comparison to the Multinomial Logit model, however, finding results for different identified classes in the data (Shen, 2009). The LCL model assumes that a discrete number of these classes are sufficient to represent the preference heterogeneity across classes, distinguishing the respondents based on unobserved variables. These classes do not contain specific responses or a set of responses from a single respondent, hence being called latent. Instead specific parameters, including socio-demographic parameters, can be included in the model generation to differentiate between classes (Hess, 2014). Note that these parameters themselves do not account for the difference in preferences, but instead underlying non-observed variables represented by each of these socio-economic parameters address the heterogeneity between respondents.

$$P_{iq|s} = \frac{e^{V_{iq|s}}}{\sum_{j=1}^{J} e^{V_{jq|s}}} \tag{1}$$

Where,

- $P_{iq|s}$ is the choice probability of choosing alternative *i* for individual *q* in latent class *s*;
- $V_{iq|s}$ is the level of utility that alternative *i* provides for individual *q* in latent class *s*.

3.3 Monte Carlo simulation

Based on the socio-demographic characteristics of a persons household, the probability to belong to either of the classes is determined using the results from the generated LCL regression model. As each of the socio-demographic indicators influences the chance to belong to either of the two non-observed latent classes identified from the LCL regression model, a deterministic trip utility can be composed for every individual. In this study, however, trip utilities for population groups as a whole were analyzed using a probabilistic approach through Monte Carlo simulations (Train, 2003). This approach is depicted in Figure 3.

First, distributions of socio-demographic distributions (age, income and household size) have been distinguished within the survey results. Second, population groups were identified for which the job accessibility levels have been analyzed based on target groups identified by the municipality of Utrecht as potential residents of the Merwedekanaalzone (Gemeente Utrecht, 2019). Three different population groups were distinguished within the case study; Starters (Aged between 18 and 35), Families (Household size of over two) and Senior Adults (Age of over 50). A reference population group was used as being the average household in a low-car or car-free development area, not filtering on any of the socio-economic variables but instead taking into account the entire survey sample. A Monte Carlo simulation of 10.000 draws from the socio-demographic distribution in the survey results is used to generate synthetic population groups. These synthetic population groups are not an observed population group, but rather a random combination of potential socio-demographic characteristics in the survey distribution. As a result, average trip utilities on the four public transport components (costs, travel time, walking time and waiting time) are found, serving as input for the job accessibility analysis.

