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Urban Planning (ISSN: 2183–7635)
2023, Volume 8, Issue 3, Pages 56–68
https://doi.org/10.17645/up.v8i3.6549

Article

Car Use: A Matter of Dependency or Choice? The Case of Commuting in Noord-Brabant

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Submitted: 30 November 2022 | Accepted: 17 March 2023 | Published: 25 July 2023

Abstract

Car use in the sprawled urban region of Noord-Brabant is above the Dutch average. Does this reflect car dependency due to the lack of competitive alternative modes? Or are there other factors at play, such as differences in preferences? This article aims to determine the nature of car use in the region and explore to what extent this reflects car dependency. The data, comprising 3,244 respondents was derived from two online questionnaires among employees from the High-Tech Campus (2018) and the TU/e-campus (2019) in Eindhoven. Travel times to work by car, public transport, cycling, and walking were calculated based on the respondents' residential location. Indicators for car dependency were developed using thresholds for maximum commuting times by bicycle and maximum travel time ratios between public transport and car. Based on these thresholds, approximately 40% of the respondents were categorised as car-dependent. Of the non-car-dependent respondents, 31% use the car for commuting. A binomial logit model revealed that higher residential densities and closer proximity to a railway station reduce the odds of car commuting. Travel time ratios also have a significant influence on the expected directions. Mode choice preferences (e.g., comfort, flexibility, etc.) also have a significant, and strong, impact. These results highlight the importance of combining hard (e.g., improvements in infrastructure or public transport provision) and soft (information and persuasion) measures to reduce car use and car dependency in commuting trips.

Keywords

built environment; car dependency; car use; infrastructure; Noord-Brabant; preferences

Issue

This article is part of the issue "Car Dependency and Urban Form" edited by Kobe Boussauw (Vrije Universiteit Brussel), Koos Fransen (Vrije Universiteit Brussel / Ghent University), and Enrica Papa (University of Westminster).

1. Introduction

Since Benz developed the first car in 1885, it has become the dominant mode of transport on our streets. In addition to the practical advantages for individuals such as speed and flexibility, cars are also considered a symbol of social status and identity and an enabler for economic growth (Alshammari et al., 2022; Lau, 2013). However, this individual freedom comes with a price of increasing negative externalities such as greenhouse gas emissions, congestion, air and noise pollution, social exclusion, and physical inactivity (Merom et al., 2018; Saeidizand et al., 2022; Van Wee, 2013). To counteract these negative externalities, governments have implemented policy measures to promote the use of sustainable transport and reduce car usage. However, moving away from the car system is no easy feat. This difficulty of moving away from a car-dominated system, for both individuals and society at large, is also referred to as "car dependency" (Mattioli et al., 2016). Car dependency is associated with elevated levels of car ownership and use, a lack of attractive sustainable transport alternatives, and a sprawling, decentralised, and unattractively built environment (Jeekel, 2013; Newman & Kenworthy, 1989; Saeidizand et al., 2022).

The extent to which people experience car dependency varies. At elevated levels of car dependency, a viable alternative for car use is not available. This structural car dependency is related to factors such as the lack of a supporting built environment and transport infrastructure for alternative modes. Research has shown that these two factors are strongly intertwined. Extensive car use goes hand in hand with the suburbanisation of residential neighbourhoods and the decentralisation of employment, amenities, and retail facilities. This in turn leads to the marginalisation and stigmatisation of sustainable transport modes which increases dependency on the car. These feedback mechanisms lead to a self-reinforcing cycle of car dependency (Litman & Burwell, 2006; Wegener & Fuerst, 2004). Previous studies also showed that the characteristics of the built environment have a significant effect on the extent and the share of car use, although results are mixed. The built environment indicators in these studies can be summarised under the 5 Ds: density, diversity, design, destination accessibility, and distance to public transport (hereafter PT; Ewing & Cervero, 2010). Overall, the accessibility indicators (e.g., distance to downtown, job accessibility by car/PT) proved to exert the strongest influence on travel behaviour. This is probably because accessibility integrates the potential proximity effects of other Ds such as density, diversity, and distance to PT (Ewing & Cervero, 2010). While most studies focused on the residential built environment, others also incorporated the characteristics of the employment locations. Results showed that the employment location and the multimodal accessibility and availability of free parking at these locations are important determinants of commuter modal choice (Maat & Timmermans, 2009; Vale et al., 2018; Wang et al., 2015).

In addition to structural factors, car dependency also stems from personal and household factors. For instance, dual-earner households with children may consciously choose to own one or more cars because they have to combine multiple activities and destinations in their daily schedule which requires speed, flexibility, and convenience (Mattioli et al., 2016). Furthermore, psychological factors such as car-oriented habits, perceptions, and attitudes can contribute to people's perceived level of car dependency and higher levels of car use (Anable, 2005; Gärling et al., 1998; Haustein & Hunecke, 2007; Schwanen et al., 2012; Van de Coevering et al., 2016). Importantly, characteristics of the transport network and transport-related attitudes also play a role in people's long- and medium-term life choices regarding their residential environment and work location. Due to the increase in travel speeds, people have reduced residential mobility and instead increased commuting distances (Beige & Axhausen, 2017; Cullen, 1978; Van Acker et al., 2010). In that sense, it can be argued that people make themselves car-dependent as they increasingly organise their lives around the car, slowly developing a car-oriented lifestyle over time (Van Acker & Witlox, 2010). Longitudinal analyses have also shown that (a) long- and medium-term choices regarding the residential environment and places of employment, (b) decisions around vehicle ownership and PT season tickets, and (c) daily choices regarding commuting are strongly intertwined (Beige & Axhausen, 2008).

While a rich body of literature has developed around the structural, personal, and psychological determinants of car use, fewer studies conducted a detailed assessment of the level and nature of car dependency on trip level (Mattioli et al., 2016). This study aims to contribute to the current knowledge by assessing the level of structural car dependency and determinants of car commuting among non-car dependent commuters towards two separate campus locations, the Campus of the Technical University of Eindhoven (TU/e-campus) and the High-Tech Campus Eindhoven (HTCe), in the Brainport region around Eindhoven in the Netherlands. We specifically aim to address the following research question: To what extent is car commuting towards the campus locations a matter of car dependency or choice, and what factors contribute to car use among non-car-dependent commuters?

