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The Effect of Socio-Economic and Spatial Characteristics on Acceptable Travel Distances

Master's Thesis

Submitted by:

Linus Jakob Piesch

Student Number: S4842014

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Supervisor:

Felix Pot, M.Sc.

University of Groningen

Faculty of Spatial Sciences

M. Sc. Economic Geography

Abstract

Transport geography research suggests the existence of acceptable travel distances (ATDs) as maximum distance thresholds which determine whether a person travels to a particular destination or not. ATDs are usually based on assumptions on desired behavior or derived from actual travel behavior. However, those assumptions have been shown to mismatch perceived accessibility. Travel behavior is also the result of both choice and constraints, which makes it difficult to evaluate if the identified distances are desirable or acceptable for different population groups. This study follows a new approach using a dataset on perceived accessibility in the Netherlands to derive ATDs with the aim to analyze the effect of destination type, socio-economic and spatial factors for different transport modes on ATDs. Employing cross-tabulations and logistic regressions, this study identified distance thresholds after which the perceived accessibility by active transport modes drops substantially. Incorporating those distance thresholds in planning can incentivize the use of active transport modes. Moreover, it was found that ATDs by car are larger for men than for women for all destination types except for health care trips. ATDs by active transport modes do not automatically decrease as age increases for leisure and supermarket destinations. ATDs by public transport are always larger for urban than for rural residents, and the ATDs by car are always larger for rural than for urban residents. To promote the use of sustainable transport modes, the findings emphasize that policy makers should focus more on the proximity of leisure locations and supermarkets in neighborhoods with older populations and on rural public transport development.

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List of Abbreviations

ATD	Acceptable travel distance
ATT	Acceptable travel time
CBS	Centraal Bureau voor de Statistiek (Statistics Netherlands)
H0	Null hypothesis
m	Meter
PA	Perceived accessibility
Pr.	Probability
PT	Public transport
Std. Dev.	Standard deviation

1. Introduction

One of the main goals of any transport system is to provide access to spatially dispersed activities. Accessibility is a key concept of transport geography and planning and describes the 'potential of opportunities for interaction' (Hansen, 1959, p. 73) that transport system users have, and more specifically the ease with which a location or service can be reached (Handy & Niemeier, 1997). Accessibility can therefore be seen as essential for social and economic participation and as an important contributor to life satisfaction and well-being (Lättman et al., 2019).

The most common approach to evaluate accessibility is by using the distance to a particular opportunity for identifying a catchment area. However, this practice has important shortcomings. First, the act of traveling to a particular opportunity does not necessarily mean that the traveling person is satisfied with the trip distance. It is possible that a person goes to a destination and nevertheless perceives the destination as too far, suggesting that the destination is not viewed as accessible. Second, using the approach of identifying a catchment area assumes that a universal acceptable travel distance (ATD) as maximum distance threshold exists and that destinations within this distance are always reachable for everyone. This is particularly relevant as research has shown that accessibility is not only shaped by distances, but also by individual and subjective characteristics of the traveling person, such as demographic and socio-economic characteristics (Aday & Andersen, 1974; Geurs & van Wee, 2004). Researchers have in fact identified a substantial mismatch between calculated and perceived accessibility (Curl et al., 2015; Lotfi & Koohsari, 2009). Hence, in the last years literature has increasingly focused on the phenomenon that accessibility is perceived differently from individual to individual. The key conclusion is that accessibility cannot be captured purely objectively based on calculated distances. Unfortunately, maximum distance thresholds are usually determined by using objective accessibility. Consequently, ATDs obtained by utilizing accessibility perceptions offer a promising research gap which this study will focus on. The advantage is that, although looking at actual travel behavior, the distances to destinations which are perceived as too far and therefore as inaccessible can be excluded. Additionally, accessibility perceptions of different socio-economic and spatial sub-groups can be taken into account. The main goal of this thesis is therefore to gain a better understanding of ATDs for various destination types and of the socio-economic and spatial factors influencing them. The research question is the following:

Research question: How do acceptable travel distances in the Netherlands vary for different transport modes?

Sub-question 1: How does the destination type (workplace/school, health care, leisure and supermarket) influence ATDs?

Sub-question 2: How do socio-economic factors (age, gender, income, educational attainment and household size) influence ATDs?

Sub-question 3: How does the spatial context (rurality and urbanity) influence ATDs?

To answer this research question, survey data on perceived accessibility (PA) and mobility from the year 2020 are used. The ATDs were calculated by using the postcodes of home addresses and four different destination types (workplace, health care, leisure and supermarket). The novelty of this study is that accessibility perceptions of the respondents instead are used to derive ATD. This sets this study apart from data sets on accessibility which follow the logic of objectively calculatable accessibility.

The better understanding of ATD based on accessibility perceptions obtained from the study can contribute to accessibility-based transport and land-use planning in numerous ways. First, it has the potential of fostering social inclusion. Citizens with a lower socio-economic status and elderly usually perceive lower levels of (objective) accessibility (Wang et al., 2015; Hitman-Schorr et al., 2019), which puts them at risk of social exclusion. A more comprehensive knowledge of travel distance thresholds, which take into consideration accessibility perceptions, could improve policies designed to improve those groups' accessibility to opportunities. For instance, a more precise knowledge about maximum distance thresholds can help to understand at what trip length the number of transport participants drastically reduces (Rastogi & Rao, 2003). Leyden (2003) has further shown that highly accessible neighborhoods have higher levels of mutual trust, political participation and social engagement, suggesting that a further understanding of ATD and PA could contribute to a democratic societal development.

Second, a better understanding of ATD has important implications for sustainability and health. With an enhanced knowledge about the maximum distances that a person is willing to go in a particular destination, transport planners can focus on the improvement of active transport mode (walking, cycling and e-biking) and public transport infrastructure and provision based on those maximum distances (Rahul et al., 2020). For example, when is the ATD for walking and cycling exceeded so that cars are used? This could make an important contribution to the shift towards low-carbon mobility. Additionally, walking and cycling as well as the accessibility to facilities for physical activity show potential for improving health (Boehmer et al., 2006; Scott et al., 2007).

Third, the current shift of spatial planning towards an accessibility-oriented approach and away from a mobility-oriented approach (Handy, 2020; European Commission, 2022) illustrates the high political relevance of the topic and the importance of accessibility evaluation. Although accessibility has been in investigation since the late 1950s, accessibility planning instruments and indicators are often still seen as 'incomprehensible and rigid black boxes' (Te Brömmelstroet et al., 2014, p. 4). Unfortunately, accessibility measures are therefore often sufficiently included in planning practice (Boisjoly & El-Geneidy, 2017). Finally, the currently discussed '15-minute city' (based on the idea of easy accessibility within 15 minutes by foot or bike) can serve as an illustrative example (C40 Knowledge Hub, 2020). Although it has already been implemented in some neighborhoods around the world, its comprehensive application requires a precise understanding of all factors ATD and PA.

2. Theoretical framework

This chapter lays the theoretical framework for the analysis of ATDs using accessibility perceptions. First, the key concepts accessibility and mobility are defined and distinguished. Second, the factors influencing ATDs will be discussed. Eventually, a conceptual model is developed which will summarize the key theoretical components of perceived accessibility.

2.1. Accessibility

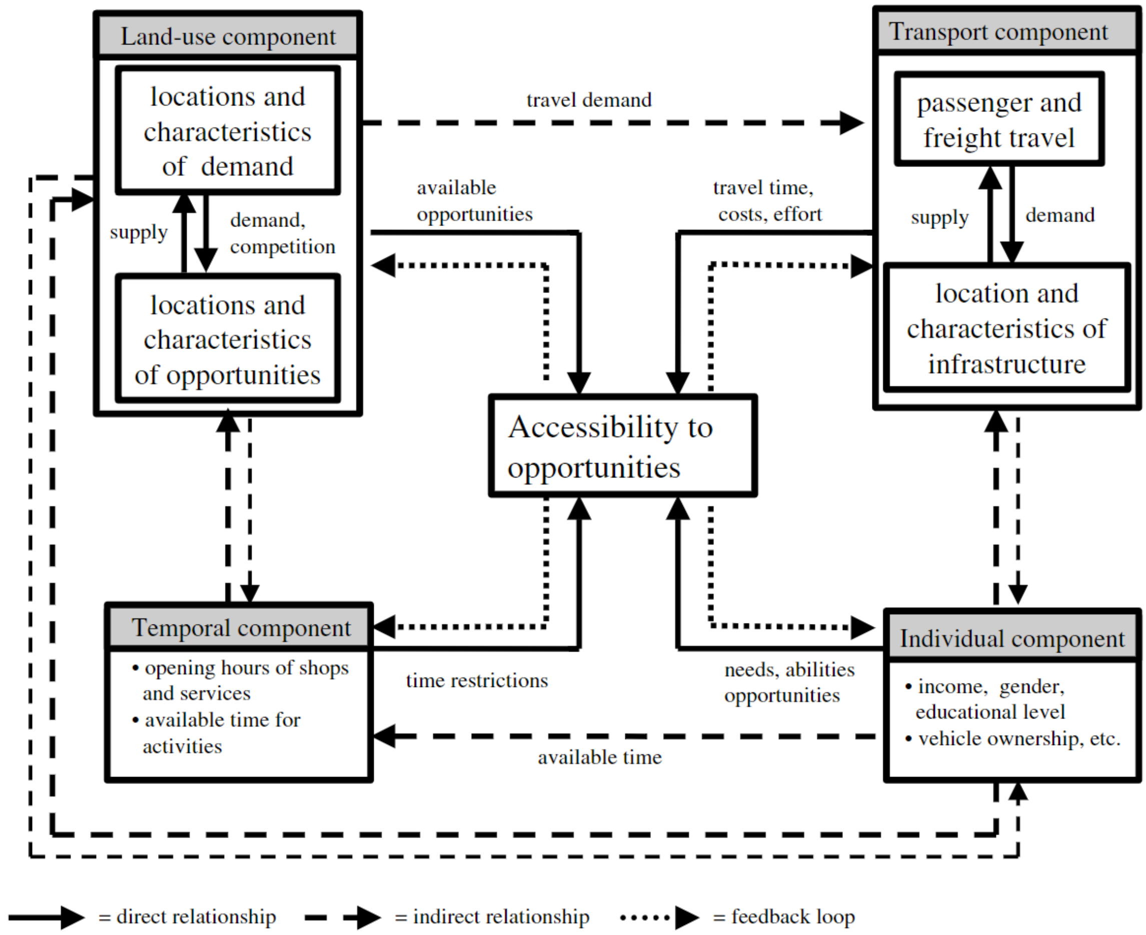
In 2020, Susan Handy published an article with the title "Is accessibility an idea whose time has finally come?". In that paper, she elaborates why accessibility faces so many conceptual and practical difficulties even though the concept of accessibility has been investigated since the late 1950s. This suggests that accessibility is no unambiguous concept. Both academics and policy makers have mis-defined accessibility and confused it with mobility (El-Geneidy & Levinson, 2006; Handy, 2005, 2020). For a concise understanding of accessibility, a first essential step is distinguishing it from mobility. Mobility describes the 'ability to travel, the potential for movement' (Handy, 1994, p. 6). Miller (2020) states that it involves the actual movement of people. As such, mobility describes transportation as an end in itself regardless of reaching a destination or activity. Mobility is therefore the dominant concept when looking into a leisure bike ride or a run. In those examples, the purpose of the trip is not to access a location or activity, but rather the process of moving around.

However, moving from one place to another does not guarantee social and economic inclusion of people. Here, accessibility comes into play. One of the first academics to define accessibility in a planning context was Walter Hansen (1959), who describes it as the 'potential of opportunities for interaction' (p. 73), and more specifically the ease or difficulty with which a location or service can be reached (Handy & Niemeier, 1997). This opportunity-based understanding of accessibility suggests that high levels of accessibility do not necessarily lead to higher levels of social interactions or inclusion.

Geurs and van Wee (2004) identify four key components that shape accessibility, which are illustrated in Figure 1: land use, transport system, temporal and individual components. Land-use and transport system are both related to space and how it is utilized. The land-use component does commonly refer to what activities take place where as well as to the concentration of those activities (Rodrigue, 2020). This leads to a supply-demand relationship. For example, the existence of jobs, health care and leisure locations and supermarkets in a particular area together with the demand influences the accessibility to those destinations and opportunities. The transport component relates to the transportation system and describes the disutility of an individual to cover the distance between origin and destination (Geurs & van Wee, 2004). Especially the time, costs and effects connected to the trip to a particular opportunity are essential. As such, the transport component represents the component which mobility-based planning builds on. This highlights once more the differences between mobility and accessibility. Out of the four accessibility components visualized in Figure 1, land-use and transport system are arguably the most important determinants of accessibility. In this sense, Ben-Akiva and Lerman (1979) define accessibility as the benefits provided by a transportation and land-use system.

Besides land-use and transport, accessibility is shaped by non-spatial factors. Figure 1 includes a temporal and an individual component of accessibility. While the temporal component describes restrictions regarding different day or night times, the individual component is much broader and covers needs, abilities and opportunities of people. As such, the individual component entails the subjective or perceived dimension of accessibility. It was first recognized by Aday and Andersen (1974) who distinguished a geographical/spatial (objective) and a socio-organizational (subjective) accessibility dimension. Yet, only in the last years research interest in PA has significantly increased (among others, see Curl et al., 2015; Friman et al., 2020; Lättman et al., 2018; Lättman et al., 2019; Scheepers et al., 2016; Van der Vlugt et al., 2019; Vitman-Schorr et al., 2019). The influence of subjective accessibility on overall accessibility is now incorporated in almost all accessibility definitions. The main take-away is that the spatial accessibility components illustrated in Figure 1 are perceived differently from individual to individual. Consequently, the mere fact that a particular location is physically close or quickly reachable does not automatically make this location accessible.

Figure 1: Accessibility components



Source: Geurs and van Wee (2004)

In general, an outcome-based and an opportunity-based understanding of PA can be distinguished (Pot et al., 2021). On the one hand, outcome-based definitions evaluate the benefits that accessibility offers, such as social inclusion. Guided by this understanding of PA, Lättman, Olsson, et al. (2016) developed a perceived accessibility scale for assessing PA when using public transport. This scale focusses primarily on 'how easy it is to live a satisfactory life using the transport system' (Lättman, Olsson, et al., 2016, p. 257). This suggests that activities which are perceived as accessible always lead to social inclusion, which does not seem very realistic. On the other hand, the more neutral opportunity-based understanding of PA emphasizes that activities might not always be desirable and therefore do not lead to social inclusion (Pot et al., 2021). This understanding is most useful for this study because it does not aim to measure the eventual social inclusion, but rather focuses on perceived access to a potentially inclusion-enhancing opportunity. In the remainder the definition by Pot et al. (2021) is used, defining perceived accessibility as 'the perceived potential to participate in spatially dispersed opportunities' (p. 2).

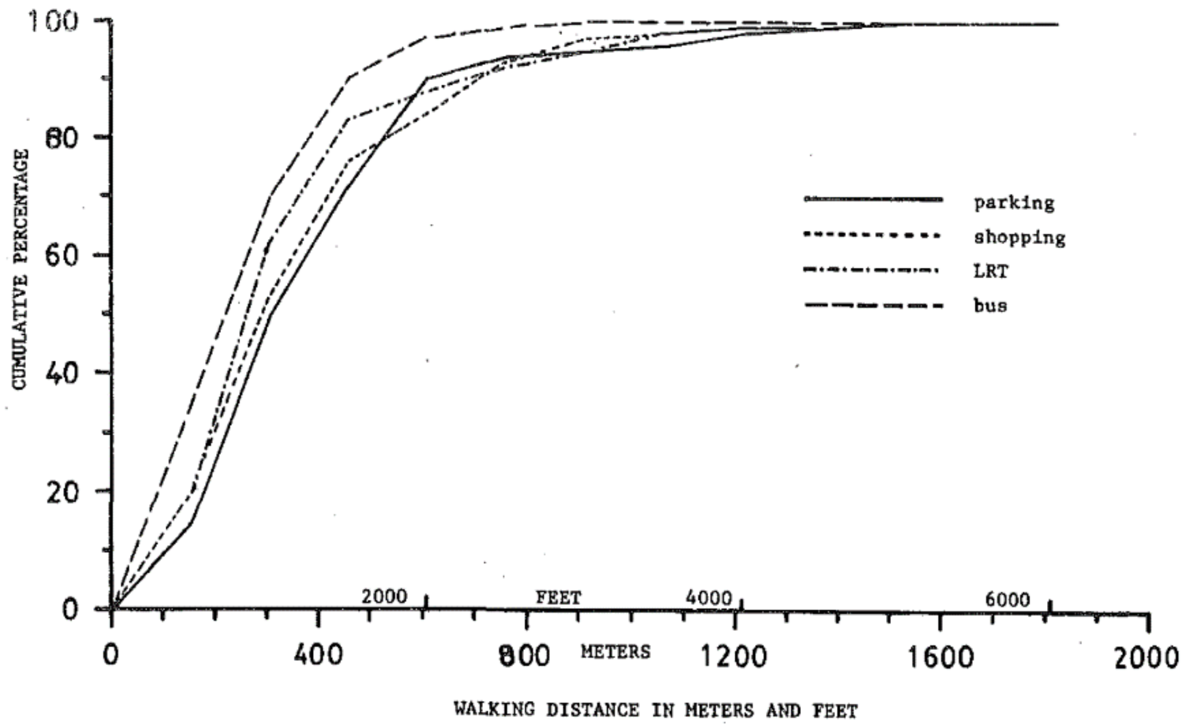
2.2. Determinants of acceptable travel distances

2.2.1. Distances

Distances are a key element in accessibility research and therefore one of the main determinants of perceived accessibility. Perhaps the most prominent model is the gravity model in which distance serves as an impedance factor for interactions between people (Fotheringham, 1981). This means that the further a destination is located the less accessible it is perceived. Increasing distance consequently leads to a decay in perceived accessibility, suggesting that the distance decay function is monotonically decreasing. The distance decay parameter can also be interpreted as the willingness of individuals to travel (Iacono et al., 2008; Martinez & Viegas, 2013). Consequently, knowing which distances are appropriate and which too large is essential to reach the goal of the transportation system, which is providing access to spatially dispersed activities. However, the decay function has rarely been investigated using perceived accessibility data (Martinez & Viegas, 2013).

ATDs are based on distance decay functions. They were first presented by Prianka Seneviratne (1985) who investigated thresholds in walking distances. He defined an ATD as the maximum distance that a commuter is willing to walk before choosing an alternative, faster transport mode. This definition was later picked up by Arasan et al. (1994) and Rastogi and Rao (2003). The authors derived ATDs from cumulative frequency distribution functions. This function matches a given distance (x-axis) with the corresponding percentage of people (y-axis) which would decide to make a trip with a distance shorter than the respectively shown distance (Seneviratne, 1985). An example of a cumulative frequency distribution of different travel distances is given in Figure 2. The slope at any given distance of the curve gives the proportion of people that would be affected by a change in trip distance. Consequently, the point on the curve with the highest change rate would then mark the distance where the most people would be affected by a distance change. This point can be called critical travel distance (Seneviratne, 1985). Seneviratne (1985) and Arasan et al. (1994) found that this critical distance mostly corresponds to a value between the 81st and the 85th percentile of the individuals making the trip in case of a shorter distance.

Figure 2: Cumulative frequency distribution of travel distances



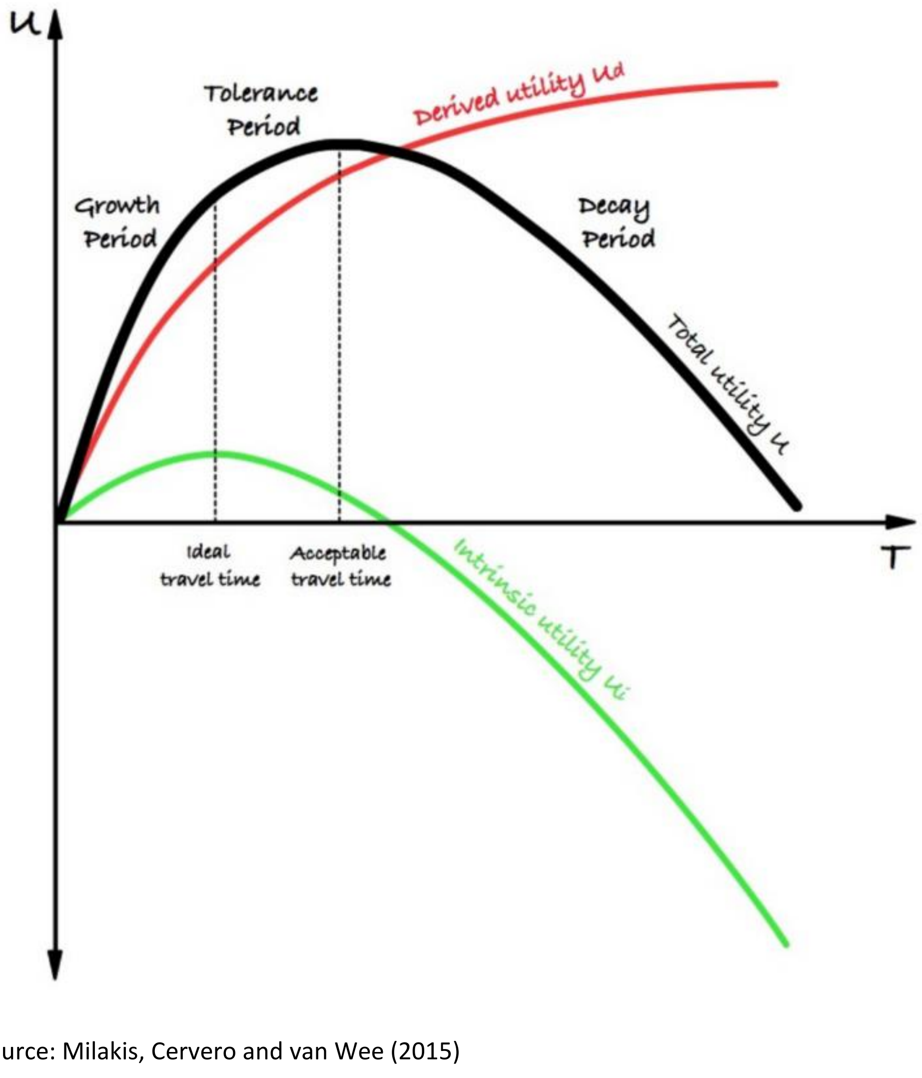
Source: Seneviratne (1985)

Although ATDs were first only used to trips on foot, the concept can be applied for all transport modes. ATDs then refer to the maximum distance that someone would travel with a particular transport mode before shifting to a faster transport mode or before not traveling at all. Although the point of the curves in Figure 2 with the highest change rate corresponds to a critical travel distance, it is important to note that all distances in Figure 2 are considered ATDs. Cumulative frequency distributions assume that by traveling a particular distance to a destination, this distance is considered acceptable. However, actual travel behavior does not necessarily determine the acceptability of a particular distance. For example, someone might be unhappy with the distance to the nearest supermarket and nevertheless go to this supermarket for grocery shopping. Furthermore, someone might travel to a new workplace or new leisure location and then realize that the travel distance is too long in hindsight (Milakis & van Wee, 2018). This is an important weakness of deriving the acceptability of travel distances from actual travel behavior.

A more accurate way of understanding ATD, which takes this issue into account, is to understand ATDs as the outcome of a utilitarian process. As such, an ATD is the distance to a particular opportunity where the total utility of reaching this opportunity is maximized, as visualized in Figure 3. This approach was first developed by Milakis, Cervero and van Wee (2015) when investigating at acceptable travel times (ATTs) and then replicated by Milakis, Cervero, van Wee, et al. (2015) and Milakis and van Wee (2018). As each ATD corresponds to a particular ATT, depending on the transport mode, ATTs and ATDs can be seen as the two sides of the same coin. The theory which ATTs are based on can therefore be transferred to ATDs. The total utility covers both the intrinsic utility and the derived utility. The derived utility is the utility associated with the activity at the trip destination, while the intrinsic utility describes any other trip-related utility, such as joy and pleasure of traveling (Milakis, Cervero, & van Wee, 2015). The authors intended to find the point of total utility by asking respondents how satisfied they are with a range of hypothetical travel times. Additionally, respondents were asked about their ideal travel time. This way both the ideal travel time and the ATT (see Figure 3) could be determined. It is important to mention that the ATD is always higher than the ideal travel distance (see Figure 3). Thus, the ATD corresponds to the maximum distance that a person is willing to invest to reach a particular opportunity. What also stands out from Figure 3 is that there is no initial decline in total utility. Total utility does only decrease after the ATD/ATT. This contradicts the logic behind the distance decay function, which suggests that accessibility always decreases monotonically with increasing distance.

The advantage of understanding ATD as determined by utility is that utility takes the subjective dimension of accessibility more into account than the approach described earlier. As established in Chapter 2.1, accessibility is influenced by individual factors. This is closely linked to utility, as the total utility gained by reaching a destination might vary from individual to individual. The maximum ATD/ATT can be determined directly without using percentiles as described earlier.

Figure 3: Utility-based ATT/ATD concept



Source: Milakis, Cervero and van Wee (2015)

ATDs differ greatly by the destination type. Often three destination types are differentiated: trips to workplace, school or university, trips to leisure locations and trips to shopping locations. Previous research has shown that people travel furthest to leisure locations and workplace (Iacono et al., 2008; Larsen et al., 2010; Yang & Diez-Roux, 2012). A reason for the fact that commuting trips are relatively long is that people tend to use faster travel modes (such as cars or trains), which allows them to cover greater distances (Iacono et al., 2008). Shortest ATDs have been reported for shopping (Larsen et al., 2010; Yang & Diez-Roux, 2012). However, ATDs vary substantially by the transport mode chosen, which will be outlined in the following paragraph.

2.2.2. Transport mode

ATDs were found to differ according across transport modes. They are shortest for trips on foot, then increase for bicycle and increase again for PT (Iacono et al., 2008). ATDs are largest for car as transport mode (Iacono et al., 2008). The main reason for differences between travel modes is that ATDs correspond to the average travel speed (Marchetti, 1994). The distances which can be covered during a fixed time period differ by transport mode. ATDs are shortest for travel modes that offer a low travel speed (such as walking or cycling), while ATDs are largest for travel modes that offer a high travel speed (such as car).

For trips on foot, 813 m and 653 m were found as mean and medium trip distance, respectively, in the Northern American metropolitan context (Montreal, Canada) (Larsen et al., 2010). Those values were derived from the self-reported travel behavior of respondents over the course of the past 24 hours. 85% of the trips had a distance of 1,403 m or less from origin to destination (85^{th} percentile) (Larsen et al., 2010). Using a similar method (recording all trips of the last 24 hours in the metropolitan area Minneapolis-Saint Paul, United States), Iacono et al. (2008) found that around 90% of the walking trips cover a distance of 1,000 m and less. Walking trip distances have furthermore been found to be relatively constant across destination types (Iacono et al., 2008). For trips by bicycle, 3,140 m and 2,242 m were identified as mean and median trip distances, respectively, by Larsen et al. (2010). 85% of the bicycle trips correspond to a distance of 5,517 m and less (Larsen et al., 2010). Bike, e-bike and walking are often grouped as active transport modes because they offer health benefits and can be seen as substitutes to car trips (Larsen et al., 2010; Scheepers et al., 2016; Ton et al., 2019).

