Fietsen naar de tramhalte: simultane modellering van voortransport- en haltekeuze

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Samenvatting

Wereldwijd wordt er gestuurd op een toename van duurzame vervoerkeuzes voor een betere leefbaarheid en bereikbaarheid. Vooral in de steden waar de samenleving groeit en de dichtheden groter worden is een verandering in kijk op de mobiliteit noodzakelijk om de burgers tevreden te stellen. De integratie van fiets en openbaar vervoer (OV) kan hier aan bijdragen. Wanneer de fiets wordt gebruikt als voortransportmiddel wordt het invloedsgebied van het OV vergroot ten opzichte van lopen waarmee het een beter alternatief wordt voor niet-duurzame vervoermiddelen.

Om de combinatie fiets en OV te vergroten zullen effectieve klantgerichte maatregelen genomen moeten worden. Hiervoor is meer inzicht nodig is de factoren die een rol spelen bij de keuzes voor voortransportmiddel en halte. Hier is tot op heden nog weinig over bekend op het stedelijk niveau. Door de keuzes in één onderzoek te combineren wordt de afweging duidelijk tussen het voortransportmiddel en de OV-reis, en kunnen de effecten op het invloedsgebied van het OV bepaald worden. Dit is gedaan op basis van data van HTM-tramreizigers in Den Haag middels een simultaan discreet keuzemodel van voortransportmiddel en halte keuze.

Resultaten geven aan dat reizigers in het algemeen liever lopen dan fietsen naar de tramhalte. Daartegenover staat dat de afstand naar de tramhalte lopend 2,1 keer zwaarder weegt dan als men fietst. Dat betekent dat bij een langere afstand fietsen aantrekkelijker wordt dan wandelen. Frequente fietsers zijn meer geneigd om ook naar de tramhalte te fietsen, terwijl frequente tramreizigers juist minder vaak fietsen naar de tram. De aanwezigheid van fietsparkeervoorzieningen vergroot het invloedsgebied van een tramhalte, maar de grootste impact op het invloedsgebied van fietsers is de OV-reistijd. Verbeteringen aan het OV-systeem, zoals minder haltes en/of hogere frequenties kunnen dan ook zorgen voor een groter geaccepteerde fietsafstand (fietskeuze) tot de halte.

Op basis van deze resultaten lijkt het mogelijk de fiets-OV combinatie ook op stedelijk niveau te stimuleren. Hierdoor kan duurzame mobiliteit op stedelijk niveau betere concurrentie bieden aan de auto, wat lijdt tot een aantrekkelijkere en beter leefbare stad.

1. Introduction

Governments worldwide are aiming for an increase in sustainable mode use, i.e. transit, walking, and cycling [1]. When trips with these modes replace car trips, they can reduce emissions and congestion and positively impact health. Integration of bicycle and transit can increase catchment areas of transit compared to walking [2], [3]. The mass capacity of transit can be supplemented by the flexibility and efficient space-use of bicycles. This integration could provide better competition to the car and with that increase sustainability, livability and accessibility of urban areas. Effective measures, that improve the integration, need to be implemented to increase the use of the bicycle-transit combination. Two key questions arise when investigating the bicycle-transit combination; (i) which station do individuals use for entering the transit system? and (ii) when do they cycle to access the station? Understanding which factors influence the station and access mode choice in relation to the bicycle-transit combination can serve as valuable input for these measures.

Increasingly studies investigate these questions, where several classes of factors influencing the access mode and/or station choice are identified [4], [5]. Individual variables, such as age, gender, and income have been found to influence the access mode choice. Characteristics of the station, such as service quality, parking facilities, and geographical location, as well as characteristics of the access journey are found to influence both choice dimensions. And finally, characteristics of the transit journey have been found to influence station choice.

Most studies have investigated either access mode [6], [7] or station choice [8], [9]. However, studying the combination of these choice dimensions could shed a light on important trade-offs that cannot be captured otherwise. Few studies have investigated this combination [10]–[15], where a variety of access modes has been investigated, such as walking, cycling, transit, and car (driver or passenger). These studies all cover train stations, which is a transit mode generally used at the regional/national level. At the urban level, the combination has not yet been studied, even though the modal share of the bicycle is known to be lower [16], [17]. Furthermore, the access distance of the bicycle to the train is found to be significantly higher than urban transit systems [17], [18]. Hence, the question rises which factors influence the combined choice at the urban level and how does this differ from the national/regional level.

The objective of this study is to identify the factors influencing access mode and station choice at the urban level. By accommodating both choice dimensions, the trade-offs between the access and transit journey can be investigated. Travel behavior data is collected in the city of The Hague, Netherlands, one of the major cities in the country, which is characterized by a fairly dense tram-line network. Using discrete choice models, we investigate which factors are relevant for the combined choice of access mode and tram station, accounting for socio-economic, station, tram journey, and access journey characteristics. In this study the destination is treated as given, to focus on the trade-offs between access journey and transit journey. The station choice set, that serves as input for the choice model, is defined for each individual, by first identifying all stations within a certain radius from their home and then applying elimination-by-aspects to reduce the choice set to the consideration choice set. The access mode choice set is limited to the most common access modes at the urban level in the Netherlands (i.e. walking and cycling) [19].