This article uses the results of a questionnaire that was distributed among employees of businesses in both campus locations. It starts with an assessment of the level of car dependency. Different thresholds were used to distinguish between people that are structurally car-dependent (due to the lack of alternatives) and people that are not structurally car-dependent but use the car based on choice (related personal and psychological factors). Subsequently, bivariate descriptive analyses and binomial logit modelling are conducted for the non-car-dependent commuters to determine which factors contribute to their car use, including socio-demographics, mode choice preferences (comfort, flexibility, etc.), characteristics of the residential location, and the quality of different transport modes for the commute trip.

This article adds to the existing knowledge through the development of indicators for car dependency based on travel time ratios of PT and cycling times to car travel times. Travel time ratios have been used more often, especially in PT-related research, but there are few studies which incorporated travel time ratios for PT and cycling simultaneously. In addition, this study analyses the determinants of car commute choice for non-car-dependent commuters who have at least one viable alternative (PT or cycling) available. To date, few studies on commute mode choice took car dependency into account.

We start this article with a description of the questionnaire and the data. Subsequently, we will elaborate on the methods for determining the level of car dependency and the development of binomial regression models for car use. Thirdly, the results of the descriptive analysis and the logit models will be discussed. Finally, we will discuss the implications of research outcomes for policy.

2. Questionnaire and Data

2.1. Questionnaire

The data used for this research was derived from a self-administered online questionnaire that was conducted amongst employees of the TU/e-campus and HTCe in 2019 and 2018, respectively. The geographical location of the campuses and their characteristics differ considerably (Figure 1). The TU/e-campus (1) is located in the central part of Eindhoven and is close to the central railway station enabling an easy egress trip either on foot or by bicycle. The campus is also easily accessible by car, although roads in the city are prone to congestion. For employees, parking is available for a fixed fee of €2 per day. The HTCe (2) is located on the city fringe, next to the A2/A67 highway and has direct highway access. The campus is accessible by PT via a bus line that takes approximately 30 minutes from the central railway station. Parking is free. In line with the strong bicycle culture in the Netherlands, both campus locations have a high-quality bicycle infrastructure which enables safe and smooth accessibility.

The questionnaire was developed by Brabant Mobiliteitsnetwerk (BMN), a collaboration between regional road authorities and 260 companies, divided over 21 communities. BMN started in 2014 and aims to actively facilitate employers to promote behavioural change from car commuting to more sustainable modes of transport. A standardised survey was developed to offer leads to employers about effective access and mobility facilities, interventions and incentives, and the possibility to benchmark one with the other.

The questionnaire was divided into three main parts distinguishing home and work location data, mode choices, and socio-demographic control variables. In the first part, the mobility perspective was questioned, where the survey aimed to gain insights into home-work distances, travelling in peak hours, and flexibility in working hours. In the second part, respondents were asked about their current modal choice and were also asked to select three mode choice preferences that were important for this choice from a total list of eight factors including speed, flexibility, comfort, reliability, cost, health, weather conditions, and the environment. The third part of the questionnaire included questions regarding socio-demographics including gender and age.

2.2. Data About Transport and the Built Environment

To derive the travel distances and travel times per employee, the survey asked for the zip codes (four digits) of the home locations. Based on the home and work location of each employee, the fastest route was calculated using digital networks for car, bicycle, and PT. To distinguish car travel times with and without congestion, a distinction was made between on- and off-peak period networks using average observed car travel speeds per network segment. For cycling, network speeds and travel times were derived from empirical GPS cycling data from a national cycling incentive project (the National Bike Counting Week). Travel times for PT were based on the actual bus services, incorporating travel times, the number of transfers, and waiting times. For each employee, the fastest route between the home and work location was calculated using the different networks as input for the analyses, where the insights of multimodal travel times were combined with the main mode of transport stated in the survey.

The combination of the questionnaire data and the travel time data provided a unique dataset that enabled us to determine the level of structural car dependency and to develop a modal that explains why non-car-dependent commuters choose to use the car. In addition,

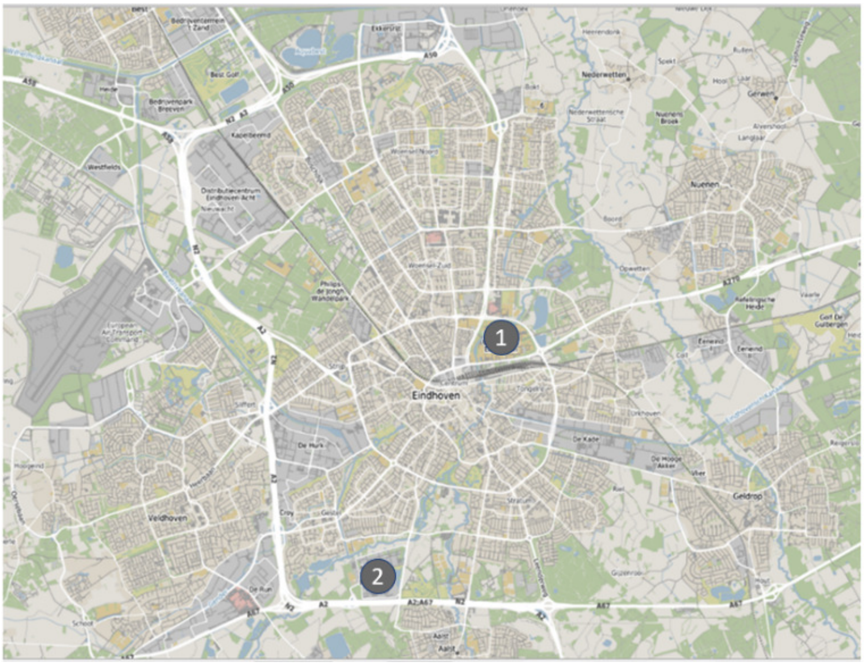

Figure 1. Campus locations.

characteristics of the respondents' residential location (PC4 level) were retrieved from Statistics Netherlands (CBS), including residential density, zonal car ownership, and distances to train stations and the main road (CBS, 2020).