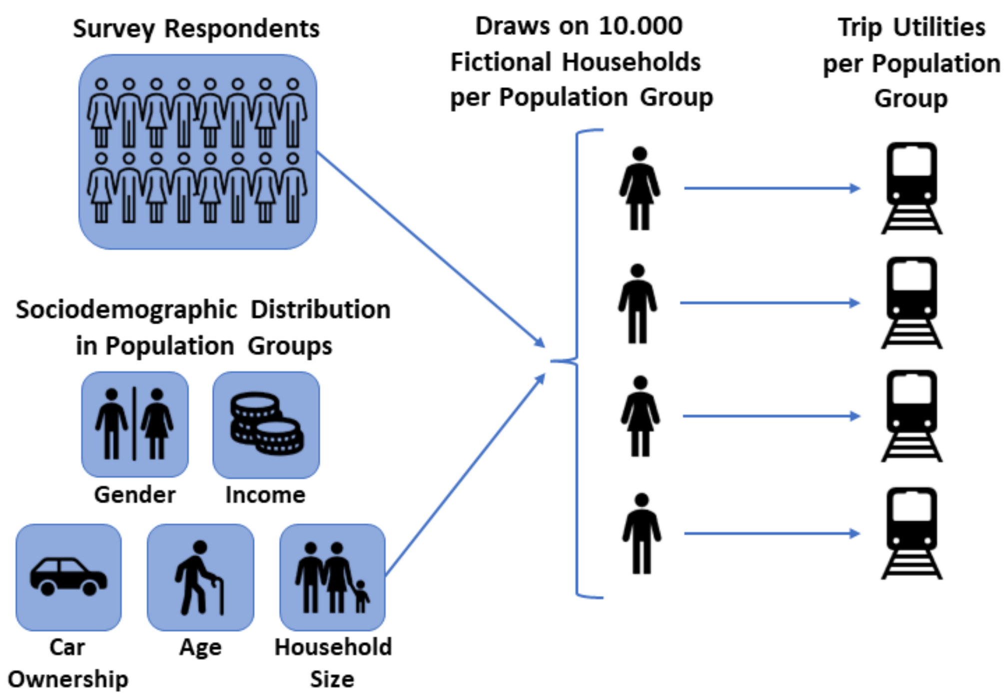


Figure 3. Methodological design of Monte Carlo Simulation

3.4 Job accessibility analysis of low-car and car-free development areas

To perform a job accessibility analysis a standard potential accessibility function with detailed impedance functions was used, as seen in Equation (2). While most of these impedance functions are based on a single cost such as travel distance or travel time, within this research multiple factors are considered to affect job accessibility. Therefore, an impedance function that includes a combination of these characteristics is constructed. This results in a probability to make a certain trip, that is dependent on the utility that it provides for a specific individual with regard to the trip characteristics. By making use of this probability impedance function it is not only possible to include the availability of a trip (space-time component), but also to include the level of utility that the trip provides to a particular individual (behavioral component).

$$A_{i,s} = \sum_{j=1}^{J} O_j * P_{i,j,s,t} \tag{2}$$

Where,

- $A_{i,s}$ is the provided job accessibility in origin *i* for population group *s*;
- O_j are the number of available activities (here; jobs) in destinations *j*;
- $P_{i,j,s,t}$ is the probability that the trip between origin *i* and destination *j* is being made by an individual from population group *s*, dependent on the trip characteristics *t*.

Furthermore, the imbalance between the demand for and supply of spatially distributed activities (competition effects) is considered in the job accessibility analysis. Equation (3) depicts the influence of competitors on the level of job accessibility. In this equation a competition effect was incorporated by including the population in the analysis zones, making use of the Shen Index (Pritchard et al., 2019; Shen, 1998) that incorporates competition for opportunities at all destinations *j*. This index provides a ratio between the accessible jobs and the population that can reach these jobs, using a decay or impedance function for both. Equation (4) depicts the probability for inhabitants to make a trip, both for inhabitants from the origin zone and for inhabitants who compete, based on the level of utility that the trip gives. This probability is dependent on both the utility that the trip characteristics provide for an individual, as well as on the trip characteristics of the actual trip between origin and destination.

$$O_j = \frac{o_j}{\sum_i P_i \, p_{i,j,s,t}} \tag{3}$$

$$p_{i,j,s,t} = e^{\sum_t \beta_{s,t} X_{i,j,t}} \tag{4}$$

Where,

- O_j is the number of available job opportunities in destination *j*, considering the number of inhabitants that have a probability to compete for the opportunities;
- o_j is the total number of job opportunities in destination *j*;
- P_i is the total number of inhabitants in origin *I*;
- $p_{i,j,s,t}$ is the probability that the trip between origin *i* and destination *j* is being made by an individual from population group *s*, dependent on the trip characteristics *t*;
- $\beta_{s,t}$ is the relative increase or decrease in utility of trip characteristic *t* in population group *s*;
- $X_{i,j,t}$ is the actual value of trip characteristics *t* within a trip between origin *i* and destination *j*.

3.5 Used data and geographic information system model

A GIS network as seen in Figure 4 was established, which is able to find multi-modal transport trip characteristics from origins within the province of Utrecht to every considered postcode area. By minimizing the total travel resistance, trips in the model are assumed to be done on foot, by public transportation or by a combination of walking and public transportation. With out-of-vehicle (waiting time, walking time) trip characteristics expected to being perceived significantly more negative compared to in-vehicle time (Gunn et al., 1985; Hossain et al., 2015; Wardman, 2001), the model minimizes the travel resistance based on Equation (5). Costs are not included when minimizing travel resistance.

$$Travel\ resistance = in - vehicle\ time + 2(waiting\ time + walking\ time) \qquad (5)$$

