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Cycling or walking? Determinants of mode choice in the Netherlands

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ABSTRACT

Interest into active modes (i.e. walking and cycling) has increased significantly over the past decades, with governments worldwide ultimately aiming for a modal shift towards active modes. To devise policies that promote this goal, understanding the determinants that influence the choice for an active mode is essential. The Netherlands is country with a large and demographically diverse active mode user population, mature and complete active mode infrastructure, and safe environment. Mode choice research from the Netherlands enables a comparison on relevant determinants with countries that have a low active mode share. Furthermore, it can provide quantitative input for policies aiming at an active mode shift. This paper estimates a mode choice model focusing on active modes, while including a more comprehensive set of modes (i.e. walking, cycling, public transport and car). Based on data from the Netherlands Mobility Panel (MPN) in combination with an additional survey focused on active modes (coined PAW-AM), this study estimates which determinants influence mode choice. The determinants can be categorized as individual characteristics, household characteristics, season and weather characteristics, trip characteristics, built environment, and work conditions. The results show that all categories of determinants influence both walking and cycling. However, the choice for cycling or walking is affected by different determinants and to a different extent. In addition, no active mode nest was found in the model estimation. Cycling and walking should thus be regarded as two distinguished alternatives. Furthermore, the results show that active mode use is most sensitive to changes in the trip characteristics and the built environment.

1. Introduction

In the past decades, interest into active modes (i.e. walking and cycling) has significantly increased. A high share of active modes in terms of the number of trips has many potential benefits. At the individual level it can provide health benefits due to increased activity levels, and at the network level it might reduce traffic jams and the associated emissions when substituting the car. Governments worldwide have set goals for increasing the active mode share (Pan-European Programme, 2014). Ultimately, they are aiming for a modal shift from motorized to active modes. This transition could be achieved by designing effective policies. Understanding which determinants influence the choice for an active mode can serve as valuable input for these policies.

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Several countries already have a high share of active mode use, i.e. the Netherlands, Denmark, and Germany (Pucher and Buehler, 2008). In the Netherlands, the active mode share in terms of the number of trips was 44% in 2017 and more than half of these were cycling trips (CBS, 2018). Pucher and Buehler (2008) make a distinction between the cycling rich countries and other countries where cycling is uncommon, such as the USA, Canada, and the UK. They identify that even though more kilometers are cycled in the Netherlands, the fatality and accident rates are much lower compared to the cycling poor countries, indicating a very safe cycling environment. Fishman (2016) identifies the Dutch mature and complete cycling infrastructure as the main contributor to the safe environment. Furthermore, Fishman (2016) stresses that in the Netherlands the cycling population is much more diverse in terms of socio-demographic compared to other countries. Women are known to cycle more than men (Heinen et al., 2010) and also elderly people are active bicycle users (Fishman, 2016). Fishman (2016) identifies that there is a knowledge gap concerning active mode choice from countries like the Netherlands, that have mature infrastructure, are safe, and where cyclists' demographics are diverse. This would enable the possibility to make a comparison on relevant determinants for active mode choice between cycling rich and cycling poor countries. Furthermore, when investigating active mode choice in Netherlands there is no need to oversample the cycling population, because a representative sample of the population suffices to ensure a large enough sample of cyclists.

Fishman (2016) argues that the Dutch are 'blind to cycling', meaning that cycling is such an ordinary activity that it has not been warranted much attention, both by practitioners and researchers. Only recently this has started to change. Dutch transport planning models, such as LMS (Rijkswaterstaat, 2018), are used by governmental authorities to assess the impact of policies. These models are tailored to the car and public transport. In line with Fishman's (2016) argument, the active modes have not received much attention. Walking and cycling are combined into 'slow modes' and often evaluated as 'rest-category' (de Jong et al., 2007). In order to correctly estimate the impact of policies, it is essential to include behaviorally accurate mode choice models in these transport planning models. Consequently, research on active mode choice in the Netherlands would benefit both practice and research.

The objective of this study is to identify the determinants influencing the choice for an active mode of transport when considering a more comprehensive set of modes (i.e. car, public transport, bicycle and walking) in the Netherlands, which is characterized by high share of active mode use. This paper presents findings from a discrete mode choice model estimated using census data. We investigate the influence of different categories of determinants on mode choice, e.g. trip characteristics, socio-demographics and the built environment. The results of this study can be used in two ways: first, the findings can facilitate planning and policy measureas in other countries that aim for high active mode penetration and second, the model can improve the representation of active modes in the models that are part of the Dutch transport planning models.

In this paper, Section 2 identifies and categorizes determinants influencing active mode choice, which serve as input for this study. Section 3 gives a description of the data collected for this research, and it explains the data merging and filtering process and provides an overview of the data in terms of descriptive statistics. In Section 4, the specification of the mode choice models is detailed, with focus on the identification of the individual mode choice set and the specification of the discrete choice model. In Section 5, the results of the model estimation are reported and discussed. Section 6 addresses a discussion of the results. Finally, Section 7 provides conclusions of this study and provides directions for future research.

2. Determinants of active mode choice

In this study we focus on the determinants of active mode choice when considered as part of a more comprehensive set of modes. Therefore, this literature review focusses on the determinants that influence walking and cycling. We refer the reader to the literature review sections in for example Buehler (2011) and Paulley et al. (2006) for studies on public transport and car mode choice determinants.

Many studies have investigated which determinants are important in active mode choice. It is possible to divide these determinants into six categories (Hunt and Abraham, 2007; Heinen et al., 2010). These are individual characteristics, household characteristics, trip characteristics, built environment, season and weather characteristics, and work conditions. This section briefly discusses the main findings from literature reviews that focus on cycling and walking, with respect to determinants from each category.

2.1. Individual characteristics

The individual characteristics pertain to all determinants related to the person, e.g. socio-demographics, ability to use a mode, and ownership or availability of modes. The socio-demographics have often been investigated, however for both walking and cycling mixed results are found. Often, literature claims that men cycle more often than women (Fraser and Lock, 2010; Muñoz et al., 2016). Heinen et al. (2010) confirm this for countries with low cycling penetration, however in countries with high cycling penetration, such as the Netherlands and Denmark, women are found to cycle more often than men. Regarding age, mixed results have been found for both walking and cycling (Mitra, 2013; Handy et al., 2014; Heinen et al., 2010). Young people are often found to cycle more (Muñoz et al., 2016) and old people to cycle less (Fraser and Lock, 2010), albeit the results are inconclusive. Often a higher education level is linked to lower cycling levels (Heinen et al., 2010), while again mixed results have been reported in the literature (Muñoz et al., 2016).

The availability of a car has a negative association with the probability to walk or cycle (Mitra, 2013; Heinen et al., 2010), whereas the availability of a bicycle has a positive association with cycling (Heinen et al., 2010; Handy et al., 2014; Fraser and Lock, 2010). The relationship between bicycle availability and walking has not been investigated insofar.

2.2. Household characteristics

The household characteristics relate to the other people in the household and their influence on the active mode choice. The size and composition of the household are known to relate to mode choice. For example, the number of children is negatively associated with the choice for walking to the supermarket (Maley and Weinberger, 2011). Hamre and Buehler (2014) confirm this negative association for both walking and cycling (the latter was not significant). Heinen et al. (2010) state that having no children increases the probability of cycling. Income is often identified as a determinant of active mode choice, however mixed results are reported regarding the directionality of the relationship (Mitra, 2013; Handy et al., 2014; Heinen et al., 2010; Muñoz et al., 2016).

2.3. Season & weather characteristics

Cyclists and pedestrians are more exposed to the seasonal and weather conditions than a person travelling by car or using public transport. Generally, summer and autumn are mentioned as the most favorable seasons for cycling and walking (Böcker et al., 2013; Heinen et al., 2010). Winter is negatively associated with active mode travel. Wang et al. (2016) report that environments with cold winters and warm summers are less attractive for active mode users. Regarding the daily weather conditions, mostly the impact of rain and temperature have been studied (Böcker et al., 2013, Heinen et al., 2010). Temperature is found to have a non-linear effect, where cold and very hot weather are negatively associated with active mode use. Regarding rain, mixed results have been found (Böcker et al., 2013, Heinen et al., 2010). Other studies do not explicitly mention temperature or rain, but investigate the influence of extreme or adverse weather, which is negatively associated with active mode use (Wang et al., 2016; Fraser and Lock, 2010).

2.4. Trip characteristics

The most investigated trip characteristics are distance and travel time. They are highly correlated and sometimes considered equivalent, however in cycling research, distance is often investigated (Mitra, 2013; Handy et al., 2014; Winters et al., 2017; Fraser and Lock, 2010; Heinen et al., 2010; Muñoz et al., 2016). Longer distances are found to be negatively associated with active mode use. Heinen et al. (2010) suggest a non-linear relationship between distance and bicycle use, penalizing longer distances more adversely. Distance is related to the built environment, because land use and density of the built environment largely determine how far destinations are located in relation to residential areas (Handy et al., 2014). Other trip characteristics are less often investigated. The day of the week was found to influence cycling choice. During weekdays the bicycle has a larger probability to be chosen (Hansen and Nielsen, 2014). Furthermore, a recreational trip purpose is found to have a positive association with cycling (Fraser and Lock, 2010).