2.3. Data Description

BMN distributed the questionnaires to the employees of the companies located at both campus locations. Unfortunately, we do not have detailed information about the response rates. However, generally, the response rates for the BMN questionnaires were high (averaging around 50%) as all companies are actively involved in the regional BMN community. After data cleaning, the total number of records in the combined dataset was 3,244. Around 40% of the respondents work at TU/e-campus and the remaining 60% are HTCe workers. Table 1 summarises the basic description of the dataset after data cleaning. It includes the basic demographic characteristics of respondents, information about their residence and work location, and travel modes for commuting.

As can be seen in Table 1, the majority of respondents are male. Due to the technical nature of the jobs on these two campuses, this is in line with expectations. Almost all the respondents are between 25 and 65 years old and evenly distributed in this range with a slight peak for the level of 45- to 55-year-olds. More than 75% of respondents work more than four days a week and can be categorised as full-time workers. Less than 10% of the sample are occasional workers with one or two working days. The majority of the respondents (54%) work at home at least once a week. The primary mode for commuting is the mode of travel that commuters often use for work trips. Besides the primary mode, some of them (60%

Table 1. Basic description of total respondents in the cleaned dataset (*N* = 3,244).

Variable	Level	Number	Share
Age (year)	Under 25	61	2%
	25 to 34	40	23%
	35 to 44	780	24%
	45 to 54	919	28%
	55 to 64	696	22%
	Over 65	48	1%
Gender	Male	2,214	68%
	Female	1,030	32%
Work location	TU/e-campus	1,321	41%
	HTCe	1,923	59%
Working days in a week	1	129	4%
	2	171	5%
	3	467	14%
	4	1,018	32%
	5	1,459	45%
Working from home	At least one day a week	1,742	54%
Primary mode for commuting	Car	1,570	48%
	PT	345	11%
	Bicycle	1,222	38%
	Walk	51	1%
	Other	56	2%
Secondary mode for commuting	Car	724	22%
	PT	467	15%
	Bicycle	530	16%
	Walk	126	4%
	Other	94	3%
	Non	1,303	40%
Urbanisation level of residence location (Density: Number of addresses per square km)	Extremely urban (>2,500)	779	24%
	Strongly urban (1,500–2,500)	888	28%
	Moderately urban (1,000–1,500)	649	20%
	Hardly urban (500–1,000)	660	20%
	Not urban (<500)	268	8%

of respondents) also use another mode for commuting, although less frequently. Two modes of car and bicycle form the major modes for commuting as primary as well as secondary modes. Nearly half of the sample uses the car as the primary mode for commuting, while 38% use a bicycle. PT, walking, and other modes are used less often. Except for the non-urban areas, the shares of urbanisation level of respondents' residence locations are quite evenly distributed over the other four categories with slightly higher shares in the higher urbanisation levels.

3. Methodology

The flow chart depicted in Figure 2 illustrates the analysis structure of this research. An important step in this research was identifying to what extent car use is a necessity and to what extent it is a matter of choice. We defined different indicators and thresholds to categorise the respondents into car-dependent and non-car-dependent commuters and conducted a sensitivity analysis to show the effect of different assumptions on the calculated level of structural car dependency. Based on the sensitivity analyses we chose a fixed set of indicators and thresholds and clustered commuters into the car-dependent and non-car-dependent groups. Based on these clusters, we used descriptive analyses and developed a binomial logit model to analyse which factors influence the choice for car commuting when viable sustainable alternatives are available. Next, we will elaborate on the measures of car dependency and the model structure.

The literature overview in the introduction showed that structural and personal factors affect people's level of car dependency. Our measure for car dependency focused on the structural part and specifically on the multimodal accessibility of the work locations in the form of travel time as described in Section 2.2. As shown in Table 1, car, bicycle, and PT are the main modes of commuting. For each respondent, the travel time by car is compared to the travel time by PT and bicycling. People are considered to be car-dependent if travel times of PT and bicycling are not competitive enough.

Two measures were defined to determine car dependency based on these three modes' travel times: acceptable cycling time (ACT) and PT/car travel time ratio (PTC ratio). For bicycling a maximum ACT was chosen as, due to the lower average speed, the bicycle is mainly a competitive option for relatively short commutes. For PT, a ratio between PT and car travel time was chosen as a basis for the indicator of car dependency as both travel modes allow for longer-distance commuting. When travel times for both modes are comparable (ratio = 1.0), commuters are distributed evenly over car and PT, but the share of PT users decreases rapidly as the PT/car travel time ratio increases (Van den Heuvel & Van Goeverden, 1993).

For the ACT and PTC ratio, cut-off values were selected to enable the allocation of respondents to the car-dependent and non-car-dependent commuter groups. To arrive at a well-considered choice, a sensitivity analysis was conducted. Figure 3 shows the relationship between the values for the ACT and the PTC ratio and the resulting number of car-dependent commuters. For both measures, the line represents the effects of different values assuming that the other measure remains constant (ACT = 25 minutes and PTC ratio = 2). The graph reveals that the number of car-dependent commuters strongly depends on the selected thresholds. An ACT of

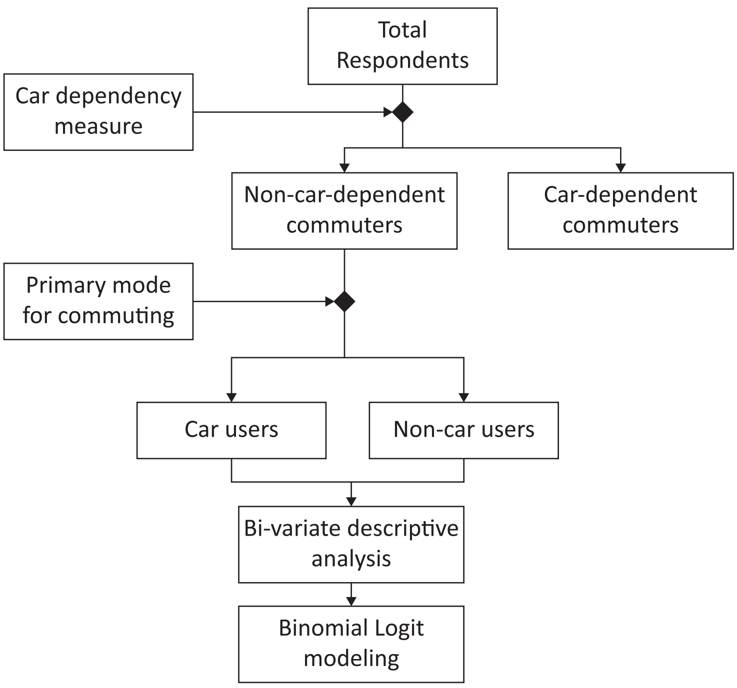

Figure 2. Analysis structure and respondent classification.