Job opportunities, as well as competitors, have been aggregated within every area, using census data from Statistics Netherlands (Dutch: Centraal Bureau voor de Statistiek, CBS) and labor data from Provincial Job Opportunity Register (Dutch: Provinciaal Arbeidsplaatsen Register, PAR) and National Information System for Job Opportunities (Dutch: Landelijk Informatiesysteem van Arbeidsplaatsen, LISA). First, data from OpenStreetMap (OSM) is used to determine streets suitable to traverse by foot. To account for connectivity issues in the OSM network, a Python script has been developed considering several types of intersections and reshaping edges and nodes in the street network in case of faulty connectivity. This does not change the actual street pattern network but triples the number of nodes and edges in the transport network. Secondly, a separate layer is created for each of the different forms of public transport available in Utrecht, being bus, tram and train transport. A third layer represents the waiting time when accessing the public transport network as well as transfer time from one public transport service to another, increasing travel impedance in terms of boarding costs and waiting time. To obtain the in-vehicle time for passengers, operational timetable data from local transport operators has been used. Waiting time in the model is based on the operational frequency of the transferring connection during commuter travel times (08:30-09:30 AM), which results in an average waiting time of half the headway between two services.

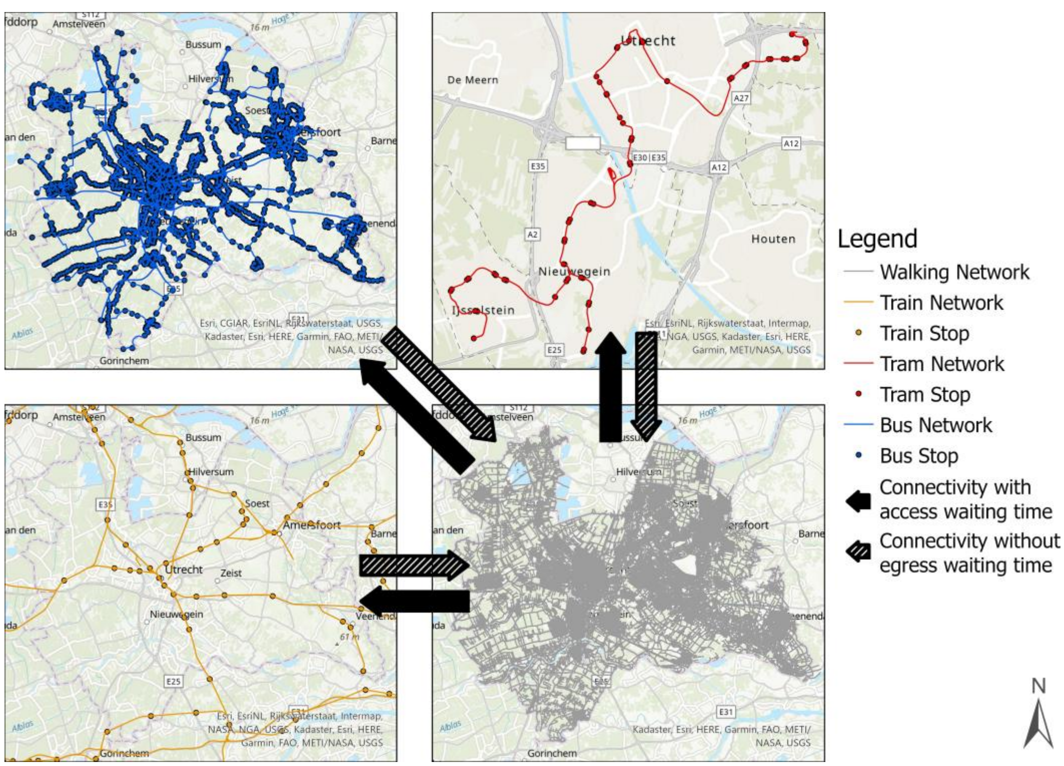


Figure 4. Overview of GIS network and the connectivity between layers

4 Results

4.1 Survey results

Table 3 shows the results of the conducted survey. All socio-demographic characteristics that have been collected within the low-car development areas are compared with results from nationwide research, being the Mobility Panel Netherlands (MPN) (Hoogendoorn-Lanser et al., 2015). This data is collected by The Netherlands Institute for Transport Policy Analysis (KiM), determining travel patterns both on an individual and a household level.