In the Dutch context, PT was found to be an attractive alternative to cars in cities with 100,000 inhabitants and more (Wiersma et al., 2016). Traffic conditions and congestion have furthermore been found to influence accessibility by car and PT. This suggests that in areas with much traffic and congestion, such as urban areas, ATDs by PT tend to be higher than in areas with little traffic and congestion, such as rural areas.

Research on PA with e-bikes as transport mode are scarce. Up to the present moment there is no research on PA or ATDs by e-bike in comparison to other transport modes. Due to the electrical support that e-bikes offer, it can be assumed that ATDs associated with e-bikes are larger than those of regular bikes. Kroesen (2017) found that e-bikes mostly serve as a substitute for bikes and to a lesser extend as a substitute for car and public transport. However, in some cases substitution of car as transport modes has also been reported (Plazier et al., 2017; Söderberg f.k.a. Andersson et al., 2021).

2.2.3. Individual determinants

Besides destination type, individual socio-economic characteristics influence accessibility perceptions. Gender has been found to have a significant effect on travel distances with men walking slightly longer distances than women in the North American context (Larsen et al., 2010; Yang & Diez-Roux, 2012). The same effect was observed in developing countries like India (Arasan et al., 1994; Rahul & Verma, 2014). Regarding the trip destination, studies have shown that women generally travel shorter distances to their workplace (see Fanning Madden, 1981; Hanson & Johnston, 1985; McGuckin & Nakamoto, 2005, among others). In the Netherlands, women's daily commuting time (0.3 hours) is only half of the men's commuting time (0.6 hours) (Gimenez-Nadal & Molina, 2014). At the same time, women tend to travel larger distances for leisure and non-work related trips (Gordon et al., 1989; Sánchez et al., 2014). A main reason is that women tend to work closer to their homes. Furthermore, women are disproportionately engaged in household and care work duties (Barbieri et al., 2017). This suggests that many non-work trips are associated with household or care work duties. Although women tend to travel larger distances for non-work related trips, they use cars less than men (Vance & Iovanna, 2007). Studies on PA have also found that women generally exhibit higher levels of PA than men (Lättman et al., 2018; Lättman et al., 2019; Olsson et al., 2021; Van der Vlugt et al., 2019).

Previous research concludes that age is another important individual determinant of ATDs. Elderly (aged 64 and older) have the shortest walking distances in the Northern American context (Larsen et al., 2010; Yang & Diez-Roux, 2012). People aged 19 – 44 traveling the largest distances by active transport modes (Larsen et al., 2010). The car is clearly the most popular transport mode among older adults and elderly, whereas PT is used rarely (Lättman et al., 2019). Elderly and people in their thirties furthermore report the lowest PA levels by PT (Lättman, Friman, et al., 2016). This suggests that older adults and elderly might be restricted in choosing between transport modes. As active transport modes require an adequate physical state, those are less attractive, while the car is the most attractive transport mode. Interestingly, the general trend that women perceive higher levels of accessibility is reversed for older women, indicating that, for the oldest, women perceive lower levels of accessibility than men (Lättman et al., 2019).

The effect of income on ATD differs between destination type. In the United States, low-income groups walk longer distances to their workplace than high-income groups, while high-income groups walk longer distances for recreational activities (Yang & Diez-Roux, 2012). In developing countries such as India, ATD by active transport modes (walking and cycling) decreases with an increase in income (Rahul & Verma, 2014). Furthermore, ATD are likely to differ by transport mode, especially because transport modes are associated with very different costs. While e-bike and car are associated with higher costs, bike and walking are associated with lower costs. Because of this, it could be hypothesized, for example, that ATD by e-bike and car are larger for high-income groups and shorter for low-income groups.

Educational attainment has been found to have an insignificant effect on PA by PT by Olsson et al. (2021). However, education has shown to have a strong relationship with the trip distances by car or PT. Distance to workplace grows as education levels increase (Schwanen et al., 2001; Turner & Niemeier, 1997). It is therefore likely that education somehow influences PA levels.

There is no study which specifically investigates the effect of household size on PA. However, it has been found that households with children perceive the lowest levels of accessibility by PT (Lättman, Friman, et al., 2016). Large households with children are characterized by different activities, such as taking children to care facilities and school. This might make some transport modes, such as bikes or walking, less attractive, and might lead to shorter ATDs for large households. At the same time, large households might be more time restricted since having children imply additional activities and trips. This might lead to a preference for faster transport modes and lower ATDs of large households.

Vehicle ownership (at the household level) has been found to sometimes influence PA by Van der Vlugt et al. (2019). This suggests that the PA of a destination by car, for example, might be higher when possessing one or more cars. The underlying assumption is that when a particular mode of transport is available in larger quantities, then people will use this mode of transport more often. Besides cars this might also apply to (e-)bikes. Two results by Larsen et al. (2010) seem to confirm this and suggests that non-car households tend to switch to other transport modes, which will likely decrease PA by car. First, individuals without a driver's license (aged 17 and younger) and people over 65 years, which are less likely to own a car, have the highest share of walking trips of all age groups. Second, individuals from households without a car travel greater distances by bike than households with a car. There are also associations across transport modes. Car ownership decreases PA by PT (Olsson et al., 2021) and causes car-owning households to walk shorter distances (Rahul & Verma, 2014). Unfortunately, there are no studies which explicitly investigate the effect of disabilities on accessibility perceptions. Nonetheless, Van der Vlugt et al. (2019) found that barrier-free environments significantly enhance accessibility perceptions, and concluded that mobility restrictions have a significant association with PA.

It is eventually important to emphasize that attitudes and preferences are also factors shaping PA. If the (perceived) quality of a transport mode is high, then the PA by this transport mode often also increases. Lättman, Friman, et al. (2016) found that the perceived quality of PT (easiness and user-friendliness, among others), is positively correlated to the perceived accessibility of PT. In case of positive perceived quality, travelers might therefore have larger ATD for PT. At the same time, feelings of (un)safety (for instance associated with PT) also shape attitudes and can therefore lead to a low level of PA (Lättman, Friman, et al., 2016; Lotfi & Koohsari, 2009; Wang et al., 2015). Eventually, personal preferences have positive effects on PA. If walking accessibility important to a person, then this person also exhibits higher levels of PA on foot (Van der Vlugt et al., 2022).

Eventually, it is important to emphasize that this chapter is non-exhaustive and only lists key factors which shape PA. On the one hand, this stems from the large variety of destinations and transport modes which will be investigated in this study. On the other hand, determinants can also influence each other (for example, perceived quality of a particular transport mode can lead to a personal preference to use that transport mode). This makes it difficult to distinguish the original cause.

2.2.4. Spatial determinants

First, it is important to consider that there are substantial differences in land-use and transport system characteristics between cities and the countryside. Urban areas are, on the one hand, densely populated and usually exhibit advanced PT infrastructure. On the other hand, externalities like traffic congestion make car usage less attractive. Rural areas tend to have less PT infrastructure and less traffic congestion. Due to the absence of alternative transport modes and the relatively large distances, the car is also the default mode of transport in all Western countries especially among rural residents, resulting in car dependency in many rural areas (Wiersma et al., 2016). Since the land-use and transport system are known to shape PA (see Figure 1), the discrepancies between rural and urban areas make differences in ATDs likely.

The mentioned differences in land-use and transport system characteristics also have an effect on the use of active transport modes. For example, Yang and Diez-Roux (2012) found that rural residents tend to walk shorter distances than urban residents. In the Dutch context, people living in urban-center neighborhoods are more likely to use active transport modes (Scheepers et al., 2013). This confirms that the limited attractiveness of alternative transport modes, such as cars, and the physical proximity of origin and destination makes active transport modes more attractive and more utilized in the urban context than in the rural context.

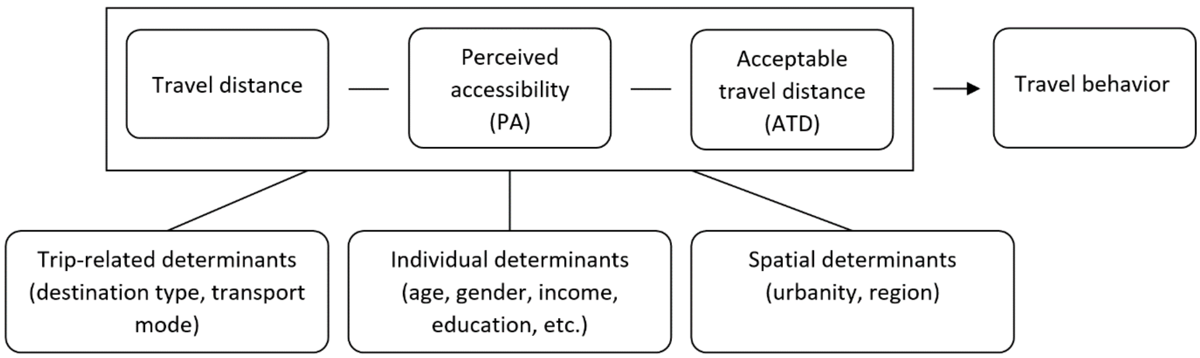
2.3. Conceptual model

Based on the theory elaborated above, the conceptual model in Figure 4 was developed. It visualizes the key determinants that influence travel distances, PA and ATD. Those key determinants eventually lead to the travel behavior of an individual.

The conceptual framework can be explained with a person traveling a particular distance to a particular destination type, for example to a leisure opportunity. The person evaluates the perceived (in)accessibility of the leisure destination and derives an ATD for this type of destinations. Although the true ATD for this destination type cannot be observed, this study utilizes PA to approximate the ATD. It is important to note that using PA scores instead of objectively calculated or measured accessibility to derive ATDs is a novel approach which sets this study apart from other studies which use objective accessibility to derive ATDs.

Travel distances, PA and ATD are influenced by three main determinant groups: trip-related determinants, individual determinants and spatial determinants. First, destination type and/or trip purpose (for example, workplace, school, university, leisure, supermarket, among others) play a role. Second, socio-economic characteristics (age, gender, income, education level and household size) are expected to influence travel distance, PA and ATD. Third, this study focuses on spatial determinants, more precisely on what effect urbanity and rurality in the Dutch context have.

Figure 4: Conceptual model of ATDs derived from PA



3. Methodology

This chapter introduces the reader to the data and the empirical approach used to answer the research questions. Furthermore, it explains the data transformations and generation of variables required for the analyses. Eventually, the variables are operationalized for the statistical analysis.

3.1. Data description

The aim of this study is to analyze the effect of socio-economic and spatial determinants on ATD for different destination and by different transport modes while using PA as a proxy to derive ATD. The data used in this study stems from a cross-sectional survey on travel behaviors, mobility and accessibility perceptions in the Netherlands. The data was collected in February and September 2020. The data differentiated between four destination types (workplace/study place, leisure, health care and supermarket) and five transport modes (car, bike, e-bike, public transport and walking). For leisure and health care, the data set contains information on the last visited location of the respective destination type. For supermarket, it refers to the most used supermarket. For workplace, it refers to the place where most of the work or study time is spent. For all combinations of destination type and transport mode, the respondent answered whether they perceive the destination as accessible or not with a given mode of transport. By asking this, the data minimizes the possibility that actual travel behavior might not correspond to ATDs. For example, someone can travel a particular distance and nonetheless might rate this distance as not acceptable. By asking respondents about their accessibility perceptions, ATD can therefore be identified more accurately. The point of reference is always their home address. For example, the question regarding the workplace/study place was as follows:

My workplace/study place is easily accessible from my home by the following modes of transport:

1. *Car*
2. *Public transport*
3. *Bicycle*
4. *E-bike*
5. *Walking*

The original survey data covered 3,789 individuals. For this study only individuals with valid home and destination postcodes could be used. After the process of data cleaning and dropping of missing values, 1,176 individuals and a total of 3,200 observations are used in this study.

3.2. Empirical approach

This study employs a quantitative approach to answer the research question. The quantitative approach is two-fold: First, descriptive statistical analyses in the form of cross-tabulations chi-square tests are employed. Second, binary logistic regressions are run. As elaborated in the conceptual model in Figure 4, the transport mode and the destination type play an important role in determining PA, which is used as a proxy for ATD. Therefore, ATDs are very different across destination types and transport modes. As the data contain PA for each destination type and transport mode, separate regression models for each destination type and transport mode were used.

Cross-tabulation chi-square tests are used to analyze the relationship between two categorical variables. In this study, the relationship between trip distance as a categorical variable and the binary variable PA is assessed. The chi-square test tells whether distance and PA are related or independent. First, this will help to determine in which cases there is a statistically significant relationship between distance and PA. Furthermore, this will give insights into the effect of increasing distances. The percentage of individuals perceiving a particular destination as accessible can be observed across the

20%-quantiles of distance. A substantial percentage decrease could indicate a cut-off distance range where people do not perceive the destination as accessible anymore.

For the regression part, there are two types of suitable statistical models to answer the research question. On the one hand, a binary logistic regression can be run. Logistic regressions estimate the probability that the dependent variable equals 1. Applied to this study, this refers to the probability that a particular location is perceived as accessible with a particular transport mode. On the other hand, an ordered logistic regression can be used because the scale of accessibility perceptions has a meaningful logical order and the real distance between the categories is unknown (Mehmetoglu & Jakobsen, 2017). The dependent variable PA could be divided into, for example, *very accessible*, *accessible*, *neutral,* and *not accessible*. However, the focus of this study is not on differentiating between *very accessible* and *accessible*, but rather on distinguishing *accessible* and *not accessible*. Furthermore, the category neutral is hard to interpret unambiguously. Therefore, binary logistic regression is preferred over ordered logistic regression. To ensure robust results, two statistical models were employed to answer the research question. Approach 1 uses distances as a continuous variable and approach 2 contains distances as a categorical variable. Both approaches are described by the following regression equation:

$$P_{(Destination\ type,\ \ travel\ mode)} = \alpha + \beta_1 * Distances + \beta_2 * (Socioeconomic * Distance) + \beta_3 * (Urbanity * Distance) + \varepsilon$$

where P represents the probability of perceiving a location or opportunity as accessible for a given destination type by a given transport mode. All models are variations of this regression equation, and depending on the destination type and travel mode, particular independent variables were included or left out for specific models.

Two interactions were included based on previous research elaborated in Chapter 2. It suggests that the effect of distances on PA might be different women compared to men (Gordon et al., 1989; Larsen et al., 2010; McGuckin & Nakamoto, 2005; Rahul & Verma, 2014). Theory and research also indicate that the effect of distances on PA might be different for urban compared to rural areas (Curl et al., 2015; Vitman-Schorr et al., 2019). The interaction terms between distance and gender and between distance and urbanity were therefore added to the model. Interactions between distances and income and distances and age were found not to enhance the model fit. Furthermore, they led to collinearity issues and insignificant chi-square model statistics, indicating that there is no overall effect of the independent variables, taken together, on the dependent variable. Those interactions were therefore not included. As the data sets and sample sizes are different for each destination type, the model specification is adapted and run separately for each destination type. For some model combinations, certain variables had to be left out because of collinearity issues or missing values. This is specified in Appendix II.

Originally, a third regression was employed which runs separate regressions for each distance category and therefore tests whether the destination is perceived as accessible for a given distance category. However, due to the low number of observations, those models did not deliver reliable results. Including the destination type as an independent variable did substantially increase the number of observations but reports the effect of socio-economic and spatial characteristics independent of the destination type. This was found not to be useful because PA is most likely influenced by the destination type. The third regression approach was therefore not executed. The empirical approach was carried out using the software STATA 17.

3.3. Operationalization of the dependent variable

The aim of this study is to analyze the effect of socio-economic and spatial determinants on ATD for different destination types and by different transport modes while using PA as a proxy to derive ATD. Perceived accessibility serves as the dependent variable. A five-point scale was used in the original survey to evaluate perceived accessibility (*totally disagree, disagree, neutral, agree, totally agree*). For this study, this categorical variable was transformed into a binary variable with 0 coded for *not accessible* and 1 coded for *accessible* (similar to Scheepers et al., 2016). *Totally disagree* and *disagree* were assigned to the category *not accessible* and *agree* and *totally agree* were assigned to the category *accessible*. Since *neutral* cannot be unambiguously assigned to either *accessible* or *not accessible*, the observations for *neutral* were dropped. The binary accessibility variable is summarized for the different destination – transport mode combinations in Table 1. Table 1 shows furthermore that each destination type has a different sample size. This emphasizes once more that it is necessary to run separate models for each destination type.

Table 1: Summary of the dependent variable perceived accessibility by transport mode – destination combination

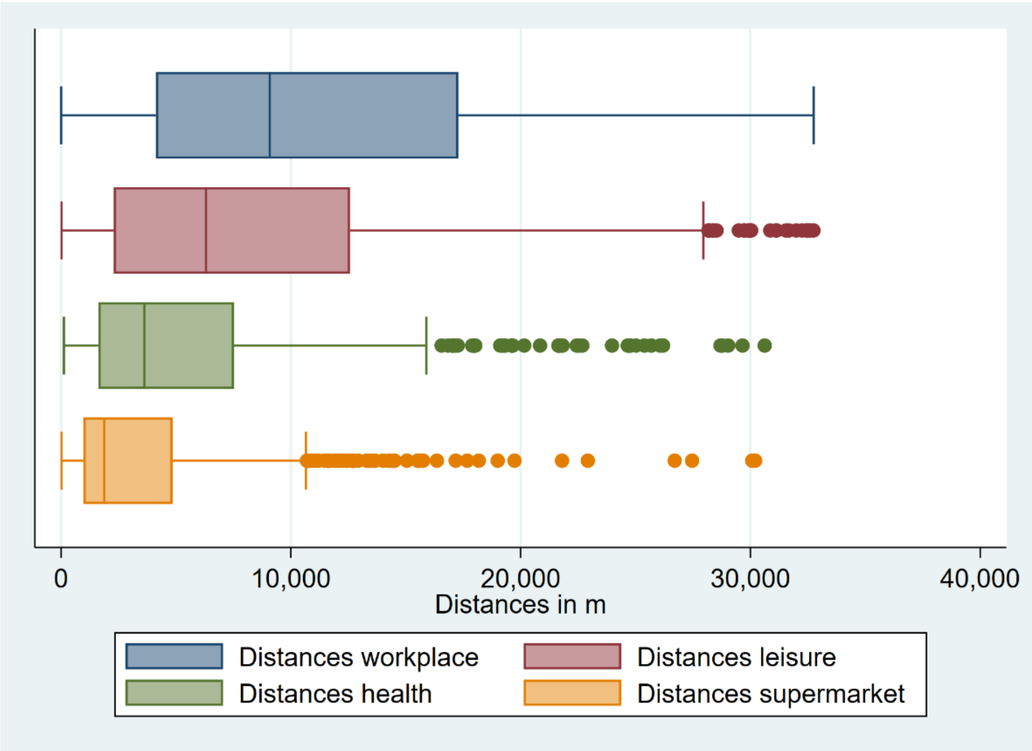
Mode of transport	Sample size	Number of respondents perceiving as accessible	Percentage of respondents perceiving as accessible
Workplace – car	1,072	997	93
Workplace – bike	1,072	809	75.5
Workplace – e-bike	1,072	820	76.5
Workplace – PT	1,072	276	25.3
Workplace – walking	1,072	574	53.5
Leisure – car	1,600	1,505	94.1
Leisure – bike	1,600	1,184	74
Leisure – e-bike	1,600	1,206	75.4
Leisure – PT	1,600	402	25.1
Leisure – walking	1,600	806	50.4
Health care – car	955	879	92
Health care – bike	955	679	71.1
Health care – e-bike	955	682	71.4
Health care – PT	955	263	27.5
Health care – walking	955	496	51.9
Supermarket – car	2,058	1,933	93.9
Supermarket – bike	2,058	1,365	66.3
Supermarket – e-bike	2,058	1,398	67.9
Supermarket – PT	2,058	477	23.2
Supermarket – walking	2,058	902	43.8

3.4. Operationalization of the independent variables

3.4.1. Distance

As elaborated in Chapter 2 and as shown in the conceptual model in Figure 4, distance is a key determinant of ATD. Distance was therefore included as independent variable in the regressions. Distances to the different destinations were not included in the original data set and were thus generated by using the 6-digit (alphanumeric) postcodes. Those postcodes usually refer to a particular street section and represent on average 15-20 households (Scheepers et al., 2016). In cases in which only the 4-digit (numeric) postcodes were given, those were used. Using the postcodes, the distances between the respondent's home and the respective destination were calculated using a Google Distance Matrix API. The Distance Matrix API uses the fastest route by car. It is therefore expected to be very accurate for distances traveled by car. However, it is possible that the distances for other transport modes are inaccurate. It is assumed though that bikes and e-bikes mostly use the same streets, which minimizes the risk of inaccurate distances for trips by bike and e-bikes. The reason is that there might exist foot and bike paths that are shorter and faster than car-accessible streets. However, it is assumed that these inaccuracies do not substantially influence the results. The distance distribution is illustrated in Figure 5. The trends in the distance distribution are in line with previous research which usually reports larger trip distances for work and leisure and shorter trip distances for shopping (Larsen et al., 2010; Yang & Diez-Roux, 2012).

Figure 5: Distribution of ATD by destination type



Distance was included both as a continuous and as a categorical variable in the regression noted above to observe whether the sign, strength and significance of the coefficients change between the two models and for the different distance categories. This way the robustness of the coefficients can be ensured. For including distances as a categorical variable, different cut-off values were chosen for each destination type because of the unequal distance distribution among destination types (see Figure 5). For example, while 26.38% of all supermarket trips are shorter than 1,000 meters, only 3.64% of all workplace trips are shorter than 1,000 meters. The distances were grouped in five categories per destination type. 20%-quantiles were used as cut-off values, resulting in five groups that hold approximately the same number of observations summarized in Table 2. This approach makes comparisons across destination types in terms of 20%-quantiles possible.

Table 2: Tabulation of distance as categorical variables

Destination type	Distance in meter	Frequency
Workplace	3,483 m and less	214
	3,484 – 7,950 m	211
	7,951 – 14,130 m	218
	14,131 – 21,840 m	213
	21,841 m and more	216
	Total	1,072
Leisure	1,659 m and less	318
	1,660 – 4,152 m	322
	4,152.5 – 8,665 m	320
	8,666 – 16,996 m	319
	16,997 m and more	321
	Total	1,600
Health care	1,187 m and less	189
	1,188 – 2,417 m	191
	2,418 – 4,582 m	191
	4,583 – 9,446 m	192
	9,447 m and more	192
	Total	955
Supermarket	820 m and less	409
	821 – 1,410 m	414
	1,411 – 2,752 m	410
	2,753 – 5,572 m	410
	5,573 m and more	415
	Total	2,058

3.4.2. Socio-economic and spatial determinants

In accordance with the conceptual framework in Figure 4, socio-economic and spatial determinants are included as independent variables in the regressions. Most socio-economic determinants were already included in the data set. Only data on urbanity were originally not included in the survey and were therefore generated. To determine urbanity of the home addresses of the respondents, a database provided by the CBS on numeric postcodes from 2020 was used (CBS, 2022a). The CBS classifies the degree of urbanity in five categories: very highly urban, highly urban, moderately urban, little urban and non-urban (CBS, 2022c). For this thesis, urbanity was coded as a binary variable that states whether a home address postcode is *urban* (urbanity=1) or *not urban* (urbanity=0) using numeric 4-digit postcodes. *Urban* includes the CBS-classifications very highly urban, highly urban and moderately urban. This category entails all postcode areas with an density of more than 1000 addresses per square kilometer (CBS, 2022c). *Not urban* includes the CBS-classification little urban and non-urban. This category entails all postcode areas with a density of less than 1,000 addresses per square kilometer (CBS, 2022c). This classification is in accordance with the definition of rural by the CBS (2022b) which defines rural areas as municipalities with less than 1,000 addresses per square kilometer.

Table 3 offers an overview of the key independent variables included in the analysis. As mentioned earlier, distances are included as continuous variable in approach 1 and as categorical variable in approach 2. Multiple categorical independent variables were re-coded in fewer, more aggregated categories. Most importantly, this was necessary because of the low number of remaining observations per categories after the data cleaning process. For example, education was re-coded from six to four categories and income was merged from eight to five categories.

Table 3: Summary statistics of key independent variables

Independent variable	Categories	Number of Observations	Mean	Std. Dev.	Min.	Max.
Destination type	1 = Supermarket 2 = Health care 3 = Leisure 4 = Workplace	3,200	2.473	1.129	1	4
Distances to workplace		1,072	12,656.146	9,280.516	4	32,755
Distances to most used supermarket		2,058	3,472.602	3,976.837	20	30,204
Distances to last visited health care location		955	5,962.706	6,598.816	122	30,621
Distances to last visited leisure location		1,600	9,060.461	8,548.624	20	32,744
Distances to most used supermarket (categorical in 20%-quantiles)	0 = 820 m and less 1 = 821 – 1,410 m 2 = 1,411 – 2,752 m 3 = 2,753 – 5,572 m 4 = 5,573 m and more	2,058	2.046	1.395	0	4
Distances to workplace (categorical in 20%-quantiles)	0 = 3,483 m and less 1 = 3,484 – 7,950 m 2 = 7,951 – 14,130 m 3 = 14,131 – 21,840 m 4 = 21,841 m and more	1,072	1.985	1.41	0	4
Distances to last visited leisure location (categorical in 20%-quantiles)	0 = 1,659 m and less 1 = 1,660 – 4,152 m 2 = 4,152.5 – 8,665 m 3 = 8,666 – 16,996 m 4 = 16,997 m and more	1,600	2.053	1.429	0	4
Distances to last visited health care location (categorical in 20%-quantiles)	0 = 1,187 m and less 1 = 1,188 – 2,417 m 2 = 2,418 – 4,582 m 3 = 4,583 – 9,446 m 4 = 9,447 m and more	955	1.972	1.428	0	4
Age		3,159	44.13	14.387	12	82
Gender	0 = Male 1 = Female	3,157	0.559	0.497	0	1
Educational attainment	1 = Primary school 2 = Secondary education (LTS, huishoudschool, VMBO, MAVO, MULO, MBO-1, (HAVO, pre-university, HBS, MBO-2, 3, or 4) 3 = Higher vocational education 4 = University	3,170	2.566	0.773	1	4
Income	1 = €2,000 and less 2 = €2,001 - €3,000 3 = €3,001 - €5,000 4 = €5,001 and more 5 = Don't know/prefer not to say	3,136	3.067	1.203	1	5

Independent variable	Categories	Number of Observations	Mean	Std. Dev.	Min.	Max.
Household size		3,176	2.59	1.401	1	10
Urbanity	0 = Rural 1 = Urban	3,200	0.35	0.477	0	1

3.4.3. Control variables

In addition to the key independent variables in Table 3, control variables were added to the models. Those are not of main interest in this study theory, but previous research has shown that they influence PA. Because of the big variety of factors influencing PA (as elaborated in Chapter 2) not all influencing factors could be controlled for. The control variables in this study were therefore restricted to vehicle ownership, walking behavior, attitude towards PT and disabilities. For vehicle ownership, the number of cars, bikes and e-bikes per household were included as categorical variables. For walking behavior, the frequency of walking in days were added as a categorical variable (ranging from *never* to *4 or more days a week*). Attitudes towards PT were proxied by the possession of a PT subscription and by the question whether an individual deems the OV chipkaart as easy to understand, both operationalized as binary variables. Eventually, disability was added as a binary variable for each transport mode. For car as transport mode, two disability variables (one for disability during day and one for disability during night) were included.