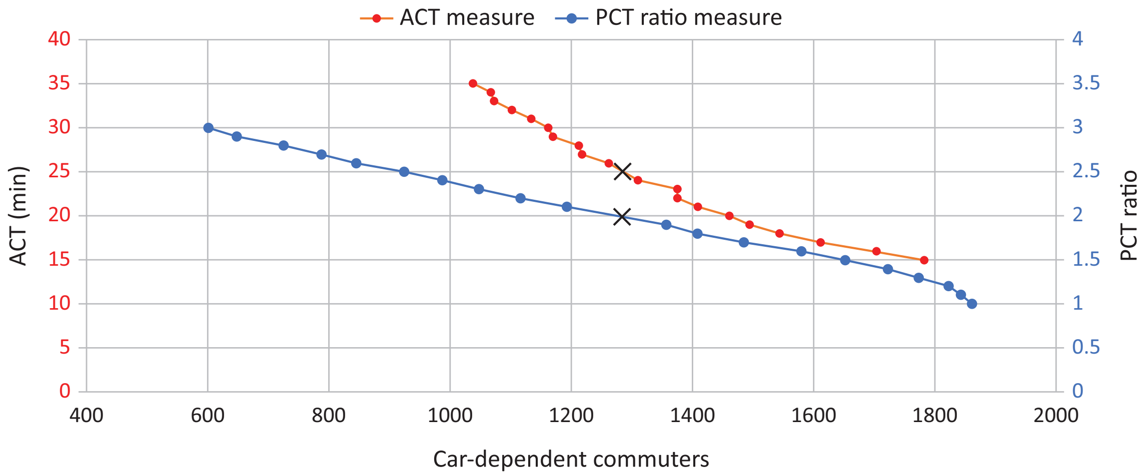

Figure 3. ACT and PCT ratio effects on the number of car-dependent commuters.

35 minutes results in 1,037 car-dependent commuters (32%), while an ACT of 15 minutes would mean that 1,782 commuters (55%) are car-dependent. A PTC ratio of 2, which means that commute times for PT are allowed to be twice as long as the travel time by car, leads to 1,284 car-dependent commuters (40%), while a ratio of 1 (same travel time) would result in 1,862 commuters (57%) being identified as car-dependent.

To select an appropriate value for the ACT, an additional travel time decay function for bicycle commuting was calibrated using data from the Dutch National Travel Survey (ODiN; CBS, 2022). This function reveals the relationship between travel time and the share of bicycle commuting. Specifically, it shows the share of bicycle commuters who currently travel for the corresponding travel time or less. For this research, we used the 80% cut-off value for the ACT which equals 25 minutes. This means that 80% of bicycle commuters in the Netherlands travel 25 minutes or less for commuting purposes. For commuters with an estimated bicycle time towards the work location above 25 minutes, bicycling is not considered a viable alternative. This applies to 1,868 respondents (58%) in our sample. This cut-off value is in line with previous research in this field that considers 7.5 km and approximately 25 to 30 minutes of cycling time as the maximum for bicycle commuting (Milakis & Van Wee, 2018; Scheepers et al., 2015).

For the PCT ratio, we used the results from the sensitivity analysis and the literature and selected a conservative value of 2.0, which means that for commutes where travel time by PT is more than twice the travel time by car, PT is not considered a viable alternative. Using this threshold, the campus locations are not sufficiently accessible by PT for approximately 80% of the commuters. This shows that the competitive position of PT is not favourable for commute trips, a finding that is supported by a recent study into the accessibility of jobs and amenities in the Netherlands by Bastiaanssen and Breedijk (2022). The combined effect of the ACT and PTC ratios provides insight into the overall car dependency of respondents. Considering an ACT of 25 minutes and a PCT ratio of 2.0, the number of car-dependent commuters equals 1,284 (40%). For these respondents, PT or bicycling is not a viable alternative. The remaining 1,960 respondents (60%) have at least one option available and are considered to be non-car-dependent commuters. The next section explores the level and the determinants of car use for these non-car-dependent commuters using bivariate analysis and binomial logit modelling.

4. Results

4.1. Bivariate Analysis of Non-Car-Dependent Commuters

The non-car-dependent commuters differ from the overall sample in several characteristics. Regarding age and gender, the non-car-dependent commuters are a bit younger, and the share of females is a bit higher. Table 2 presents the characteristics of car-dependent and non-car-dependent commuters with the most significant differences. Regarding the work location, a larger share of non-car-dependent commuters works at the TU/e-campus. Not surprisingly, compared to the overall sample, the share of car use among non-car-dependent commuters is lower (31%) and the share of bicycle use is higher (53%). The shares of PT use (13%) and walking (3%) are also higher but to a lesser extent. This shows that the travel times for the bicycle and PT compared to the travel time by car are important determinants of commute mode choice. At the same time, almost one-third of the non-car-dependent commuters use the car while an alternative is available. Also, the differences in modal choice indicate that especially the bicycle competes with car usage while this applies to a much lesser extent to PT and walking. In Table 2, the modal choices of non-car-dependent commuters and their determinants are explored in more detail.

Table 3 shows the average commuting times by different transport modes for all non-car-dependent

Table 2. Basic description of the car-dependent and non-car-dependent commuters (*N* = 3,244).

Variable	Level	Car-dependent commuters		Non-car-dependent commuters	
		Number	Share	Number	Share
Work location	TU/e-campus	228	18%	1,093	56%
	HTCe	1,056	82%	867	44%
Primary mode for commuting	Car	969	76%	601	31%
	PT	95	7%	250	13%
	Bicycle	180	14%	1,042	53%
	Walk	1	0%	50	2%
	Other	39	3%	17	1%
Urbanisation level of residence location (Density: Number of addresses per square km)	Extremely urban (>2,500)	113	9%	666	34%
	Strongly urban (1,500–2,500)	235	18%	653	33%
	Moderately urban (1,000–1,500)	271	21%	378	19%
	Hardly urban (500–1,000)	452	35%	208	11%
	Not urban (<500)	213	17%	55	3%

commuters and their subgroups of car commuters and non-car commuters. A comparison of the average commuting times shows that travel times for car commuters are significantly higher compared to their non-car commuting counterparts. The travel time by bicycle differs in particular, indicating that the car commuters reside at significantly larger distances from their work location.