The table presents notable differences between the collected responses and the MPN respondents. Residents in a low-car development area are more often (self-)employed and on average earn a higher yearly income per household compared to respondents of the MPN survey. This indicates that living car-free is easier to accomplish for higher-income households. Persons over 60 years of age are less represented within low-car development areas. Instead, households with residents between 30 and 40, or between 50 and 60 years old are more often present within the sample. A possible explanation for the low number of older-aged persons in the sample is that these people are more constrained by habitual patterns compared to younger people and that they are therefore hesitant to give up car ownership or to relocate to the recently realized areas.

Table 3. Socio-demographic distribution in this research (Survey) and in Dutch nationwide research (MPN)

Type	Option	Survey (%)	MPN (%)
Gender	Male	51.3	47.0
	Female	43.3	53.0
	Other/Prefer not to say	5.4	0.0
Occupation	Self-employed	12.6	3.6
	Employed	65.9	47.2
	Student	1.6	10.9
	Retired	15.4	20.5
	Unemployed/Incapacitated	2.1	8.5
	Housewife/Husband	0.5	7.3
	Unknown	1.6	1.9
Income	Minimum	1.3	6.3
	Below Average	8.2	19.5
	Average	18.4	22.3
	1-2x Average	29.1	24.7
	2x Average	11.4	4.9
	More than 2x Average	20.9	6.7
	Unknown	10.8	15.6
Age	18 – 29 years	12.6	19.2
	30 – 39 years	19.8	18.6
	40 – 49 years	12.1	15.1
	50 – 59 years	18.1	17.8
	60 years or older	20.9	29.3
	Unknown	16.5	0.0

Household composition	Couple with children	24.7	27.8
	Couple no children	38.0	28.8
	Single	35.4	36.6
	One-parent family	1.9	6.5
Household size	1 person	34.2	36.2
	2 persons	41.1	32.6
	3 persons	6.3	11.4
	4 persons	16.5	14.1
	More than 4 persons	1.9	5.7
Car ownership	No cars	47.6	19.7
	1 car	48.8	54.6
	2 cars	3.6	18.8
	3 or more cars	0.0	6.9
	Car driver's license	85.4	87.2
	No car driver's license	14.6	12.8
Current commuting travel mode	On foot	7.7	0.9
	(Electric) Bike	49.5	7.9
	Train	15.9	6.0
	Bus/Tram/Metro	0.5	3.2
	Car	23.6	53.5
	Other	2.7	28.6
Preferred commuting travel mode	On foot	6.7	3.4
	(Electric) Bike	64.2	34.8
	Train	12.3	3.2
	Bus/Tram/Metro	2.2	2.2
	Car	12.9	52.4
	Other	1.7	3.9

As expected within the investigated areas, car ownership is considerably different from the nationwide average. Most of the areas do not explicitly prohibit households from owning a car, resulting in areas being low-car with almost half of the households still owning one or more cars. It can be noticed, however, that the number of households possessing more than one car is minimal. This implies that households that live in a low-car area in almost every situation opt to dispose of any extra cars. Looking at the share in driver's license, while also taking into account the high-income levels in the sample, this car ownership reduction is not due to their capacities or financial situation but instead indicates that the respondents deliberately choose not to own a car or to own a smaller number of cars. Most of the respondents that possess a car state that the reason for this is the mobility that it provides compared to other transport modes. Fewer respondents state that their destinations are better accessible using a private car. Thus, it can be observed that both the mobility aspect and the accessibility impact of public transport are perceived as worse compared to private car usage by the respondents that own a car. Moreover, the feeling of freedom or control when using a private car is frequently mentioned by respondents. This is in line with the reduction in cars from multiple cars to one car, indicating that at least one car is necessary for many households in occasional situations or when public transportation connections are insufficient.

Regarding the current and preferred commuting travel mode, it can be noticed that already a large share of respondents in the low-car areas are using a bicycle as their main commuting transport mode, whereas within the nationwide sample over half of the respondents are commuting by car. This indicates that possibly residential self-selection has taken place in these low-car areas, resulting in inhabitants that purposely choose to live close to their job location. Within both samples, a large number of people respond that their preferred commuting mode is by bicycle. It is not observed why there is a difference between the current and the preferred commuting travel mode, potentially due to job locations not being within a suitable cycling distance.

From the descriptive statistics, promising influential socio-demographic characteristics can be distinguished. Whereas all of the socio-demographic characteristics will be tested within the LCL model, it is expected that especially age, income and car ownership are influential due to the differences between the survey population and the nationwide population.