3.4.4. Diagnostic testing

For each transport mode and destination type two models were estimates, one with distances as a continuous independent variable and one with distances as a categorical variable. For workplace as destination type, the control variables disability day and disability night had to be left out because of the low number of observations and collinearity. The likelihood ratio chi-square test is significant ($p<0.05$) for most models, which indicates that those models predict the dependent variable better than an empty model and that at least one independent variable is significantly different from 0. However, the models for PA by PT for health care, leisure and supermarket as trip destination have insignificant chi-square statistics, suggesting that there is no statistically significant effect of the independent variables, taken together, on perceived accessibility. Even after reducing those models to fewer key independent variables, they still give insignificant chi-square statistics. Running models separately for each 20%-quantile of distance only gives significant models ($p<0.1$) for the first two 20%-quantiles for leisure, and all models for health care and supermarket give insignificant chi-square statistics. This study can thus only provide regression results for PT for workplace as destination.

The models with distance as a categorical variable were found to have a better model fit (indicated by McFadden's Pseudo R-squared). Although the Pseudo R-squared is not equivalent to the R-square of linear regression, it can be used cautiously to evaluate the model fit of models which use the same dataset (UCLA, 2022). Because of the difficulties in interpreting the Pseudo R-squared, estimates from both models for each transport mode are used in the following, except when one model is not significant.

The logistic regression models are tested on the relevant model assumption to ensure the models' consistency and efficiency. The logistic regression assumptions are (Mehmetoglu & Jakobsen, 2017):

1. The model must be correctly specified.
2. No important variable should be left out and no unnecessary variable should be included.
3. Each observation is independent from the other observations.
4. No independent variable must be a linear function of another independent variable.

To test assumptions 1 and assumption 2, linktests in STATA were performed for all models. This test was significant for in total 5 models, suggesting that those models might be mis-specified. However, as model specification is foremost a theoretical question and based on previous research and because of the high sensitivity of the linktests, those models were included regardless. Eventually, influential cases can be a problem in logistic regressions with a low number of observations, like in the models for workplace and health in Table 1 (Mehmetoglu & Jakobsen, 2017). Influential cases are analyzed for workplace as destination type in Appendix IV. Although there are some outliers for each model detected in Appendix IV, for simplicity it is assumed that those do not substantially influence the correctness of the coefficients.

4. Results

This chapter presents the results of the cross-tabulations chi-square tests and regression models. Key results are visualized in diagrams and graphs. The complete cross-tabulations and regression results can be found in Appendix I (Table 5, Table 6, Table 7 and Table 8) and Appendix II (Table 9, Table 10, Table 11 and Table 12).

4.1. Workplace

According to the cross-tabulations and chi-square tests of independence, the relationships between distance to workplace and PA are statistically significant ($p<0.05$) for all transport modes. This is strong evidence for a relationship between the categorical variable distances to workplace and PA. Figure 6 visualizes the percentage of respondents that rate their workplace as accessible by different transport modes for the 20%-quantiles of distance. The most striking result is that the share of respondents is the highest for car as transport mode, with a share of 90.2 – 95.8% of respondents perceiving their workplace as accessible by car. The percentages are particularly larger for larger distances (last three 20%-quantiles). This means that there is no decay in PA, but rather a slight increase in PA as distances increase. This result is in line with prior expectations since the car offers the highest travel speed and is therefore most suitable for going longer distances.

When going by active transport modes (bike, e-bike and walking), PA does generally decrease as distances increase. This suggests that the effect of increasing distances is reversed compared to car as transport mode. The share of respondents perceiving their workplace as accessible by (e-)bike decreases relatively slow in the first four 20%-quantiles, whereas it drops substantially in the fifth quantile. This indicates that the respondents might easily travel distance up to 21,000 m by (e-)bike to their workplace and might then reach their maximum ATD after this threshold. The data furthermore show that the share of respondents that perceive their workplace as accessible by e-bike is higher than that for bikes for larger distances. Although the difference is rather small, this confirms the prior assumption that e-bikes can be used to cover larger distances more easily than bikes. Interestingly, around half of the respondents perceive the workplace as accessible on foot for the fourth and fifth 20%-distance-quantiles (distances larger than 14,130 m). This corresponds to 111 respondents for the 4th 20%-quantile and 108 respondents for the 5th 20%-quantile. This result seems highly unlikely. It is possible that those respondents did not interpret the question regarding walking well or comfortably, but rather assessed the walking environment to the destination. Some might also have combined commuting trips with physical exercise (running).

PT is perceived as the as least accessible transport mode with only 20.6 - 30.8% of the respondents perceiving their workplace as accessible using PT. This is in line with results by Lättman et al. (2018) who found that the lowest PA levels among all transport modes usually correspond to PT. Although PT is most attractive for shorter distances (first and second quantile) with around 30% of the respondents perceiving their workplace as accessible, there is no clear PA distance decay for larger distances. Therefore, the relationship between the share of respondents that perceive their workplace as accessible, and distances seems non-gradual and weakest for PT.

Figure 6: Perceived accessibility to workplace for different distance categories

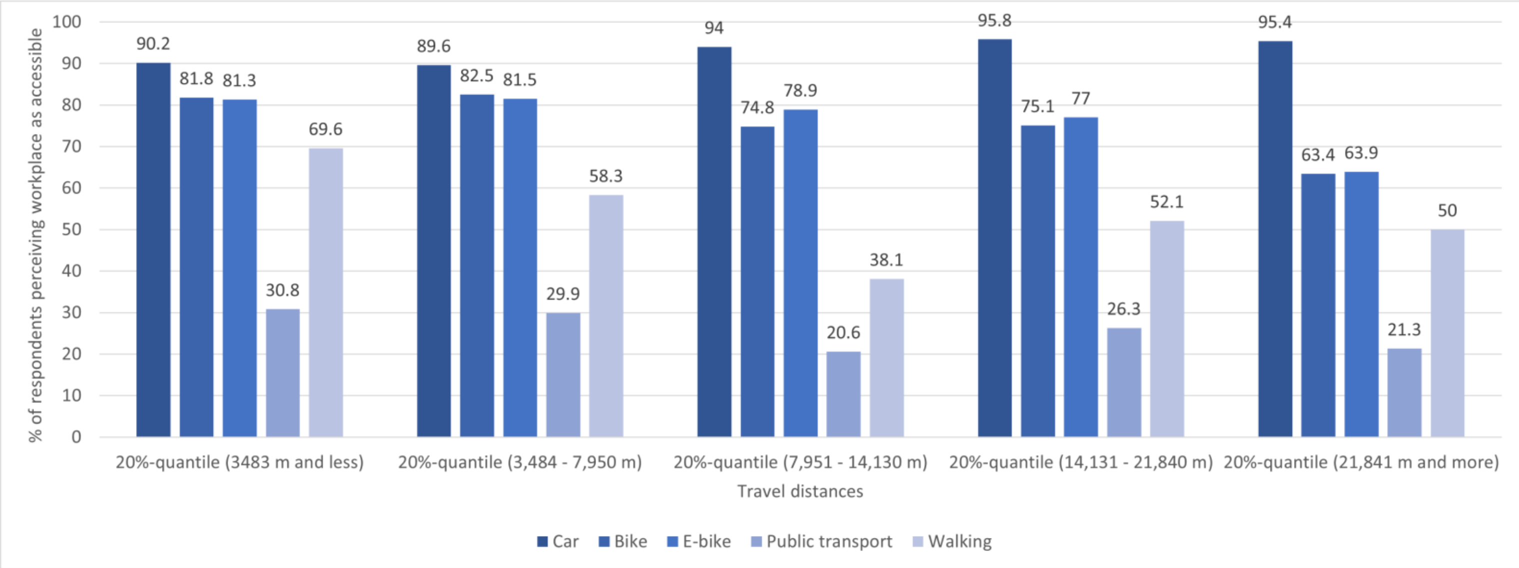
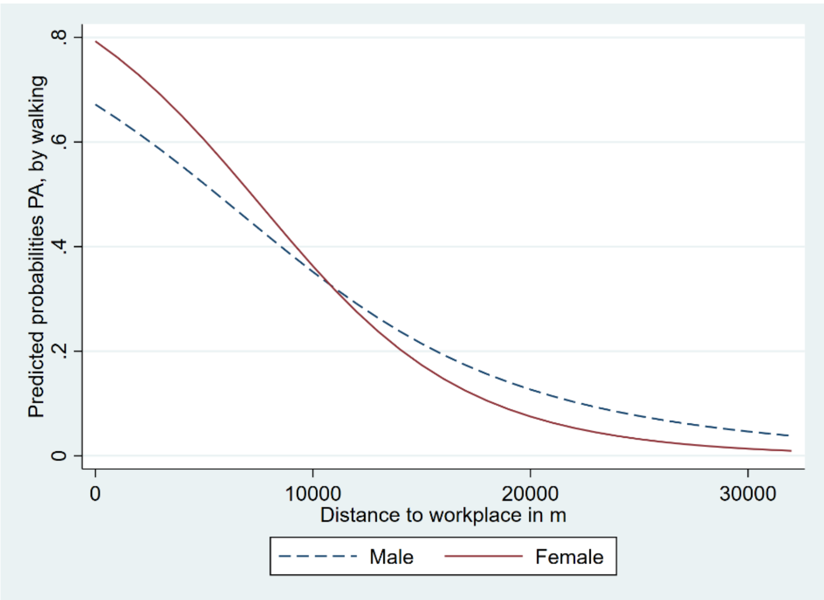


Figure 7: Marginal effect of gender on PA workplace, by walking



The effect of gender on PA is significant for workplace trips on foot. The predicted probabilities are plotted in Figure 7.[1] For distances to the workplace shorter than approximately 11,000 m on foot, the results show that women perceive their workplace as more accessible than men. For distances larger than 11,000 m on foot, the results indicate that men perceive their workplace as more accessible than women. This relationship was verified by running two separate models (one for distances < 11,000 m and one for distances > 11,000 m). Figure 7 suggests that women are more sensitive to large walking distances to their workplace, resulting in shorter ATDs than for men when walking. This might be associated with the fact that women tend to work closer to their homes, as outlined in Chapter 2. This partially contradicts previous research stating that women exhibit higher levels of PA than men (Lättman et al., 2018; Lättman et al., 2019; Olsson et al., 2021; Van der Vlugt et al., 2019), which suggests higher ATDs for women. For the other transport modes, the effect of gender is unclear since the sign of the coefficient of gender varies between model 1 (distance as continuous variable) and model 2 (distance as categorical variable).

[1] All graphs were plotted with distances as continuous variable to allow more precise plots. It is however also possible to plot them using distances as categorical variable.

Age has a statistically significant effect on PA for workplace trips by car, bike and e-bike. The probabilities for different age groups for workplace are visualized in Figure 8. The probabilities are almost constant for all given distances and substantially increase as people get older. Individuals aged 40 and older have probabilities greater than 0.8 to perceive their workplace as accessible by car, while the probabilities for people aged 20 are smaller than 0.3. This indicates that ATDs by car increase as people get older, which is also in line with previous expectations. The increase could be connected to higher incomes that people have as they get older. The flexibility that cars offer (compared to PT) also might be more important for older people than for younger people. The results are reversed for active transport modes (bike, e-bike and walking), as exemplary shown in Figure 9 for biking. This indicates that younger people are more likely to perceive their workplace as accessible by active transport modes. Thus, the ATD of young people is high and diminishes as they age. This is in line with prior expectation too, as older people tend to be less mobile and more dependent on the car. There are barely any differences between biking and e-biking.

Figure 8: Marginal effect of age on PA workplace, by car

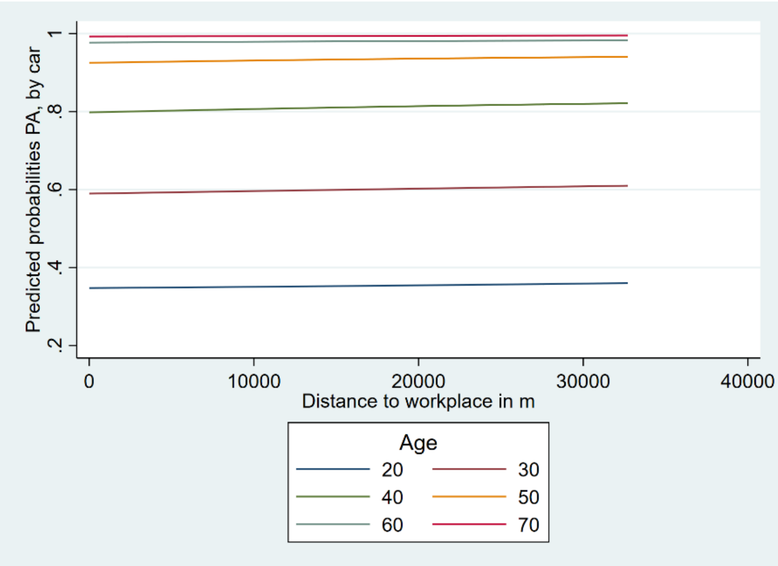
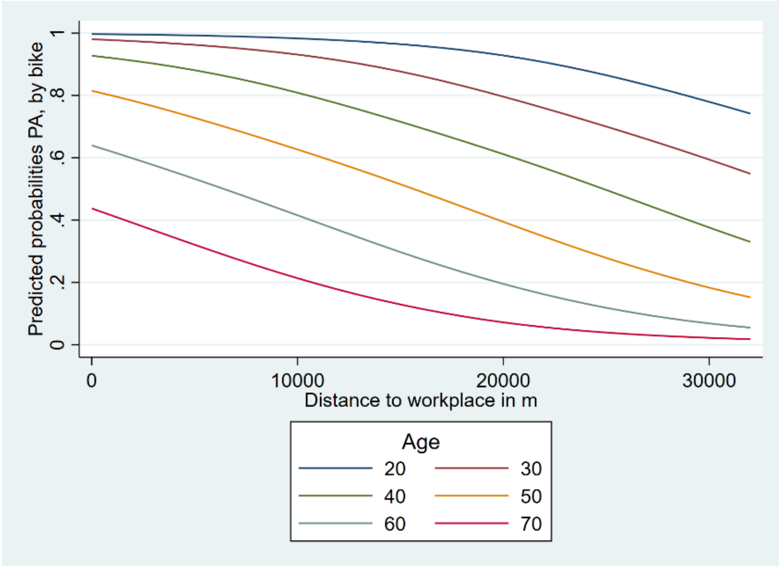


Figure 9: Marginal effect of age on PA workplace, by bike



The variable education is only significant for one category of education for car as transport mode and distance as a categorical variable. For workplace trips by car, the categories primary education and university are omitted, which makes it difficult to interpret the effect of education. What furthermore stands out is that there is no gradual relationship between PA and higher education attainment. The probability to perceive the workplace as accessible does not increase or decrease as the education level increases or decreases. This suggests that ATDs do not increase or decrease as the education level increases or decreases. An exception seems to be PT. Here, individuals with higher educational levels (higher vocational education and university) have lower levels of predicted PA for commuting trips, which suggests shorter ATDs for individuals with higher educational attainment. This relationship is however not statistically significant.

Income is significant for e-bike as transport mode. High-income groups (income>5,000€) report the highest predicted probabilities of PA, as plotted in Figure 10. Therefore, the ATD by e-bike of high-income individuals is the higher than for low-income groups. The effect is most probably connected to the high costs of e-bikes (compared to biking, walking or PT). E-bikes might not be seen as a realistic option for low-income households, which is why those households perceive destinations as little accessible by e-bikes. A similar relationship can be observed for active transport modes in general (although not always significant). For instance, Figure 11 plots the probabilities of perceiving the workplace as accessible on foot. High-income groups have higher probability and thus higher ATD. This might confirm the hypothesis by Van der Vlugt et al. (2019) which states that high-income groups may have higher expectations regarding sustainable mobility. This might cause them to use the low-emission transport modes like biking and walking more often than low-income groups.

Figure 10: Marginal effect of income on PA workplace, by e-bike

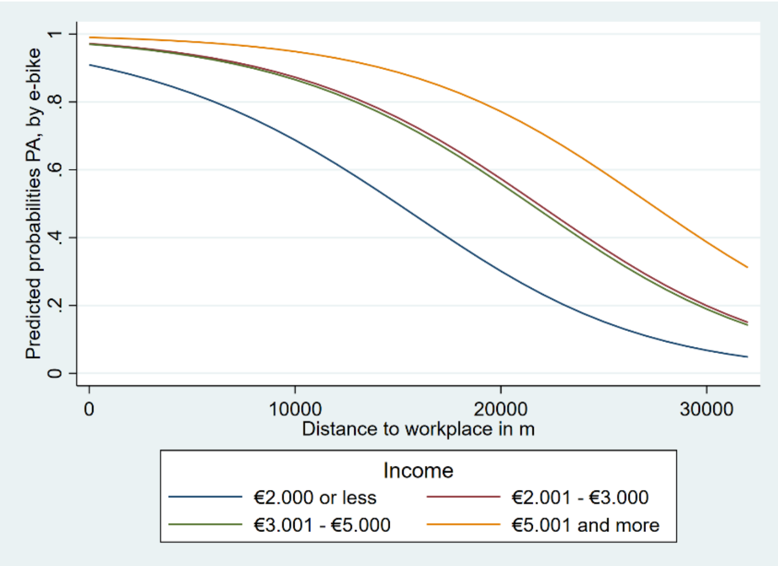
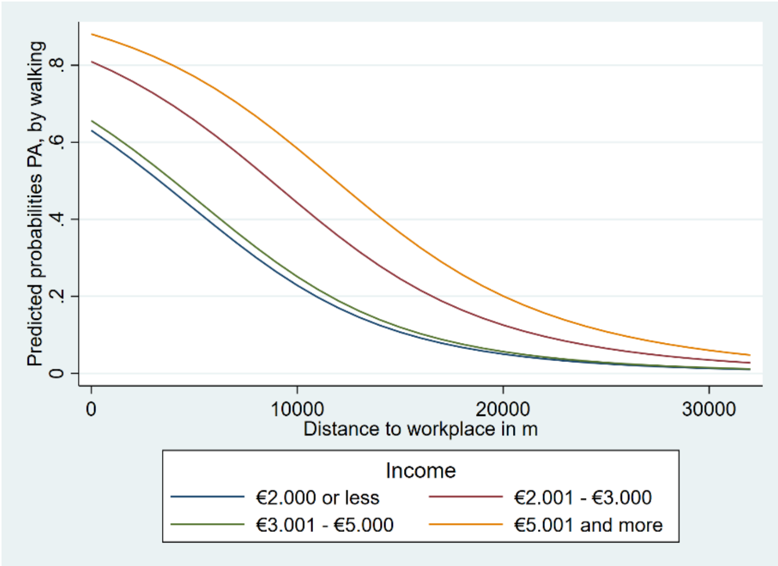


Figure 11: Marginal effect of income on PA workplace, by walking



Household size is significant for bike as transport mode but has different signs in model 1 and 2. The effect of household size can therefore not be interpreted conclusively. Urbanity has a negative effect on PA for car, bike and e-bike. The effect is significant for bike and e-bike illustrated in Figure 12. The figure suggests that rural residents perceive their workplace as more accessible by (e-)bike for distances shorter than 23,000 m. Interestingly, for distances greater than 23,000 m, urban residents are more likely to perceive their workplace as more accessible by (e-)bike. For distances shorter than 23,000 m, Figure 12 suggests that rural residents have larger ATDs for (e-)bike commuting trip. The trend is reversed for PT as transport mode. The probabilities to perceive the workplace as accessible by PT are plotted in Figure 13. The key message is that urban residents are substantially more likely to perceive the workplace as accessible by PT. Urban residents have therefore larger ATDs when using PT. This is in line with prior expectations regarding the poorer PT provision in rural areas. After plotting the effect of urbanity on perceiving the workplace as accessible by car in Figure 14, it becomes visible that car and PT are complementary travel modes in the urban/rural context. Especially for short and intermediate distances, rural residents perceive their workplace as relatively inaccessible by PT and relatively accessibly by car.

Figure 12: Marginal effect of urbanity on PA workplace, by bike

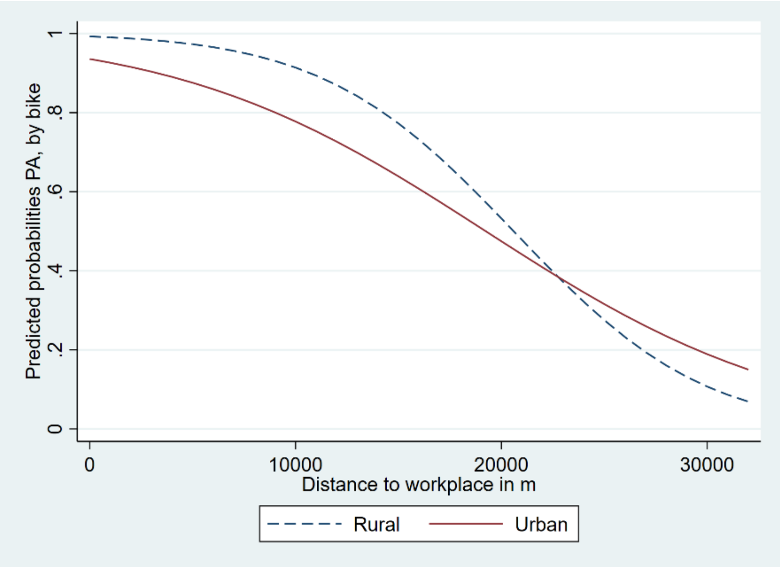


Figure 13: Marginal effect of urbanity on PA workplace, by PT

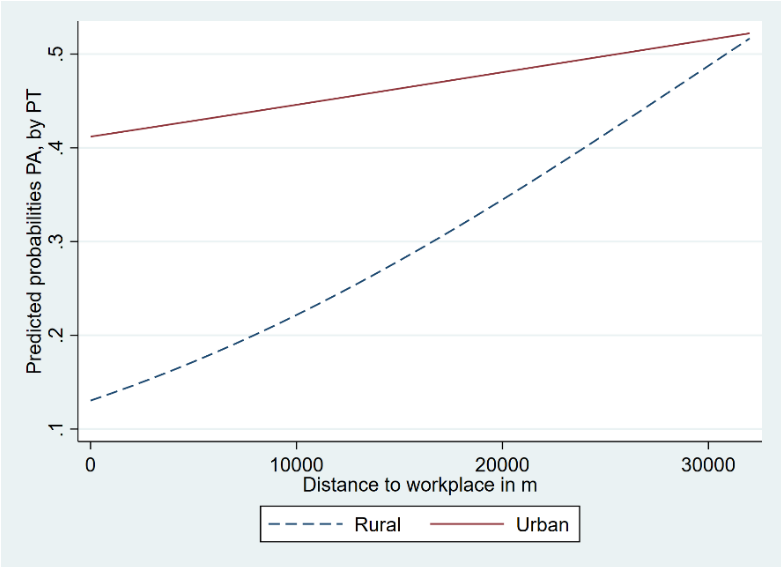
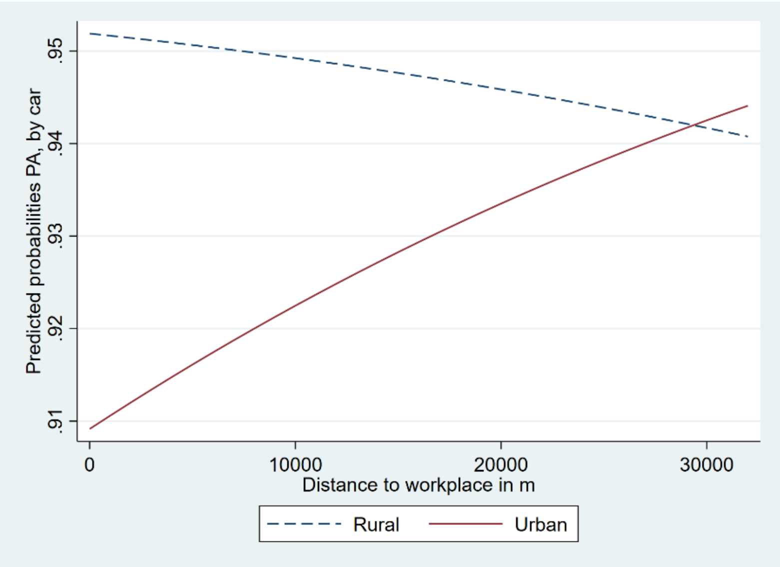


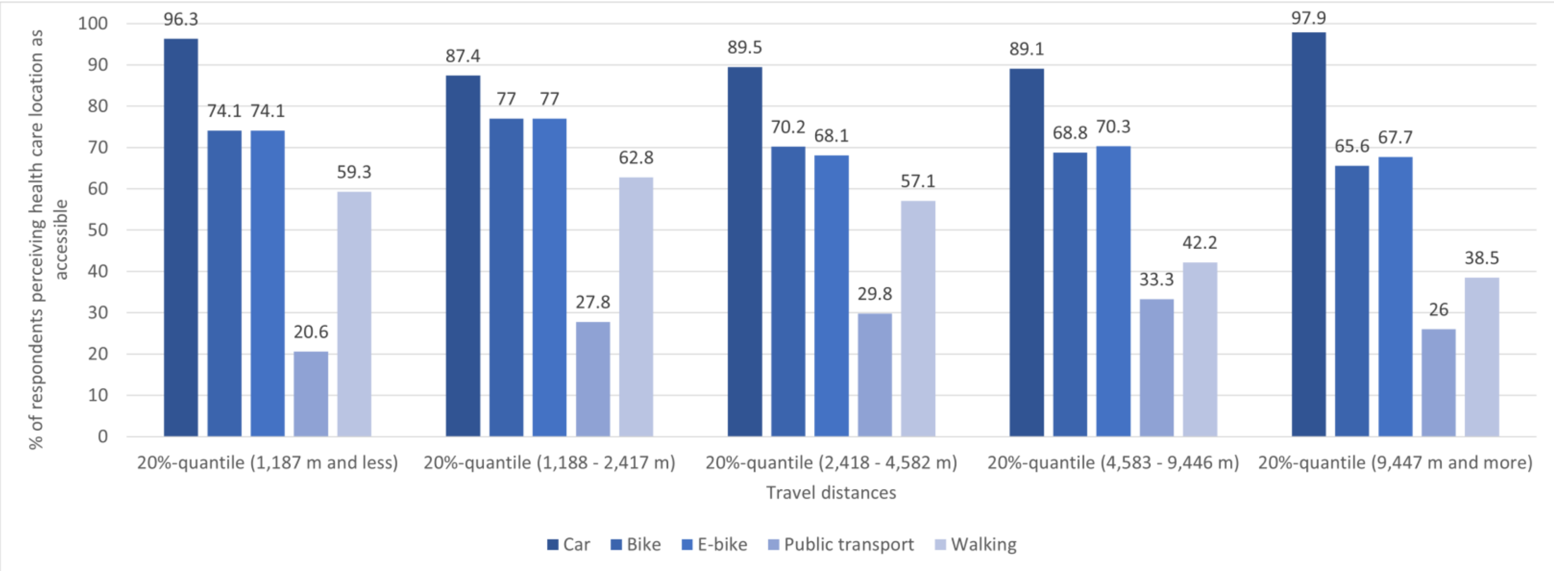
Figure 14: Marginal effect of urbanity on PA workplace, by car



4.2. Health care

For trips to the last visited health care location, the relationship between the trip distances and the perceived accessibility per transport mode is significant ($p<0.05$) for car, PT and walking. It is not significant for bike and e-bike, so we fail to reject the H0 that distance and PA are independent for those two transport modes. Figure 15 therefore shows the percentages of respondents that perceive their last visited leisure location as accessible for the five 20%-quantiles of distance. The health care location is perceived as most accessible by car for all categories of distance. The percentage of respondents who perceive the health care location as accessible by car is highest for the short and large distance (first and fifth 20%-quantile). This suggests that the car is viewed as most attractive for those distances. The share of respondents who perceive the health care location as accessible by bike and e-bike is particularly high for the first and the second quantile (distances < 2,418 m). The accessibility perceptions between bike and e-bike do not differ for short distances. Only for distances larger than 4,582 m, the share of respondents who perceive the destination as accessible by e-bike is slightly higher than that associated with bike. For walking as transport mode, there is a drop in the share of respondents who perceive the health care location as accessible in the fourth 20%-quantile. This indicates that the majority of the ATDs for health care visits for walking might be shorter than approximately 4,500 m. At the same time, 38.5% of the respondents still perceive distances larger than 9,400 m as accessible on foot. As those distances are relatively large, this again suggests the that respondents might not have interpreted the question as intended (see workplace as transport mode). PT is connected to the lowest share of respondents of all transport modes, which is again in line with Lättman et al. (2018). The share of respondent who perceive the health care location as accessible by PT is largest for the third and fourth 20%-quantile. This suggests that people choose PT mostly for medium distances and avoid it for very short or very large distances.