2.5. Built environment

The built environment pertains to road infrastructure (e.g. percentage of cycle path or sidewalks along the route), aesthetics (e.g. proximity to parks), and area characteristics (e.g. presence of shops and population density). The built environment is especially relevant for active modes, as they are more (directly) exposed to the surroundings compared to car and public transport users. The presence, density, and continuity of active mode infrastructure (e.g. bicycle lanes or paths and sidewalks) is positively associated with active mode usage (Heinen et al., 2010; Mitra, 2013; Handy et al., 2014; Fraser and Lock, 2010). Facilities related to cycling, such as bicycle parking, are also positively associated with cycling (Heinen et al., 2010). Regarding the aesthetics, the literature states that the presence of among others parks, street plantation, playgrounds, benches, and garbage bins are positively associated with both walking and cycling (Wang et al., 2016; Fraser and Lock, 2010; Heinen et al., 2010). Traffic lights were found to have a mixed relationship with cycling and have not been studied in a broader mode choice context (Heinen et al., 2010). Land use is found to be strongly related to active mode use. A mixed land use environment encourages active mode use, whereas low residential density discourages active mode use (Mitra, 2013; Wang et al., 2016; Winters et al., 2017; Fraser and Lock, 2010; Heinen et al., 2010; Muñoz et al., 2016). At a more aggregate level, small and medium size cities are positively correlated with bicycle use and the city center is more attractive for cycling compared to the suburbs (Heinen et al., 2010). Furthermore, areas with high population density are attractive for active mode use (Wang et al., 2016; Fraser and Lock, 2010; Muñoz et al., 2016).

2.6. Work conditions

Finally, the work conditions relate to the facilities that are offered by the employer. This comprises for example facilities at the workplace, reimbursement for travelling to work using a certain mode, and working hours and flexibility thereof. Heinen et al. (2010) and Handy et al. (2014) state that the availability of facilities related to the car, for example (free) parking options, negatively relate to the choice for cycling. Furthermore, Heinen et al. (2010) identify a positive relationship between facilities that are beneficial for cyclists, such as lockers or showers and bicycle choice. Providing incentives or reimbursement for both the bicycle and public transport have a positive association with cycling (Muñoz et al., 2016; Handy et al., 2014; Winters et al., 2017). Public transport requires access and egress for which both walking and cycling are often used. The use of the bicycle as access and egress mode also boosts the use of the bicycle on other occasions. On the other hand, if the car is incentivized or reimbursed a negative association is found with bicycle use (Handy et al., 2014). Furthermore, if car usage is disincentivized, evidence suggests that this does not benefit bicycle use, but instead increases public transport use (Braun et al., 2016). Finally, regarding working hours, the literature suggests that having a part-time job is more positively associated with cycling compared to a full-time job (Heinen et al., 2010).

Evidently, the significance of determinants belonging to each of the six categories has been previously investigated. Notwithstanding, the directionality and magnitude has not always been conclusive. Furthermore, there is a need to map and perform a more complete analysis of the determinants influencing mode choice (Handy et al., 2014; Heinen et al., 2010), so that trade-offs among determinants and their relative importance can be established by performing a joint model estimation. This ensures that not only the influence of the individual determinants on the mode choice is quantified, but also their relative influence. The latter is essential to support policy makers in determining what to focus on when the goal is increasing the modal share of active modes. This study addresses determinants from all categories to investigate both the individual and relative importance of modal choice determinants.

3. Data collection and preparation

This section covers the data collection (3.1) and preparation of the data for this study (3.2). Furthermore, the selection and preparation of the determinants that potentially influence mode choice (3.3) is addressed. Finally, the final dataset is described in terms of individual characteristics (3.4) and reported trip characteristics (3.5).

3.1. Data collection

In this study census data from the Netherlands Mobility Panel (MPN) is used, which is a longitudinal household panel that has started in 2013 and is designed to investigate changes in travel patterns of a fixed panel of individuals and households over a longer period of time. This panel is to a large extent representative for the Dutch population, except for a slightly lower share of low-income individuals and teenagers. Every year, the members of the panel fill in a three-day travel diary, a household survey and a personal survey. In the travel diary they report among other things, the trips made, the modes used and the distances covered. The household survey relates to household characteristics and the ownership and availability of modes, whereas the personal survey focuses on mode preference for certain activities and their attitudes towards motorized modes. The panel comprises about 2000 households, totaling 4000 individuals. For more information on the MPN surveys the reader is referred to Hoogendoorn-Lanser et al. (2015).

Even though the MPN census data is a very rich data source, capturing most of the influence categories of determinants identified in Section 2, it lacks data on the built environment. Previous research has established the importance of this category. They reported, for example, a positive association between active mode use and cycling infrastructure (Heinen et al., 2010; Mitra, 2013; Handy et al., 2014; Fraser and Lock, 2010), presence of parks, street green, playgrounds, benches and garbage bins (Wang et al., 2016; Fraser and Lock, 2010; Heinen et al., 2010), and high population density levels (Wang et al., 2016; Fraser and Lock, 2010; Muñoz et al., 2016). Consequently, it is essential to also collect data on the built environment. In 2017 an additional survey (coined PAW-AM), which addresses among other things elements of the built environment that are present in the respondents' neighborhood, was designed to enrich the MPN dataset. Besides the elements of the built environment, the survey focuses on complementary information with respect to active mode use. This survey was distributed among respondents of the MPN survey, who indicated that they walked or cycled at least once in the last year. The goal was to target active mode users, consequently we excluded 1.3% of the respondents of the MPN panel that did not walk or cycle and are assumed to be largely inactive.

3.2. Data preparation

To be able to investigate the influence of all categories of determinants on mode choice, the MPN surveys (household, personal and travel diary) and the PAW-AM survey need to be merged. Only respondents that have filled in both the MPN and PAW-AM surveys are included in this study, resulting in a total of 2871 respondents.

In the travel diary several filters are applied to identify which of the 26,192 trips (made by all respondents) can be used for this study. Trips are excluded in the following cases: (1) tours in which the origin is also the destination and no intermediate stop is made, (2) trips of which the reporting is unreliable or inconsistent (e.g. due to large detours, incorrect address information or uncertainty about the reported mode), (3) trips that are made as part of professional driving (e.g. truck drivers), (4) trips outside the Netherlands, (5) non-home based trips and (6) trips that are made by rarely chosen or available modes (e.g. skateboard or boat). The reason for excluding tours and professional driving trips is because the motivation for choosing a mode might be different from normal trips. Non-home based trips (i.e. not starting from home) are excluded because of the dependency on the mode of transport that was used before, for example if a person makes the first trip by car, he or she generally needs to return the car back home, which introduces a dependency that results in limited and/or fixed mode choice set. Conversely, trips starting at home provide no limitations in choosing a mode other than the availability of the mode to the person.

Furthermore, the data collection for the MPN surveys took place in autumn 2016 (September – November), whereas the PAW-AM survey was distributed in June 2017. This means that life events (e.g. a new job, different working hours, a new house or the birth of a child) need to be taken into account. That is, if a respondent has experienced a life event, the data from the MPN survey should not be matched to the PAW-AM survey and these respondents are excluded. The reason is that their travel behavior could have significantly changed due to these events, creating a mismatch in the data. The final dataset that is available for this study consists therefore of 6368 trips and 1864 individuals.

Table 1
Determinants that are known to influence mode choice in literature and are available in the dataset for inclusion in the model estimation procedure.

Individual characteristics	**Trip characteristics**
Gender	No. trips on day of travel
Age	Departure time
Education	Trip purpose
Ethnicity	No. individuals in travel group
Ethnicity parents	Travel time
Occupation	
Driver's license	**Built environment**
Body Mass Index (BMI)	Urbanization level
Transit subscription	Metropolitan area (Amsterdam, Rotterdam, Eindhoven, Den Haag, Utrecht)
Company car	Nature in neighborhood (green, water, park)
Bicycle/car in household	Street furniture in neighborhood (garbage bins, playgrounds)
Mode used for going to high school	Traffic related aspects in neighborhood (speed bumps, cycle paths, cycle parking spots, traffic lights)
Mode used in the last half year	Buildings in neighborhood (shops, restaurants, schools, public buildings, hospitals, sports centers, flats, offices, industry)
Household characteristics	**Work conditions**
No. household members	Working hours per week
No. children in household	Travel compensation (bicycle, public transport, car)
Household income	
Season & weather	
Extreme weather	
Month of travel	

3.3. Selecting and processing potential determinants

Based on the determinants identified in the literature reviews (Section 2) and the availability of data in the MPN and PAW-AM surveys, potential determinants that influence mode choice are selected for this study. Table 1 shows an overview of all the determinants selected for this study. Note that all categories of variables are represented in this list, enabling the comparison of the relative importance of various determinants.