4.2 Latent class logit model and trip utilities

With the use of the discrete choice model in the survey as described in the Methodology section, a latent class logit (LCL) model is generated. This model relates to a standard choice experiment in which the respondent has a binary choice between options A and B that is dependent on the relative influence of the independent trip characteristics. Within this model, multiple latent classes, as well as different socio-demographic indicators, are considered to predict the probability to use public transportation for a commuting trip with given trip characteristics. A model with two latent classes best describes the collected data. Within each class, coefficients for the different trip characteristics and coefficients for socio-demographic characteristics are determined, which are illustrated in Table 4. Based on these socio-demographic characteristics, individuals will have different likelihoods to belong to one of the two classes and will thus perceive job accessibility differently. While socio-demographic characteristics cause individuals to belong to different classes, the underlying motive of an individual to value trip characteristics differently cannot be captured; hence, the classes are called latent.

Table 4. Latent Class Logit model

	Coefficient	Beta	Std. Error	90% CI Low	90% CI High
Trip utilities Class 1	Costs	-0.011	0.0159	-0.0122	-0.0103
	In-vehicle time	-0.050	0.0102	-0.0504	-0.0493
	Walking time	-0.256	0.0400	-0.259	-0.254
	Waiting time	-0.093	0.0266	-0.0949	-0.0918
Trip utilities Class 2	Costs	-0.096	0.0501	-0.0990	-0.0931
	In-vehicle time	-0.019	0.0169	-0.0207	-0.0188
	Walking time	-0.083	0.0526	-0.0863	-0.0802
	Waiting time	-0.191	0.0714	-0.196	-0.187
Class probabilities Class 2	Costs	-4.427	0.879	-4.478	-4.376
	In-vehicle time	-0.917	0.290	-0.934	-0.900
	Walking time	0.045	0.0114	0.0440	0.0453
	Waiting time	1.326	0.192	1.315	1.337
Log-likelihood	-173.81				
AIC Model	371.62				
AIC Minimum	485.77				

Figure 5 provides a graphical representation of the perception of trip characteristics in Class 1 and Class 2. As expected, it can be noticed that an increase in any of the trip characteristics will have a negative influence on the probability to complete a trip. The magnitude of this influence will however differ based on the perception of the individual. Within both Class 1 and Class 2, walking time and waiting time are perceived as worse compared to in-vehicle time. This is in line with the literature, as Hossain et al. (2015) state that as a rule of thumb out-of-vehicle time in the form of walking and waiting time can be considered to be twice as inconvenient in contrast to in-vehicle time. The same study states that the level of provided utility decreases relatively quickly when small walking distances need to be overcome, while this reduction in utility is less notable for additional distances over 150 meters. Wardman (2001) also states that this inconvenience is higher for walking and waiting, compared to in-vehicle time, but only around 60%. In their multi-modal transport model, Gunn et al. (1985) find evidence that the disutility of walking time and waiting time is respectively 2.4 and 1.8 times higher compared to in-vehicle time. Other modelling studies state that in comparison to in-vehicle time, walking time (1.5 to 2.0 times in-vehicle time) is better appreciated than waiting time (1.5 to 2.5 times in-vehicle time) (Wardman, 2004).