This study contributes to the state-of-the-art by investigating, for the first time, the joint access mode-transit station combination at the urban level. We present trade-offs between access journey and transit journey for each access mode and discuss the willingness to cycle to a station further away. The results of this research provide insights into behavior of transit passengers at the urban level, which may be used to design measures aiming to increase the use of bicycle as access mode to stations. Furthermore, this research provides input for planning and design of urban transit stops.

The remainder of the paper is organized as follows. Section 2 details the methodology for identifying the choice set and modelling the joint access mode and tram station choice. In Section 3, the data collection and preparation is described. The results of the choice set generation and discrete choice models are reported and discussed in Section 4. Finally, Section 5 concludes the paper.

2. Methodology

This section discusses the methodology for modelling the joint access mode and tram station choice. First, the set of alternatives considered by individuals needs to be defined. Choice set identification is an important step, especially, where the number of feasible options is considerably large as is the case with station alternatives in urban transit networks. The set of access modes for urban transit is limited (i.e. walking and cycling). In the choice set identification phase, the two choice dimensions are treated separately. The focus in this section is on identifying the subset of access stations that are in individuals' consideration sets (2.1). Afterwards, the approach towards modelling the joint access mode and station choice is discussed (2.2).

2.1 Identifying the Tram Station Choice Set

Whenever the number of alternatives is large, it is hypothesized that individuals are likely to apply simple heuristic decision rules to first form their consideration set before performing a comprehensive evaluation to arrive at their final choice [20]. Such rules are typically non-compensatory, wherein constraints are applied on individual attributes of alternatives rather than accounting for trade-offs between attributes. Common non-compensatory decision models include disjunctive/conjunctive, lexicographic, and elimination-by-aspects (EBA). EBA models, which are applied in this study, combine parts of the former two models and use both attribute-ranking and threshold specification. Starting with the most important attribute, all alternatives not satisfying its threshold are eliminated and this is repeated until all attributes are exhausted. Although originally proposed as a probabilistic model [21], most choice set generation applications apply EBA as a deterministic model [20]. This study uses the calibration methodology proposed in Shelat et al. [22] (although slightly adjusted), to avoid having to assume behavioral parameters, that is, attribute ranking and thresholds, of the EBA model.

This study applies EBA such that the parameters remain constant over time and across different individuals, and the model not require assumptions regarding the choice set size. A threshold is estimated that identifies the maximum value of each attribute in the final choice set (S_n^i) relative to the smallest value of that attribute in the master choice set (MS_n^i, see Figure 1). Note that MS_n^i for individuals are not necessarily disjoint, implying that individuals can have the same stations in their set. Thus, while the threshold parameters are constant, their dependency on MS_n^i may result in variation of final threshold values across individuals or over time. The behavioral parameters are calibrated by comparing all feasible alternatives against observed choices and optimizing the balance between the efficiency with which unobserved alternatives are excluded and the coverage of observed choices.

Thus, to identify S_n^i for each individual, first, MS_n^i consisting of all feasible access stations is identified by setting a maximum threshold distance Z from their home locations. Next, attributes required for the EBA model are obtained. Finally, the EBA model is calibrated and applied to identify all origin stations considered by individuals for their respective destination stations, as explained below.

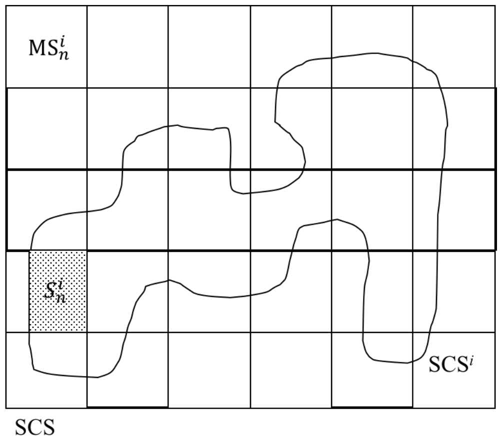

Figure 1: Visualization of the different choice sets

Trip attributes

Attributes input to the EBA model can be from different parts of the journey, because are all likely to be important for station choice. The following attributes are used for choice set identification: (i) Euclidian access distance, and (ii) total transit travel time and (iii) number of transfers associated with the transit trip. While the above attributes are important for consideration set formation, there likely are other attributes that are relevant in the final evaluation. Therefore, alternatives dominated for these three attributes are not removed to avoid placing extra behavioral restrictions on the choice analysis.