Table 4 shows the characteristics of commuters' work and residence locations. The results indicate that the work location and the built environment characteristics of the residential location play a role in the non-car-dependent commuter's modal choice. Commuters towards the HTCe use the car more often than their counterparts at the TU/e-campus even if they are in the

Table 3. The average transport network factors for non-car-dependent commuters.

Variable	Unit	All non-car-dependent	Car commuters non-car-dependent	Non-car commuters non-car-dependent
Travel time to work by bicycle	Minutes	69	110	51
Travel time to work by PT	Minutes	42	54	36
Travel time to work by car (peak)	Minutes	22	30	18
Travel time to work by car (off-peak)	Minutes	16	22	13

Table 4. Built environment factors for non-car-dependent commuters.

Variable	Unit (Level)	All non-car-dependent	Car commuters non-car-dependent	Non-car commuters non-car-dependent
Work location	TU/e-campus	1,093	266	827
	HTCe	867	335	532
Density of residence location	Number of addresses per km^2	2,229	1,749	2,442
Distance to the nearest train station	Km	4.1	5.0	3.7
Distance to the nearest main train station	Km	5.5	7.4	4.7
Distance to the nearest main road	Km	2.6	2.8	2.5
Car ownership	Vehicle per household	1.0	1.1	0.9

Note: Main roads are provincial or national roads.

non-car-dependent commuter group. Among car commuters, the density of the residence location is significantly lower (1,749 versus 2,442 addresses per square kilometre). This implies that commuters residing in residential areas with lower densities are more inclined to commute by car. This may be because distances to train stations are beyond the distance that people are willing to walk or cycle. Although the Dutch are famous for their extensive bicycle use towards railway stations (Kager & Harms, 2017), these feeder trips to the railway station usually do not exceed 3 or 4 kilometres (CBS, 2022). Of course, residents can also take the bus to a railway station, but this often involves suboptimal transfers at the railway station due to the lack of synchronisation between bus and train services or due to travel time variations that result in missed transfers (Gkiotsalitis & Maslekar, 2018). The distance to the main road is larger for car commuters which may be related to the fact that car commuters reside more often in hardly urban and non-urban areas. Average zonal household car ownership levels are also slightly higher in car commuters' residential areas.

In addition to the structural factors, personal and psychological factors affect car commute choice. Table 5 includes preferences for respondents' modal choices. Each respondent was asked to choose the three most important factors that influence their modal choice. Overall, speed was the factor that was chosen most often, among car commuters as well as non-car commuters. So even though speed is an important asset of car usage, it does not seem to be the decisive factor as non-car commuters also attach value to speed. Compared to non-car commuters, car commuters attach more importance to the flexibility and the comfort of car use. In line with findings from Koetse and Rietveld (2009), commuters also seem more inclined to use the car due to weather conditions. For non-car commuters, factors such as environmental issues, health, cost, and to a lesser extent reliability play a role. The latter is probably related to the fact that most non-car commuters use the bicycle for commuting which is less sensitive to delays. As commuters to and from the HTCe are inclined to use the car more often, we analysed their mode choice preferences separately. As expected, the HTCe commuters select factors that are associated with car commuting (speed, comfort, and weather) more often and select the cost of the commute, associated with less car commuting, less often. Interestingly, not all factors preferred among HTCe commuters are associated with car commuting. They choose flexibility less often compared to the TU/e-campus commuters while they choose health more often. As for considerations regarding the environment, scores are comparable.

4.2. Binomial Logit Model

To evaluate which factors influence non-car-dependent commuters' mode choices, a logit model was calibrated which predicts the odds of a certain outcome occurring based on a set of independent variables. As our primary focus was on the choice between car commuting versus non-car commuting, we decided to fit a binary logit model which predicts the odds of people choosing to commute by car rather than by an alternative commute mode (PT, cycling, walking, and other modes). To check for mode-specific effects, we also calibrated a multinomial logit model, on all 3,244 respondents, yielding specific coefficients for each transport mode. As the coefficients of this model were in line with the results of the binomial model, and because we were interested in the odds of car use amongst non-car-dependent commuters, we decided to include only the results of the binomial model in this article. Table 6 shows the model results, including the coefficients, *p*-values, and odds ratios. The coefficients show the direction of influence (positive or negative), and the *p*-values show the level of significance. Only variables with a p-value of 0.05 or less were included in the model. As the coefficients of the models are in logit units, they are difficult to interpret. Therefore, they are exponentiated and translated into odds ratios. In this model, the odds ratios can be interpreted as the increase in odds of car commuting relative to non-car commuting for each unit increase in the independent variable. What's important to note, is that the odds ratios in logit models are not standardised. This means that odds ratios and the relative influence of

Table 5. Distribution of mode choice preference factors for non-car-dependent commuters.

Variable	Factor	All non-car-dependent	Car commuters non-car-dependent	Non-car commuters non-car-dependent	TU/e-campus employees	HTCe employees
Mode choice preferences	Speed	47%	54%	44%	45%	50%
	Flexibility	38%	48%	34%	39%	36%
	Comfort	21%	31%	16%	16%	27%
	Reliability	19%	13%	22%	17%	23%
	Cost	21%	8%	27%	28%	12%
	Health	28%	7%	38%	23%	35%
	Weather	20%	30%	15%	13%	28%
	Environment	21%	1%	29%	21%	20%

Table 6. Binomial logit model coefficient estimation (car versus non-car commuting).