Figure 15: Perceived accessibility to health care location for different distance categories



According to the regression results, age does not have a significant effect on PA. Nonetheless, there is a clear negative effect of age on PA for the active transport modes, indicating that PA decreases as respondents age. The probabilities are very similar to workplace (see Figure 9) and indicate that ATDs decrease with age. For car as transport modes, the relationship between increasing age and ATD is reversed, as visualized in Figure 16. While older people consistently have higher PA levels, the probability to perceive the destination as accessible also increases as distances increase. This means that the ATD increase with age when going by car.

Figure 16: Marginal effect of age on PA health care, by car

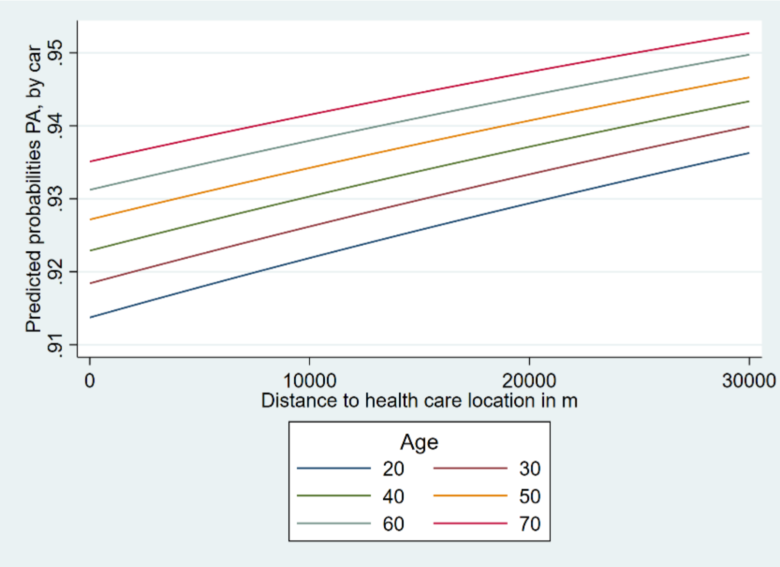
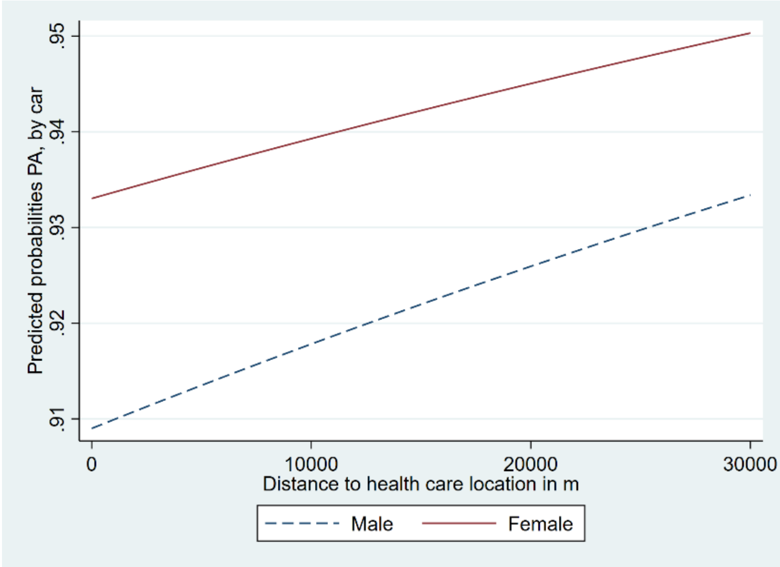


Figure 17: Marginal effect of gender on PA health care, by car



The effect of gender is mostly positive, suggesting that women perceive higher levels of accessibility. This effect is significant and clear for car as transport mode and plotted in Figure 17. This indicates that the ATD of women is higher than for men. When looking at the active transport modes, it becomes visible that the differences in probabilities to perceive the health care location as accessible are small for short and very large distances and greatest for medium and large distances (see Figure 31 and Figure 32 in Appendix III). Women are therefore especially likely to perceive larger distances as accessible by active transport modes. Women's ATDs is furthermore higher than those of men for active transport modes.

Education and income are not significant for almost of the variable's categories. There is no clear gradual relationship between higher educational attainment and PA. What stands out is that individuals with only primary school education are associated with the highest predicted probabilities for the transport modes walking and PT. Moreover, respondents with a university degree have substantially higher probabilities of perceiving health care locations as accessible by e-bike than respondents with lower education levels. Individuals with household incomes of more than 5,000€ are substantially less likely to perceive health care locations as accessible by PT, as visualized in Figure 18. The ATD of high-income households is therefore shorter than that of low-income households. At the same time, high income households are substantially more likely to perceive health care locations as accessible by car, as visualized in Figure 19. In this scenario, the ATD of high-income households is therefore larger than that of low-income groups. The figures suggest that there might be a complementary relationship between PT and car for high-income groups. While their ATD for PT is short, it is large for car.

Figure 18: Marginal effect of income on PA health care, by PT

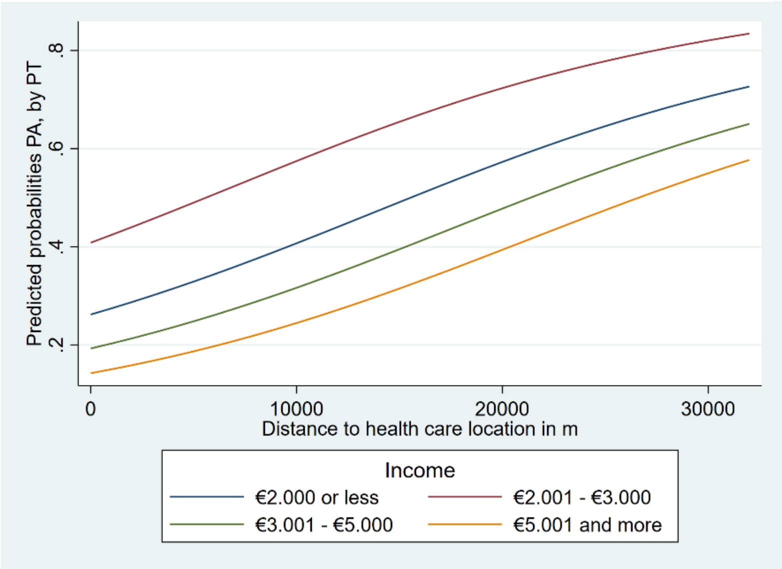
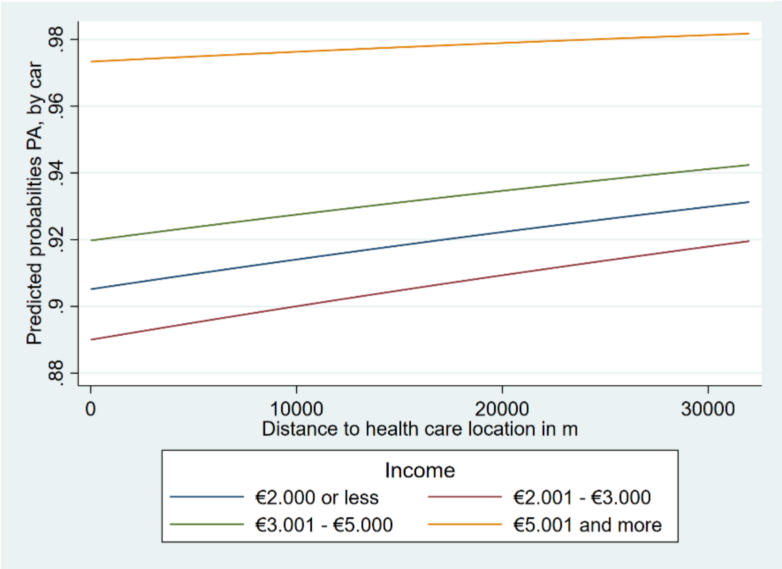


Figure 19: Marginal effect of income on PA health care, by car



The coefficients of household size are not significant and very small. This suggests that household size does only marginally influence ATDs. The variable urbanity is negative for car and positive for active transport modes. Although the coefficients are only significant for car, interesting relationships emerge. First, the coefficients suggest that urban residents are more likely to perceive health care locations as accessible when using active transport modes. This means that ATDs of urban residents are higher for active transport modes than those of rural residents. Second, urban residents are less likely to perceive health care locations as accessible by car, as plotted in Figure 20. This suggests that ATDs of rural residents by car are larger than those of urban residents. Third, urban residents are more likely to perceive health care locations as accessible by PT, as plotted in Figure 21. This indicates that urban residents are associated with higher ATDs when using PT than rural residents. This is in line with previous expectations and emphasizes that rural residents prefer the car over PT to get to health care destinations, whereas urban residents prefer PT over the car.

Figure 20: Marginal effect of urbanity on PA health care, by car

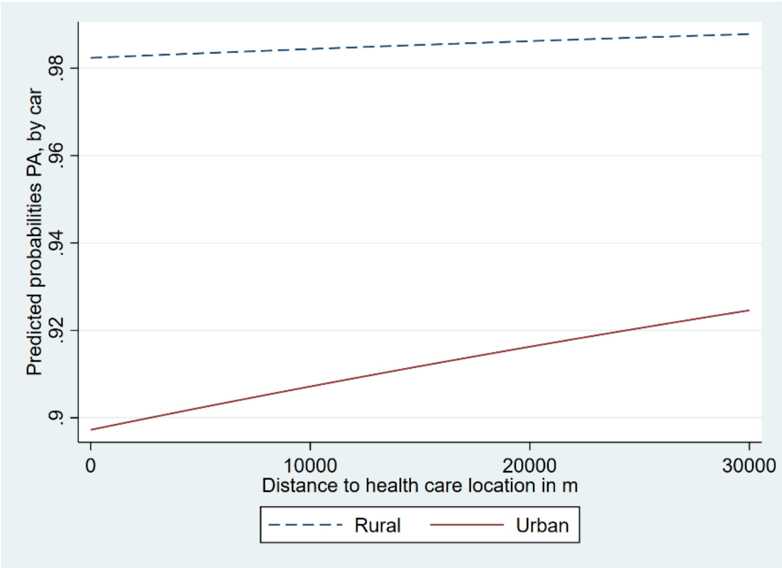
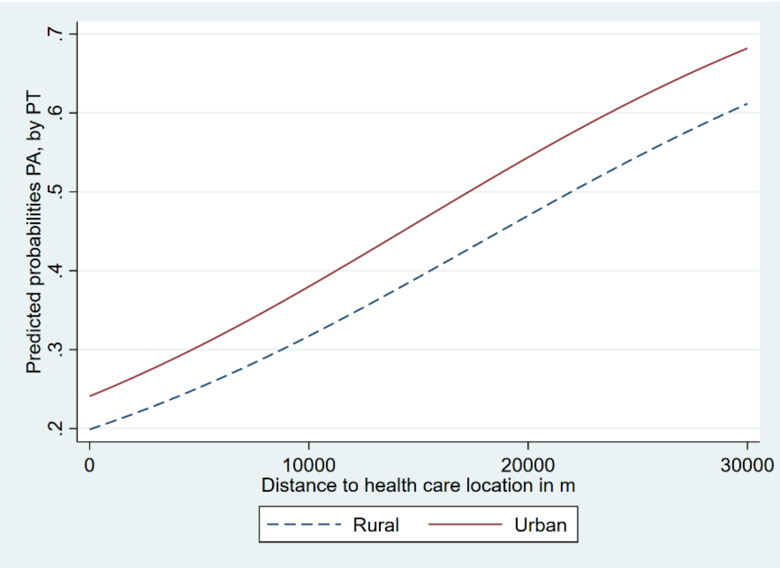


Figure 21: Marginal effect of urbanity on PA health care, by PT



4.3. Leisure

For leisure trips the relationships between distances as categorical variables (in five 20%-quantiles of distance) and PA are significant ($p<0.05$) only for the transport modes bike, e-bike and walking. For car and PT, the relationships are not significant, indicating that the two variables are not associated. Figure 22 shows the percentages of respondents that perceive their last visited leisure location as accessible for each transport mode. The diagram shows that the car is most attractive transport mode, with which the leisure location is perceived as accessible by over 93% of the respondents. The share of respondents who perceive the leisure location as accessible by bike and e-bike is very high for the first four quantiles and does then drop by 10% in the fifth quantile.

The relationship between distance and perceived accessibility for leisure trips appears to be more linear than for workplace. For bike and e-bike, the percentage of respondents who perceive their last visited leisure location as accessible decrease for distances larger than 4,000 m. Figure 22 suggests that accessibility perceptions are the highest for the second 20%-quantile for bikes and for the first 20%-quantile for e-bikes. In the fifth 20%-quantile (for distances larger than 17,000 m), the share of respondents perceiving the leisure location as accessible by (e-)bike drops by 10%.

The relationship for walking is almost linear for distances shorter than 15,000 m. However, for 15,000 m and more, the percentage of respondents that perceive the leisure location as accessible on foot stagnates. At first sight those distances seem to be too large to be walkable. A possible explanation is again that respondents rather evaluated the walking environment at the destination. Furthermore, it is possible that respondents also considered sport activities like walking or running in their responses, although this was meant to be excluded. It can be assumed that the correct percentage for large distances is smaller than shown in Figure 22 and that the perceived accessibility on foot for the leisure location decreases gradually as distances to the leisure location increase.

Figure 22: Perceived accessibility to leisure location for different distance categories

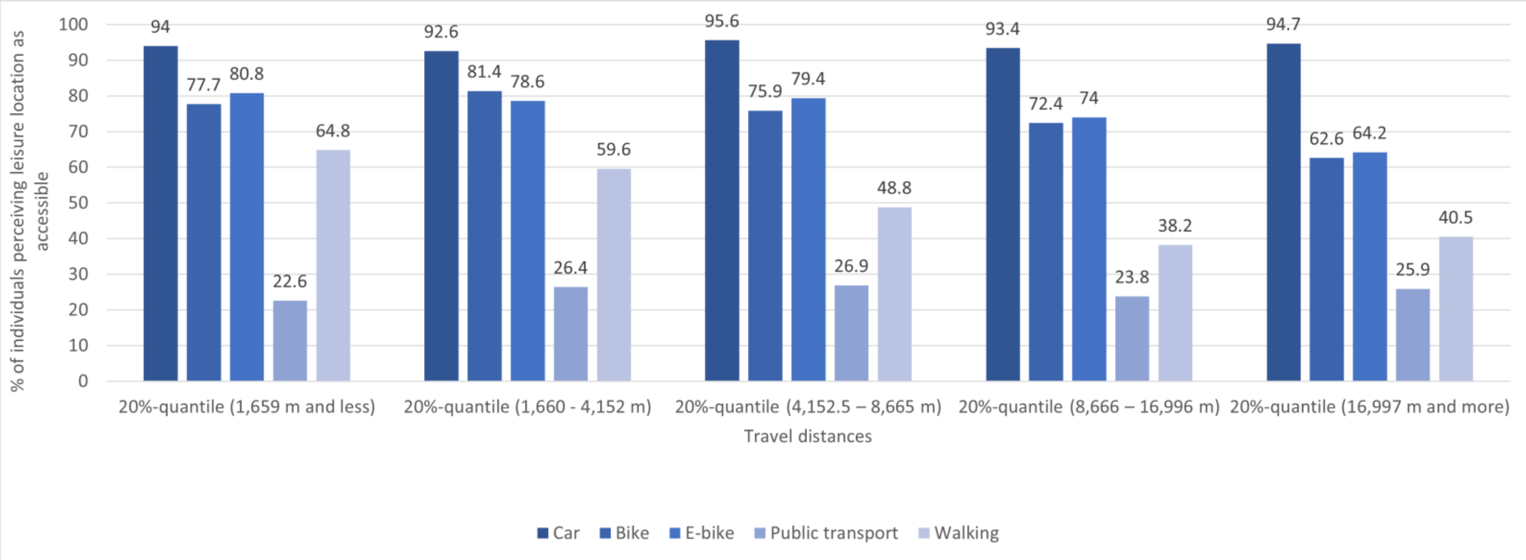
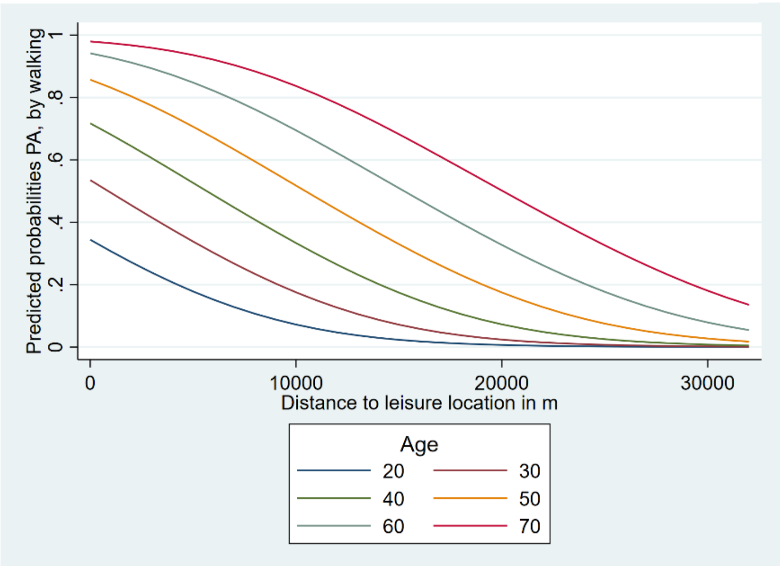


Figure 23: Marginal effect of age on PA leisure, by walking



As expected, the effect of age is positive for car as transport mode, indicating that older people have higher probabilities of perceiving leisure locations as accessible by car. The older people are, there higher are therefore their ATDs. Interestingly, the effect of age is not negative for all active transport modes, as expected based on theory. While the effect of age is negative for (e-)bikes, it is positive and significant for walking trips, which is visualized in Figure 23. The figure illustrates that older and elderly are substantially more likely to perceive leisure destinations as accessible than younger people with quite pronounced differences in predicted probabilities between the age groups. Older people consequently have higher ATDs than younger people for walking to leisure locations. Keeping in mind mobility restrictions and the dependency on cars of older people, this seems counterintuitive. A possible explanation is that older adults travel less and to fewer destinations, particularly regarding leisure activities (Lättman et al., 2019). Consequently, the remaining destinations they walk to might be chosen more carefully with potentially larger distances.

The effect of gender on PA depends on the distance to the leisure destination. The probabilities for perceiving the leisure location as accessible by car are plotted in Figure 24 and show that women are more likely to perceive the destination as accessible for shorter distances (distances < 10,000 m), while men are more likely to perceive distances larger than 10,000 m as accessible. For active transport modes, men are usually associated with a higher probability of perceiving the leisure location as accessible for relatively short distances (distances < 10,000 m). This is statistically significant for trips on foot and illustrated for walking in Figure 25. Although the differences are small, this suggests that women tend to have larger ATDs than men for walking trips to leisure locations.

Figure 24: Marginal effect of gender on PA leisure, by car

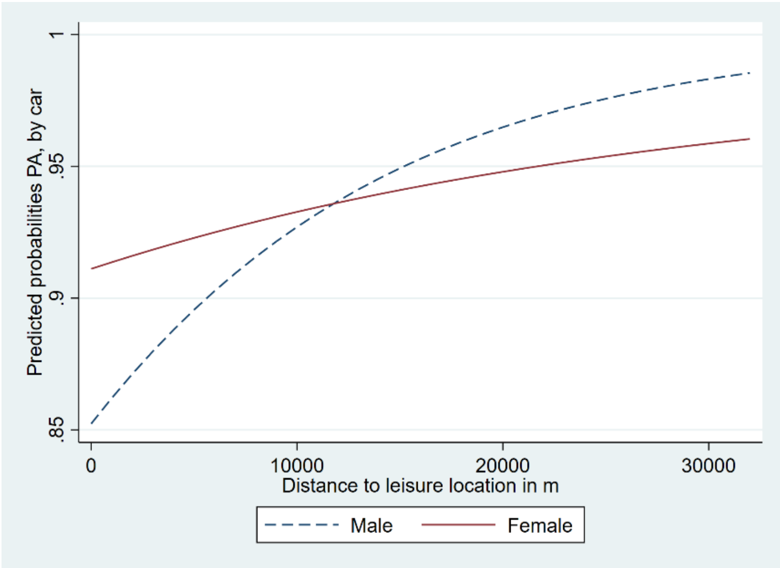
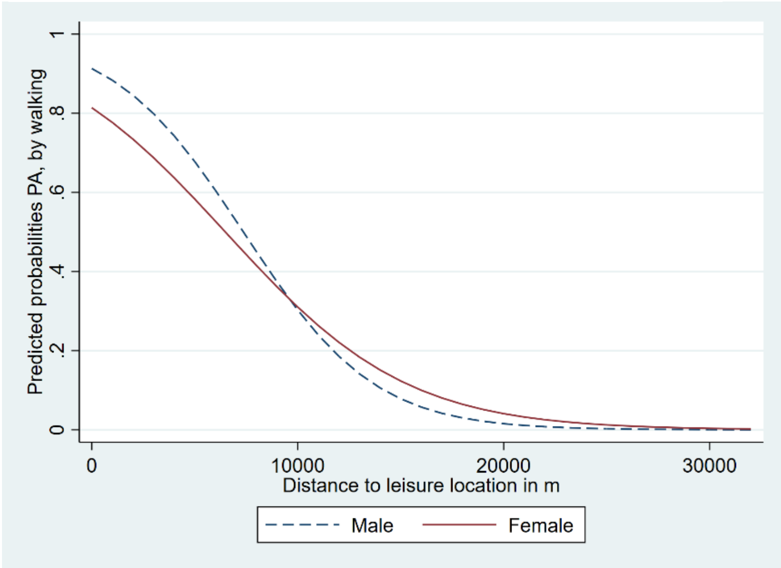


Figure 25: Marginal effect of gender on PA leisure, by walking



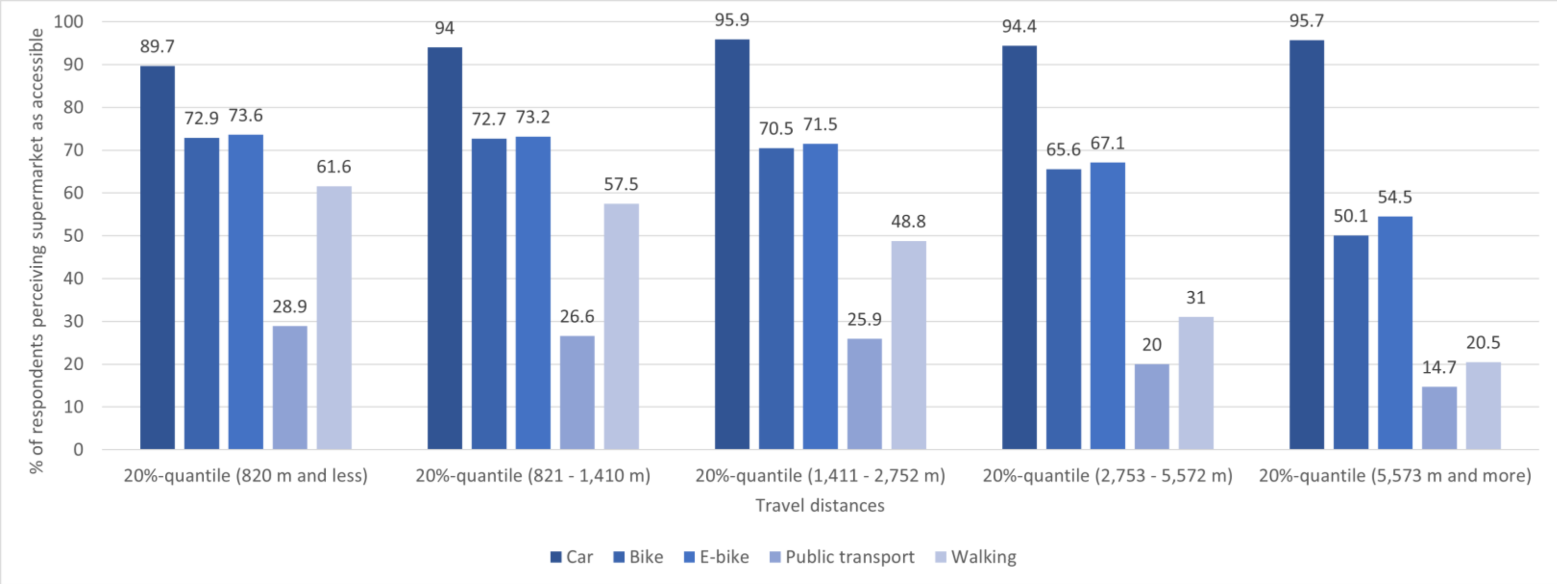
There seems to be no gradual or clear relationship between the education level and PA and between the household income and PA for leisure locations. What stands out is that individuals with a university degree have the lowest probabilities of perceiving the leisure location as accessible by car and foot. Increasing household size has a small positive effect on PA of leisure locations and the effect is significant for walking as transport mode. This means that individuals from large households are slightly more likely to perceive leisure locations as accessible than individuals from small households, as illustrated in Figure 34 in Appendix III. However, the differences in probability are very small. Therefore, the ATDs of large households are only slightly larger than those of small households for walking trips to leisure locations. For car as transport mode the effect is reversed and more pronounced, especially for short distances. Thus, individuals from large households are less likely to perceive the destination as accessible by car compared to individuals from small households. Their ATDs are larger.