For the transit trip attributes, the general transit feed specification (GTFS) data associated with the network is used to generated different routes between stations using the same procedure as in [22]. Individuals are allowed an egress trip of less than 200m between the destination station of the main trip and the observed destination station. The best routes between each pair of stations are selected as those that perform best on the total transit time and number of transfers; the main trip attributes are obtained from these best routes.

EBA calibration

Combining the MS_n^i for all individuals, a super choice set (SCS) of all feasible origin station alternatives for all individuals is obtained. Alternatives in the SCS are uniquely identified by the individual and the origin station. Application of the EBA model will eliminate certain alternatives from the SCS, resulting in the identification of a subset: the identified super choice set (SCS^i). The choice sets for individuals whose observed choices remain in this subset can be used in the subsequent choice modelling step.

As mentioned before, the EBA calibration involves optimizing the balance between two indicators, (i) coverage – the proportion of observed choices in the SCS^i, and (ii) efficiency – the proportion of unobserved but feasible alternatives excluded from the SCS^i.

When the SCS^i is the same as the SCS, coverage is one while efficiency is zero. Depending on the data, the desired balance between these indicators may be different – this is controlled by the multiplier variable in the following indicator, which is minimized:

$$x = \text{multiplier} \times coverage - efficiency \tag{1}$$

The calibration uses a straightforward brute force optimization algorithm that tries all possible attribute ranking permutations and attribute thresholds from a pre-defined search space [22]. For each permutation, the first ranked (i.e., most important) attribute is selected, the threshold minimizing x for that attribute is obtained, alternatives not satisfying the threshold are eliminated, and this is repeated sequentially until all attributes are exhausted. At the end of this process, each attribute ranking permutation is associated with a set of attribute thresholds and, thus, an SCS^i. Amongst, the different SCS$^{i'}$s obtained, the one that has the smallest value for the optimization indicator, x, over the whole set is selected. For each individual n the final station choice set S_n^i is defined, which is access mode independent.

2.2 Joint Choice Model Specification

The joint choice is modelled using discrete choice modeling. An alternative consists of an access mode and a station, given destination station d. The stations (S_n^i) are identified using the EBA methodology. As mentioned before, two modes (M_n) are considered available, i.e. walk and bicycle, as these are most prevalent at the urban level [17]. The total choice set for each individual n is defined as follows [23]:

$$C_n = S_n^i \times M_n, \text{ where } S_n^i = \{s_1, s_2 \ldots s_{[S]}\} \text{ and } M_n = \{m_{\text{bicycle}}, m_{\text{walk}}\} \tag{2}$$

where C_n is the set of simultaneous mode and station alternatives. The total utility of the joint choice is composed of a systematic (observed) and random (unobserved) component for each individual n (which we omit from the formulation in the remainder for reasons of clarity). In the joint choice between access mode and tram station choice several characteristics are identified that influence only one choice dimension, whereas others influence both. Together these characteristics compose the systematic component of the utility. We tested two models, MNL and Nested Logit (NL). In the first, the assumption is that an unobserved component is present for the joint choice, but this is not the case for each individual dimension. In the latter, additionally an unobserved component is present that relates to either of the individual choice dimensions. The NL specifications did not benefit the explanatory power of the model, suggesting that no unobserved component related to individual choice dimensions is present in the dataset. The total utility function of the MNL model is defined as:

$$U_{sm} = V_s + V_m + V_{sm} + \varepsilon_{sm} \quad \forall (s, m) \in C_n \tag{3}$$

where V_{sn} is the systematic utility that is common for station s and individual n, V_{mn} represents the systematic utility for mode m and individual n, and V_{smn} represents the joint utility for both station s and mode m. The joint probability for choosing an access mode and station is defined as:

$$P(s, m) = \frac{e^{V_s + V_m + V_{sm}}}{\sum_{(s', m') \in C_n} e^{V_{s'} + V_{m'} + V_{s'm'}}} \tag{4}$$

which is also called joint logit [23].

Each of the systematic utility components consists of observed characteristics related to (a combination of) the individual, aspects of the trip, and the tram station. The systematic utility function related to the access mode is specified the following way:

$$V_b = \beta_b + \beta_s * \text{socio} + \beta_r * \text{region} + \beta_m * \text{general mode use} + \beta_p * \text{trip purpose} \tag{5}$$

$$V_w = 0 \tag{6}$$

where walking is the reference. The choice for access mode is expected to depend on the socio-demographics, region, general mode use that is relevant to the choice (in this case the tram and bicycle use), and the purpose of the trip. Furthermore, a mode specific constant captures the preferences that cannot be captured with the variables mentioned. The systematic utility for tram station choice is defined as follows:

$$V_{station_s} = \beta_s * \text{station}_s + \beta_t * \text{tram journey}_s \tag{7}$$

where the choice for tram station s, which is unlabeled, is expected to depend on station characteristics and tram journey characteristics. The joint access mode and station utility is defined as follows:

$$V_{b\ station_s} = \beta_{ba} * \text{access journey}_{bs} + \beta_{bp} * \text{bicycle parking}_{bs} \tag{8}$$

$$V_{w\ station_s} = \beta_{wa} * \text{access journey}_{ws} \tag{9}$$

where the joint station and access mode utility is expected to be depended on the access journey characteristics and in case of the bicycle also bicycle parking options. The model is estimated iteratively with the aim of finding the best performing model in terms of final log-likelihood, adjusted rho-square, AIC, and BIC. The models are estimated using PythonBiogeme [24].