In the dataset both travel time and distance are known. These two determinants are highly correlated, therefore only one can be included in the model estimation. The distance and travel time are self-reported by the respondents. Regarding public transport, journey planners usually express the trip in travel time, therefore it is expected that the respondents are able to recall the duration of the trip, but they might not know the distance of the trip. Therefore, travel time is preferred over distance.

The travel time is only available for the mode used to make the trip. This means that the travel times need to be calculated for the non-used modes. This procedure is covered in Section 3.3.1. Furthermore, by analyzing the differences between the reported time by the chosen mode and the calculated time for that mode, the quality of reporting can be assessed. Based on this assessment, a decision is made on whether the use of the reported travel time in the model estimation is valid. This analysis is described in Section 3.3.2.

3.3.1. Calculation of the travel times for non-used modes

Because only the reported mode is provided per trip, travel times of the alternative, non-chosen modes need to be calculated. These are calculated using the Google Directions API. This API does not allow for performing calculations for past events, therefore in order to create similar conditions for most trips, the calculations were made on a weekday during the day. This affects both public transport (PT) and car, as timetables usually change over the day, especially in the evening/night and traffic jams arise in morning and evening peaks. Therefore, regarding PT, all trips made between 22 h and 5 h were checked in a journey planner to see if there was a PT option available. If no PT option was available, the alternative was marked unavailable. For the car this validation is not possible, as the amount of traffic on the road differs per day and peak-hour period, this means that some discrepancies can be expected in the calculated travel times.

For 1366 trips, the PT travel time was equal to the walking time, indicating that instead of providing an option to use train, bus, tram, or metro, the journey planner advised to walk. Furthermore, in 57 occasions no PT route could be found (and the distance was not walkable). In these situations, PT is not an option and the alternative was marked as unavailable. Next to that, for one trip no car alternative was found (destination was on an island), for five trips no walking alternative was found and for five trips no cycling alternative was found. The reason for not finding routes is the availability of roads in the network of the Google Directions API. For active modes it searches for roads where active modes are allowed. These alternatives are all marked as unavailable in the choice set.

3.3.2. Analysis of travel times for used modes

To check whether the reported travel times are reasonable and can be used in the model estimation, the travel time of the chosen mode was also calculated using the Google Directions API. Fig. 1 shows the mean of the calculated minus the reported travel times, plotted against classes of the reported travel times.

Fig. 1 illustrates that people report shorter PT travel times compared to the calculated travel time, especially for short trips. This might be due to ignoring access and/or egress travel time, but only reporting the in-vehicle time. For the car the reported travel times

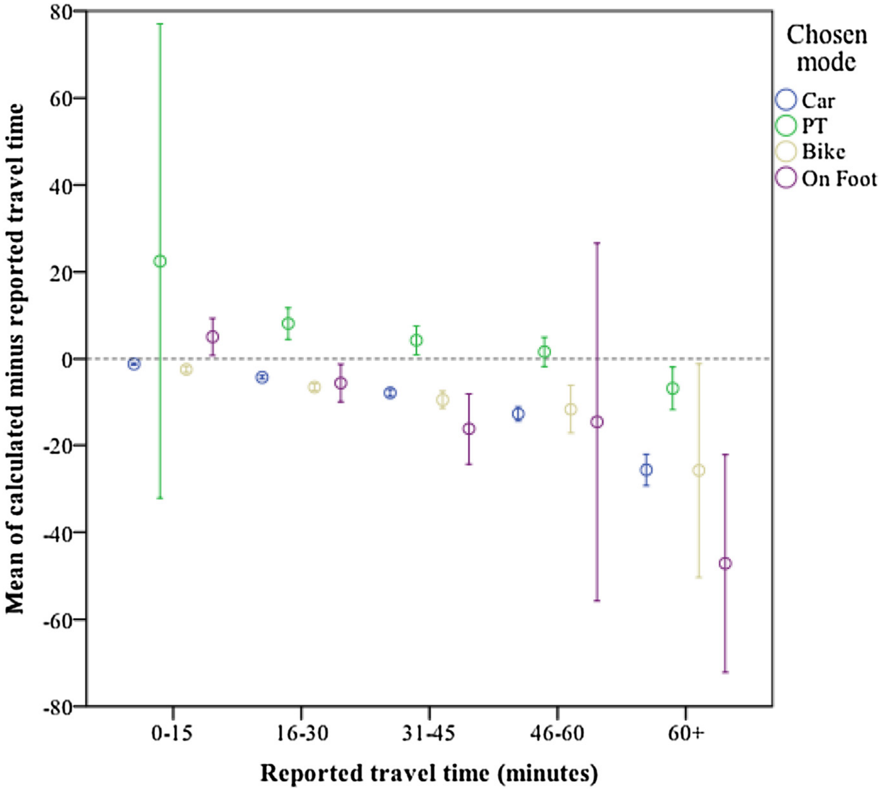

Fig. 1. Mean and 95% confidence interval of difference between calculated and reported times.

are over reported, with increasing error for increasing travel time. This could be due to congestion, where the maximum speed cannot be reached. However, it is impossible to check this, because the traffic situation during the trips cannot be recalled. Travel time for cycling trips is also over reported (the extent of overestimation is comparable to the car, but with larger error bars). The calculated travel time is based on the shortest route, but literature suggests that the distance is not the only factor determining cycling route choice (e.g. Ton et al., 2017; Menghini et al., 2010). This indicates that the extent of over reporting could be less severe in reality. The same occurs for walking, although 97% of the trips are below 30 min in duration. Summarized, differences between reported and calculated travel times are generally low and can be explained. As the reported travel times also include potential traffic jams or delays, the reported travel time is used in the model estimations.

3.4. Characteristics of the respondents

The final merged and filtered dataset contains 1864 individuals from all over the Netherlands. The breakdown of their socio-demographics, household size, place of residence and ownership characteristics is described in Table 2.

As mentioned before, the sample contains individuals who have cycled and walked at least once during the last year. The distribution of the individuals over age shows that many elderly people are present in the sample (almost 20% is 65 years or older), which indicates that elderly Dutch citizens still use active modes of transport. The surveys are distributed among individuals of 12 years and older, therefore no individuals with a lower age are present in the dataset. The education level shows the highest completed level of education. Consequently, teenagers who are currently studying, have a lower level of education, compared to when they will finish their studies. The low level of education contains finished studies up to the level of pre-vocational secondary education (‘VMBO’ in Dutch), whereas the medium level of education contains finished studies up to the level of either secondary vocational education (‘MBO’ in Dutch) or pre-university education (‘VWO’ in Dutch). The highest level of education includes university education. The result is that a relatively large part of the sample has completed a low level education. More than 82% of the individuals in the dataset live in a household consisting of multiple individuals, which is higher than average for the Dutch population. Furthermore, most individuals live in an urban environment. Finally, most people in the sample own a car and bicycle. The bicycle ownership is high (compared to other countries) with 91%, but in line with the national active mode share. Whereas, only 32% of the respondents in the sample have a type of PT subscription (e.g. travel with discount or travel for free on a fixed line).

3.5. Characteristics of the reported trips

The final dataset contains 6368 trips made by car (passenger and driver), public transport (train, tram, bus, and metro), bicycle

Table 2
Characteristics of the individuals in the dataset.

		Frequency	Percentage (%)
Gender	Male	852	45.7
	Female	1012	54.3
Age	12–24	266	14.2
	25–34	257	13.8
	35–44	293	15.7
	45–54	377	20.2
	55–64	309	16.5
	65–74	234	12.5
	75 +	128	6.8
Professional situation	Employed	1054	56.5
	Unemployed	249	13.4
	Retired	337	18.1
	Student	224	12.0
Working hours	0–12 h per week	772	41.4
	12–35 h per week	524	28.1
	35 + hours per week	568	30.5
Education level	Low	477	25.6
	Medium	732	39.3
	High	655	35.1
No. of householdmembers	1	333	17.9
	2	640	34.3
	3	256	13.7
	4	426	22.9
	5 +	209	11.2
Urbanization level	Urban	957	51.3
	Sub-urban	357	19.2
	Rural	550	29.5
Ownership	Car	1359	72.9
	Bicycle	1696	91.0
	PT - subscription	604	32.4

(electric and normal bicycles) and on foot. Table 3 provides an overview of the characteristics of the trips made by all individuals in the dataset.

About 43% of all the trips in the dataset are made using active modes. In line with expectations, travel time and distance are on average higher for car and PT compared to active modes, as the latter are mostly used for short-range trips. On the other hand, the median distance for the car is much shorter with 8 km (for PT this is 27.8 km). This shows that overall the car is chosen more often for short distances than PT. Consequently, the car can compete with cycling and walking for short distance trips. The standard deviations for traveled distances are higher than the mean values, which is due to the long tail for traveled kilometers (e.g. maximum traveled distance by car is 260 km). PT consists of inter-city and intra-city travel. The relatively high mean travel time for PT is therefore mainly due to the large share of inter-city trips in the data (traveled mostly by train). About half of the trips made by PT are work related, which is also reflected in the low percentage of trips made in the weekend. Cycling is mostly used for leisure activities. Notwithstanding, 21.5% of the cycling trips are work related. The relatively low percentages for the main trip purpose of car (27.4%) and bicycle (22.6%) indicate that compared to walking and PT, these modes are used for more diverse trip purposes.