The effect of the variable urbanity is non-significant for all transport modes. It is ambiguous for car and walking and can therefore not be interpreted clearly. For bike trips, urban residents are more likely to perceive leisure destinations as accessible, as visualized in Figure 33 in Appendix III. This suggests that the ATDs of urban citizen corresponding to bike trips to leisure destinations might be higher than those of rural citizens. This might be connected to better bike infrastructure in urban areas, which incentivize bike use. Because the effect is not significant, it is not interpreted further.

4.4 Supermarket

For trips to the most used supermarket, the relationships between the distances categories and PA are significant ($p<0.05$) for all transport modes. Therefore, we can reject the H0 that the two variables are independent. The percentage of respondents who perceive their most used supermarket as accessible for different distant categories is shown in Figure 26. The gradual decline in PA is very pronounced for the transport modes bike, e-bike, PT and walking. People seem to be more sensitive to larger distances to supermarkets than to other destinations. The data confirm this: 75% of the respondents agree that there needs to be a supermarket close to their home. Conversely, the share of respondents who perceive the supermarket as accessible by car does increase as distances increase. In contrast to workplace and health care, the trend for supermarket is that further locations are generally seen as more accessible by car. The share of respondents who perceive the supermarket as accessible by (e-)bike drops substantially by 15% after the fourth 20%-quantile (at around 5,500 m), suggesting a threshold value in ATD of supermarkets. Another threshold value can be identified after the third 20%-quantile for walking (for distances larger than 2,700 m), where to share of respondents who perceive the supermarket as accessible on foot drops by more than 15%.

Figure 26: Perceived accessibility to supermarket for different distance categories



Age has as statistically significant effect on supermarket trips by car, with older respondents perceiving the destination as more accessible than younger respondents (Figure 27). Older respondents therefore have higher ATDs. Interestingly, older individuals are also slightly (but non-significantly) more likely to perceive the supermarket as accessible by the active transport modes bike and walking, indicating slightly higher ATDs of older people with those transport modes. As trip distances to the supermarket are the shortest of all destinations (see Figure 5), this suggests that old respondents are willing to cycle or walk very short distances. Furthermore, the effect of gender on PA is partly significant and is visualized in Figure 28. The graph shows that women are more likely to perceive supermarkets as accessible by car for very short distances, while men are more likely to do so for larger distances. Therefore, ATDs of men by car are larger for trips to supermarket than those of women. Eventually, men have also higher probabilities to walk to the supermarket for larger distances, confirming that men generally have slightly larger ATDs when walking.

Figure 27: Marginal effect of age on PA supermarket, by car

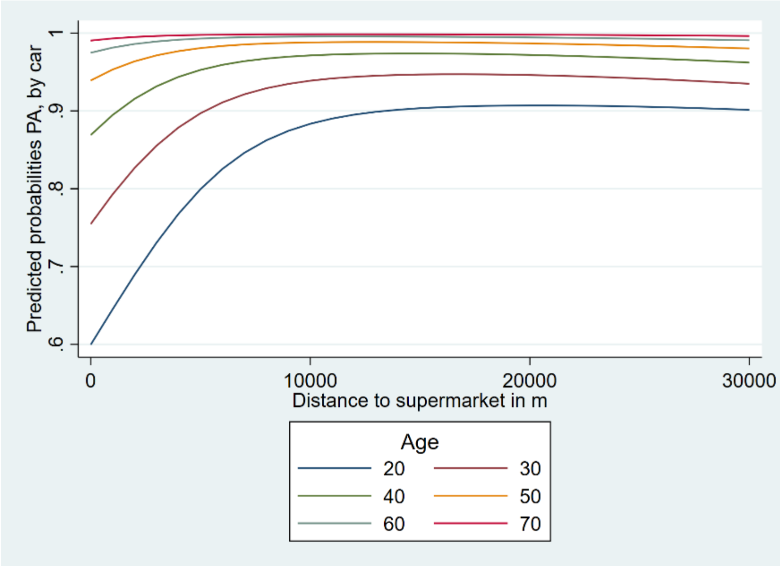
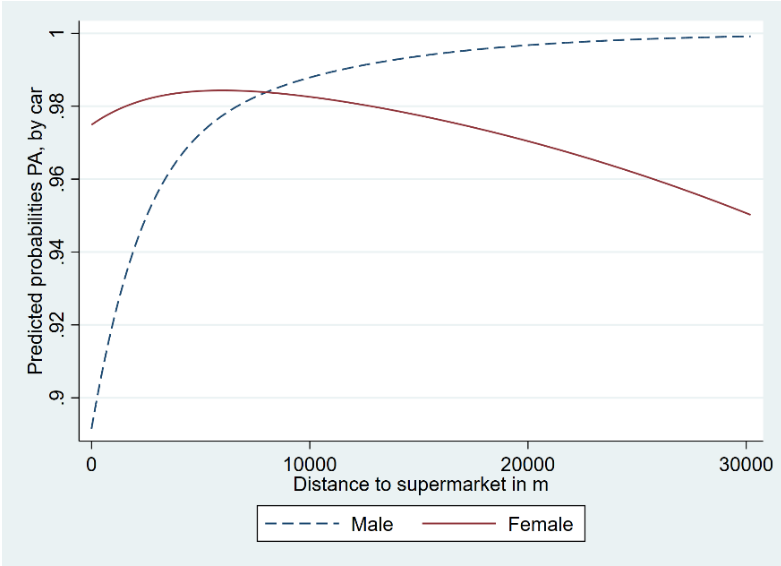


Figure 28: Marginal effect of gender on PA supermarket, by car



For educational attainment there appears to be no clear relationship with PA. The effect of income on the probabilities of perceiving the supermarket as accessible is only significant for car, where individuals from households with low incomes (incomes<2,000€) have substantially lower probabilities than higher-income groups (see Figure 35 in Appendix III). This suggests that low-income groups have shorter ATDs than high-income groups. An explanation might be the high costs related to the car. Household size is significant for car, bike and e-bike and has a negative effect on PA of supermarkets. This means that individuals from large households are less likely to perceive the supermarket as accessible than individuals from small households. The ATDs for large households are therefore shorter than for small households. A possible explanation is that large households are more time-constrained and consequently prefer shorter distances for grocery shopping. Eventually, urbanity has a significant effect on PA of supermarkets. Urban residents are substantially less likely to perceive the supermarket as accessibly by car, as illustrated in Figure 29. It suggests that ATDs of rural residents in this scenario are higher than for urban residents. This confirms that cars are the most attractive transport mode in rural areas also for grocery shopping. At the same time, urban residents are substantially more likely to perceive the supermarket as accessible by active transport modes, as plotted exemplary for bike in Figure 30. When using active transport modes, ATDs for urban residents are therefore higher than for rural residents. This shows that active transport modes are used substantially less in the rural context. A possible explanation is the higher population density in urban areas. Consequently, amenities like supermarkets are usually nearer, which makes the use of active transport modes less attractive and the use of cars more attractive for urban residents.

Figure 29: Marginal effect of urbanity on PA supermarket, by car

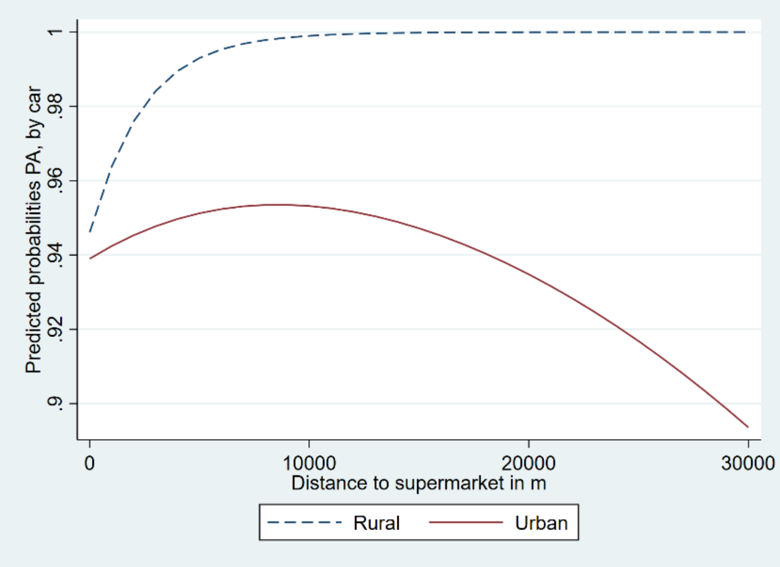
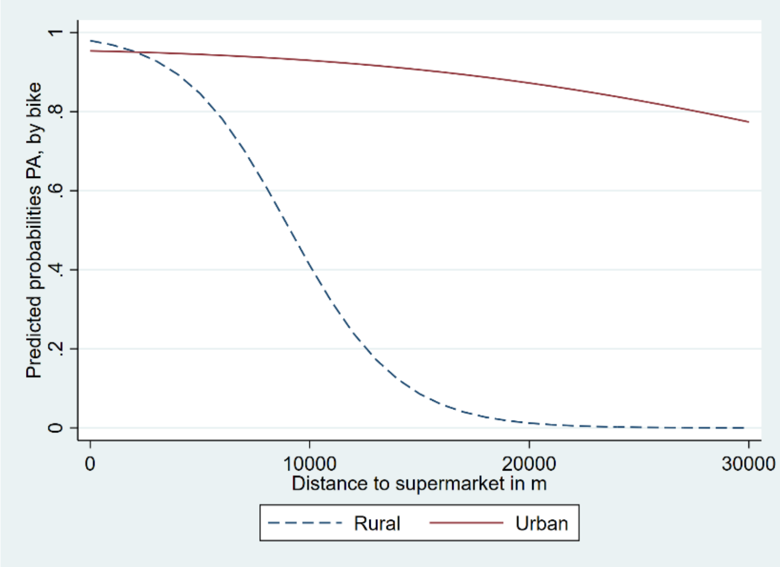


Figure 30: Marginal effect of urbanity on PA supermarket, by bike



5. Discussion

This chapter interprets the results of the research question in the context of this study. The main research question is how ATDs in the Netherlands vary for different transport modes. The sub-questions are (1) how the destination type (workplace/school, health care, leisure and supermarket) influences ATDs, (2) how socio-economic factors (age, gender, income, educational attainment and household size) influence ATDs, and (3) how the spatial context (rurality and urbanity) influences ATDs. Eventually, some study limitations are discussed.

Regarding sub-question 1, the cross-tabulations identified multiple thresholds at which the share of respondents who perceive the destination as accessible by active transport modes declines substantially. Those thresholds can serve as evidence for planning the 15-minute city, where all daily amenities should be reachable with active transport modes. A substantial drop in the share of respondents who perceive the destination as accessible by active transport modes suggests a likely shift to faster transport modes, such as car or PT. Given the low attractiveness of PT as transport mode compared to the high attractiveness of cars found in this study, a shift towards the car is substantially more likely. For workplace trips, the share of respondents who perceive the destination as accessible by (e-)bike is relatively large for the first four quantiles (Figure 6). For distances larger than 21,000 m however, the share decreases by more than 10%. This suggests that workplace locations should not be located further than 21,000 m from residential areas to incentivize the use of transport of active transport modes and disincentivize the use of cars. At the same time, although distances up to 21,000 m by bike seem quite large, this study found that there is a high percentage of respondents who might be willing to travel those distances by (e-)bike. This suggests that (e-)bike paths are particularly important for routes between residential areas and areas where workplaces are located.

Regarding leisure locations, similar conclusions can be drawn. The share of respondents who perceive the leisure destination as accessible by (e-)bike drops substantially for distances larger than 17,000 m (Figure 22). Hence, it is likely that respondents substitute active transport modes by the car for distances larger than 17,000 m. Leisure locations should therefore not be located further than 17,000 m from residential areas.

Regarding supermarkets, two threshold values were found. First, the share of respondents who perceive the supermarket as accessible on foot drops by more than 15% in the third 20%-quantile (for distances larger than 2,700 m). Second, the share of respondents who perceive the supermarket as accessible by (e-)bike drops by 15% after the fourth 20%-quantile (distances larger than 5,500 m), suggesting a threshold value in ATDs to supermarkets. Looking at the supermarket provision in the Netherlands, people currently live on average 2,100 m away from their primary supermarket (van Gelder, 2022). This suggests that most people live within the approximate threshold of 2,700 m which this study identified for walking. Nonetheless, CBS data indicate that the distance depends strongly on the region. People living in rural provinces like Drenthe and Friesland live furthest away from the nearest supermarket, which also might not necessarily be the primary supermarket (Baydar et al., 2010). CBS data confirms that there are multiple municipalities where some grocery stores are located further than 3,000 m away (Baydar et al., 2010). This indicates potential in current grocery provision planning to incentivize the use of active transport modes in certain municipalities, particularly in rural areas.

Table 4: Result summary

<table>
<tr><th>Destination type / Determinants</th><th>Workplace</th><th>Health care</th><th>Leisure</th><th>Supermarket</th></tr>
<tr><td rowspan="2">Gender (men vs. women)</td><td>Walking: ATDs of men larger</td><td>Active transport modes: ATDs of women larger
Car: ATDs of women larger</td><td>Walking: ATDs of women slightly larger</td><td></td></tr>
<tr><td></td><td></td><td>Car: ATDs of men larger</td><td>Car: ATDs of men larger</td></tr>
<tr><td rowspan="3">Age (younger vs. older individuals)</td><td colspan="4">Car: ATDs increase with age</td></tr>
<tr><td colspan="3">Active transport modes: ATDs decrease with age</td><td></td></tr>
<tr><td></td><td></td><td>Walking: ATDs increases with age</td><td>Active transport modes: ATDs increases with age</td></tr>
<tr><td>Education (low-educated vs. high-educated)</td><td></td><td>E-bike: ATDs of high-educated larger</td><td></td><td></td></tr>
<tr><td>Income (high-income vs. low-income groups)</td><td>E-bike: ATDs of high-income groups larger
Active transport modes: ATDs of high-income groups tend to be larger</td><td>PT: ATDs of high-income groups shorter
Car: ATDs of high-income groups larger</td><td></td><td>Car: ATDs of low-income groups shorter</td></tr>
<tr><td>Household size (large household vs. small household groups)</td><td></td><td></td><td></td><td>Car, (e-)bike: ATDs decrease with household size</td></tr>
<tr><td rowspan="3">Urbanity (urban vs. rural)</td><td colspan="4">Car: ATDs of rural residents larger</td></tr>
<tr><td>PT: ATD of urban residents larger</td><td>PT: ATD of urban residents larger</td><td></td><td></td></tr>
<tr><td>(E-)bike: ATDs of rural residents larger</td><td></td><td>Bike: ATDs of urban residents larger</td><td></td></tr>
</table>

Note: (Partially) significant relationships are in bold.

Table 4 answers sub-questions 2 and 3 and provides an overview of the important relationship between socio-economic and spatial characteristics and ATDs. The table reports that ATDs of men are significantly larger when walking to their workplace. As walking is the slowest transport mode, it is most likely chosen by subgroups which are less time constrained. This applies particularly to commuting trips, since those are usually done every day. This result therefore indicates that women are more time-constrained when going to their workplace. This is in line with previous research. A possible explication is that women spend more time carrying out care work than men, such as cooking, cleaning and taking children to care facilities and schools (Barbieri et al., 2017). Consequently, being less constrained in time most likely leads to higher ATDs for men than for women when walking to their workplace. At the same time, women's ATDs are slightly larger when walking to leisure locations (statistically significant). Considering that women are more time-restricted, this might seem counterintuitive. A possible explication is that women prefer active transport modes, such as walking, in the context of going to leisure locations. This presumption seems to be confirmed by health care trips. Here, ATDs of women are larger than those for men for active transport modes, although this is not significant.

Table 4 shows that ATDs for men by car are usually larger. This applies to leisure and supermarket locations, while health care destinations form an expectation where women are associated with larger ATDs. It is in line with previous research showing that men use the car more often than women (Vance & Iovanna, 2007). This suggests that substituting cars by alternative transport modes will have different effects on men than on women. Since shorter ATDs are easier to substitute by the slower active transport mode, men might be more affected than women (because men's ATDs by car are larger). Interestingly, a statistically significant finding of this study is that women have larger ATDs by car when going to health care destinations. This is in line with previous research, which shows that women travel larger distances for non-work-related trips (Gordon et al., 1989; Sánchez et al., 2014). Most importantly, this might contribute to dependencies of women on fast transport modes like cars when accessing health care locations. Especially if there are no suitable alternatives to the use of cars (for example in case of insufficient PT provision), then this has the potential of impeding health care accessibility for women. However, further research is needed to confirm this.

The results regarding age are very clear. On the one hand, the ATDs by car of older individuals are significantly higher than those of younger people. Older individuals were found to almost exclusively use the car. On the other hand, the ATDs of younger people are significantly higher than those of older individuals for active transport modes and younger individuals tend to use more active transport modes. This confirms that the car is perceived as the de-facto sole mode of transport for older adults and elderly because of mobility restrictions. It is in line with previous research showing that older people use active transport modes less because of mobility constraints (Larsen et al., 2010; Yang & Diez-Roux, 2012).

However, this study found two exceptions to this. Older respondents walk significantly further to leisure destinations than younger respondents and the use of active transport modes increases with age (although not significantly) when considering only supermarket trips. As already mentioned, the increased use of active transport modes for accessing leisure locations is most likely caused by the phenomenon that older adults and elderly generally travel less and to fewer destinations (Lättman et al., 2019). Consequently, the remaining destinations might be chosen with an emphasis on the accessibility with active transport modes. This suggests that older adults and elderly are well aware of the health benefits that walking and (e-)biking offer. Although further research remains important to confirm this, this suggests that the placement of leisure and supermarket destinations in walking and biking distance to the residences of older people could increase the use of those transport modes.

Respective walking and cycling paths could furthermore be designed to offer higher convenience for elderly, such as giving crossing preference to pedestrians and cyclists and avoid descents and ascents.

With respect to the household income, the results show that ATD are significantly larger for high-income groups for workplace trips. As the costs related to e-bikes are substantially higher than those of regular bikes, this implies that e-bikes are more attractive to high-income groups. It is important to keep in mind that the respondents' ATDs are larger for e-bikes than for bikes and that an increased use of e-bikes could in some cases contribute to a substitution of cars. However, this substitution potential does at the moment mostly apply to high-income groups, as lower-income groups do not have the financial means necessary for purchasing and using e-bikes. Adequate policies could therefore address the costs of e-bikes and thus make e-bikes more attractive for middle- and low-income groups. Possibilities are tax reductions for e-bike purchases or e-bikes as part of work travel plans, as well as convenient and safe e-bike parking facilities at the workplace (Jones et al., 2016; Plazier et al., 2018). This way, the ATDs for e-bikes of middle- and low-income groups could be increased, which might provide incentives for a modal shift from car to e-bike for commuting trips.

Regarding the effect of education, the only clear relationship found is that higher educated individuals have larger ATDs by e-bikes. However, as this relationship is not significant and because higher education levels are often associated with higher incomes, this finding is not discussed further. This study did not find evidence to support generally larger ATDs for higher educated individuals in reaction to generally larger distances to their workplace (Schwanen et al., 2001; Turner & Niemeier, 1997). Regarding the effect of household size, the only significant result is that the ATDs of large household are significantly shorter than those of small households for supermarket trips for the transport modes car and (e-bike). This is partially in line with prior expectations that (e-)bikes might be less suitable for large household, as those households are often characterized by the presence of children. Those households are usually characterized by specific child-related activities, like talking children to childcare facilities, schools or leisure activities. Consequently, (e-)bikes might be less attractive for activities like taking children to childcare facilities and schools. Regarding cars, the shorter ATDs of individuals from large households to supermarkets can be explained by the fact that large households are more time constrained, as elaborated in Chapter 2. Members of large household might therefore prefer closer supermarkets with the aim to minimize the time spent for grocery store trips.

Regarding sub-question 3, Table 4 clearly shows that the ATDs of rural residents by car are larger than those of urban residents. At the same time, the ATDs of urban residents by PT are larger than those of rural residents. Those results are in line with prior theoretical elaborations stating that PT are more attractive in the urban context in the Netherlands (Wiersma et al., 2016). Since negative externalities like traffic congestion are less present in rural areas, rural residents are willing to go larger distances by car. Additionally, there are less alternatives to the car in rural areas. First, slower transport modes, such as walking and biking, are less viable because of the generally large travel distance. Second, PT provision is lower in rural areas because of the lower population density. Not only are there less routes, but also buses or trains run less frequently than in urban areas. The results of this study can therefore serve as evidence to better adapt rural PT to the requirement of the rural populations. Investments in PT in rural areas should reflect the needs of rural populations and should not simply replicate PT systems in cities. If PT options are perceived as more competitive to the car, then rural residents might shift from the car to PT. Possibilities are demand-responsive PT infrastructure, community transport services and PT service with flexible routes (Coutinho et al., 2020; Velaga et al., 2012). At the same time, as this study utilizes perceived accessibility, it is possible that rural populations simply might not perceive PT as a viable option although it is objectively a viable option. This could for example be the case because people might be used to automatically go by car without considering other alternatives. This is confirmed by the survey data, as 70.56% of the respondents living in rural areas state that they automatically use the car when they go somewhere. Therefore, it is not only important to enhance PT infrastructure and provision, but also to address perceptions of rural inhabitants to incentivize the use of alternative transport modes to the car.

The results regarding the use of active transport modes in the spatial context are less clear. It was found that the ATDs of urban residents for biking are larger when going to leisure destinations. At the same time, ATDs of rural residents when going to their workplace by (e-)bike are larger than those of urban residents. Both relationships are not statistically significant. This study can therefore not confirm prior findings that urban residents generally have larger ATDs than rural residents for active transport modes (Scheepers et al., 2013; Yang & Diez-Roux, 2012). Further research is required to confirm whether the differences in ATDs for rural and urban residents in fact vary across destination types.

At last, this study found that respondents perceive destinations by e-bike as slightly more accessible than by regular bikes, especially when looking at larger distances (4th and 5th 20%-distances-quantile) (see Figure 6, Figure 15, Figure 22 and Figure 26). This is the case for all destination types, although the phenomenon seems to be more pronounced for leisure trips. This result confirms the hypothesis stated in Chapter 2 that ATD for e-bikes is higher than for bikes. Especially for medium and large distances, adequate policies could therefore contribute to a substitution of cars by e-bikes for larger distances, as already suggested by previous research (Plazier et al., 2017; Söderberg f.k.a. Andersson et al., 2021). This might be particularly important for trips to leisure destinations, as the differences between bike and e-bike are a little more pronounced. In general, charging facilities and infrastructure, which allow to travel larger distances could be improved (Plazier et al., 2018).

Several limitations regarding the conceptual and methodological approach of this study should be noted. An important shortcoming is that this study only includes trips from home to other locations. For example, if a respondent usually goes to the supermarket on their way back from the workplace, this study was not able to capture the levels of PA of that supermarket. This pattern is referred to as trip chaining in transport research. Although trip chaining is less common for walking and biking, it is quite common for car and PT trips (Primerano et al., 2008). This could lead to a situation in which a respondent rates a particular location as inaccessible from home but is in reality very satisfied with the accessibility of the location, for example because it is located close to the respondent's workplace.

Furthermore, perhaps the greatest limitation of this study is the small sample size. The explanatory power of the regression results is therefore limited. The reason was mostly that respondents entered incorrect or unprecise addresses or postcodes, which made it impossible to calculate travel distances. The consequence was that some observations could not be used for the analysis. Furthermore, many respondents did not give information on trips for all destination types. This made it impossible to estimate a model for all destination types and lead to separate modes for each destination type with fewer observations. The regression results in Appendix II report relative low numbers of observations per model ranging from 140 to 529 observations. The number of observations was particularly low for workplace and health care as destination types. The low number of observations had some important consequences for the explanatory power of the regression outcomes and eventually for the results of this study, which will be outlined in the following. The most important consequence of the low number of observations is that type II errors are more likely to occur (Columb & Atkinson, 2015). Type II error refers to failing to reject the H0, consequently stating that there is no statistically significant relationship between independent and dependent variable, although there is in fact a statistically significant association. However, this was taken into consideration by cautiously interpreting also statistically insignificant coefficients (especially when the sign and the strength of if the coefficient were similar in both models for the destination – transport mode combination). Another consequence of the low number of observations is that some categories of independent variable were empty because of the lack of respective observations. For example, this is the case for household size (categories *4* and *5 and more*) or for education (category *primary school*) for PA workplace by car. This made the interpretation of those covariates difficult. Furthermore, influential cases in logistic regressions with a low number of observations can lead to biased coefficients (Mehmetoglu & Jakobsen, 2017). For workplace quite some outliers were detected in Appendix IV. Despite the suitability and benefits which binary logistic regressions offer for this study, the results might be biased. Finally, the explanatory power of this study is compromised by the non-significant models of PT for health care, leisure and supermarket. Due to this, a comparison of PA by PT across destination types was not possible.

Eventually, this study is limited by the fact that the survey data was collected during in the year 2020 during the COVID-19 pandemic. This applied mostly to the data collected in February 2020 when COVID restrictions like temporary closure of shops and leisure destinations, curfews and remote work regimes were in force. For example, 59.5% of the respondents stated that the COVID-19 crisis has an impact on the way they travel. This especially affects trips by PT, as 62.7% of the respondents say that they travel less by PT due to the COVID-19 crisis. The results for PT as transport mode could therefore be distorted. At the same time, as most restrictions were lifted in September 2020, data collected in this month is expected to be influenced less by COVID-19.

6. Conclusion

By using data on PA instead objective accessibility or actual travel behavior, this study uses a novel approach to derive ATDs. This approach takes the importance of individually perceived accessibility for the travel decision more into consideration and contributes to further incorporation of accessibility in planning and policy making (Handy, 2020). The main research question is how ATDs in the Netherlands vary for different transport modes. The sub-questions are (1) how the destination type (workplace/school, health care, leisure and supermarket) influences ATDs, (2) how socio-economic factors (age, gender, income, educational attainment and household size) influence ATDs, and (3) how the spatial context (rurality and urbanity) influences ATDs.