3. Data collection and preparation

The Hague is the third-largest city of The Netherlands. The modal split of trips within the municipality of The Hague is as follows: 36% car, 13% transit, 21% bicycle and 30% walking [25]. The municipality states that they are committed to a growth in the number of bicycle trips by 25% in 2030 and by 50% in 2040 [26]. More space will be accommodated for the bicycle and better transfer options with transit are created, including bicycle facilities at stops [27]. Furthermore, transit use is expected to increase further in the coming years. With the system running almost at its maximum capacity, other options to expand are being investigated. Increasing the capacity of transit will come at high costs, while better integration with cycling serves as a sustainable and (cost-)efficient alternative. In this section, the data collection method and final sample are discussed (3.1). Furthermore, the tram station and access mode characteristics identified for the joint model are presented (3.2).

3.1 Data Collection and Sample Characteristics

Data of the travel behavior of tram users is collected through a revealed preference survey, which was executed on-board tram lines in The Hague [2]. Different tram lines were targeted to ensure varying spatial and population characteristics. Respondents were asked to fill out a questionnaire containing questions about their current journey from origin to destination (including first station, last station and transfer points), general use of tram and bicycle, and individual characteristics. The questionnaires were distributed in April

2018. During the data collection period no extreme weather, tram disruptions or other major disturbances were encountered.

Nowadays, bicycles are available at both the home- and activity-end of a trip, with the increasing presence of shared-bicycle systems. However, during the data collection period these systems were not yet available in The Hague, therefore we focus on the *home-end* of the trip only, where the bicycle is considered available. The majority of the Dutch citizens owns one or more bicycles, therefore this seems a valid assumption [28]. A total of three filtering criteria were applied to the dataset of Rijsman et al. [2], being (i) the respondent has to live in the The Hague region, (ii) the access mode used is walking or cycling, and (iii) the information provided at the home-end needs to be reliable.

A total of 353 usable responses is collected for this research, which is reduced to 307 respondents by applying the EBA methodology. The characteristics of the final sample are shown in Table 1. The distribution of the ages of the respondents is representative for tram travelers in The Hague, as is the distribution of trip purposes. Regarding the tram use frequency, the individuals that travel 4-7 days/week are overrepresented in the sample [19]. The gender distribution is in line with the Dutch population [29]. Finally, the share of the population living outside The Hague (i.e. in Delft, Zoetermeer, or Rijswijk) is slightly overrepresented due to the tram lines that were targeted [19].

Table 1: Characteristics of the sample, journeys made, access modes used, and tram stations

Category	Description	Share	Category	Description	Mean/ Share	Std. Dev.
Socio-demographics	Male	48%	Trip purpose	School	25%	
	Female	52%		Work	32%	
	<=27 years	47%		Recreational	43%	
	28-40 years	20%				
	41-64 years	24%	Journey characteristics	in-vehicle time (min)	18.2	9.99
	65=< years	9%		waiting time (min)	5.7	2.0
	Dutch	62%		transfers	0.06	0.23
	Non-Dutch	38%				
			Access modes			
Region of The Hague	Center	25%	Bicycle	Time (min)	5.5	3.7
	South	13%		Distance (km)	0.44	0.3
	North-East	15%	Walk	Time (min)	4.8	2.0
	West	20%		Distance (km)	1.36	0.64
	Other	28%				
			Station characteristics	Bicycle parking	0.5	0.5
Cycling frequency	4-7 days/week	34%		Access to train	0.06	0.23
	1-3 days/week	25%		Access to bus	0.41	0.49
	less than weekly	41%		Access to metro	0.04	0.2
Tram use frequency	4-7 days/week	53%		Access to (other) trams	0.54	0.5
	1-3 days/week	23%				
	less than weekly	24%				

3.2 Description of Explanatory Variables

The in-vehicle time for the observed trips is on average 18.2 minutes (Table 1), with 5.7 minutes of waiting time and a very limited number of transfers (maximum one). A total of 91.2% of the individuals walked to the tram station, the other 8.8% cycled. This means that the number of cyclists is in the sample is higher than the 5.8% in general [19]. Using the Google Directions API, the travel time and distance from the home location to the chosen and alternative tram stations is calculated, which differ per mode. The average travel times towards the chosen station are comparable for walking and cycling, the average distances are rather different. This confirms that the bicycle has a larger catchment area compared to walking [2], [3].