4. Specification of the mode choice model

This section describes the mode choice model specification for this study. The approach for identifying the mode choice set for each individual is described in Section 4.1. Furthermore, the specification of the discrete mode choice model is presented in Section 4.2. Finally, the model estimation process is elaborated upon in Section 4.3.

Table 3
Characteristics of the trips in the dataset.

	Share of trips Percentage	Travel distance [km] Mean (s.d.)	Travel time [min.] Mean (s.d.)	Largest trip purpose category Purpose (%)	Trips in the weekend Percentage of total trips (%)
Car	51.6%	18.4 (27.4)	23 (22)	Work (27.4%)	27.5
PT	5.3%	39.7 (41.1)	66 (39)	Work (42.6%)	14.6
Bicycle	32.4%	2.9 (3.2)	13 (12)	Leisure (22.6%)	19.0
On foot	10.7%	0.7 (0.7)	9 (9)	Shopping (37.6%)	26.0

4.1. Identification of the individual mode choice set

When using revealed preference data only the reported mode is known. In choice modeling, the non-chosen but alternative modes need to be identified too. This is a non-trivial task as not every individual has the same set of modes available.

Several mode choice studies were identified from literature that focus on active modes, consider the full spectrum of modes, and use revealed preference data. These studies all use different heuristics for the identification of the individual's mode choice set. Munshi (2016) did not apply any restrictions to the choice set and included all modes for every trip and person, regardless of availability of the modes. Wardman et al. (2007) also did not specify any restrictions in the model estimation, but for forecasting they distinguish between shorter trips ($<$ 12 km) and longer trips ($>$ 12 km) and car availability. Kamargianni and Polydoropoulou (2013) applied very strict reasoning as they excluded individuals living more than 2.1 km away from their destination (i.e. school in their case), due to the unavailability of walking for longer distances. This way they made all alternatives available to the entire sample, with the goal of matching the revealed preference data to their stated preference survey (which included all modes). The most detailed heuristics were introduced by Gehrke and Clifton (2014), who stated that if a person travels alone, he or she needs to be in possession of a driver's license and a car needs to be available in the household for the car to be included in the choice set. If a person travels with others, this criterion is not effectuated as this person could travel as a passenger in a car that is not owned by anyone in the household. Regarding PT, they introduced a maximum allowable distance to the nearest stop criterion, which they set to 0.5 mile for bus and 1.0 mile for train. The bicycle also needs to be available in the household, additionally they allowed for a maximum travel time of 2 h, assuming that the cycling speed is 10 mph. For walking, they allowed for the same maximum travel time, with a speed of 3 mph.

In this study, the heuristics introduced by Gehrke and Clifton (2014) will be applied and adapted to the Dutch situation. Consequently, the PT, bicycle and walking heuristics are adapted. Gehrke and Clifton (2014) exclude PT trips for individuals who live further than a certain distance. In the Netherlands, people use a variety of access modes and as a result thereof the one-mile boundary is considered too small. In order to avoid a false exclusion of PT from the choice set, we choose to set no distance boundary to PT travel, but as mentioned in Section 3.3.1, the PT route should have been identified in the Google Directions API. For the active modes, a maximum travel time of 2 h is too generous given the reported travel times in the data. The maximum reported travel time for cycling is 130 min, where 99% of the individuals have travel time lower than 60 min. For walking these values are respectively 75 min and 50 min. Therefore, it seems most plausible to adjust to the 99% travel time, as this captures the potential choice for active modes for the vast majority of individuals. Similar to Gehrke and Clifton (2014) this study will use an equal limit for both modes, which is set to 60 min. Summarizing, the following heuristics are introduced for identifying the mode choice set:

- Car: Driver (drivers' license and car available), Passenger (travelling with other individual(s));
- PT: Route identified in Google Directions API;
- Bicycle: Bicycle available and calculated travel time $< =$ 60 min (mean speed = 16.7 km/h);
- On foot: Calculated travel time $< =$ 60 min (mean speed = 4.8 km/h).

The results of implementing these heuristics, in terms of the choice set sizes per trip are reported in Table 4. 1.9% of the individuals are captive users for their trip, which are mainly PT trips, but also car and bicycle. These captive users influence the choice model, as they will have a 100% probability of choosing the only mode which is available to them. When not all modes are available to a person, mostly walking is excluded. This is due to the fact that the travel time on foot is longer than 1 h. For 31.9% of the trips all modes are available, which means that in these cases all of the above mentioned criteria are met.

4.2. Discrete choice model specification

In this study, three different mode choice models are estimated with an increasing level of complexity. First, we start with a multinomial logit (MNL) model with the utility function for alternative i and observation n at time$t$ specified in the following way (Ben-Akiva and Bierlaire, 1999):

$$U_{int} = V_{int} + \varepsilon_{int},\ i \in C_n \tag{1}$$

where V_{in} is the deterministic utility for alternative i (which is part of the choice set C_n) and observation n at time$t$ and ε_{int} represents the random error term, which captures uncertainty and is independent and identically (i.i.d.) Gumbel distributed.

Table 4
Mode choice set size per individual per trip.

Mode choice set size	Frequency (%)	Frequency of including mode in the choice set				
		Car (%)	PT (%)	Bicycle (%)	Walk (%)	Total (%)
1	1.9	14.3	84.9	0.8	0.0	100
2	21.5	74.3	81.3	28.3	16.1	200
3	44.8	84.9	59.7	99.1	56.3	300
4	31.9	100.0	100.0	100.0	100.0	400

Second, since multiple trips per individual are observed, serial correlation can be expected in the error terms of one individual. We therefore test for a panel effect using a mixture of MNL models with a normal distribution of the panel effect error term $\alpha_{in}\ N(0, \Sigma)$. The utility function for alternative i and observation n at time t is then adapted from Eq. (1) in the following way:

$$U_{int} = V_{int} + \alpha_{in} + \varepsilon'_{int},\ i \in C_{nt} \tag{2}$$

where α_{in} represents the panel effect and ε'_{int} represents the random error term that is independent over observations and time and is i.i.d. Gumbel distributed.

Finally, the population is likely to exhibit taste heterogeneity. Therefore, the third and final model that is estimated is the mixed MNL (MMNL) model. The utility function for the MMNL is an extension of Eq. (2), due to the expected presence of a panel effect, and is specified in the following way:

$$U_{int} = V_{int} + \alpha_{in} + \xi_{int} + \varepsilon''_{int},\ i \in C_{nt} \tag{3}$$

where ξ_{int} represents the error term that captures the taste heterogeneity that is independent over time t and is normally distributed and ε''_{int} represents the random error term that is i.i.d. Gumbel distributed. All models are estimated using the Python Biogeme package (Bierlaire, 2016).

The MNL i.i.d. assumption may be violated in case alternatives are correlated. In mode choice literature hierarchy in choices – for example motorized versus active modes – is often identified. This calls for the introduction of nested logit models (e.g. Barros et al. (2015)). To identify whether this hierarchy is also present in the Dutch situation, we tested for the presence of an active mode nest using the nested logit model. However, we found no significant results for the nest, indicating that mode choice is not hierarchical with respect to active modes.

In addition to MMNL, Latent Class Models (LCM) offer an alternative model structure for capturing taste heterogeneity. The reader is referred to Greene and Hensher (2003) and Hess (2014) for a discussion and comparison of model properties and performance. MMNL, unlike LCM, requires Monte-Carlo simulations as part of the model estimation process. In contrast, in the LCM, each parameter needs to be estimated for each class, consequently significantly increasing the number of parameters compared to the MMNL and thus also increasing the computation time. Furthermore, LCM is more sensitive to data quality, as potential limitations show faster (e.g. confounding, wrong signs or correlations). For this study, we experimented with both methods but experienced that the LCM model did not converge properly, therefore we adopt the MMNL model.

4.3. Model estimation process

In the estimation process, the significant variables identified in the best MNL model are used as input for the more complex models. The result of this process is that several parameters are found to be insignificant. Therefore, we have chosen to optimize the MMNL model with respect to model fit, by only including parameters that significantly increase the model fit (tested by means of a likelihood ratio test). This means that some insignificant parameters can be present in the model, but model fit decreases if these are fixed to zero.

In the MMNL model the car is the reference alternative, i.e. whenever dummy variables are used in the model, the parameter for the car is fixed to zero.

The comparison on model performance is tested by considering four criteria: the final log-likelihood, the adjusted rho-square, the Bayesian Information Criterion (BIC), and the Akaike Information Criterion (AIC). The goal is to maximize the first two and minimize the latter two criteria.

5. Model estimation results

This section describes and discusses the results of the model with the highest performance, which is the MMNL model. Section 5.1 presents the results of the MMNL model, and compares the findings to general body of literature. The focus of the discussion is on the active modes. Section 5.2 addresses the performance of this model and compares its performance to the other models that are estimated. Section 5.3 concludes with the most important findings in comparison to the already existing body of literature.