Regarding sub-question 1, the cross-tabulations confirm that ATDs are longest for workplace trips, decrease for leisure and health care and are shortest for supermarket trips, which is in line with previous research based on ATDs derived by objective accessibility. Findings on distance thresholds for which respondents do not perceive their destination as accessible anymore by active transport modes can be incorporated into planning and policy making to incentive the use of (e-)bikes, bring health benefits and decrease emissions and pollution. For example, the results suggest that (e-)bike paths between residential and workplace areas for distances up to 21,000 m should be prioritized. With respect to supermarket, the results show that stores should not be located further than approximately 2,700 m from residents, which might be the case in some predominantly rural Dutch regions at the moment.

With respect to sub-question 2, it was found that although men generally have larger ATDs by car, the ATDs of women by car are larger for health care destinations. Planning interventions with the objective to contribute to the substitution of car trips should therefore take on a gender-sensitive approach. Furthermore, older people were generally found to have shorter ATDs by active transport modes. However, important exceptions suggest that older people are willing to more often walk and cycle to leisure and supermarket locations than younger people. Especially in the light of aging societies, planning should therefore prioritize proximity to those destination types. Another finding is that higher incomes and higher educational attainment are connected larger ATDs by e-bikes. Policies targeted at reducing costs related to e-bikes could therefore contribute to an increased use of e-bikes among lower-income groups, especially for commuting trips.

Regarding sub-question 3, this study clearly finds that rural residents have significantly larger ATDs by car than urban residents and that rural residents have significantly shorter ATDs by PT. This relationship is reversed for urban residents. If policy makers want to provide incentives for switching from cars to PT in rural areas, then PT systems in rural areas need to be more adapted to the requirements of the local rural populations.

7. References

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8. Appendices

Appendix I: Cross-tabulations

Table 5: Cross-tabulation perceived accessibility and distances to workplace

Distances to workplace	Perceived accessibility by car			Perceived accessibility by bike			Perceived accessibility by e-bike			Perceived accessibility by PT			Perceived accessibility by walking		
	Not accessible	Accessible	Total	Not accessible	Accessible	Total	Not accessible	Accessible	Total	Not accessible	Accessible	Total	Not accessible	Accessible	Total
3,483 m and less	21	193	214	39	175	214	40	174	214	148	66	214	65	149	214
	15	199	214	52.5	161.5	214	50.3	163.7	214	158.9	55.1	214	99.4	114.6	214
	9.81	90.19	100.00	18.22	81.78	100.00	18.69	81.31	100.00	69.16	30.84	100.00	30.37	69.63	100.00
3,484 – 7,950 m	22	189	211	37	174	211	39	172	211	148	63	211	88	123	211
	14.8	196.2	211	51.8	159.2	211	49.6	161.4	211	156.7	54.3	211	98	11	211
	10.43	89.57	100.00	17.54	82.46	100.00	18.48	81.52	100.00	70.14	29.86	100.00	41.71	58.29	100.00
7,951 – 14,130 m	13	205	218	55	163	218	46	172	218	173	45	218	135	83	218
	15.3	202.7	218	53.5	164.5	218	51.2	166.8	218	161.9	56.1	218	101.3	116.7	218
	5.96	94.04	100.00	25.23	74.77	100.00	21.10	78.90	100.00	79.36	20.64	100.00	61.84	38.16	100.00
14,131 – 21,840 m	9	204	213	53	160	213	49	164	213	157	56	213	102	111	213
	14.9	198.1	213	52.3	160.7	213	50.1	162.9	213	158.2	54.8	213	98.9	114.1	213
	4.23	95.77	100.00	24.88	75.12	100.00	23.00	77.00	100.00	73.71	26.29	100.00	47.89	52.11	100.00
21,841 m and more	10	206	216	79	137	216	78	138	216	170	46	216	108	108	213
	15.1	200.9	216	53	163	216	50.8	165.2	216	160.4	55.6	216	100.3	115.7	213
	4.63	95.37	100.00	36.57	63.43	100.00	36.11	63.89	100.00	78.70	21.30	100.00	50.00	50.00	100.00
Total	75	997	1,072	263	809	1,072	252	820	1,072	796	276	1,072	498	574	1,072
	75	997	1,072	263	809	1,072	252	820	1,072	796	276	1,072	498	574	1,072
	7.00	93.00	100.00	24.53	75.47	100.00	23.51	76.49	100.00	74.25	25.75	100.00	46.46	53.54	100.00
	Pearson chi2(4) = 11.1554 Pr = 0.025			Pearson chi2(4) = 27.1665 Pr = 0.000			Pearson chi2(4) = 25.5360 Pr = 0.000			Pearson chi2(4) = 10.0126 Pr = 0.040			Pearson chi2(4) = 46.4068 Pr = 0.000		

Note: First row has observed frequencies, second row has expected frequencies, and third row has observed row percentages.

Table 6: Cross-tabulation perceived accessibility and distances to leisure location

Distances leisure	Perceived accessibility by car			Perceived accessibility by bike			Perceived accessibility by e-bike			Perceived accessibility by PT			Perceived accessibility by walking		
	Not accessible	Accessible	Total	Not accessible	Accessible	Total	Not accessible	Accessible	Total	Not accessible	Accessible	Total	Not accessible	Accessible	Total
1,659 m and less	19	299	318	71	247	318	61	257	318	246	72	318	112	206	318
	18.9	299.1	318	82.7	235.3	318	78.3	239.7	318	238.1	79.9		157.8	160.2	318
	5.97	94.03	100.00	22.33	77.67	100.00	19.18	80.41	100.00	77.36	22.64	100.00	35.22	64.78	100.00
1,660 – 4,152 m	24	298	322	60	262	322	69	253	322	237	85	322	130	192	322
	19.1	302.9	322	83.7	238.3	322	79.3	242.7	322	241.1	80.9		159.8	162.2	322
	7.45	92.55	100.00	18.63	81.37	100.00	21.43	78.57	100.00	73.60	26.40	100.00	40.37	59.63	100.00
4,152.5 – 8,665 m	14	306	320	77	243	320	66	254	320	234	86	320	164	156	320
	19.0	301.0	320	83.2	236.8	320	78.8	241.2	320	239.6	80.4	320	158.8	161.2	320
	4.38	95.63	100.00	24.06	75.94	100.00	20.63	79.38	100.00	73.13	26.88	100.00	51.25	48.75	100.00
8,666 – 16,996 m	21	298	319	88	231	319	83	236	319	243	76	319	197	122	319
	18.9	301.9	319	82.9	236.1	319	78.6	240.4	319	238.9	80.1	319	158.3	160.7	319
	6.58	93.42	100.00	27.59	72.41	100.00	26.02	73.98	100.00	76.18	23.86	100.00	61.76	38.24	100.00
16,997 and more	17	304	321	120	201	321	115	206	321	238	83	321	191	130	321
	19.1	301.9	321	83.5	237.5	321	79.0	242.0	321	240.3	80.7	321	159.3	161.7	321
	5.30	94.70	100.00	37.38	62.62	100.00	35.83	64.17	100.00	74.14	25.86	100.00	59.50	40.50	100.00
Total	95	1,505	1,600	416	1,184	1,600	394	1,206	1,600	1,198	402	1,600	794	806	1,600
	95	1,505	1,600	416	1,184	1,600	394	1,206	1,600	1,198	402	1,600	794	806	1,600
	5.94	94.06	100.00	26.00	74.00	100.00	24.63	75.38	100.00	74.88	25.12	100.00	49.63	50.38	100.00
	Pearson chi2(4) = 3.1992 Pr = 0.525			Pearson chi2(4) = 33.9715 Pr = 0.000			Pearson chi2(4) = 31.6359 Pr = 0.000			Pearson chi2(4) = 2.2188 Pr = 0.696			Pearson chi2(4) = 69.0631 Pr = 0.000		

Note: First row has observed frequencies, second row has expected frequencies and third row has observed row percentages.

Table 7: Cross-tabulation perceived accessibility and distances to health care location

Distances health	Perceived accessibility by car			Perceived accessibility by bike			Perceived accessibility by e-bike			Perceived accessibility by PT			Perceived accessibility by walking		
	Not accessible	Accessible	Total	Not accessible	Accessible	Not accessible	Accessible	Total	Total	Not accessible	Accessible	Total	Not accessible	Accessible	Total
1187 m and less	7	182	189	49	140	189	49	140	189	150	39	289	77	112	189
	15	174	189	54.6	134.4	189	54	135	189	137	52	289	90.8	98.2	189
	3.70	96.30	100.00	25.93	74.07	100.00	25.93	74.07	100.00	79.37	20.63	100.00	40.74	59.26	100.00
1,188 – 2,417 m	24	167	191	44	147	191	44	147	191	138	53	191	71	120	191
	15.2	175.8	191	55.2	135.8	191	54.6	136.4	191	138.4	52.6	191	91.8	99.2	191
	12.57	87.43	100.00	23.04	76.96	100.00	23.04	76.96	100.00	72.25	27.75	100.00	37.17	62.83	100.00
2,418 – 4,582 m	20	171	191	57	134	191	61	130	191	134	57	191	82	109	191
	15.2	175.8	191	55.2	135.8	191	54.6	136.4	191	138.4	52.6	191	91.8	99.2	191
	10.47	89.53	100.00	29.84	70.16	100.00	31.94	68.06	100.00	70.16	29.84	100.00	42.93	57.07	100.00
4,583 – 9,446 m	21	171	192	60	132	192	57	135	192	128	64	192	111	81	192
	15.3	176.7	192	55.5	136.5	192	54.9	137.1	192	139.1	52.9	192	92.3	99.7	192
	10.94	89.06	100.00	31.25	68.75	100.00	29.69	70.31	100.00	66.67	33.33	100.00	57.81	42.19	100.00
9,447 m and more	4	188	192	66	126	192	62	130	192	142	50	192	111	81	192
	15.3	176.7	192	55.5	136.5	192	54.9	137.1	192	139.1	52.9	192	92.3	99.7	192
	2.08	97.92	100.00	34.38	65.63	100.00	32.29	67.71	100.00	73.96	26.04	100.00	61.46	38.54	100.00
Total	76	879	955	276	679	955	273	682	955	692	263	955	459	496	955
	7.96	92.04	100.00	28.90	71.10	100.00	28.59	71.41	100.00	72.46	27.54	100.00	48.06	51.94	100.00
	Pearson chi2(4) = 23.2259 Pr = 0.000			Pearson chi2(4) = 7.4087 Pr = 0.116			Pearson chi2(4) = 5.9927 Pr = 0.200			Pearson chi2(4) = 8.4730 Pr = 0.076			Pearson chi2(4) = 36.2607 Pr = 0.000		

Note: First row has observed frequencies, second row has expected frequencies and third row has observed row percentages.

Table 8: Cross-tabulation perceived accessibility and distances to supermarket

Distances supermarket	Perceived accessibility by car			Perceived accessibility by bike			Perceived accessibility by e-bike			Perceived accessibility by PT			Perceived accessibility by walking		
	Not accessible	Accessible	Total	Not accessible	Accessible	Not accessible	Accessible	Total	Total	Not accessible	Accessible	Total	Not accessible	Accessible	Total
820 m and less	42	367	409	111	298	409	108	301	409	291	118	409	157	252	409
	24.8	384.2	409	137.7	271.3	409	131.2	277.8	409	314.2	94.8	409	229.7	179.3	409
	10.27	89.73	100.00	27.14	72.86	100.00	26.81	73.59	100.00	71.15	28.85	100.00	38.39	61.61	100.00
821 – 1,410 m	25	389	550	113	301	414	111	303	414	304	110	414	176	238	414
	25.1	388.9	550	139.4	274.6	414	132.8	281.2	414	318	96	414	232.5	181.5	414
	6.04	93.96	100.00	27.29	72.71	100.00	26.81	73.19	100.00	73.43	26.57	100.00	42.51	57.49	100.00
1,411 – 2,752 m	17	393	410	121	289	410	117	293	410	304	106	410	210	200	410
	24.9	385.1	410	138.1	271.9	410	131.5	278.5	410	315	95	410	230.3	179.7	410
	4.15	95.85	100.00	29.51	70.49	100.00	28.54	71.46	100.00	74.15	25.85	100.00	51.22	48.78	100.00
2,753 – 5,572 m	23	387	410	141	269	410	135	275	410	328	82	410	283	127	410
	24.9	381.1	410	138.1	271.9	410	131.5	278.5	410	315	95.2	410	230.3	179.7	410
	5.61	94.39	100.00	34.39	65.61	100.00	32.93	67.07	100.00	80.00	20.00	100.00	69.02	30.98	100.00
5,573 m and more	18	397	415	207	208	415	189	226	415	354	61	415	330	85	415
	25.2	389.9	415	139.7	275.3	415	133.1	281.9	415	318.8	96.2	415	233.1	181.9	415
	4.34	95.66	100.00	49.88	50.12	100.00	45.54	54.46	100.00	85.30	14.70	100.00	79.52	20.48	100.00
Total	125	1933	2,058	693	1,365	2,058	660	1,398	2,058	1,581	477	2,058	1,156	902	2,058
	6.07	93.93	100.00	33.67	66.33	100.00	32.07	67.93	100.00	76.82	23.18	100.00	56.17	43.83	100.00
	Pearson chi2(4) = 17.6363 Pr = 0.001			Pearson chi2(4) = 67.4346 Pr = 0.000			Pearson chi2(4) = 48.3409 Pr = 0.000			Pearson chi2(4) = 30.7985 Pr = 0.000			Pearson chi2(4) = 207.4000 Pr = 0.000		

Note: First row has observed frequencies, second row has expected frequencies and third row has observed row percentages.

Appendix II: Regression results

Table 9: Regression results for workplace as destination type

Perceived accessibility workplace	Car	Car	Bike	Bike	E-bike	E-bike	PT	PT	Walking	Walking
Distances work (ref= 3,483 m and less)		0.000 (0.000)		-0.000 *** (0.000)		-0.000 *** (0.000)		0.000 ** (0.000)		-0.000 *** (0.000)
3,484 – 7,950 m	-3.800 ** (1.844)		0.626 (1.402)		1.276 (1.334)		0.666 (1.736)		-1.575 (1.047)	
7,951 – 14,130 m	-1.191 (1.844)		-2.304 (1.484)		-1.922 (1.382)		-0.056 (1.892)		-2.871 ** (1.173)	
14,131 – 21,840 m	0.497 (1.647)		-1.460 (1.468)		1.464 (1.802)		3.292 ** (1.385)		-2.808 *** (0.999)	
21,841 m and more	-0.419 (3.061)		-5.380 *** (1.456)		-4.315 *** (1.397)		1.645 (1.131)		-3.884 *** (1.190)	
Age	0.336 ** (0.168)	0.199 (0.128)	-0.191 (0.122)	-0.209 * (0.113)	-0.230 * (0.122)	-0.204 ** (0.123)	-0.162 (0.106)	-0.083 (0.093)	-0.131 (0.095)	-0.093 (0.087)
Age^2	-0.003 * (0.002)	-0.002 (0.001)	0.002 (0.001)	0.002 * (0.001)	0.002 * (0.001)	0.003 ** (0.001)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Female	-0.409 (1.729)	0.702 (1.064)	0.413 (1.088)	-0.343 (0.961)	0.768 (1.043)	-0.204 (0.930)	-0.570 (1.209)	0.237 (0.672)	1.701 ** (0.833)	0.745 (0.595)
Education (ref=primary)										
Secondary education	2.430 * (1.308)	1.258 (0.912)	0.885 (1.650)	1.471 (1.509)	0.762 (1.741)	1.882 (1.544)	-0.220 (1.743)	0.182 (1.286)	1.877 (1.429)	1.270 (1.281)
Higher vocational education	1.721 (1.158)	0.951 (0.877)	-0.437 (1.750)	0.399 (1.543)	0.161 (1.826)	1.368 (1.572)	-1.000 (1.792)	-0.462 (1.358)	1.048 (1.448)	0.275 (1.282)
University	Omitted	Omitted	0.031 (1.799)	0.500 (1.583)	0.468 (1.879)	1.359 (1.614)	-0.728 (1.844)	-0.353 (1.404)	1.841 (1.565)	0.331 (1.343)
Household income (ref=<2,000€)										
2,001 – 3,000€	1.657 (1.622)	0.443 (1.236)	0.388 (0.844)	1.068 (0.798)	0.691 (0.864)	1.374 * (0.801)	0.328 (0.838)	0.593 (0.743)	1.241 (0.801)	1.050 (0.666)
3,001 – 5,000€	-0.766 (1.565)	-1.012 (1.323)	1.074 (0.812)	1.180 (0.787)	0.960 (0.840)	1.301 * (0.781)	-0.071 (0.848)	0.153 (0.774)	-0.454 (0.796)	0.131 (0.663)

Perceived accessibility workplace	Car	Car	Bike	Bike	E-bike	E-bike	PT	PT	Walking	Walking
5,001 and more	-2.571 (2.071)	-1.406 (1.511)	1.454 (0.965)	1.719 * (0.939)	2.197 ** (1.032)	2.478 ** (0.970)	0.491 (1.015)	0.636 (0.897)	1.317 (0.883)	1.660 ** (0.788)
Don't know/prefer not to say	-3.662 ** (1.754)	-2.229 (1.393)	-0.049 (0.939)	0.906 (0.868)	0.598 (0.976)	1.672 * (0.894)	-0.548 (0.949)	-0.379 (0.851)	0.425 (0.962)	0.574 (0.772)
Household size	0.462 (0.467)	0.183 (0.346)	0.564 ** (0.253)	-0.451 ** (0.227)	-0.351 (0.217)	-0.250 (0.195)	-0.170 (0.214)	-0.310 (0.192)	0.203 (0.170)	0.117 (0.147)
Urban	-0.810 (2.137)	-0.883 (1.321)	-2.459 * (1.352)	-2.404 ** (1.078)	-1.756 (1.275)	-2.473 ** (1.051)	1.705 * (0.919)	1.910 *** (0.695)	-0.455 (0.845)	1.348 ** (0.600)
Number of cars/bikes/e-bikes per household	2.137 ** (0.924)	0.183 (0.346)	0.481 ** (0.218)	0.479 ** (0.205)	0.378 (0.276)	0.301 (0.254)				
Distances work*Gender		-0.000 (0.000)		-0.000 (0.000)		-0.000 (0.000)		-0.000 (0.000)		-0.000 (0.000)
3,484 – 7,950 m * Female	3.239 (2.643)		Omitted		-0.939 (1.846)		0.191 (1.633)		-1.689 (1.081)	
7,951 – 14,130 m * Female	Omitted		Omitted		Omitted		2.476 (2.051)		-4.739 *** (1.648)	
14,131 – 21,840 m * Female	Empty		-2.459 * (1.438)		-4.262 ** (1.729)		0.451 (1.515)		-0.486 (1.198)	
21,841 m and more * Female	0.435 (2.321)		-0.368 (1.371)		-0.589 ** (1.296)		-0.285 (1.501)		-1.491 (1.429)	
Distances work*Urbanity		0.000 (0.000)		-0.000 * (0.000)		0.000 (0.000)		- 0.000 (0.000)		-0.000 ** (0.000)
3,484 – 7,950 m*Urban	Omitted		Omitted		Omitted		0.925 (1.526)		1.535 (1.092)	
7,951 – 14,130 m * Urban	Empty		2.732 (1.857)		1.478 (1.823)		-0.516 (1.365)		3.254 ** (1.657)	
14,131 – 21,840 m * Urban	Omitted		1.252 (1.857)		-1.625 (1.798)		-2.478 * (1.382)		-1.502 (1.439)	
21,841 m and more * Urban	0.609 (3.149)		2.435 (1.536)		1.488 (1.454)		Omitted		-0.476 (1.520)	
Disability bike, e-bike, PT and walking (respectively)			-1.916 (0.939)	-2.354 **	-1.831 **	-2.113 **	-1.553	-1.091	-0.145	-0.121

Perceived accessibility workplace	**Car**	**Car**	**Bike**	**Bike**	**E-bike**	**E-bike**	**PT**	**PT**	**Walking**	**Walking**
				(0.951)	(0.873)	(0.845)	(1.288)	(1.215)	(0.835)	(0.752)
PT subscription							-1.713 *** (0.534)	1.170 ** (0.457)		
OV chipkaart easy							1.615 * (0.816)	1.340 * (0.775)		
Constant	-8.150 (4.627)	-5.310 (3.350)	7.256 ** (2.721)	8.274 *** (2.487)	7.835 *** (2.744)	9.157 *** (2.597)	0.678 (2.724)	-0.503 (1.961)	1.805 (1.668)	0.573 (1.417)
Distance variable	Categorical	Continuous	Categorical	Continuous	Categorical	Continuous	Categorical	Continuous	Categorical	Continuous
McFadden's Pseudo R-squared	0.4362	0.3289	0.4083	0.4293	0.3945	0.3870	0.3190	0.2607	0.4152	0.3114
Prob > chi2	0.0013	0.0017	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Number of observations	155	222	189	233	201	232	166	182	234	234
Comment										Linktest significant (p<0.05)

Note: Standard errors are given in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.1. In the models workplace – car, disability was left out because of missing values.

Table 10: Regression results for health care as destination type

Perceived accessibility health care	**Car**	**Car**	**Bike**	**Bike**	**E-bike**	**E-bike**	**PT**	**PT**	**Walking**	**Walking**
Distances health care (ref= 1,187 m and less)		-0.000 (0.000)		-0.000 *** (0)		-0.000 *** (0.000)		0.000 ** (0.000)		-0.001 *** (0.000)
1,188 – 2,417 m	-1.019 (1.478)		3.508 *** (1.185)		-0.092 (1.396)		1.282 (1.764)		-0.207 (0.995)	
2,418 – 4,582 m	-0.947 (1.696)		3.742 *** (1.434)		-5.183 *** (1.837)		-0.006 (2.081)		-0.900 (0.930)	
4,583 – 9,446 m	-3.356 ** (1.560)		3.292 ** (1.587)		-1.704 (1.414)		4.507 ** (1.900)		-3.238 *** (0.953)	
9,447 m and more	Empty		Omitted		-5.547 *** (1.500)		3.735 ** (1.786)		-4.646 *** (1.100)	
Age	0.043 (0.135)	0.008 (0.138)	-0.156 (0.195)	-0.208 (0.176)	-0.217 (0.163)	-0.198 (0.155)	0.102 (0.120)	0.037 (0.105)	-0.007 (0.090)	-0.013 (0.086)
Age²	-0.001 (0.002)	0.000 (0.002)	0.002 (0.002)	0.002 (0.002)	0.003 (0.002)	0.002 (0.002)	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)	0.000 (0.001)
Female	1.988 * (1.197)	0.412 (0.817)	1.544 (0.950)	0.713 (1.003)	3.412 *** (1.580)	-0.656 (0.926)	1.455 (1.366)	0.757 (0.550)	0.363 (1.074)	-0.821 (0.695)
Education (ref=primary)										
Secondary education	0.933 (1.996)	0.007 (1.831)	0.576 (2.507)	0.515 (2.359)	-0.236 (1.912)	-0.299 (2.048)	-1.878 (1.368)	-1.791 (1.233)	-1.261 (1.281)	-1.013 (1.320)
Higher vocational education	0.818 (2.043)	0.312 (1.884)	0.780 (2.426)	0.536 (2.336)	0.085 (1.977)	-0.347 (2.090)	-2.285 (1.442)	-2.101 (1.308)	-2.196 * (1.281)	-1.865 (1.358)
University	-0.388 (2.142)	-0.405 (2.033)	0.702 (2.511)	0.422 (2.422)	3.294 (2.414)	3.048 (2.562)	-0.596 (1.502)	-0.514 (1.358)	-1.522 (1.392)	-1.197 (1.429)
Household income (ref=<2,000€)										
2,001 – 3,000€	-0.284 (0.974)	-0.206 (0.882)	3.034 ** (1.385)	2.559 ** (1.311)	2.086 * (1.078)	2.333 ** (1.122)	0.674 (0.714)	0.769 (0.675)	0.198 (0.677)	0.213 (0.672)
3,001 – 5,000€	-0.161 (0.953)	0.225 (0.842)	0.877 (0.926)	0.633 (0.839)	0.587 (0.828)	0.753 (0.762)	-0.395 (0.663)	-0.451 (0.639)	-0.370 (0.617)	-0.347 (0.607)
5,001 and more	1.838 (1.526)	1.576 (1.328)	1.281 (1.169)	1.780 (1.175)	1.318 (1.177)	1.820 (1.129)	-1.014 (0.804)	-0.856 (0.754)	0.240 (0.697)	0.424 (0.694)

Perceived accessibility health care	Car	Car	Bike	Bike	E-bike	E-bike	PT	PT	Walking	Walking
Don't know/prefer not to say	-0.198 (1.565)	0.673 (1.388)	1.191 (1.185)	0.730 (1.084)	2.435 (1.366)	1.781 (1.118)	-1.037 (0.946)	-0.842 (0.842)	0.536 (0.835)	0.265 (0.817)
Household size	0.169 (0.373)	-0.024 (0.296)	0.019 (0.254)	0.012 (0.246)	-0.030 (0.263)	-0.006 (0.241)	-0.182 (0.180)	-0.093 (0.170)	-0.075 (0.171)	-0.027 (0.164)
Urban	-2.028 * (1.200)	-2.098 * (1.163)	0.403 (0.960)	0.150 (0.999)	0.757 (0.709)	-0.371 (0.657)	0.512 (1.206)	0.285 (0.598)	0.119 (0.432)	0.005 (0.411)
Number of cars/bikes/e-bikes per household	1.808 ** (0.798)	1.389 ** (0.652)	0.056 (0.284)	-0.013 (0.264)	0.802 * (0.467)	0.511 (0.432)				
Distances * Gender		0.000 (0.000)		0.000 (0.000)		0.000 * (0.000)		-0.000 (0.000)		0.000 (0.000)
1,188 – 2,417 m * Female	1.757 (2.245)		Empty		Empty		-0.995 (1.630)		-0.440 (1.399)	
2,418 – 4,582 m * Female	-3.011 (1.854)		-3.567 * (1.894)		Omitted		-1.624 (1.752)		-0.696 (1.314)	
4,583 – 9,446 m * Female	Omitted		-0.010 (1.513)		-2.881 * (1.628)		-1.883 (1.640)		0.112 (1.302)	
9,447 m and more * Female	Empty		Omitted		Omitted		-2.693 (1.688)		Omitted	
Distances * Urbanity				-0.000 (0.000)				0.000 (0.000)		
1,188 – 2,417 m * Urban			Omitted							
2,418 – 4,582 m * Urban			3.194 (2.182)							
4,583 – 9,446 m * Urban			-1.273 (1.622)							
9,447 m and more * Urban			Omitted							
Disability car day	2.365 (2.568)	2.573 (2.120)								
Disability car night	-5.486 * (2.824)	-3.678 * (2.087)								
Disability bike, e-bike, PT			-2.366 **	-1.940 *	-3.305 **	-2.691 **	-1.045	-0.427	-0.421	-0.022

Perceived accessibility health care	**Car**	**Car**	**Bike**	**Bike**	**E-bike**	**E-bike**	**PT**	**PT**	**Walking**	**Walking**
and walking (respectively)			(1.235)	(1.096)	(1,523)	(1.311)	(1.320)	(1.240)	(0.965)	(0.936)
PT subscription							-0.458 (0.502)	-0.293 (0.464)		
OV chipkaart easy							0.537 (0.951)	0.425 (0.896)		
Constant	1.913 (3.085)	1.823 (2.764)	0.522 (3.318)	6.791 ** (3.106)	5.391 * (2.988)	7.007 ** (2.936)	-2.454 (0.951)	-0.697 (2.122)	3.681 (1.996)	4.218 ** (1.841)
Distance variable	Categorical	Continuous	Categorical	Continuous	Categorical	Continuous	Categorical	Continuous	Categorical	Continuous
McFadden's Pseudo R-squared	0.3385	0.2568	0.3510	0.4184	0.3672	0.4066	0.2192	0.1454	0.3140	0.3713
Prob > chi2	0.0197	0.0319	0.0012	0.0000	0.0001	0.0000	0.0358	0.0681	0.0000	0.0000
Number of observations	158	216	140	218	150	218	157	157	203	218
Comment				Linktest significant (p<0.05)						

Note: Standard errors are given in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.1. The interaction between distances and urbanity excluded for car, e-bike and walking because of collinearity.