The station characteristics comprise of the presence of bicycle parking and the different multimodal hubs (train/metro/bus/tram). Bicycle parking is present at half of the 254 tram stations. Half of the stations have bicycle parking facilities, usually bicycle hoops. Only few stations are multimodal hubs, mostly bus/tram or tram/tram hubs (with other tramlines).

4. Results and discussion

The results of the choice set generation are described in 4.1. Access mode and station are considered separately in the choice set generation. Walking and cycling are considered available to each individual, whereas the EBA model is used to generate station choice sets. The merged choice sets are used in the model estimation. The results of the estimated models are discussed in relation to the literature in 4.2. Finally, in 4.3 willingness to cycle to the tram station further away is investigated.

4.1 Generated Choice Sets

The threshold distance Z is set to 3km, thus including all stations within that radius from their home location in MS_n^i. This threshold is chosen as all walking and nearly all cycling trips in the original dataset from Rijsman et al. [2] fall under this threshold. The median and 90th percentile sizes of MS_n^i are 46 and 95, respectively. These high values are expected given the relatively compact structure of The Hague and the fairly high density of its tram network (Figure 2).

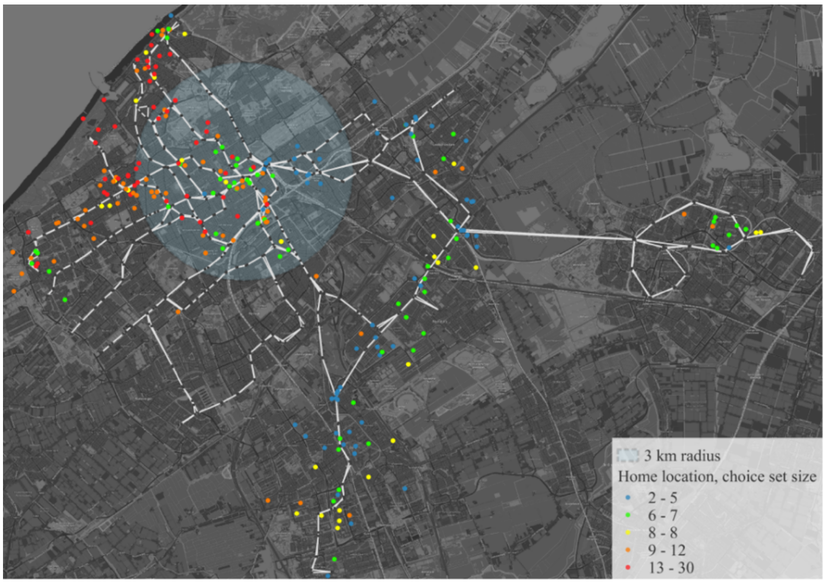

Figure 2: Tram network The Hague, home locations of all respondents and their final choice set sizes

EBA input parameters

To obtain the final choice sets, the EBA model is calibrated on access distance, total transit travel time, and number of transfers in transit. Unlike Shelat et al. [22], the threshold parameters indicate the maximum difference, rather than ratio, relative to the smallest value in MS_n^i. This is done because the latter proved to be too aggressive in the elimination of alternatives, possibly due to the variation in the smallest access distances and travel times across MS_n^i. Furthermore, since the number of observations is limited and the EBA inevitably loses some observations when balancing coverage against efficiency, the multiplier value in the optimization indicator (Eq. 1) is set to two in order to ensure a higher coverage.

EBA behavioral parameters

Calibration of the EBA model with the above settings, found that the most important attribute in the choice set formation procedure is transit travel time, followed by the number of transfers and the access distance. This indicates that travelers, on average, first eliminate stations based on transit trip characteristics, before removing those that do not match their access distance thresholds.

The search space for the threshold parameters ranged from zero to the highest possible value in the SCS and had an accuracy of one meter, one second, and one transfer for each attribute, respectively. On average, individuals accepted about 16 minutes additional travel time compared to the lowest travel time among their feasible alternatives. Given that the 3km radius used to generate MS_n^i, which often covers a significant part of the city, often the lowest transit travel time amongst feasible alternatives is rather low. Thus, a high threshold value is expected.

Regarding the number of transfers, individuals did not accept one more transfer than the minimum required. This strict constraint may have resulted from the fact that a large majority of trips in the network do not make a transfer at all. Including alternatives with extra transfers would drastically reduce the efficiency because it would introduce too many unobserved alternatives for trips with zero observed transfers.

Individuals consider stations up to 1.565km further than their nearest station. This value is greater than any of the observed maximum differences (the highest was 1.3km). Thus, it was used by the model to regulate the number of considered, but unobserved, alternatives in the choice set for the given multiplier value. For the above behavioral parameters, the observed (Figure 3a) median and 90th percentile access distances are 0.298km and 0.776km, respectively; whereas those for the maximum (Figure 3b) considered access distances in the choice set are 1.638km and 1.96km.