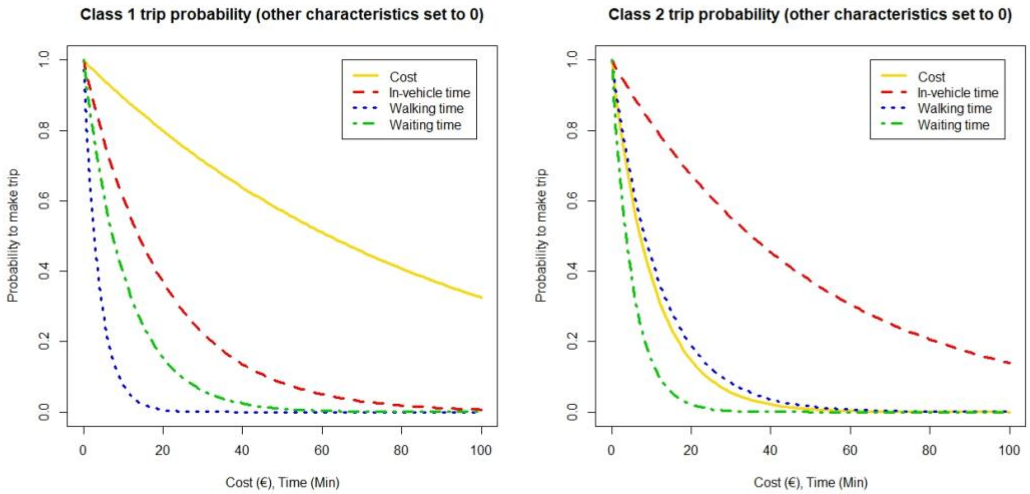


Figure 5. Trip probability for different characteristics in Class 1 and Class 2

The two classes contain a notable difference in the way time and money are perceived. Within Class 1 in-vehicle time is perceived as being more valuable compared to travel cost, while on the contrary in Class 2 travel cost is relatively more valuable compared to in-vehicle time. This corresponds with the probability to belong to a particular class, influenced by the influential socio-demographic characteristics being age, income and household size. Figure 6 provides this probability for the different socio-demographic characteristics, illustrating the relation between the increase in yearly income and the probability to belong to Class 2 in which travel costs are of less importance.

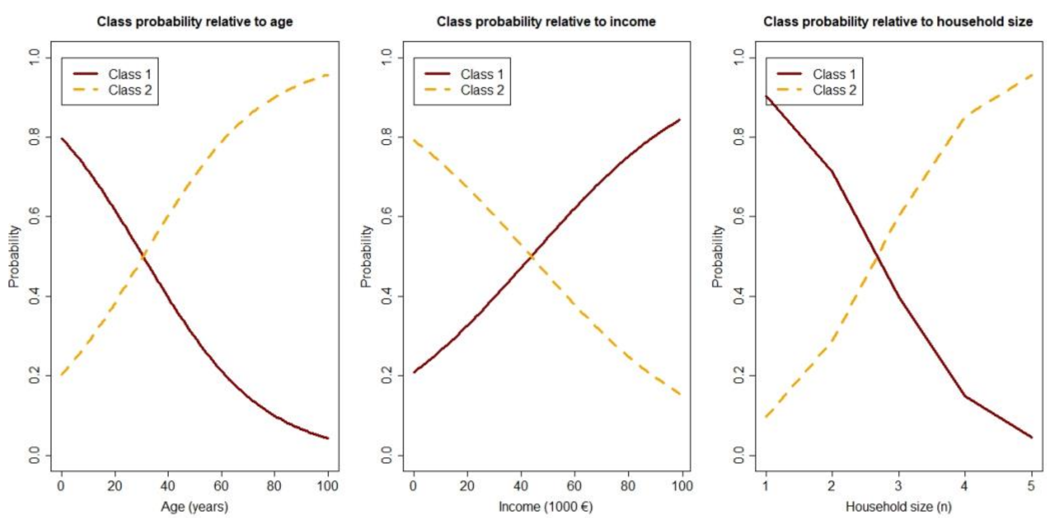


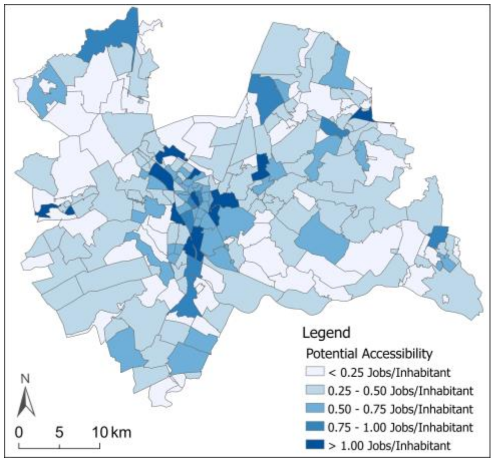
Figure 6. Class probability for different socio-demographic characteristics