Table 11: Regression results for leisure as destination type

Perceived accessibility leisure	**Car**	**Car**	**Bike**	**Bike**	**E-bike**	**E-bike**	**PT**	**PT**	**Walking**	**Walking**
Distances leisure (ref= 1,659 m and less)		0.000 * (0.000)		-0.000 *** (0.000)		-0.000 *** (0.000)				-0.000 *** (0.000)
1,660 – 4,152 m	1.535 (1.446)		1.017 (1.207)		1.412 (1.372)				-3.009 ** (1.324)	
4,152.5 – 8,665 m	-0.324 (0.971)		-0.776 (0.939)		0.253 (1.159)				-5.005 *** (1.289)	
8,666 – 16,996 m	0.256 (0.997)		-1.159 (0.894)		-0.850 (0.954)				-6.561 *** (1.354)	
16,997 m and more	0.489 (1.897)		-3.819 *** (0.885)		-3.939 *** (0.914)				-7.330 *** (1.448)	
Age	0.082 (0.108)	0.069 (0.585)	-0.033 (0.075)	-0.028 (0.074)	-0.097 (0.079)	-0.096 (0.077)			0.174 ** (0.081)	0.138 * (0.073)
Age²	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)			-0.002 ** (0.001)	-0.002 ** (0.001)
Female	0.272 (0.873)	0.690 (0.585)	-0.326 (0.986)	-0.272 (0.607)	-0.705 (0.961)	-1.170 * (0.634)			-2.667 ** (1.197)	-0.927 * (0.496)
Education (ref=primary)										
Secondary education	-0.633 (1.496)	-0.565 (1.354)	0.132 (1.272)	0.525 (1.213)	0.271 (1.272)	0.764 (1.190)			-0.929 (0.976)	-0.459 (0.979)
Higher vocational education	-1.378 (1.617)	-1.158 (1.429)	-0.150 (1.319)	0.435 (1.245)	0.698 (1.307)	1.355 (1.223)			-1.182 (1.026)	-0.594 (1.021)
University	-2.269 (1.619)	-1.992 (1.458)	0.099 (1.374)	0.458 (1.318)	0.732 (1.362)	1.117 (1.282)			-2.031 * (1.112)	-1.271 (1.073)
Household income (ref=<2,000€)										
2,001 – 3,000€	0.824 (0.901)	0.552 (0.867)	0.776 (0.751)	0.501 (0.722)	-0.004 (0.716)	-0.339 (0.668)			0.320 (0.676)	0.216 (0.611)
3,001 – 5,000€	0.078 (0.757)	-0.140 (0.722)	-0.996 (0.704)	-1.004 (0.669)	-1.212 * (0.697)	-1.207 * (0.651)			-0.338 (0.619)	-0.450 (0.565)
5,001 and more	0.133 (1.875)	-0.365 (0.822)	-0.502 (0.785)	-0.694 (0.749)	-0.656 (0.788)	-0.723 (0.723)			-0.111 (0.679)	-0.316 (0.622)

Perceived accessibility leisure	Car	Car	Bike	Bike	E-bike	E-bike	PT	PT	Walking	Walking
Don't know/prefer not to say	1.328 (0.965)	1.156 (0.947)	-0.002 (0.741)	0.100 (0.159)	-0.147 (0.733)	-0.006 (0.697)			-0.474 (0.112)	-0.490 (0.601)
Household size	-0.235 (0.179)	-0.239 (0.174)	0.053 (0.690)	0.069 (0.159)	0.100 (0.143)	0.135 (0.138)			0.215 * (0.112)	0.182 * (0.105)
Urban	0.057 (0.861)	-0.239 (0.174)	1.045 (0.690)	0.912 (0.684)	0.269 (0.709)	0.690 (0.635)			-0.584 (0.988)	0.564 (0.515)
Number of cars/bikes/e-bikes per household	1.081 *** (0.395)	1.092 ** (0.378)	0.183 (0.166)	0.230 (0.166)	0.869 *** (0.272)	0.957 *** (0.271)				
Distances leisure *Gender		-0.000 (0.000)		-0.000 (0.000)		0.000 (0.000)				0.000 (0.000)
1,660 – 4,152 m * Female	-0.143 (1.370)		Omitted		-1.198 (1.504)				2.306 * (1.357)	
4,152.5 – 8,665 m * Female	1.060 (1.361)		1.360 (1.326)		1.779 (1.566)				2.334 * (1.319)	
8,666 – 16,996 m * Female	-0.371 (1.224)		-0.400 (1.139)		0.151 (1.163)				2.961 ** (1.369)	
16,997 m and more* Female	Omitted		-0.216 (1.169)		0.890 (1.150)				2.660 * (1.589)	
Distances leisure *Urbanity		-0.000 (0.000)		0.000 (0.000)		-0.000 (0.000)				0.000 (0.000)
1,660 – 4,152 m * Urban	-1.637 (1.461)		-1.011 (1.625)		-0.290 (1.118)				0.900 (1.146)	
4,152.5 – 8,665 m * Urban	0.049 (1.287)		-0.588 (1.156)		-0.544 (1.363)				1.927 * (1.153)	
8,666 – 16,996 m * Urban	-0.629 (1.209)		-1.343 (0.929)		-0.903 (0.973)				1.241 (1.205)	
16,997 m and more* Urban	Omitted		Omitted		Omitted				0.946 (1.574)	
Disability car day	-14.856 (1019.561)	-15.519 (1474.257)								
Disability car night	13252 (1019.560)	13.748 (1474.257)								

Perceived accessibility leisure	Car	Car	Bike	Bike	E-bike	E-bike	PT	PT	Walking	Walking
Disability bike/e-bike/PT/walking			-1.379 * (0.799)	-1.316 * (0.738)	-2.508 *** (0.920)	-2.087 *** (0.761)			-0.760 (0.755)	-0.913 (0.686)
PT subscription										
OV chipkaart easy										
Constant	-0.004 (2.126)	0.097 (1.994)	3.280 * (1.919)	3.275 * (1.748)	4.389 ** (1.970)	4.907 *** (1.809)			2.127 (1.774)	0.353 (1.380)
Distance variable	Categorical	Continuous	Categorical	Continuous	Categorical	Continuous			Categorical	Continuous
McFadden's Pseudo R-squared	0.2154	0.2195	0.3464	0.3766	0.3669	0.3689			0.4265	0.3792
Prob > chi2	0.0172	0.0004	0.0000	0.0000	0.0000	0.0000			0.0000	0.0000
Number of observations	304	358	305	359	335	360			361	361
Comment										Linktest significant (p<0.05)

Note: Standard errors are given in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.1. Disability car day and disability car night was excluded because of missing values. The estimates for PT are not used because of non-significant chi-square model statistics (p>0.05).

Table 12: Regression results for supermarket as destination type

Perceived accessibility supermarket	**Car**	**Car**	**Bike**	**Bike**	**E-bike**	**E-bike**	**PT**	**PT**	**Walking**	**Walking**
Distances supermarket (ref= 820 m and less)		0.001 (0.000)		-0.000 *** (0.000)		-0.000 *** (0)				-0.001 *** (0.000)
821 – 1,410 m	1.835 (1.373)		-0.964 (1.607)		-0.258 (1.394)				-1.439 (1.570)	
1,411 – 2,752 m	-1.340 (1.029)		0.579 (1.446)		0.664 (1.529)				-2.940 ** (1.425)	
2,753 – 5,572 m	1.424 (1.373)		-1.428 (0.933)		-1.709 * (0.972)				-6.250 *** (1.390)	
5,573 m and more	-0.805 (1.375)		-2.867 *** (0.884)		-3.437 *** (0.925)				-7.115 *** (1.456)	
Age	0.197 * (0.114)	0.112 (0.096)	0.030 (0.079)	0.033 (0.078)	-0.067 (0.078)	-0.061 (0.078)			0.080 (0.071)	0.056 (0.065)
Age²	-0.002 ** (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.001)			-0.001 (0.001)	-0.001 (0.001)
Female	0.796 (0.748)	1.685 ** (0.718)	0.388 (1.047)	0.670 (0.624)	-0.290 (0.943)	0.179 (0.553)			-0.031 (1.454)	-0.527 (0.511)
Education (ref=primary)										
Secondary education	2.196 *** (0.745)	1.632 ** (0.660)	-1.364 (1.513)	-1.179 (1.385)	-0.556 (1.362)	-0.350 (1.300)			-0.996 (1.196)	-1.038 (1.275)
Higher vocational education	1.702 ** (0.807)	1.326 * (0.726)	-1.756 (1.548)	-1.778 (1.419)	-0.154 (1.391)	-0.166 (1.327)			-1.932 (1.234)	-2.004 (1.301)
University	Omitted	Omitted	-2.025 (1.603)	-1.754 (1.478)	-0.532 (1.444)	-0.201 (1.388)			-1.866 (1.261)	-1.986 (1.326)
Household income (ref=<2,000€)										
2,001 – 3,000€	2.033 ** (0.895)	1.102 (0.786)	0.923 (0.662)	0.957 (0.731)	0.866 (0.614)	0.869 (0.631)			-0.624 (0.660)	-0.842 (0.683)
3,001 – 5,000€	2.069 ** (0.826)	1.511 ** (0.760)	0.429 (0.603)	0.137 (0.612)	0.440 (0.550)	0.339 (0.537)			-1.212 ** (0.602)	-1.368 ** (0.633)
5,001 and more	3.252 *** (1.172)	1.985 * (1.018)	0.517 (0.681)	0.131 (0.701)	0.954 (0.636)	0.648 (0.625)			-0.535 (0.678)	-0.644 (0.709)

Perceived accessibility supermarket	**Car**	**Car**	**Bike**	**Bike**	**E-bike**	**E-bike**	**PT**	**PT**	**Walking**	**Walking**
Don't know/prefer not to say	1.633 * (0.950)	1.123 * (0.889)	1.324 * (0.743)	0.961 (0.750)	1.419 ** (0.693)	1.265 * (0.702)			-0.870 (0.675)	-0.940 (0.740)
Household size	-0.629 *** (0.237)	-0.409 (0.209)	-0.355 ** (0.150)	-0.406 *** (0.156)	-0.225 * (0.127)	-0.204 (0.127)			0.068 (0.117)	0.025 (0.112)
Urban	-1.325 * (0.772)	-0.146 (0.707)	0.592 (1.211)	-0.886 (0.603)	-0.465 (0.954)	-1.885 *** (0.556)			-0.974 (1.461)	-1.010 ** (0.467)
Number of cars/bikes/e-bikes per household	0.997 ** (0.491)	0.773 * (0.439)	0.347 (0.152)	0.439 *** (0.158)	0.572 ** (0.224)	0.507 ** (0.237)				
Distances supermarket *Gender		-0.000 (0.000)		-0.000 (0.000)		-0.000 (0.000)				0.000 (0.000)
821 – 1,410 m * Female	0.162 (0.772)		Omitted		-0.836 (1.555)				1.071 (1.922)	
1,411 – 2,752 m * Female	Empty		0.464 (1.490)		0.528 (1.385)				-0.823 (1.564)	
2,753 – 5,572 m * Female	-0.321 (1.781)		0.071 (1.239)		0.819 (1.188)				0.996 (1.543)	
5,573 m and more * Female	Omitted		-0.866 (1.155)		0.178 (1.069)				-0.830 (1.669)	
Distances supermarket *Urbanity		-0.001 (0.000)		0.000 *** (0.000)		0.000 *** (0.000)				0.001 *** (0.000)
821 – 1,410 m * Urban	0.162 (1.555)		Omitted		Omitted				0.973 (1.927)	
1,411 – 2,752 m * Urban	Empty		-2.186 (1.712)		-1.714 (1.529)				1.587 (1.569)	
2,753 – 5,572 m * Urban	-0.321 (1.781)		0.342 (1.637)		1.339 (1.474)				3.096 * (1.600)	
5,573 m and more * Urban	Omitted		1.197 (1.483)		2.561 * (1.474)				4.460 *** (1.698)	
Disability car day										
Disability car night										
Disability bike, e-bike, PT and walking (respectively)			-1.554 ** (0.656)	-1.531 * (0.629)	-1.783 ** (0.744)	-1.678 ** (0.657)			-0.665 (0.886)	-0.932 (0.802)

Perceived accessibility supermarket	Car	Car	Bike	Bike	E-bike	E-bike	PT	PT	Walking	Walking
PT subscription										
OV chipkaart easy										
Constant	-4.479 *** (2.785)	-2.725 (2.793)	3.713 * (2.103)	4.296 ** (1.869)	5.297 *** (1.972)	5.664 *** (1.798)			5.352 *** (2.490)	5.364 *** (1.659)
Distance variable	Categorical	Continuous	Categorical	Continuous	Categorical	Continuous			Categorical	Continuous
McFadden's Pseudo R-squared	0.2547	0.2129	0.3261	0.3750	0.2730	0.3144			0.5621	0.5010
Prob > chi2	0.0123	0.0028	0.0000	0.0000	0.0000	0.0000			0.0000	0.0000
Number of observations	370	515	429	522	449	524			529	529
Comment		Linktest significant (p<0.05)								Linktest significant (p<0.05)

Note: Standard errors are given in parenthesis. *** p < 0.01, ** p < 0.05, * p < 0.1. Disability car day and disability car night was excluded because of missing values. The estimates for PT are not used because of non-significant chi-square model statistics (p>0.05).

Appendix III: Marginal effects of variables on PA

Figure 31: Marginal effect of gender on PA health care, by walking

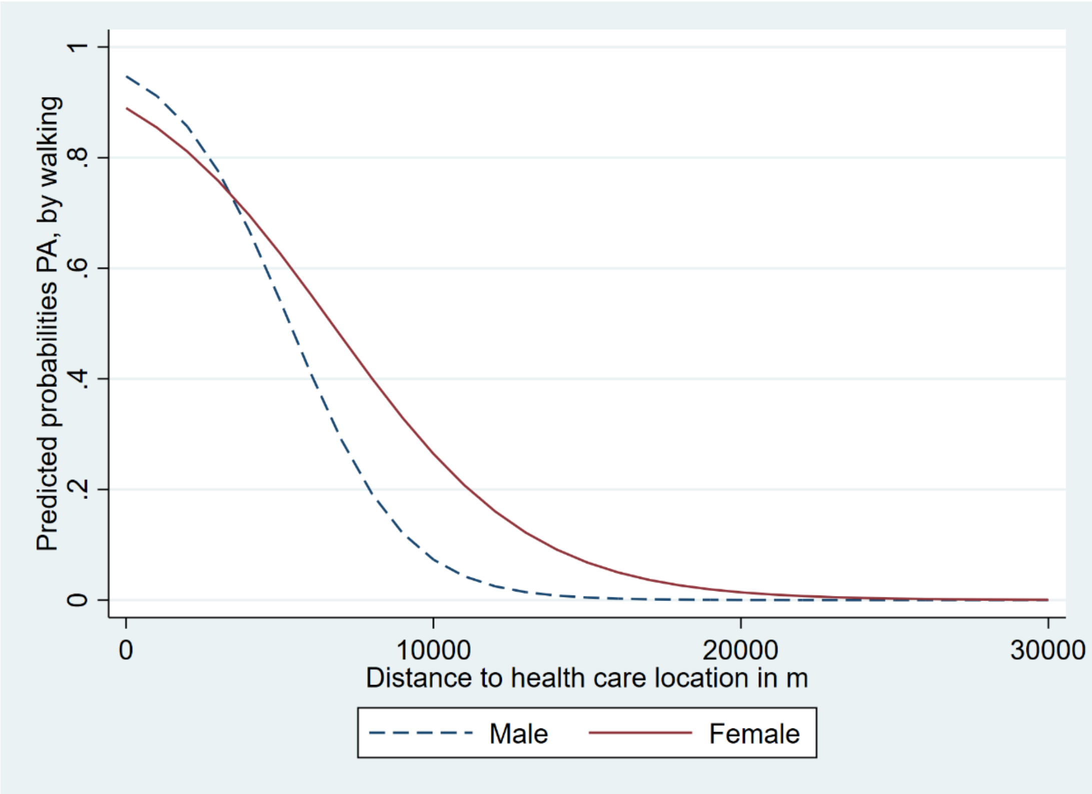


Figure 32: Marginal effect of gender on PA health care, by bike

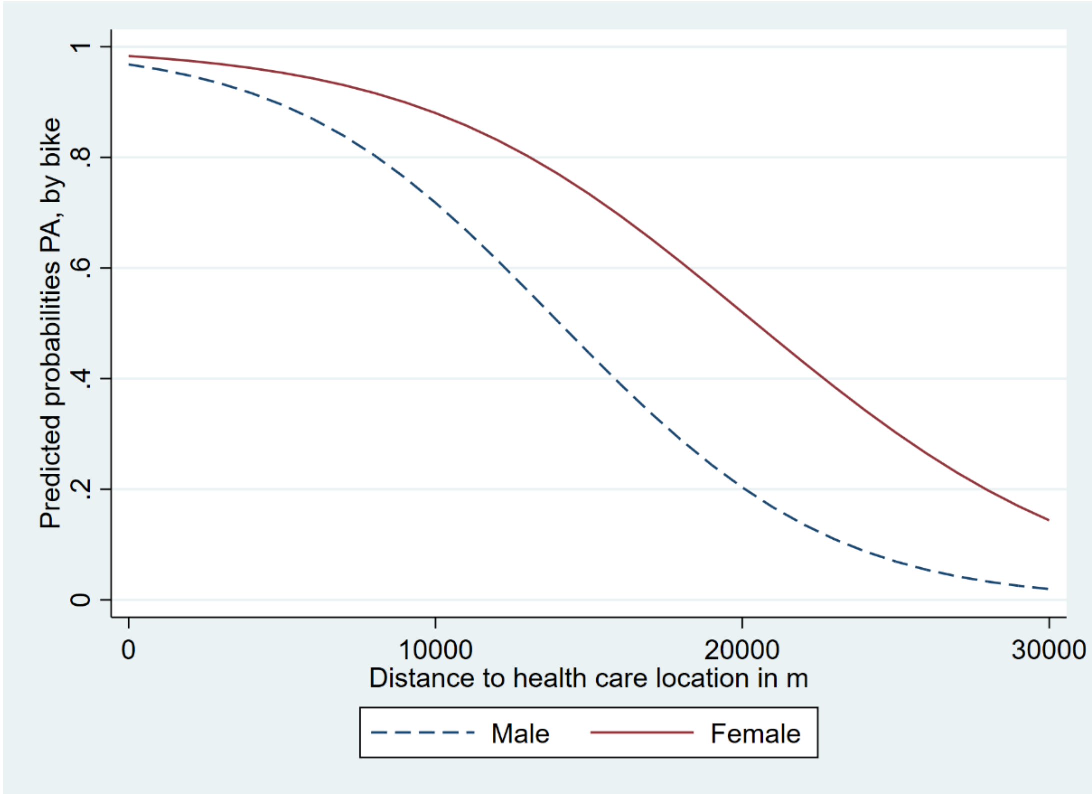


Figure 33: Marginal effect of urbanity on PA leisure, by bike

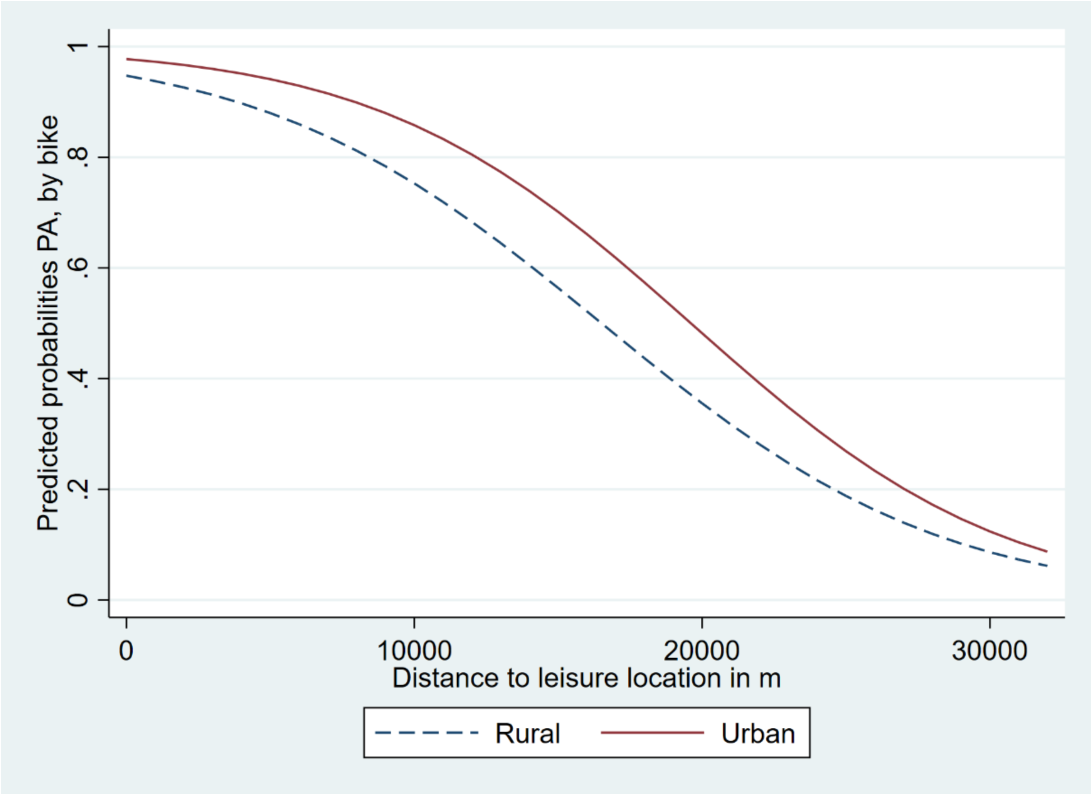


Figure 34: Marginal effect of household size on PA leisure, by walking

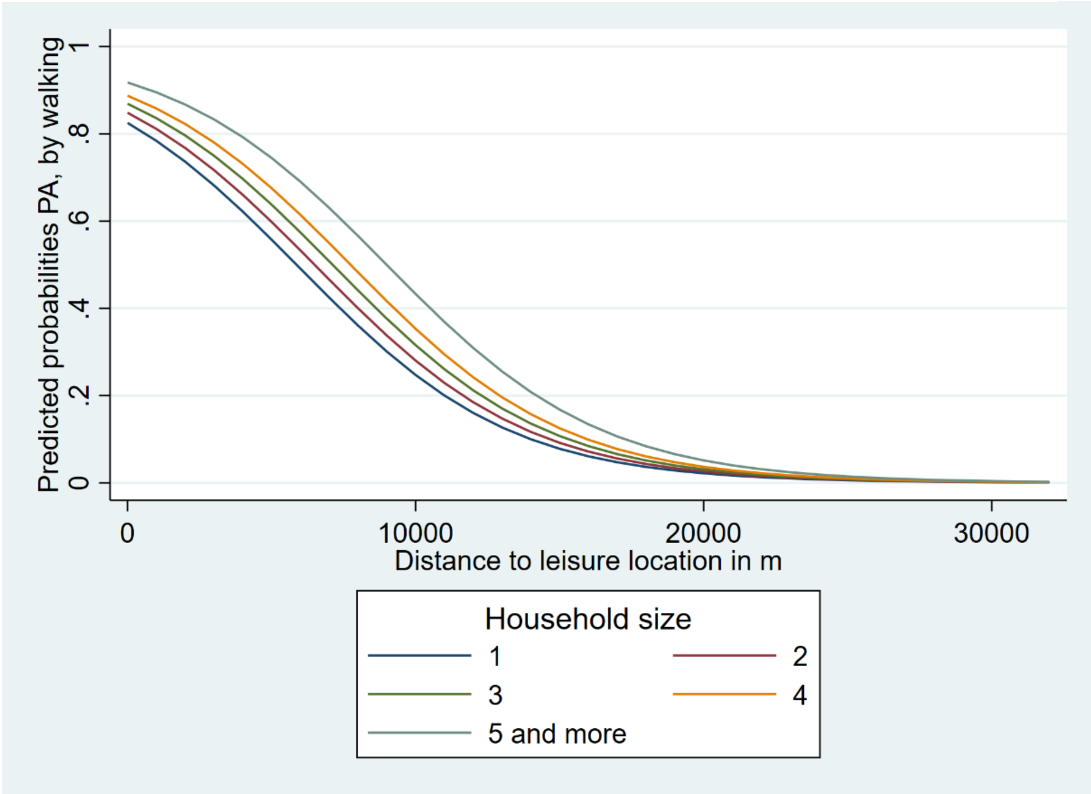
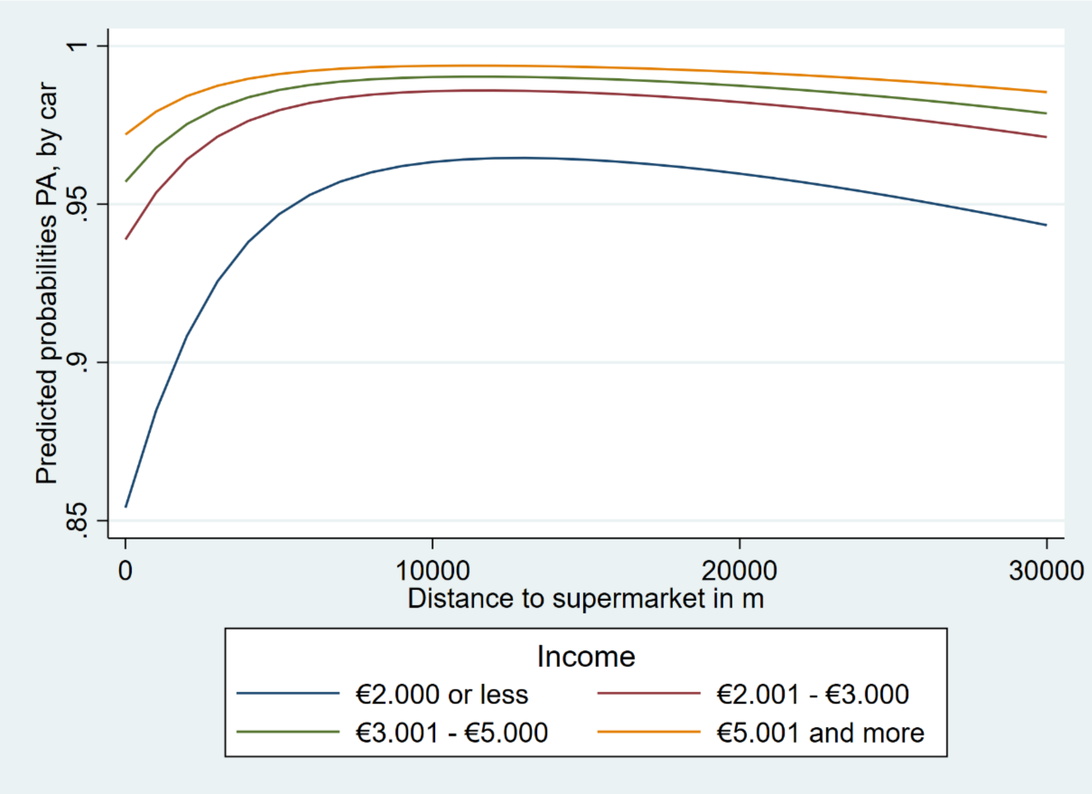


Figure 35: Marginal effect of income on PA supermarket, by car



Appendix IV: Influential cases

To test for cases that might substantially influence the model coefficients, exemplary plots comparing standardized residuals with leverage values are produced for workplace, as workplace is the destination type with the smallest number of observations per model (Fox, 1997; Kohler & Kreuter, 2005).