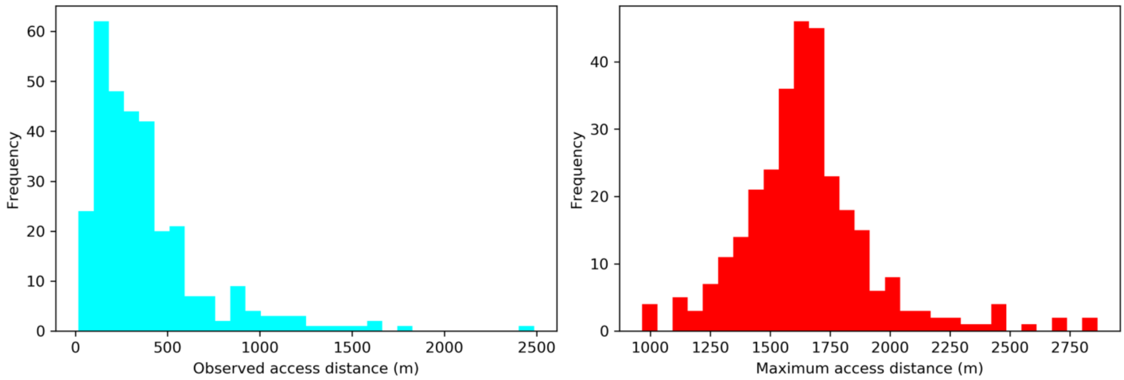

Figure 3: observed (a) and maximum access distance in the choice set (b)

Final choice sets

The final SCS^i contains observations of 308 individuals (out of 353 in the SCS) of which 307 had more than one alternative in their choice set and are therefore eligible for the subsequent choice modelling step. The median and 90th percentile sizes of S_n^i are 7 and 14, respectively. Figure 2 marks the choice set size on the home locations of the individuals. Although it also depends on the individual’s destination, the choice set sizes tend to be smaller in the regions where the tram network density is lower. To obtain the final joint choice set for each individual, the tram station S_n^i and access mode M_n sets are multiplied according to Eq. 2, resulting with a maximum choice set size C_n of 60 for the joint choice model.

4.2 Joint Tram Station and Access Mode Model

The joint model is estimated according to the specification in 2.2. The model is optimized by removing insignificant parameters up to the 90% confidence interval. Two models are presented, distinguishing mode-specific distance and mode-specific access time (Table 2). These two variables are highly correlated, consequently they cannot both be included simultaneously. Other studies investigating the joint choice e.g. [10], [15] include access distance, whereas studies related to time valuation in transit e.g. [30] include access time. To enable comparison, both models are presented, with other variables kept identical. The remainder of this section discusses the results of the estimated models.

Table 2: Estimation results of the joint tram station and access mode model.
****= significant on the 5% level, *=significant on the 10% level**

			MNL-time		MNL-distance	
Systematic Utility Components	Parameter	Levels	coef.	t-stat	coef.	t-stat
Access mode	Const. Bicycle		-5.21**	-6.14	-5.46**	-6.24
(Walking = ref.)	Const. Walk		0	-	0	-
	Age	=<40 years	0	-	0	-
		>40 years	-1.54*	-1.86	-1.65**	-2.22
	Bicycle use	4-7 days/week	1.53**	2.53	1.38**	2.51
		Less than 4 days/week	0	-	0	-
	Tram use	4-7 days/week	-1.29**	-2.12	-1.09**	-2.09
		Less than 4 days/week	0	-	0	-
Station	Access to bus	Yes	0.35*	1.87	0.37*	1.89
		No	0	-	0	-
	In-vehicle time		-0.22**	-3.67	-0.23**	-3.59
	Waiting time		-0.63**	-2.67	-0.66**	-2.76
Station	Bicycle parking	Yes	0.69	1.45	0.87*	1.83
+ Access mode		No	0	-	0	-
	Access time	Bicycle	-0.98**	-7.94	-	-
		Walk	-0.60**	-13.45	-	-
	Access distance	Bicycle	-	-	-3.71**	-8.56
		Walk	-	-	-7.86**	-13.20
Initial Log-Likelihood			-836.94		-836.94	
Final Log-Likelihood			-247.37		-244.63	
Adjusted Rho square (initial model)			0.692		0.696	
AIC			514.75		509.25	
BIC			552.02		546.52	
Number of observations			307		307	
Number of parameters			10		10	

Overall model fit

Of the two estimated models, MNL-distance has the best model fit based on all optimization criteria. Consequently, access distance has a higher explanatory power compared to access time. This finding most likely results from the fact that individuals are more willing to travel a similar time period for accessing the transit network using both modes compared to travelling a similar distance. By bicycle, with higher average speed, one can travel further in the same time period. The model fit of both models is very high, with 69%-70% of the behavior being explained by the eleven parameters included in the models. Most of the behavior can be explained by four parameters: in-vehicle time, waiting time, bicycle access distance or time, and walking access distance or time (55%-59%).