5.1. Identifying the determinants of mode choice behavior

In this section, the significant determinants of mode choice behavior are presented and discussed. The results of the model estimation are presented in Table 5.

5.1.1. Alternative specific constants

The alternative specific constants describe the preference of the population, everything else being equal. The car is taken as the reference case (i.e. set equal to zero). The bicycle constant is insignificant, which means that the overall preference is similar to that of the car. For the Dutch population this makes sense, as cycling is a major mode of transport with a high share in terms of the number of trips. However, for countries with low cycling levels, such as the USA, this will not hold and a negative constant is expected (Pucher and Buehler, 2008). Public transport has a very negative constant, implying lower preference compared to the other modes. All else being equal, one would prefer all other mode over public transport. Furthermore, the constant for walking is positive and significant. Consequently, this alternative is favored by the population all else being equal.

Table 5
Associations of individual, household, season & weather, trip, built environment, and work characteristics with the likelihood of choosing car, PT, bicycle, and walking (a = binary explanatory variable, b = reference alternative, – = not estimated, ** = significant on a 95% confidence interval, * = significant on a 90% confidence interval).

	Car[b]		PT		Bicycle		Walk	
	coef.	*t*-test	coef.	*t*-test	coef.	*t*-test	coef.	*t*-test
$\beta_{Constant}$	–	–	−46.30	−6.29**	0.08	0.16	5.35	6.57**
σ_{Panel}	–	–	−15.20	−5.8**	2.52	11.82**	2.27	8.09**
Individual characteristics								
$\beta_{Student}$ [a]	–	–	6.91	3.00**	–	–	–	–
$\beta_{Higheducation}$ [a]	–	–	–	–	0.43	1.89*	–	–
$\beta_{Transitsubscription}$ [a]	–	–	10.80	6.29**	0.54	2.24**	–	–
$\beta_{Companycar}$ [a]	–	–	–	–	−3.22	−1.75*	–	–
$\beta_{Modeusedinhighschool}$ [a]	2.04	3.72**	–	–	–	–	–	–
$\beta_{Modeuselasthalfyear}$ [a]	2.10	8.09**	7.92	6.81**	2.18	9.79**	2.95	7.91**
Household characteristics								
$\beta_{Householdmembers}$	–	–	1.98	3.28**	0.21	2.42**	−0.46	−3.66**
$\beta_{Childreninhousehold}$	–	–	−4.01	−2.54**	–	–	–	–
$\beta_{Mediumhouseholdincome}$ [a]	–	–	–	–	–	–	0.44	1.09
$\beta_{Highhouseholdincome}$ [a]	–	–	–	–	–	–	0.60	1.75*
Season & weather characteristics								
$\beta_{September}$ [a]	–	–	–	–	–	–	1.02	2.73**
Trip characteristics								
$\mu_{Traveltime}$	0.70	11.36**	0.24	8.92**	0.12	7.29**	−0.35	−6.97**
$\sigma_{Traveltime}$	−0.27	−10.51**	0.15	7.18**	–	–	0.15	5.76**
$\beta_{Weekday}$ [a]	–	–	–	–	0.81	3.92**	–	–
$\beta_{Peakhourdeparture}$ [a]	–	–	–	–	–	–	−0.56	−2.39**
$\beta_{Travelgroupsize}$	–	–	−1.80	−2.16**	−0.82	−6.62**	0.47	2.93**
$\beta_{Leisuretrippurpose}$ [a]	–	–	–	–	2.49	6.68**	2.79	6.33**
$\beta_{Worktrippurpose}$ [a]	–	–	6.51	4.95**	2.29	5.65**	2.09	3.57**
$\beta_{Schooltrippurpose}$ [a]	–	–	10.80	4.95**	5.11	7.34**	–	–
$\beta_{Shoppingtrippurpose}$ [a]	–	–	–	–	1.10	3.31**	1.65	3.96**
Built environment								
$\beta_{Amsterdam}$ [a]	–	–	5.95	2.84**	–	–	2.17	3.55**
$\beta_{Rotterdam}$ [a]	–	–	–	–	−0.99	−2.18**	–	–
β_{Urban} [a]	–	–	4.61	3.51**	–	–	–	–
$\beta_{Suburban}$ [a]	–	–	–	–	0.66	2.56**	–	–
$\beta_{Garbagebins}$ [a]	–	–	–	–	0.69	2.76**	0.85	2.37**
$\beta_{Playgrounds}$ [a]	–	–	–	–	–	–	−1.43	−3.16**
$\beta_{Bicycleparking}$ [a]	–	–	–	–	–	–	0.80	2.53**
β_{Shops} [a]	–	–	–	–	0.63	2.22**	0.99	2.65**
$\beta_{Publicbuilding}$ [a]	–	–	5.59	2.58**	–	–	–	–
$\beta_{Hospital/GP}$ [a]	–	–	–	–	−0.23	−0.87	–	–
Work conditions								
$\beta_{Travelcompensation}$ [a]	1.27	4.97**	17.6	4.57**	0.97	2.56**	–	–

5.1.2. Individual characteristics

Previous research showed that gender and age are very relevant, especially in explaining bicycle mode choice (Heinen et al., 2010; Fraser and Lock, 2010; Muñoz et al., 2016). Furthermore, Heinen et al. (2010) suggest that in cycling rich countries, such as the Netherlands, women cycle more often than men. In this study, we find that both gender and age are not explanatory variables. Cycling in the Netherlands is truly universal (Pucher and Buehler, 2008). Heinen et al. (2010) also mention that being native Dutch is positively associated with cycling. In this study we do not find a significant relationship between ethnicity and mode choice. The vast majority of our respondents is native Dutch (> 95%), presumably this shows not enough diversity to distinguish between native and non-native Dutch citizens. Furthermore, we find that having completed a high level of education (college level) increases the utility for the bicycle, compared to having a lower education level. Regarding education, the general body of literature shows mixed results (Heinen et al., 2010; Muñoz et al., 2016). Presumably, highly educated people in our sample are more aware of the health benefits related to cycling. A positive significant effect was expected for walking (e.g. Gehrke and Clifton, 2014), but was not affirmed. In line with the literature, being a student is positively related to cycling (Heinen et al., 2010).

Contrary to the majority of active mode choice studies, we find no significant relationship between the availability of car and bicycle in the household and mode choice (Mitra, 2013; Fraser and Lock, 2010; Handy et al., 2014). Pucher and Buehler (2008) show that car ownership has increased sharply in the Netherlands over the past decades, but this has not affected the use of bicycles, potentially explaining the absence of a significant relationship in this study. However, if an individual has a company car available (very small share of the sample), a significant reduction in bicycle utility is found. Trips with the company car are likely to replace trips by bicycle. Next to that, having a PT subscription positively relates to both the PT and cycling probability. The latter could be the result of access and egress transport (Handy et al., 2014; Winters et al., 2017), for which the bicycle is often used (respectively 50% and 10%) in the Netherlands (KiM, 2015). In this study we investigate the main mode choice for a trip. Consequenlty, the results suggest that the use of the bicycle as access and egress mode positively influences bicycle use in general.

Two variables related to past use of modes are tested, referring to the last year of high school and the last half year. For the former only car use has a significant and positive association with car choice. Using a car at an early age (either as passenger or driver) is thus associated with car use at a later age, whereas the other modes do not show this effect. Consequently, whether someone has cycled or walked to high school does not affect the current active mode use. For the latter, all modes test significant and increase the probability of choosing the respective mode, suggesting the formation of habits (Heinen et al., 2010).

5.1.3. Household characteristics

Previous research has established the relationship between the size and composition of the household and mode choice (Maley and Weinberger, 2011; Hamre and Buehler, 2014; Heinen et al., 2010). The results of this study are mostly in line with previous research. However, regarding the number of children (<12 years) in the household, previous research mentions a negative association with active mode use (Heinen et al., 2010). While we find a significant negative association with PT use, no significant association for the active modes is manifested. This might be due to the Dutch context, as children often cycle from an early age (Pucher and Buehler, 2008). An increasing number of individuals in the household decreases the utility for walking, but increases the utility for cycling and public transport. Pucher and Buehler (2008) state that in the Netherlands cycling is most popular among children and adolescents. More individuals in a household generally means more children and adolescents, which can explain the positive association with bicycle use.

The relationship between household income and walking is not significant at the 95% level, but only at the 90% level. For cycling we find no significant relationship. Previous research has found mixed results for the relationship between income and active mode choice, where positive, negative, as well as insignificant results are reported (Mitra, 2013; Handy et al., 2014; Heinen et al., 2010; Muñoz et al., 2016). This study therefore adds to these inconclusive results.

5.1.4. Season & weather characteristics

The month of travel or seasonality is known to influence active mode choice, with summer and autumn being the most favorable seasons (Böcker et al., 2013; Heinen et al., 2010). The data for this study was collected between September and November, hence late summer and autumn in the Netherlands. We find that September is positively associated with walking, which is in line with previous research. For cycling no significant relationship is identified. The Netherlands has a relatively mild climate (cool summers and warm winters), consequently it is possible that cycling is attractive all-year-round (Wang et al., 2016).