4.3 Suitability analysis on car-free development

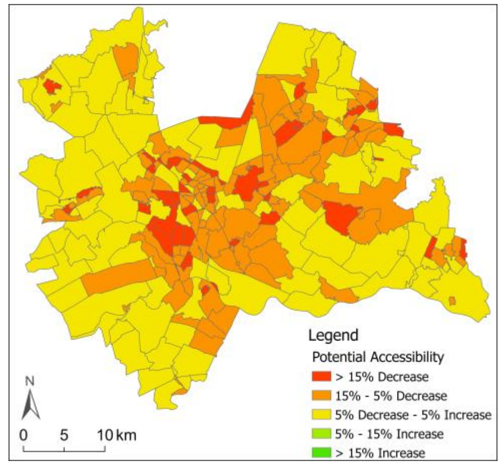
Finally, decay functions per population group were constructed using the synthetic population generation approach as described in Section 3.3. This results in different evaluations of the multi-modal commuting trip between origins and destinations depending on the socio-demographic indicators of a population group. Not only the current car-free development areas have been considered within this analysis, as other areas could potentially be allocated as car-free development areas. Thus, by implementing the framework in the entire province of Utrecht, the potential effectiveness or suitability of an area in case it will be developed as a car-free development area has been analyzed.

An overview of the job accessibility results in the province of Utrecht can be found in Figure 7, in which potential job accessibility is depicted for the different population groups. Within sub-figure (a), a reference population group is constructed showing potential job accessibility numbers without accounting for any socio-demographic differences in the population. As expected, higher job accessibility levels are observed in urban areas in proximity to public transport facilities. Within these urban areas, many jobs are available, potentially increasing potential job accessibility levels for nearby areas. Nevertheless, there are also plenty of inhabitants living in these areas, competing for the same jobs and therefore lowering potential job accessibility levels.

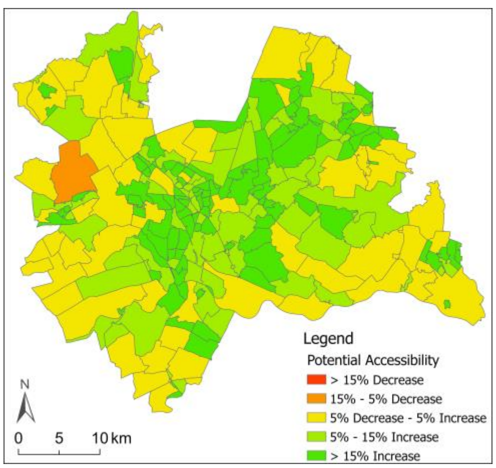
The other three sub-figures within Figure 7 demonstrate the levels of potential job accessibility levels relative to the reference population group. For starters, it can be observed that in urban areas fewer jobs are accessible. This indicates that starters observe higher travel resistances when commuting to work, resulting in lower job accessibility levels in general. Looking at potential job accessibility levels for families, on the other hand, a considerable increase is identified in many areas. For families, it is thus acceptable to commute further or to spend more finances on commuting. Potential job accessibility results for senior adults are in most areas not noticeably different, indicating that class probabilities for senior adults are situated close to the sample average.



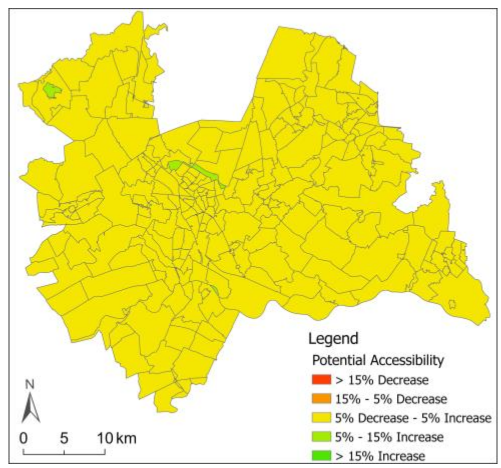
(a) Average



(b) Starters (Age between 18 and 35)



(c) Families (Household size more than 2)



(d) Senior Adults (Age over 50)

Figure 7. Potential job accessibility for different population groups in Utrecht, relative to potential job accessibility levels for an average household in the survey sample. Competition effects are determined based on a gravitational effect on the destining zone.