Figure 36: Plot standardized residuals and leverages (workplace by car, distances continuous)

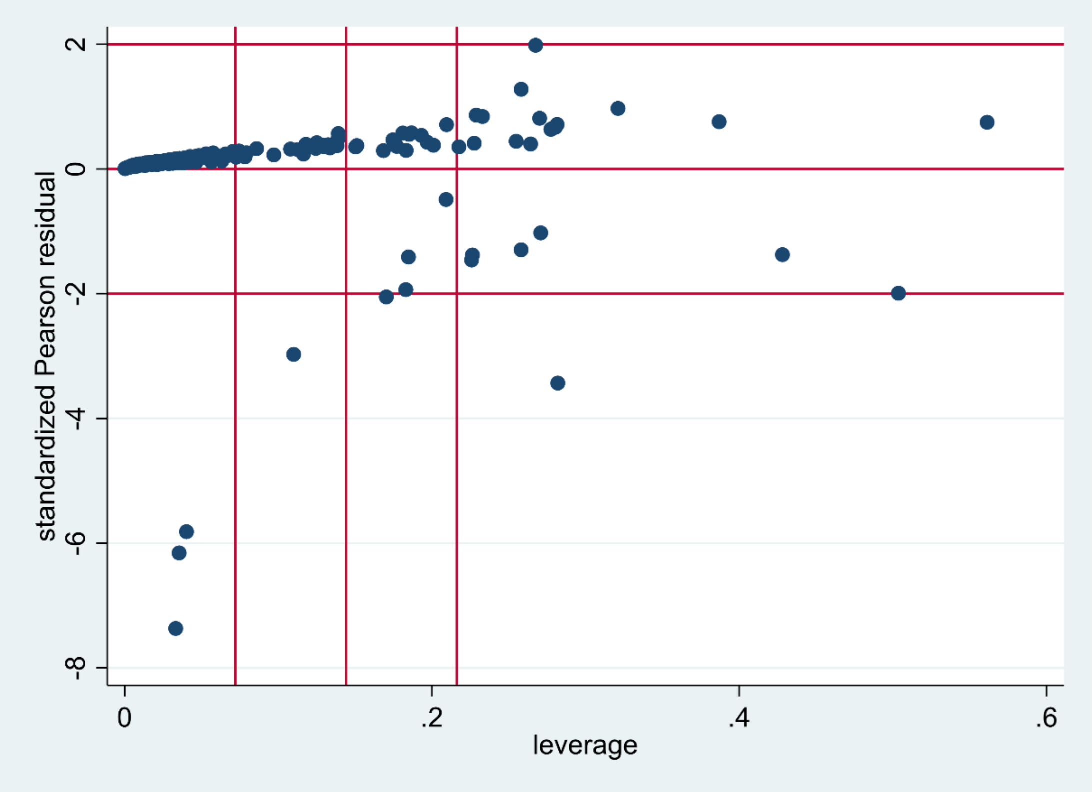


Figure 37: Plot standardized residuals and leverages (workplace by car, distances categorical)

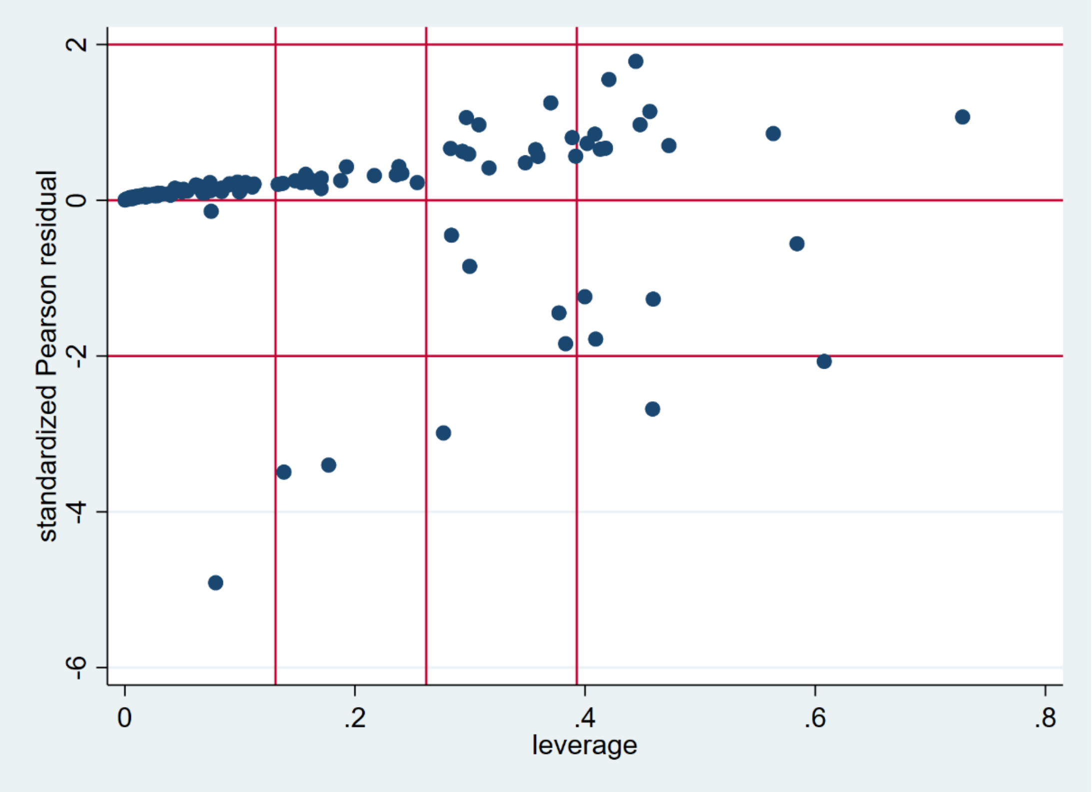


Figure 38: Plot standardized residuals and leverages (workplace by bike, distances continuous)

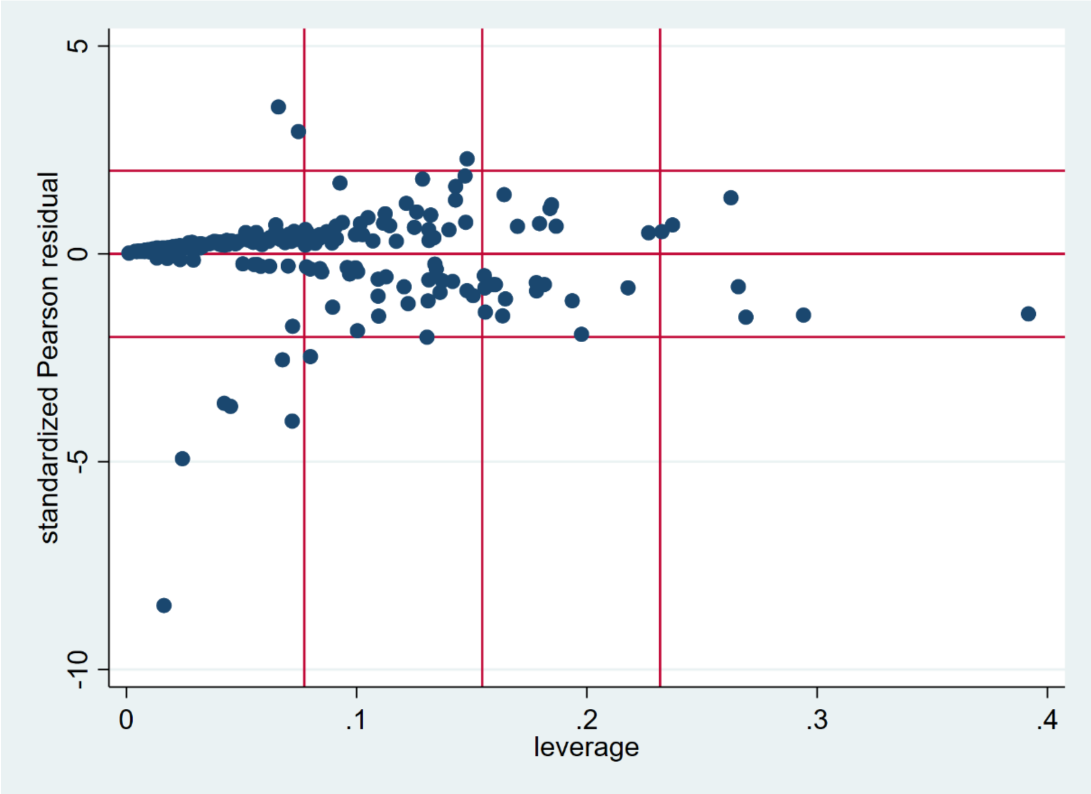


Figure 39: Plot standardized residuals and leverages (workplace by bike, distances categorical)

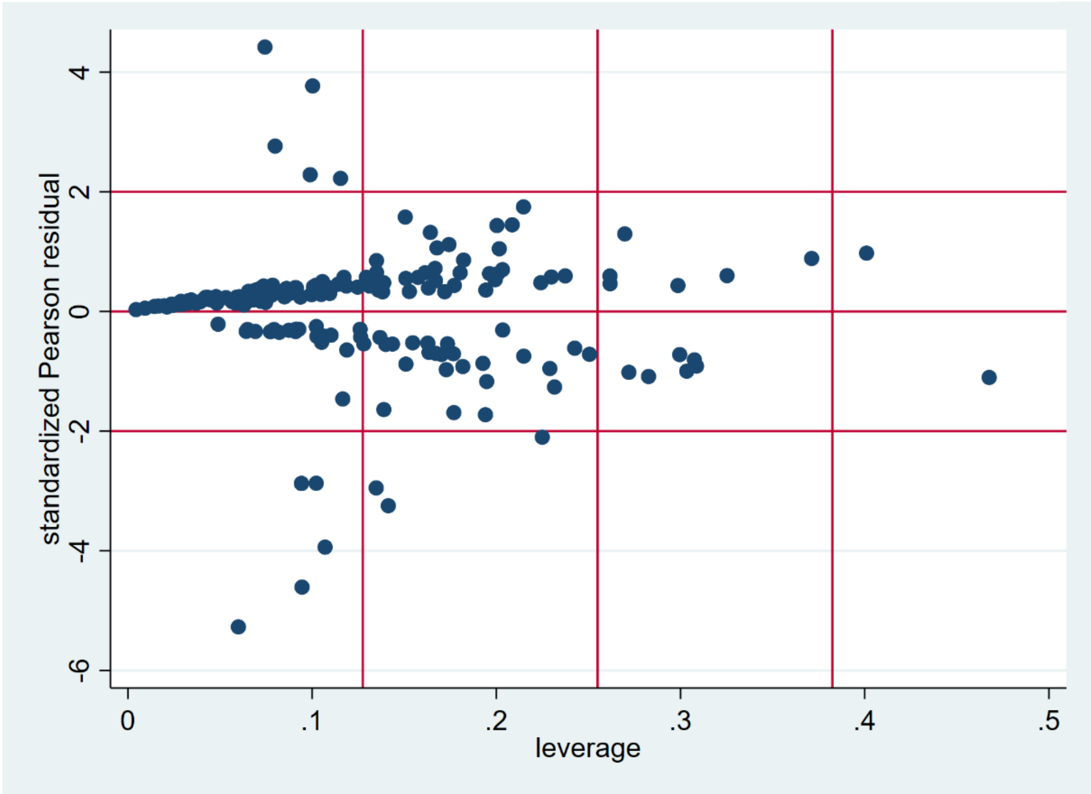


Figure 40: Plot standardized residuals and leverages (workplace by e-bike, distances continuous)

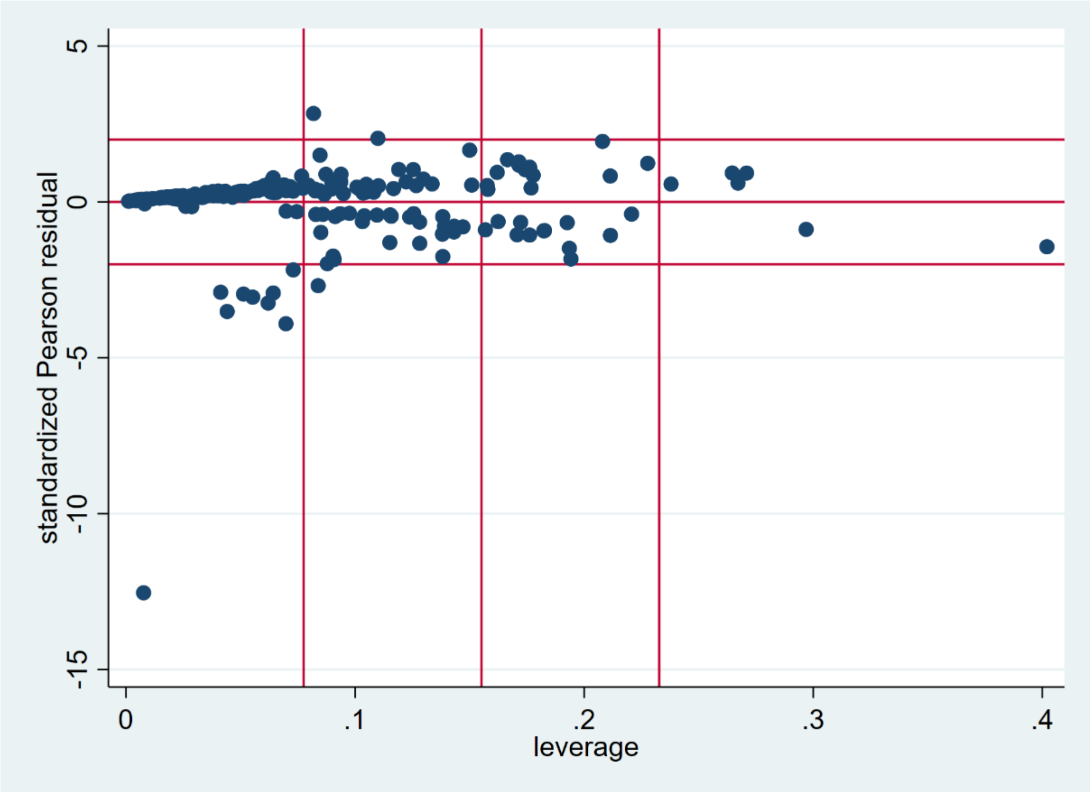


Figure 41: Plot standardized residuals and leverages (workplace by e-bike, distances continuous)

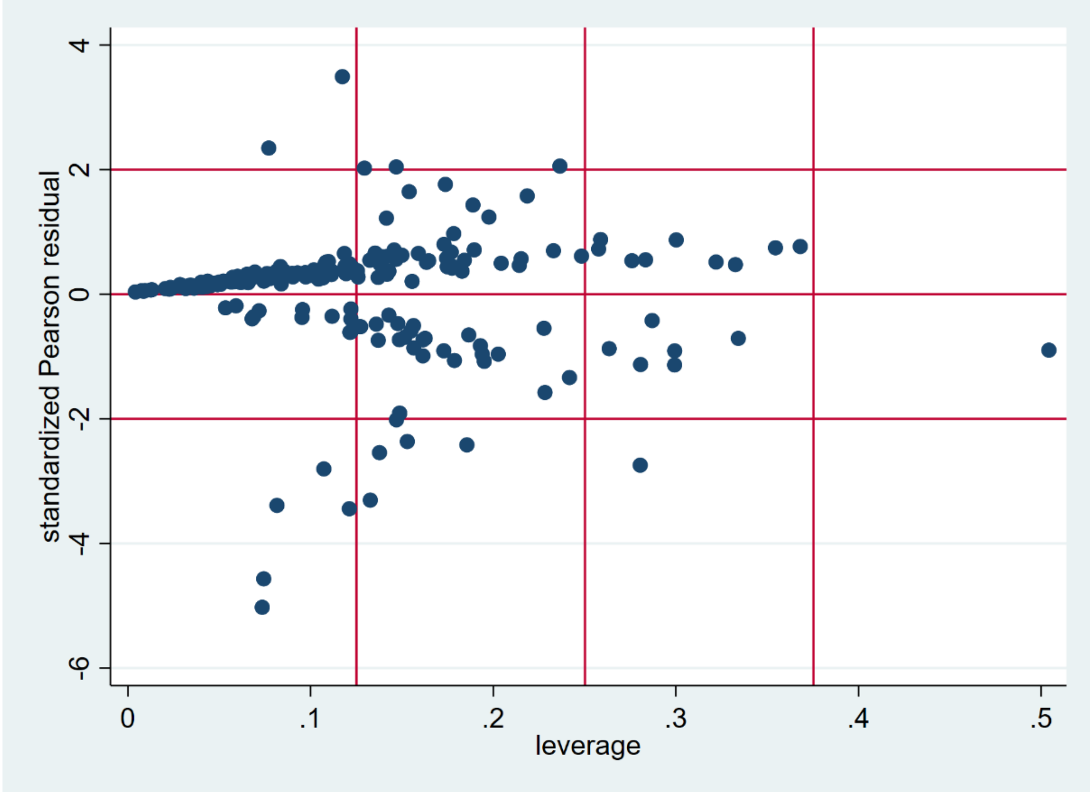


Figure 42: Plot standardized residuals and leverages (workplace by PT, distances continuous)

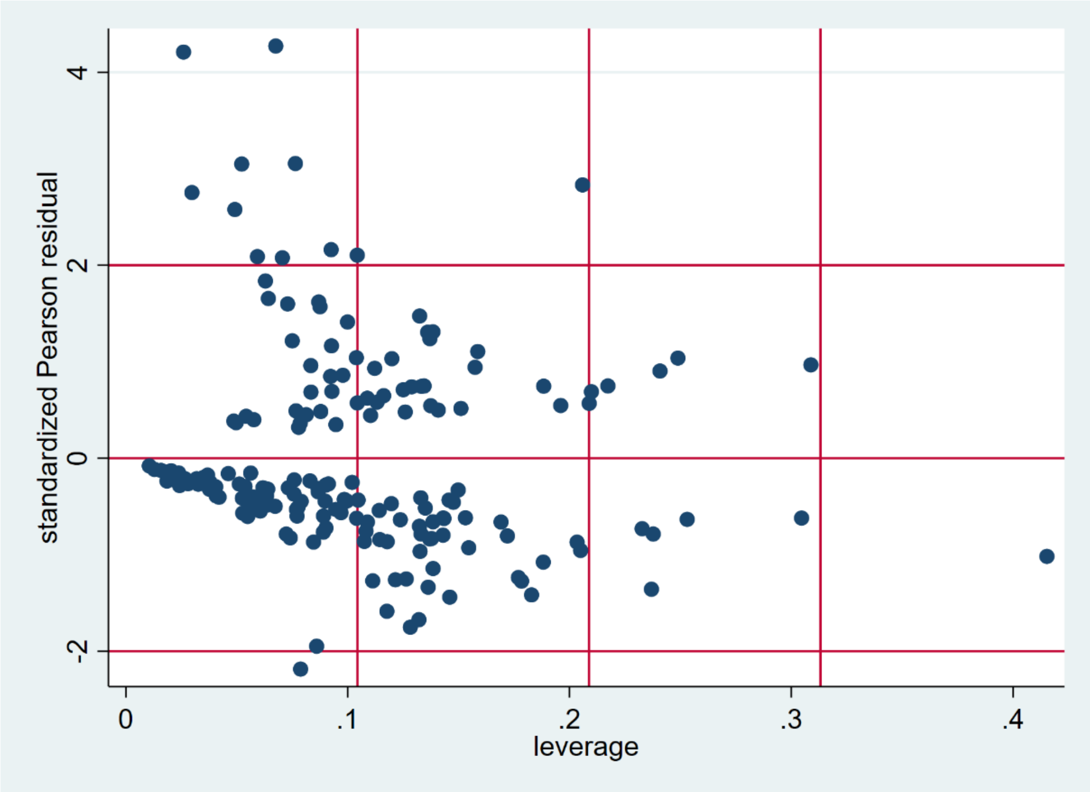


Figure 43: Plot standardized residuals and leverages (workplace by PT, distances categorical)

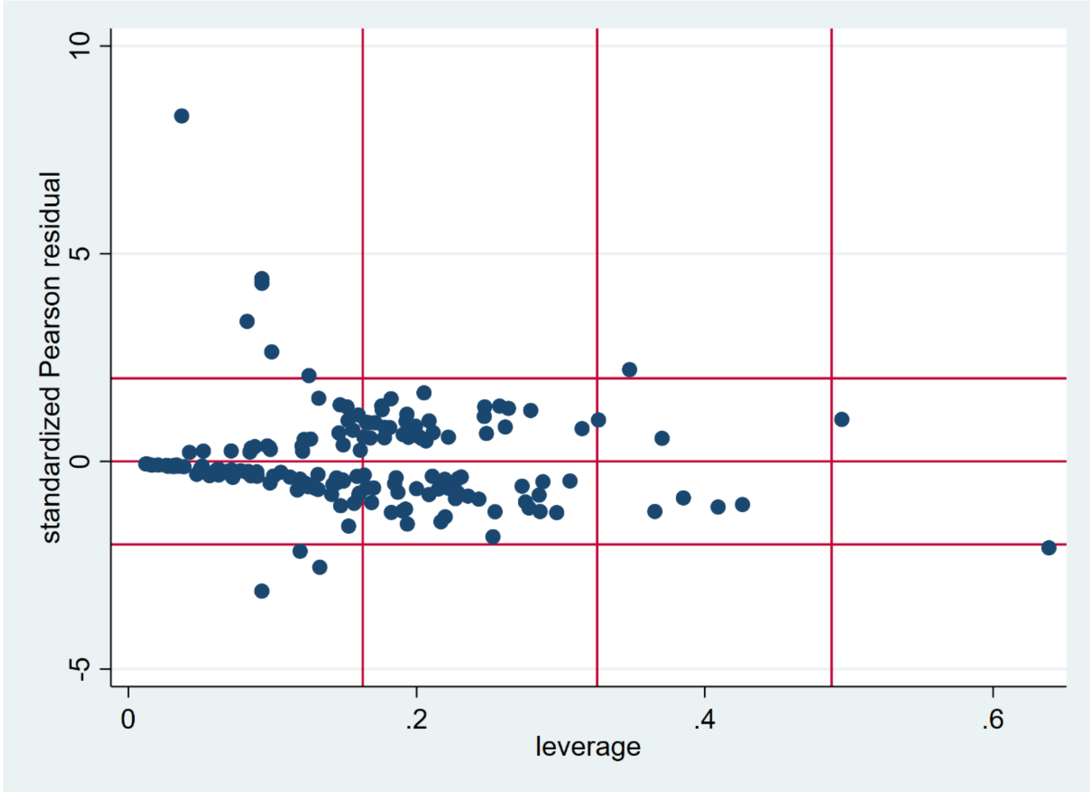


Figure 44: Plot standardized residuals and leverages (workplace by walking, distances continuous)

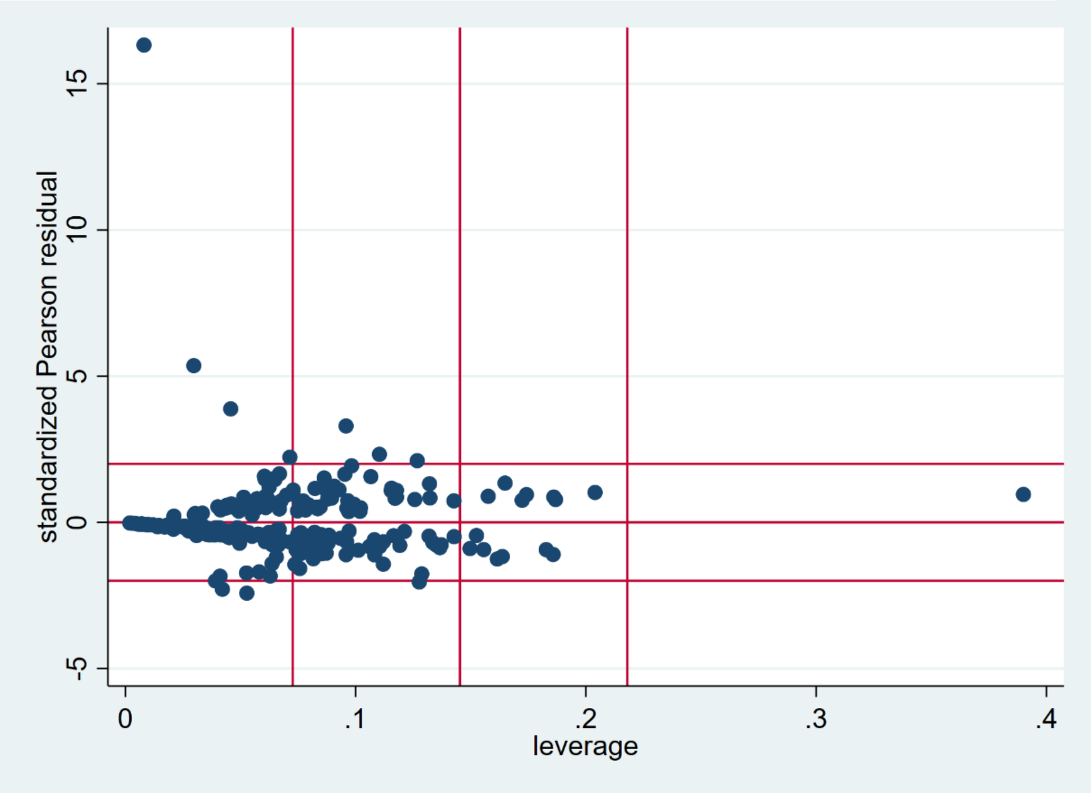


Figure 45: Plot standardized residuals and leverages (workplace by walking, distances categorical)