Furthermore, we find no relationship between extreme weather conditions and active mode use. Previous research has asserted that extreme or adverse weather is negatively associated with walking and cycling (Wang et al., 2016; Fraser and Lock, 2010). In the survey the respondents were asked if the weather conditions were extreme, therefore it reflects their subjective interpretation. The reason for not finding a relationship might again be due to the mild climate with frequent rain, which can be considered normal by the Dutch. Consequently, this study suggests that, in contrast with previous research, weather has limited impact on active mode choice.

5.1.5. Trip characteristics

As mentioned above, most active mode choice literature investigates the impact of distance on active mode choice (Mitra, 2013; Handy et al., 2014; Winters et al., 2017; Fraser and Lock, 2010; Heinen et al., 2010; Muñoz et al., 2016). Few studies investigated travel time (Heinen et al., 2010; Muñoz et al., 2016). These variables are highly correlated, so we include only one of them: travel time, which is significantly associated with mode choice. For walking, PT and the car, heterogeneity ($tt_{\text{mode}}\ N(\mu, \sigma)$)towards travel time is identified. Furthermore, the travel time parameters for car, PT and the bicycle are positive. Hence, the longer a trip (time-wise), the more likely that these modes are chosen. Generally, the literature finds negative associations between travel time and mode choice (Heinen et al., 2010; Muñoz et al., 2016). However, Heinen et al. (2010) mention that travel times should always be considered in relation to other transport modes. Consequently, these positive values should be interpreted in the context of the modal share per travel time category (Fig. 2). The shares of bicycle and walking decrease with higher travel times, whereas the shares of the car and public transport increase. Furthermore, as mentioned in Section 3.3.2 there are some differences between calculated and reported times. For example, for the car this means that delays are only present in reported travel time (traffic jams), which is the chosen alternative. The non-chosen alternatives do not register delays. Finally, an alternative model was estimated using only travel time and alternative specific constants. The estimation results are two positive travel time parameters (car and PT) and two negative (walking and cycling), which correspond to the modal shares as function of travel time. Summarizing, these arguments explain the initially counterintuitive positive parameter values, but more research is needed to further underpin this finding.

The number of trips made on a day is not significantly related to the mode chosen. Previous findings suggest that if more trips are undertaken on a given day, the car will be preferred over, for example, PT (e.g. Bhat, 1997). Potentially, due to the high active mode share in the Netherlands our dataset does not confirm this relationship.

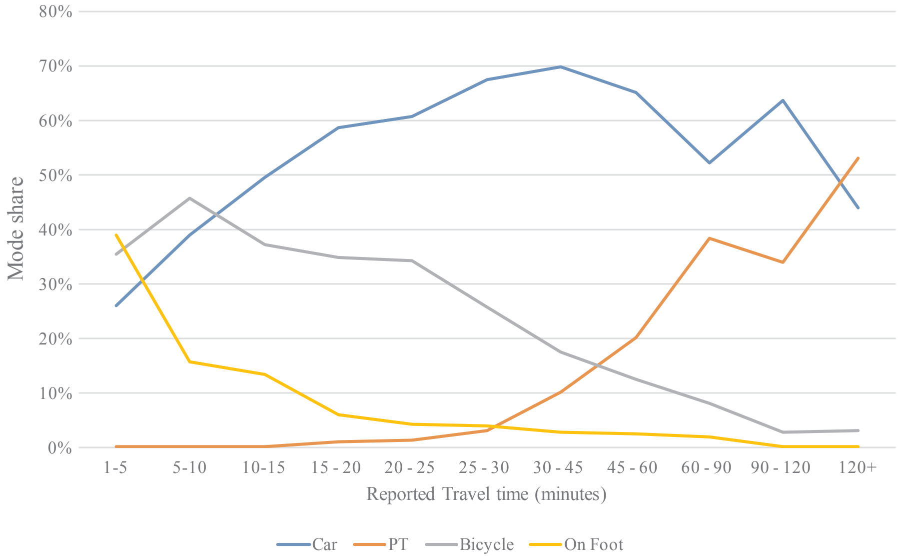

Fig. 2. Modal share per travel time category.

The moment of travel is not mentioned in the walking and cycling mode choice literature reviews. We find that it has an explanatory power for both walking and cycling. Weekday travel has a positive association with cycling, but is not significant for walking. This is is in line with findings from Denmark (Hansen and Nielsen, 2014). Peak hour travel relates negatively to walking, but does not relate to cycling. The latter might be due to time constraints (e.g. appointments or fixed work hours) for which walking is the least efficient mode in terms of speed.

The walking and cycling literature reviews also have not identified a relationship between the number of fellow travellers and mode choice. Our findings assert that for PT and cycling this relation is negative, whereas it is positive for walking. Hence, walking seems to be a good option when traveling in a larger group, but cycling and PT are less appreciated when traveling with other people.

Fraser and Lock (2010) mention that the bicycle is more frequently used for recreational trips than for other trip purposes. In this study we investigate four trip purposes: work, school, leisure, and shopping. All trip purposes are associated with mode choice. For cycling all trip purposes are significant and positive, with the the highest utilities obtained for school trips and leisure trips. For walking no effect is identified for the school trips and the largest positive impact for leisure trips. Consequently, we can conclude that for the Netherlands multiple trip purposes are positively associated with active mode use, other than only recreational trips.

5.1.6. Built environment

The respondents were asked about the presence of nature, street furniture, buildings and traffic related aspects in their neighborhood. The general body of literature has confirmed the relevance of these aspects regarding active mode choice (Heinen et al., 2010; Mitra, 2013; Handy et al., 2014; Fraser and Lock, 2010; Wang et al., 2016). Unlike previous studies, we do not find a relationship between nature and active modes for any of the tested elements (water, green, park). Note that we asked about the characteristics of the neighborhood not the trip itself, which is mostly mentioned in the literature. Regarding street furniture both garbage bins (positive) and playgrounds (negative) are correlated with active mode choice. The first is in line with literature, however the second contradicts it. Playgrounds are generally found to increase walking and cycling. These variables presumably capture variables that are not directly included in the data (proxy). Playgrounds are more frequently located in sub-urban residential areas, where distances to for example the city center are larger, consequently negatively correlated to walking. Playgrounds can also be used for walking around, which is mostly referred to in the literature, explaining the contradictory results found (Wang et al., 2016). In general, garbage bins are placed in areas where the streets are used as activity space, i.e. areas associated with a larger density of people passing by. Therefore, this variable could be positively associated with active mode choice. With respect to traffic related aspects, bicycle parking is significantly and positively correlated with walking. This relationship was previously identified for cycling, but not for walking (Winters et al., 2017; Heinen et al., 2010). Other traffic and infrastructure related aspects, such as cycle paths, traffic lights, and speed bumps for cars, do not exhibit explanatory power in this study. Previous research often emphasizes the need for infrastructure to boost active mode use (Heinen et al., 2010; Handy et al., 2014; Fraser and Lock, 2010; Mitra, 2013). In the Netherlands the density and continuity of active mode infrastructure is very high (Pucher and Buehler, 2008; Fishman, 2016). In line with these findings, previous bicycle route choice research in Amsterdam also identified no significant relationship with cycling infrastructure (Ton et al., 2017). Consequently, it is possible that in the Dutch context traffic related aspects are less important for mode choice compared to other countries. Finally, the presence of certain types of buildings (public buildings (e.g. library) and shops) is positively and significantly linked to the utility of the sustainable modes (PT, cycling and walking). This is in line with the literature, where mixed land use is described as one of the attractors of active mode use (Mitra, 2013; Wang et al., 2016; Winters et al., 2017; Fraser and Lock, 2010; Heinen et al., 2010; Muñoz et al., 2016).

Furthermore, the five largest urban agglomeration areas in the Netherlands are included in the model estimation. Residing in Rotterdam or Amsterdam contributes to explaining mode choice. Amsterdam exercises a positive parameter for walking. Especially the city center is inviting for walking as distances are short. Rotterdam has a negative parameter for cycling. It is a relatively car-oriented city, as it was reconstructed after the second world war (in the 70 s) when the car was booming. Consequently, it is deemed logical that people cycle less, everything else being equal, in Rotterdam as it is less attractive compared to other locations.

Previous research also mentions the importance of population density or urbanization level (Wang et al., 2016; Fraser and Lock, 2010; Muñoz et al., 2016; Heinen et al., 2010). We investigate a combination of these variables, as we measure the density of inhabitants per square kilometer at the municipality level. Consequently, the urban level reflects high population density, which is mostly found in larger cities. Small and medium sized cities are positively correlated with cycling (Heinen et al., 2010). In line with previous research, we find a positive suburban parameter for cycling.

5.1.7. Work conditions

Receiving a compensation for traveling to work for a certain mode increases the probability of choosing that mode. The effect of the compensation is most pronounced for PT and smallest for the bicycle. This is in line with previous research (Muñoz et al., 2016; Handy et al., 2014; Winters et al., 2017). Previous research also identifies cross-relationships, e.g. effect of car reimbursement on the use of bicycle (Handy et al., 2014; Winters et al., 2017), however we only investigate the direct relationship in this study.