Access mode

The individual specific variables are estimated with walking as a reference. Generally, walking is preferred over cycling, as shown by the very negative constant for cycling. Gender and ethnicity do not have a significant association with access mode, which is in line with a study on general mode choice in the Netherlands [28]. Only one study into the joint choice has investigated individual characteristics [11]. However, their study investigates train stations in North America, where cycling is rare and car use is high. They found that males are less likely to use the car compared to females, preferring active modes instead. Related to age, the model shows that individuals over the age of 40 are less likely to cycle to the tram stop compared to younger individuals. Chakour and Eluru [11] also found a relation with age, however they found that individuals younger than 25 are less likely to use active modes compared to the car.

The general use of bicycle and tram influences the access mode choice of individuals. An individual cycling 4-7 days/week is more likely to also use the bicycle to access the transit network. On the other hand, when individuals travel by tram 4-7 days/week, their utility for cycling decreases. Thus, individuals that are most likely cycling to the tram station (looking at general mode use) are those who cycle frequently and use transit less than 4 days/week.

Tram station

Generic station characteristics and tram journey characteristics are investigated. The first are not very important in the choice model. Unlike train stations, tram stations generally are more basic and similar to one another. The presence of a train/tram or metro/tram hub did not significantly influence the tram station choice. However, a tram/bus hub is more attractive to individuals compared to stations that only serve trams.

The number of transfers is not included in the model estimation, as the EBA method used in choice set generation already excluded stations from which the number of transfers is higher than the minimum required on an origin-destination pair. This means that although the number of transfers may be relevant, the impact on the choice behavior cannot be quantified in this choice model. The in-vehicle time and waiting time of the transit journey are valued negatively, according to expectations. The value of waiting time is about 2.8 times the value of in-vehicle time. Another study on the tram-network of The Hague, found a value of 2.5 [30], suggesting that our model is sensible. In joint choice studies, these variables are often excluded. Some studies focus purely on the characteristics of the station and exclude the transit journey [10], [11]. Others do not include waiting time [12], [14] or have merged waiting time and in-vehicle time [15], retaining us from making the comparison with similar studies.

Station + Access mode

Stations that provide bicycle parking are more attractive for cyclists. Givoni and Rietveld [15] and Debrezion et al. [10] investigated the influence of bicycle parking facilities on the joint bicycle-train station choice, where they also found a positive relationship. The impact found here is stronger compared to Debrezion et al. [10]. Givoni and Rietveld [15] found that bicycle parking facilities that are perceived as having a higher quality have stronger impact on station choice. As we do not have information on the quality of the facilities, we do not know how it impacts the choice for the tram stations.

The access time of the bicycle is valued stronger than walking (1.6 times), which is expected because the bicycle can be chosen to optimize on time. This means that the trade-off values between access time and in-vehicle time and waiting time differ per access mode. For the bicycle, the trade-offs are such that access time is valued at 4.4 times in-vehicle time and 1.5 times waiting time. Whereas, for walking these trade-offs are respectively 2.7 and 0.97 times.

Regarding access distance, walking is valued 2.1 times as high as cycling, which could be due to the extra physical effort and lower speed related to walking. Givoni and Rietveld [15] found a value of 1.43 and Debrezion et al. [10] found a value of 2.3, both for accessing train stations in the Netherlands. This means that the value for trams in this study lies within the same range. On average cycling becomes more attractive than walking for distances of 1.31km or more (by including only the constant and distance).

4.3 Willingness to Cycle Further to the Station

Based on the model estimation (MNL-Distance), the willingness to cycle further to the station can be calculated for different characteristics of the tram station, individual, and transit journey (Figure 4). This provides information on their impact on the catchment areas of cyclists at the urban level, which extends the research by Rijsman et al. [2] on catchment areas. As the model is linear-in-parameters, the willingness to cycle further can be summed for different characteristics to find the combined impact on the catchment areas of cyclists.