Variable category	Variable code	Variable description	Coefficient	*p*-value	Odds ratio
Demography	Age 35	If the respondent is younger than 35 years old = 1 Otherwise = 0	−0.7582***	0.0000	0.4685
	Gender	If the respondent is male = 1 Female = 0	−0.3858***	0.0050	0.6799
Transport network	Bikettfac	Ratio of travel time by bicycle over travel time by car (peak period)	0.2804***	0.0000	1.3237
	Carttfac	If the ratio of travel time by car in off-peak over peak period is less than 0.5 = 1 Otherwise = 0	−0.3769**	0.0500	0.6860
Urban design/form	Density	One thousand dwellings per Km^2 in the city of residence	−0.4122***	0.0000	0.6622
	Maintraindist	Distance from residence location to the nearest main train station (km)	0.0778***	0.0001	1.0809
	TU/e	If the work location is TU/e-campus (near the city centre and central train station) = 1 If the work location is HTCe = 0	−0.4084**	0.0109	1.5044
Travel preference	Comfort	If "Comfort" is one of the factors considered by the respondent for choosing travel mode = 1 Otherwise = 0	0.4079***	0.0076	1.5036
	Weather	If "Weather condition" is one of the factors considered by the respondent for choosing travel mode = 1 Otherwise = 0	0.8804***	0.0000	2.4119
	Flexible	If "Flexibility" is one of the factors considered by the respondent for choosing travel mode = 1 Otherwise = 0	0.7485***	0.0000	2.1137
	Environment	If "Environmental impacts" is one of the factors considered by the respondent for choosing travel mode = 1 Otherwise = 0	−2.9678***	0.0000	0.0514
	Cost	If "Cost" is one of the factors considered by the respondent for choosing travel mode = 1 Otherwise = 0	−1.1754***	0.0000	0.3087
	Reliable	If "Reliability" is one of the factors considered by the respondent for choosing travel mode = 1 Otherwise = 0	−0.6945***	0.0001	0.4993
	Health	If "Health" is one of the factors considered by the respondent for choosing travel mode = 1 Otherwise = 0	−1.8417***	0.0000	0.1586
CST	Constant		0.0798	0.8041	—

Notes: Reference category is non-car commuting; log-likelihood = −747.6971; McFadden's pseudo-R squared/adjusted = 0.376; *N* = 1,960 (601 car commuters and 1,359 non-car commuters); Significance = ***99% and **95%.

explanatory variables on the odds of car commuting cannot be compared if the variables do not share the same metric. As the dummy variables in our model do share the same metric (0 or 1), their relative influence can be compared. The model was calibrated based on 1,960 respondents and has a pseudo-R-squared (McFadden's pseudo-R squared/adjusted) of 0.3763. As values above 0.2 indicate a good model fit this means that our model fits the data very well (Louviere et al., 2000). The variables are classified into four categories: demography, transport network, urban design/form, and travel preferences. For a more detailed description of the variables, we refer to the second section (questionnaire and data).

The model shows that the ratio of travel time by bicycle over travel time by car has a highly significant effect on the odds of using the car for commuting. A one-unit increase in the ratio of travel time by bicycle over travel time by car (OR = 1.3237) leads to 32% higher odds of using the car for commuting. So, shorter travel times by bicycle (compared to car travel times) decrease the odds that people use the car for commuting. The overall ratio of travel time by car in off-peak over peak period was not significant, but a dummy for more extreme congestion, where peak travel times are more than twice as long, was. When this happens, the odds of using the car for commuting are reduced by 31% (OR = 0.6860). Contrary to expectations, the travel time ratio for PT did not yield any significant results.

The urban form factors also have a significant impact. An increase of 1,000 dwellings per km^2 results in a reduction of the odds of commuting by 34% (OR = 0.6622). The distance to the nearest railway station also has a significant influence (OR = 1.0809). When people live one km further from the main railway station, they have 8% higher odds of using the car for commuting. We also included a dummy variable for the work location to determine the effect of commuting to a central campus location versus a location on the city fringe. Interestingly, this proves to be one of the dummy variables with the strongest influence on commute mode choice. After controlling for the other variables, working at the TU/e-campus (compared to the HTCe) decreases the odds of car commuting by 50% (OR = 1.5044).

Travel preferences have a strong impact on the choice of car commuting. Except for the factor speed, the influence of all preferences is significant. People who considered weather (OR = 2.4119) and flexibility (OR = 2.1137) as important factors for their commute choice, have 141% and 111% higher odds respectively to commute by car. Comfort (OR = 1.5036) has a smaller, but still highly significant impact and increases the odds to commute by car by 50%. The other travel preferences have a negative impact on the odds of car commuting. For people who considered the environmental impact (OR = 0.0514) as an important factor, the odds of commuting by car are reduced by 95%. In descending order, health (OR = 0.1586), cost (OR = 0.3087), and reliability (OR = 0.4993) also reduce the odds of car commuting by 84%, 69%, and 50%, respectively.

The influence of age and gender is also significant. A dummy variable for the age variable, including respondents younger than 35 years old has a negative sign as expected (OR = 0.4685). So, the odds that people younger than 35 years old take the car for commuting is 53% lower compared to the older age groups. The negative sign for male respondents (OR = 0.6799) is surprising and implies that for males the odds of commuting by car are 32% lower than those of their female counterparts. Perhaps this is because household responsibilities for women are higher, especially when there are children involved which increases the need for speed and flexibility that is still best facilitated by the car. Contrary to our expectations, the number of working days and the number of days working at home did not significantly affect the odds of using the car when other variables were accounted for.

5. Conclusions

This study aimed to add to the current knowledge regarding car dependency by assessing the level and determinants of car dependency for commuting trips to and from two campus areas in the Netherlands. Two indicators for car dependency were defined, one based on the travel time ratio between PT and car and the other based on the ACT. A sensitivity analysis was conducted to determine the cut-off values for car-dependent and non-car-dependent commuters and descriptive bivariate analysis and binomial logistic regression models were used to explore which factors determine car commuting among the non-car-dependent respondents.

So, to what extent is car usage a matter of dependency or choice? Currently, 48% of the respondents in our sample use a car for commuting. Our results reveal that approximately 40% of these respondents can be categorised as being structurally car-dependent because cycling distances are too long, and the quality of the PT system is insufficient. This implies that commuters for which PT and/or cycling are a viable alternative, already use these modes quite often. This does not apply to all commuters, however, as 31% of the non-car-dependent commuters in our sample commute by car. Our bivariate descriptive analysis and the logit model provide a better understanding of the determinants behind this choice. As the results of both analyses are mostly aligned, we will primarily refer to the logit model for interpretation and discussion.