Previous research suggests that part-time workers are more inclined to cycle compared to full-time workers (Heinen et al., 2010). In this study, we find no relationship between working hours and mode choice. This might be related to the fact that, unlike Heinen et al. (2010), we investigate all trips, not only commuting trips.

5.2. Model performance comparison

The MMNL model, which includes heterogeneity and panel effects, results in hte best performance (out of the three models) on all performance indicators identified in Section 4.3 (see Table 6). The MMNL model cannot be compared using the likelihood ratio test as some of the parameters in the MNL and Panel effect model were removed due to insignificant results. The removed parameters are BMI (bicycle), September and October (bicycle), number of trips (PT), sport center (bike), student (bicycle) and industrial area (walk). The model has a relatively high fit, which means that the mode choice behavior is explained rather accurately – 54% of the variation in choices observed - using the determinants included in the model estimation.

5.3. Conclusions on model estimation results

The most important findings of this study, that are contradicting the general body of literature are summarized here. These contradictions are often attributed to the context of the study, as most literature stems from countries with low cycling penetration (e.g. the USA). Consequently, it could be expected that different determinants influence the mode choice and that their impact differs.

Socio-demographics variables are found less important in explaining active mode choice compared to literature. We find no significant relationship between gender, age, and ethnicity and active mode use. Car and bicycle availability on household level do not influence mode choice, whereas the existing body of literature identifies this as an important variable. Having children is not significantly related to active mode use, whereas other studies suggest a negative relationship. Weather characteristics are not relevant for active mode choice, which contradicts the general body of literature. It could be due to the way we formulated the characteristics (experience of extreme weather), but it could also be that in the Netherlands, due to the mild climate with frequent rain, weather does not impact mode choice. Travel time has a positive association with cycling, which in comparison to the other modes could be explained by the relationship between modal shares in different travel time categories. We find that the travel group size and moment of travel are relevant for mode choice, which has not been identified insofar in the active mode literature. Active mode infrastructure was found to be of limited relevance in explaining active mode choice, whereas literature states this as important determinants for cycling and walking. Mixed land use is found important for active mode use.

Table 6
Performance indicators of estimated models (** = significant on 95% level).

	MNL	Panel effect	MMNL
Initial log likelihood	−6893.85	−6893.85	−6893.85
Final log likelihood	−3535.89	−3323.88	−3110.15
Parameters	61	64	60
Sample size	6368	6368	6368
Adjusted rho − square	0.478	0.509	0.540
BIC	7606.08	7208.35	6745.85
AIC	7193.78	6775.77	6340.31
Likelihood ratio test	–	424.02**	–

Table 7
Mean and range of influence of determinants on mode choice in terms of utility points (a = binary explanatory variable, – = not estimated).

	Car		PT		Bicycle		Walk	
	Mean	Range	Mean	Range	Mean	Range	Mean	Range
Individual characteristics								
Student[a]	–	–	0.0	[0.0,6.9]	–	–	–	–
High education[a]	–	–	–	–	0.0	[0.0,0.4]	–	–
Mode used – high school[a]	0.0	[0.0,2.0]	–	–	–	–	–	–
Mode used – last half year[a]	0.0	[0.0,2.1]	0.0	[0.0,7.9]	0.0	[0.0,2.2]	0.0	[0.0,3.0]
Transit subscription[a]	–	–	0.0	[0.0,10.8]	0.0	[0.0,0.5]	–	–
Company car[a]	–	–	–	–	0.0	[−3.2,0.0]	–	–
Household characteristics								
Household size	–	–	4.0	[2.0,17.8]	0.4	[0.2,1.9]	−0.9	[−4.1,−0.5]
No. children	–	–	0.0	[−20.1,0.0]	–	–	–	–
Medium household income[a]	–	–	–	–	–	–	0.0	[0.0,0.4]
High household income[a]	–	–	–	–	–	–	0.6	[0.0,0.6]
Season & weather characteristics								
September[a]	–	–	–	–	–	–	0.0	[0.0,1.0]
Trip characteristics								
Travel time	13.6	[0.0,213.4]	7.9	[0.0,109.9]	2.3	[0.0,15.3]	−5.5	[−56.4,0.0]
Weekday[a]	–	–	–	–	0.8	[0.0,0.8]	–	–
Peak hour departure[a]	–	–	–	–	–	–	0.0	[−0.6,0.0]
Travel group size	–	–	0.0	[−9.0,0.0]	0.0	[−4.1,0.0]	0.0	[0.0,2.4]
Leisure trip purpose[a]	–	–	–	–	0.0	[0.0,2.5]	0.0	[0.0,2.8]
Work trip purpose[a]	–	–	0.0	[0.0,6.5]	0.0	[0.0,2.3]	0.0	[0.0,2.1]
School trip purpose[a]	–	–	0.0	[0.0,10.8]	0.0	[0.0,5.1]	–	–
Shopping trip purpose[a]	–	–	–	–	0.0	[0.0,1.1]	0.0	[0.0,1.7]
Built environment								
Live in Amsterdam[a]	–	–	0.0	[0.0,6.0]	–	–	0.0	[0.0,2.2]
Live in Rotterdam[a]	–	–	–	–	0.0	[−1.0,0.0]	–	–
Live in Urban area[a]	–	–	4.6	[0.0,4.6]	–	–	–	–
Live in Suburban area[a]	–	–	–	–	0.0	[0.0,0.7]	–	–
Garbage bins[a]	–	–	–	–	0.7	[0.0,0.7]	0.9	[0.0,0.9]
Playgrounds[a]	–	–	–	–	–	–	−1.4	[−1.4,0.0]
Bicycle parking[a]	–	–	–	–	–	–	0.0	[0.0,0.8]
Shops[a]	–	–	–	–	0.6	[0.0,0.6]	1.0	[0.0,1.0]
Public buildings[a]	–	–	5.6	[0.0,5.6]	–	–	–	–
Hospitals/GP's[a]	–	–	–	–	−0.2	[−0.2,0.0]	–	–
Work conditions								
Travel compensation[a]	0.0	[0.0,1.3]	0.0	[0.0,17.6]	0.0	[0.0,1.0]	–	–

6. Discussion

This section addresses the relative importance of determinants, discusses their impact on walking and cycling, and reflects on their market shares.

The relative importance of mode choice determinants is displayed in the form of the mean and range of the product of a coefficient and the corresponding variable value. This enables the identification of where the potential lies for increasing the mode shares of walking and cycling. Table 7 presents the mean and range of influence of each determinant on mode choice in terms of utility points. The mean influence for a dummy variable depends on the number of cases in which the value is one, if this is more than half of the cases, the mean is set to one, otherwise it is set to zero. For example, the interpretation of the results displayed in Table 7 for the impact of transit subscription on bicycle choice is the following: the range of [0.0,0.5] means that either there is zero impact (absence of transit subscription) or the impact is 0.5 utility points (presence of transit subscription). Furthermore, the mean is zero implying that more than half of the population does not have a transit subscription and overall the impact is zero. In case of other (continuous) independent variables, such as the impact of household size on walking choice, the interpretation is the following: the range of [−4.1, −0.5] means that additional persons in the household influence the choice for walking negatively, where the potential impact ranges between −0.5 (1 person) and −4.1 (9 persons). On average the impact is −0.9, meaning that the average household size is just under two. The values reported in Table 7 can thus be used for comparing the importance of each variable with respect to other variables for each mode alternative.

The parameters associated with PT are all relatively high in comparison to the other modes. These high parameters are needed to compensate for the very low alternative specific constant (-46.30) so that it becomes attractive for certain trips and individuals. Most likely, this is the result of the very low share of PT in the sample (5.3%), which makes higher coefficients necessary. Consequently, the determinants that are related to PT have a high mean and range of impact on the PT choice. Potentially, studies investigating mode choice in a car and PT rich environment will find different results for the PT parameters, compared to our study in a context dominated by car and bicycle travel.

Travel time is the most dominant determinant, given all determinants of all modes. The range of travel times for car and PT are larger compared to the active modes, due to their dominant role in long distance travel. This means that the range of impact for these modes is also higher. The impact on cycling and walking is comparable in size, albeit with different parameter signs. Almost all studies on active mode choice take distance or travel time into account (Mitra, 2013; Handy et al., 2014; Winters et al., 2017; Fraser and Lock, 2010; Heinen et al., 2010; Muñoz et al., 2016). Most studies focus on distance, but as we have mentioned before, distance and travel time are highly correlated and should not be included simultaneously. Often, distance and travel time are related to built environment characteristics, such as mixing of land use and population density. Consequently, our finding of travel time being the most dominant determinant is in line with the general body of literature.