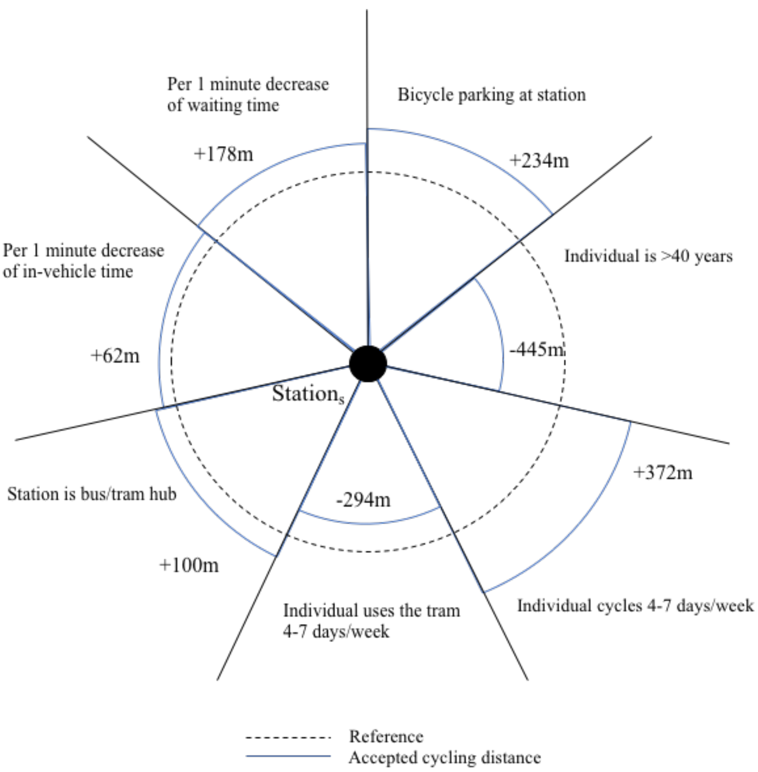

Figure 4: Willingness to cycle further to the tram station for different characteristics

A station that provides bicycle parking is more attractive to cyclists compared to stations that do not offer this, such that they are on average willing to cycle 234m more.

Consequently, catchment areas of a station can be increased when implementing bicycle parking. For a bus/tram station, a cyclist is willing to cycle 100m more. Consequently, if a bus/tram station would offer bicycle parking, a cyclist is willing to cycle 334m more.

An individual older than 40 is less willing to cycle compared to younger individuals, such that they will cycle 445m less. Consequently, if a neighborhood contains many individuals over the age of 40, the catchment areas of the stations in that neighborhood are lower compared to stations in other neighborhoods. An individual that cycles 4-7 days/week is willing to cycle 372m further compared to individuals that cycle less often, whereas high tram use has the opposite effect and reduces the cycling distance by 294m. An individual that uses both tram and bicycle often is willing to cycle 78m more than individuals that do not.

The effect of transit journey characteristics can have a large effect on the catchment area of cyclists. Per minute that their transit journey is shortened, via in-vehicle time or waiting time, an individual is willing to cycle on average, respectively, 62m and 178m further. This means that a reduction in transit time, can quickly increase the accepted cycling distance. If, for example, improvements are made towards LRT, where station density is reduced to increase travel speed and frequency, individuals are willing to cycle much longer distances.

5. Conclusions and recommendations

This paper presents the findings of a joint access mode and tram station model, applied on revealed preference data from The Hague, Netherlands, with the goal of identifying the factors relevant for the joint choice. By investigating the joint choice, trade-offs between the access journey and transit journey are calculated. Furthermore, the effects of these factors on the bicycle catchment area are investigated. Various studies have already investigated the joint choice between access mode and train station choice (national/regional level transit) [10]–[15], but this has never been investigated for the tram (urban level transit).

The joint choice is influenced by factors that are related to the access mode, the transit journey, and the combination of these. Our findings suggest that that choice for an access mode depends on individual characteristics and the general use of bicycle and tram. Age has the largest impact, followed by the general bicycle use frequency. Gender and ethnicity are not found to have a significant impact. The choice for a tram station depends on station and tram journey characteristics, where the latter are most important. The choice set generation model finds that individuals do not consider stations that result with more transfers than strictly required. The choice model results show that waiting time is judged more strictly compared to the in-vehicle time (2.8 times). The factors impacting both choice dimensions are the access journey characteristics and bicycle parking facilities. We find that walking distance is weighted more negatively than cycling distance (2.1 times).

The bicycle catchment area is influenced by all factors in the joint model. Via trade-offs the willingness to cycle further is investigated. Bicycle parking facilities increase the catchment area by 234m. Individual characteristics, which can be observed on neighborhood level largely impact the accepted distance, where older individual (40+) are accepting 445m less than younger individuals. The transit journey time (in-vehicle and waiting), has the largest impact on the willingness to cycle further. Improvements to the system, such as less stops/higher frequency (like LRT) result with a much higher accepted cycling distance. Consequently, catchment areas of tram stations can increase for cyclists when improvements are implemented to the station or transit journey.

Based on this study several recommendations for future research arise. This study was not able to identify the effect of the quality and quantity of bicycle parking facilities at urban transit stations on the joint choice. Understanding this effect could provide more insights into which facilities to provide at each station. Furthermore, we expect the bicycle-tram combination to compete with the bicycle on the urban level. It would be interesting to investigate what the trade-offs are between cycling for the entire trip and cycling to the tram station. Also, increasingly bicycle sharing systems are available, which means that an own bicycle is no longer required. This would affect when and where the bicycle can be used (both access and egress). These effects on the joint choice are not yet known, but would influence the facilities required for each station.

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