As our indicators for car dependency are based on travel time, the influence of travel time ratios is important in the context of this article. In line with findings from previous studies, the travel time ratio for cycling showed that more competitive bicycle travel times reduce the odds of car commuting. Interestingly, this does not apply to the travel time ratio for PT. The latter is not consistent with the literature (e.g., Lunke et al., 2018) and indicates that improvements in PT travel time do not have a significant influence on the choice for car commuting. Apparently, in this specific Dutch context, the bicycle is a stronger competitor for car commuting than PT. We also found that severe congestion reduces the odds of car commuting which implies that car congestion could trigger people to shift to PT or cycling (see also Sweet & Chen, 2011).

Like many researchers before us, we found that the built environment matters (e.g., Ewing & Cervero, 2010; Van de Coevering et al., 2016). A lower density of the residential location and longer distances towards the nearest railway station increase the odds of car commuting. What is interesting is the strong effect of a dummy variable for the work location which reveals that commuters to the HTCe have much higher odds of car commuting compared to their TU/e-campus counterparts. Probably, the difference in built environment characteristics is an important underlying factor as the TU/e-campus is located close to the centre and main train station while the HTCe is located at the city fringe near the highway. In addition, differences in mobility management such as company car policies and parking regulations could be factors of influence. This corroborates the findings of Maat and Timmermans (2009) who found that the characteristics of the work environment are at least as important as the residential environment for people's commuting behaviour.

Importantly, our research findings point out the significant and strong role of travel preferences. Weather and flexibility have a positive and, of all dummy variables in the model, by far the strongest influence on the odds of commuting by car. To a lesser extent, this applies to preferences for comfort. Environmental impact has the strongest negative influence on the odds of commuting by car followed by health, costs, and reliability. Previous studies also found significant influences on travel preferences (e.g., Barr et al., 2022; Koetse & Rietveld, 2009). Interestingly, while speed is considered most often an important factor for commuting, it does not significantly affect the odds of commuting by car. So, although the respondents consider speed to be an important factor for commuting (see Table 5), it does not affect people's commute mode choices.

Before we discuss the policy implications, some remarks should be made. First, we would have preferred to include more socio-demographic control variables, but they were not included in the questionnaire of BMN. Therefore, we cannot exclude the possibility that some of the model results stem from the intervening influence of other variables such as income and household composition. In particular, the higher odds of women commuting by car could be related to children in the household. Women likely have caring responsibilities for children more often which requires more flexibility (e.g., Maat & Timmermans, 2009; Vance et al., 2005). Second, this study does not take trip chaining (e.g., visiting a grocery store after work before returning home) into account. As the car is often used for trip chaining, this could lead to an underestimation of the level of car dependency in our research. Finally, our analysis involves two campus locations in the high-tech sector with unique characteristics and a clear overrepresentation of men. This means that the results of this study may reasonably be generalised to comparable campus locations but not to the general population.

For the policy implications, the high level of structural car dependency and the significant impact of mode choice preferences are of crucial importance. First, policies should aim to reduce structural car dependency in the region. One option is to build on the success of the bicycle which proved to be competitive with the car for commuting at shorter distances. Its reach can be increased by targeted investments in fast cycling routes, especially as e-bikes are gradually becoming the norm in the Netherlands. Another option is to invest in a quality leap for PT by investing in bus rapid transit systems in combination with efficient feeders and facilities for cycling, as many towns are not well connected to the railway system, a situation that is not likely to change in the future. Second, the use of PT, cycling, and walking can be encouraged among non-car-dependent commuters. Examples are psychological interventions focusing on the commuters' preferences and attitudes, financial programmes that promote PT and bicycle use, and schemes or promotional interventions that encourage a modal shift such as cycle-to-work days. Ideally, investments in the transport system are combined with these behavioural interventions to maximise their impact on sustainable commuting in the region.

Acknowledgments

This work was financially supported by the province of Noord-Brabant, The Netherlands. We would like to thank BMN for sharing the questionnaire data and for their assistance. Furthermore, special thanks to the editors of the thematic issue and two anonymous reviewers whose advice considerably strengthened this article.

Conflict of Interests

The authors declare no conflict of interests.

References

Alshammari, T. O., Hassan, A. M., Arab, Y., Hussein, H., Khozaei, F., Saeed, M., Ahmed, B., Zghaibeh, M., Beitelmal, W., & Lee, H. (2022). The compactness of non-compacted urban developments: A critical review on sustainable approaches to automobility and urban sprawl. *Sustainability*, *14*(18), Article 11121. https://doi.org/10.3390/su141811121

Anable, J. (2005). "Complacent car addicts" or "aspiring environmentalists"? Identifying travel behaviour segments using attitude theory. *Transport Policy*, *12*(1), 65–78.

Barr, S., Lampkin, S., Dawkins, L., & Williamson, D. (2022). "I feel the weather and you just know." Narrating the dynamics of commuter mobility choices. *Journal of Transport Geography*, *103*, Article 103407. https://doi.org/10.1016/j.jtrangeo.2022.103407

Bastiaanssen, J., & Breedijk, M. (2022). *Toegang voor iedereen? Een analyse van de (on)bereikbaarheid van voorzieningen en banen in Nederland* [Access for everyone? An analysis of the (in)accessibility of facilities and jobs in the Netherlands]. PBL.

Beige, S., & Axhausen, K. W. (2008). Long-term and mid-term mobility decisions during the life course: Experiences with a retrospective survey. *IATSS Research*, *32*(2), 16–33.

Beige, S., & Axhausen, K. W. (2017). The dynamics of commuting over the life course: Swiss experiences. *Transportation Research Part A: Policy and Practice*, *104*, 179–194.

Cullen, I. G. (1978). The treatment of time in the explanation of spatial behavior. In T. Carlstein, D. Parkes, & N. Thrift (Eds.), *Human activity and time geography* (pp. 27–38). Edward Arnold.

Ewing, R., & Cervero, R. (2010). Travel and the built environment: A meta-analysis. *Journal of the American Planning Association*, *76*(3), 265–294.

Gärling, T., Gillholm, R., & Gärling, A. (1998). Reintroducing attitude theory in travel behavior research: The validity of an interactive interview procedure to predict car use. *Transportation*, *25*(2), 129–146.