The impact of determinants on active modes is generally comparable in size, albeit each mode is influenced by a different set of determinants. Very often, in literature, either cycling or walking is investigated (Heinen et al., 2010; Handy et al., 2014; Muñoz et al., 2016; Fraser and Lock, 2010; Buehler and Dill, 2016) or cycling and walking are treated as being very similar (e.g. active mode travel or physical activity) (Winters et al., 2017; Mitra, 2013; Wang et al., 2016). Importantly, this study shows that walking and cycling are influenced by different determinants. Consequently, in policy development it is wise to separate both modes, as otherwise the desired effect might not be reached. In model estimation, this means that both the active modes should be distinguished. When going into more detail in the categories of determinants that influence each mode, we see that the impact of individual characteristics is much stronger for cycling than for walking. Although literature assigns more importance to the individual characteristics, compared to our findings (Heinen et al., 2010; Handy et al., 2014). Moreover, household characteristics are more important in explaining the choice to walk than to cycle. Consequently, it is deemed plausible that the cycling literature reviews did not find household characteristics to be bicycle choice determinants (Heinen et al., 2010; Fraser and Lock, 2010; Handy et al., 2014; Muñoz et al., 2016). Trip characteristics influence both walking and cycling, and we find similar impact sizes. Only trip purpose affects cycling more than walking, as more trip purposes seem to be relevant for cycling. Finally, even though different characteristics related to the built environment influence walking and cycling, the overall impact seems comparable in size.

The categories of determinants that have the largest influence on cycling are trip characteristics, individual characteristics and built environment. For walking, the respective categories are trip characteristics, built environment and household characteristics. Consequently, policy measures aimed at increasing the level of walking and cycling are most likely to influence modal usage by targeting trip characteristics. Directly targeting trip characteristics is unfortunately not possible. However, based on our findings, investing in a more livable built environment may benefit active modes too. For example, by creating a mixed land-use environment with residential and recreational areas, which are equipped with street furniture. Finally, the individual and household characteristics cannot be influenced by means of active mode policy. However, they can provide insight into which segments of the population to target, for example large families or people with high education, which are most prone to response to changes in cycling and walking attributes. The two categories of determinants that have the most limited effect on active mode choice are season and weather characteristics and the work conditions. However, this could be due to the way we define these characteristics and may differ in contexts which exhibit conditions that are not prevalent in the Dutch context (Böcker et al., 2013; Heinen et al., 2010; Muñoz et al., 2016).

When calculating the impact of altering some of the variables (e.g. as the result of policy measures or campaigns) on the market shares, we see that the trade-off is mostly between the car and active modes. PT shares remain consistently low. The base scenario for this population predicts the following market shares: 44.8% car choice, 1.6% PT choice, 43.5% bicycle choice, and 10.0% walking choice. When altering variables, these shares change. As a first example, if everyone would get a company car, all else being equal, the market shares of the car and walking would increase by 13.5% and 7.8% respectively, while it would reduce the share of cycling by 21.3% and not affect PT use. If, as a second example, everyone would be reimbursed for cycling to work, all else being the same, the market shares would change as follows: the share of the car and walking would decrease by 4.1% and 2.2% respectively, while increasing the bicycle share by 6.3% and again no effect on the PT share. A third example is providing a transit subscription for everyone, all else being the same. The market share for PT remains again unaffected. The bicycle share increases by 2.8%, while the share of the car and walking decrease by respectively 1.9% and 0.9%. Winters et al. (2017) state that literature suggests that promoting PT results in higher bicycle share, which is confirmed in this exercise. These market share calculations suggest that the car and walking act as complementary modes, whereas the car and bicycle are competing modes. Literature often finds that the car and PT are competitors (e.g. Ye et al., 2007). Braun et al. (2016) find that providing incentives not to use the car to work increases PT use instead of active mode use. These studies originate from countries with low bicycle shares, consequently the two modes with the highest market shares are the car and PT, making them competitors. This also shows that policy measures and incentives, taken from studies in low bicycle countries or cities, cannot be directly transferred to other contexts, such as the Netherlands.

7. Conclusions and future research directions

This paper presents the findings of a mode choice model for the Netherlands, focusing on active modes while including a more comprehensive set of modes (i.e. car, public transport, bicycle, walk), aimed at understanding the determinants of choosing a mode in relation to the other modes. The Netherlands has a very high active mode penetration, a safe environment for walking and cycling, mature and complete active mode infrastructure, and a demographically diverse population of active mode users (Fishman, 2016). Consequently, investigating mode choice in the Netherlands can enrich active mode choice literature, which mostly refers to contexts where cyclying is an uncommon mode of transport. We compared our findings in terms of the determinants of influence on active mode choice and their relative importance. Choice models were estimated based on travel diary and survey data of the Netherlands Mobility Panel enhanced with a survey that addressed, among other things, the built environment (coined PAW-AM) comprising of 6368 trips performed by 1874 individuals in the year 2016.

Based on a review of the literature on the determinants that influence active mode choice, a total of six categories of determinants were identified: individual characteristics, household characteristics, season and weather characteristics, trip characteristics, built environment and work conditions. In line with previous studies, our findings suggest that determinants belonging to all categories are relevant for explaining modal choices while the extent of their influence varies for the different modes. Contrary to the existing body of literature, we find that the socio-demographic determinants are less important in explaining active mode choice. We do not find significant relationships for gender, age, and ethnicity. This most likely stems from the diverse cycling population in the Netherlands, whereas in other countries young males are most likely to cycle (Heinen et al., 2010; Fishman, 2016). Furthermore, we find that weather is a less important determinant than suggested in the literature. While previous research reported that rain, high and low temperatures, and hot and cold climates negatively affect active mode use, we do not find a significant relationship between weather and active mode use. This might be due to the definition of our weather variables (e.g. perceived extreme weather), however even the extreme weather does not seem to affect Dutch active mode users. Finally, we conclude that active mode infrastructure, such as bicycle paths, does not influence active mode choice. This contradicts the main body of literature, however given that the active mode infrastructure in the Netherlands is already mature and complete (Fishman, 2016), it is possible that this does not anymore affect the choice among travel alternatives.

Even though all categories of determinants are included in this research, not all potential explanatory variables are included in this study. Especially, determinants related to the work conditions could be enriched in future studies. Furthermore, determinants that are related to the social surroundings of individuals, thus opinions/attitudes and behavior of the people around the individual, could be investigated, as previous research has showed the potential of these factors (Heinen et al., 2010; Muñoz et al., 2016). However, if attitudes and opinions are included, different models need to be estimated that can accommodate subjective variables (such as hybrid models (Vij and Walker, 2016)). Furthermore, the built environment is now related to the neighborhood of the respondent. This could be enriched with information about the neighborhood of the destination or along the trip.

In most mode choice studies walking and cycling are conjoined. In this study, the presence of an active mode nest was investigated, which represents correlations between modes, suggesting a hierarchical choice structure. No such structure could be identified. Furthermore, the determinants that influence walking and cycling are distinctive. The individual characteristics mostly affect cycling, whereas the household characteristics mostly influence walking. Roughly the same trip characteristics influence both active modes, however their overall impact is different. Besides, regarding the built environment both active modes are influenced, but by different determinants. Both the absence of an active mode nest and the identification of different parameters for walking and cycling suggest that cycling and walking should be considered and treated as two independent alternatives.

From a policy perspective, several of the categories of determinants can be directly or indirectly influenced. If the goal is to stimulate the use of active modes, the trip characteristics and built environment are the most relevant categories. The trip characteristics can only be influenced indirectly. For example, by adapting the infrastructure in such a way that travel time savings are generated (e.g. more crossing locations for pedestrians, so that waiting time is reduced; more passages for pedestrians between street blocks, reducing walking distances, especially in sub-urban areas). The built environment can be influenced directly, for example by creating mixed land use environment where residential and recreational areas are combined, which are equipped with street furniture. Because walking and cycling are influenced by different determinants, different policy measures might be needed to influence each of the modes. Consequently, targeting active modes might not provide the desired result. Furthermore, this study suggests that the car and bicycle are competitors, whereas in countries where cycling is uncommon, it is likely that the car and public transport are competitors. Transferring the results to other countries should thus be done with care, also because both this study and the already existing body of active mode choice literature suggest that different determinants are important and to a different extent, for countries with low and high bicycle mode shares.

From a modelling perspective, the use of revealed preference data seems promising, given the results that show that there is sufficient variability in the data (otherwise more parameters would have been insignificant). Furthermore, individuals show clear preferences towards modes that are influencing their decision (homogeneity of choice within the individual) based on the panel effect estimates. Finally, the mixed multinomial logit model shows a significant improvement compared to the most commonly used multinomial model, allowing to capture taste heterogeneity towards determinants.

Additional future research directions entail collecting longitudinal data for all identified determinants, so that the causal relationship can be identified. This helps policy-makers by ensuring that investments are most impactful in achieving policy goals. Moreover, longitudinal data can be instrumental in modelling more explicitly how previous experiences with each mode influence current behavior, e.g. by using Markov chains, which capture the dependency towards previous choices. Next to that, the inclusion of a cost variable in the model could help understand trade-offs between modes in monetary terms. Furthermore, this study only covers trips consisting of a single mode. For a better and more complete picture of the entire mode set also multimodal trips should be included.

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