5 Conclusion

This paper proposes an analytical framework to determine potential job accessibility in car-free development areas for population groups with different socio-demographic characteristics. Approximately 170 residents in three different low-car areas in the Netherlands have responded to a stated choice survey regarding transport use and their perception of different transport modes and trip characteristics. The collected responses are used to estimate a Latent Class Logit regression model that depicts trip impedance within different socio-demographic groups. Combined with a multi-modal transportation network model that determines trip characteristics in the province of Utrecht, the LCL regression model is able to determine potential job accessibility levels for different population groups in the province of Utrecht.

From a first descriptive analysis of the survey results, it can be noticed that the population characteristics of the examined low-car areas are different from the nationwide population. Households on average consist of fewer people, while income levels are generally higher than average. Around half of the households do not possess a car, while the other half of the households only possess a single car. This indicates that households persist to possess a single car as an emergency solution and dispose of extra cars as it is not necessary in fulfilling their mobility needs. Commuting trips in low-car development areas are mostly performed by bicycle, which implies that residents either self-select to live close to their working location or find a job close to their residence.

The main findings of this research are listed below:

- The synthetic population approach used in this research allowed the estimation of detailed decay functions accounting for socio-demographic commuting preferences within the population, as input for location-based accessibility measurements. Significant job accessibility differences have been found between population groups, demonstrating that differences are present in transport characteristic perceptions that need to be accounted for.
- The developed framework is very practical as the socio-demographics-based decay functions are easily interpretable also from a non-technical perspective. This makes the approach useful for the transport planning practice, allowing to better consider transportation needs within population groups and thus offering more tailor-made solutions in specific areas based on these needs.
- Consequently, this study proves that LCL models are useful to determine population segments with different individual and household characteristics when analysing potential job accessibility levels. A framework is provided that is capable to include these characteristics, determining the suitability for car-free development areas in Utrecht. and offering accessibility analyses that better represent different needs and wishes in the population.

5.1 Limitations and future work

An important component of this research is the constructed regression model which utilized the survey data. However, the number of survey respondents remained relatively low which can potentially lead to accuracy issues for the estimated parameters. Therefore, a future study with a larger number of respondents would be beneficial to validate the findings of this research. Nonetheless, the LCL model outputs were used to demonstrate the usefulness of the proposed framework which resulted in relevant outcomes.

Another limitation of the framework is the assumption that for every mode of public transport, trip characteristics such as cost and waiting time are perceived equally. This results in one estimated coefficient for trip characteristics across different types of public transport. In reality, however, trip characteristics are potentially evaluated differently between different modes of public transport. An example of this can be found in the waiting time at different types of transfer stations. That is, waiting time at a bus stop might be perceived as worse than waiting time at a train station. A data collection effort that would allow a distinction between types of public transport is a promising future direction to increase the validity of the research outcome.

Furthermore, trip characteristics other than the ones utilized in this study can be incorporated into the accessibility model. In the current framework, only the aspects that directly influence travel time or travel costs were considered. However, trip characteristics such as security or comfort can be included within the discrete choice experiment and will be perceived differently from individual to individual. Nevertheless, it is worth mentioning that such additions may pose different challenges as more choice options would require increasing the choice set and can potentially confuse the respondents.

5.2 Policy implications

With more and more cities focusing on the development of low-car and car-free development areas to create a healthy urban environment, the applied framework can be used by policy makers to establish equitable outcomes for all inhabitants in terms of accessibility. With transport users having different perceptions based on their individual preferences, this framework can identify the level of potential accessibility for different population groups when considering possible locations for low-car or car-free developments. This ensures that not only the average potential accessibility levels are considered but that also preferences from minorities within the population can be recognized, hence being able to provide the most equitable outcome. However, when doing so it should be emphasized that potential job accessibility is not the only indicator to determine a suitable location for these developments and that other (non-transport related) aspects need to be considered as well.

Considering the Netherlands as being a bicycle-oriented country, it can be questioned that the combined use of cycling and public transport should be considered instead of the combination of walking and public transportation. With small adjustments to the constructed spatial network, policy makers could use the provided framework to estimate accessibility levels using a bike-and-ride principle. This would require a distinction in walking and cycling infrastructure that is already provided in the OpenStreetMap data as applied in this research, as well as an adjusted decay function to account for cycling time to a public transport station. Subsequently, this provides the possibility to analyze potential accessibility levels for both walking and cycling as well as a combination using one of the two and public transportation.

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