Gkiotsalitis, K., & Maslekar, N. (2018). Towards transfer synchronization of regularity-based bus operations with sequential hill-climbing. *Public Transport*, *10*(2), 335–361.

Haustein, S., & Hunecke, M. (2007). Reduced use of environmentally friendly modes of transportation caused by perceived mobility necessities: An extension of the theory of planned behavior. *Journal of Applied Social Psychology*, *37*(8), 1856–1883.

Jeekel, H. (2013). *The car-dependent society: A European perspective* (1st ed.). Routledge. https://doi.org/10.4324/9781315614311

Kager, R., & Harms, L. (2017). *Synergies from improved cycling-transit integration: Towards an integrated urban mobility system* (International Transport Forum Discussion Papers, No. 2017/23). OECD. https://doi.org/10.1787/ce404b2e-en

Koetse, M. J., & Rietveld, P. (2009). The impact of climate change and weather on transport: An overview of empirical findings. *Transportation Research Part D: Transport and Environment*, *14*(3), 205–221. https://doi.org/10.1016/j.trd.2008.12.004

Lau, J. C. Y. (2013). Sustainable urban transport planning and the commuting patterns of poor workers in a historic inner city in Guangzhou, China. *Habitat International*, *39*, 119–127.

Litman, T., & Burwell, D. (2006). Issues in sustainable transportation. *International Journal of Global Environmental Issues*, *6*(4), 331–347.

Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: Analysis and applications*. Cambridge University Press.

Lunke, E. B., Fearnley, N., & Aarhaug, J. (2018). Public transport competitiveness vs. the car: Impact of relative journey time and service attributes. *Research in Transportation Economics*, *90*, Article 101098. https://doi.org/10.1016/j.retrec.2021.101098

Maat, K., & Timmermans, H. J. P. (2009). Influence of the residential and work environment on car use in dual-earner households. *Transportation Research Part A: Policy and Practice*, *43*(7), 654–664. https://doi.org/10.1016/j.tra.2009.06.003

Mattioli, G., Anable, J., & Vrotsou, K. (2016). Car dependent practices: Findings from a sequence pattern mining study of UK time use data. *Transportation Research Part A: Policy and Practice*, *89*, 56–72.

Merom, D., Humphries, J., Ding, D., Corpuz, G., Bellew, W., & Bauman, A. (2018). From "car-dependency" to "desirable walking"—15 years trend in policy-relevant public health indicators derived from household travel surveys. *Journal of Transport & Health*, *9*, 56–63. https://doi.org/10.1016/j.jth.2018.01.008

Milakis, D., & Van Wee, B. (2018). "For me it is always like half an hour": Exploring the acceptable travel time concept in the US and European contexts. *Transport Policy*, *64*, 113–122. https://doi.org/10.1016/j.tranpol.2018.02.001

Newman, P. G., & Kenworthy, J. R. (1989). *Cities and automobile dependence: An international sourcebook*. Gower Publishing.

Saeidizand, P., Fransen, K., & Boussauw, K. (2022). Revisiting car dependency: A worldwide analysis of car travel in global metropolitan areas. *Cities*, *120*, Article 103467. https://doi.org/10.1016/j.cities.2021.103467

Scheepers, C. E., Wendel-Vos, G. C. W., Van Wesemael, P. J. V., den Hertog, F. R. J., Stipdonk, H. L., Int Panis, L. L. R., Van Kempen, E. E. M. M., & Schuit, A. J. (2015). Perceived health status associated with transport choice for short distance trips. *Preventive Medicine Reports*, *2*, 839–844. https://doi.org/10.1016/j.pmedr.2015.09.013

Schwanen, T., Banister, D., & Anable, J. (2012). Rethinking habits and their role in behaviour change: The case of low-carbon mobility. *Journal of Transport Geography*, *24*, 522–532. https://doi.org/10.1016/j.jtrangeo.2012.06.003

Statistics Netherlands. (2020). *Kerncijfers wijken en buurten 2020* [Key figures districts and neighborhoods 2020].

Statistics Netherlands. (2022). *ODIN, Dutch national travel survey*. https://www.cbs.nl/nl-nl/longread/rapportages/2022/onderweg-in-nederland--odin---2021-onderzoeksbeschrijving?onepage=true

Sweet, M. N., & Chen, M. (2011). Does regional travel time unreliability influence mode choice? *Transportation*, *38*, 625–642. https://doi.org/10.1007/s11116-011-9335-z

Vale, D., Viana, C. M., & Pereira, M. (2018). The extended node-place model at the local scale: Evaluating the integration of land use and transport for Lisbon's subway network. *Journal of Transport Geography*, *69*, 282–293.

Van Acker, V., & Witlox, F. (2010). Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. *Journal of Transport Geography*, *18*(1). 65–74.

Van Acker, V., Van Wee, B., & Witlox, F. (2010). When transport geography meets social psychology: Toward a conceptual model of travel behaviour. *Transport Reviews*, *30*(2), 219–240.

van de Coevering, P., Maat, K., Kroesen, M., & Van Wee, B. (2016). Causal effects of built environment characteristics on travel behaviour: A longitudinal approach. *European Journal of Transport and Infrastructure Research*, *16*(4), 674–697.

Van den Heuvel, M. G., & Van Goeverden, C. D. (1993). *De verplaatsingstijdfactor in relatie tot de vervoerwijzekeuze* [The travel time factor in relation to the transport mode choice]. Delft University of Technology.

Van Wee, B. (2013). The unsustainability of car use. In T. Gärling, D. Ettema, & M. Friman (Eds.), *Handbook of sustainable travel* (pp. 69–83). Springer. https://doi.org/10.1007/978-94-007-7034-8_5

Vance, C., Buchheim, S., & Brockfeld, E. (2005). Gender as a determinant of car use: Evidence from Germany. In *Research on Women's Issues in Transportation Conference Proceedings* (Vol. 2, pp. 59–67). The National Academies Press.

Wang, C. H., Akar, G., & Guldmann, J. M. (2015). Do your neighbors affect your bicycling choice? A spatial probit model for bicycling to The Ohio State University. *Journal of Transport Geography*, *42*, 122–130.

Wegener, M., & Fuerst, F. (2004). *Land-use transport interaction: State of the art*. SSRN. http://doi.org/10.2139/ssrn.1434678

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