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Transportation Research Procedia 32 (2018) 268–278

Transportation Research Procedia

www.elsevier.com/locate/procedia

International Steering Committee for Transport Survey Conferences

Travel mode choice modeling from cross-sectional survey and panel data: the inclusion of initial nonresponse

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Abstract

To develop models of transport mode choice, mobility cross-sectional survey or panel data can be used. However, the extent to which data from these sources yield accurate parameter values and probabilities is influenced by nonresponse possibly leading to a nonresponse bias. The main research objective of the current study is to assess whether the inclusion of initial nonresponse in a nested logit mode choice model leads to changes in parameter values and more adequate estimated probabilities. The results show that not taking account of nonresponse may lead to a negligibly small overestimation of the choice for car as passenger and bicycle along with an underestimation of the choice for car as driver and e-bike of the same magnitude. Based on the models in this paper, it is not possible to conclude that including the willingness to participate in a mode choice model leads to substantial improvements, but more research is needed to fully assess the value of including willingness.

Keywords: Netherlands Mobility Panel; MPN; transport mode choice; hybrid choice model; nested logit model; nonresponse bias

1. Introduction

Decision-making in transport planning requires the prediction of impacts of proposed policies on mode choice behaviour (Ben-Akiva, 1973) . These predictions are typically obtained from travel mode choice models. In order to estimate these models, cross-sectional and panel survey data can be used. However, the extent to which these models yield accurate parameter estimation results is influenced by nonresponse. According to Stopher et al. (2006), high rates of nonresponse are generally associated with a nonresponse bias. Nonresponse bias is a function of the response rate

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10.1016/j.trpro.2018.10.049

as well as of the difference between respondents and non-respondents on the variables of interest. For example, research has shown that for mobility surveys, households with both high and low mobility rates show a relatively higher level of nonresponse and there is therefore a risk that these households are underrepresented (Richardson & Meyburg, 2003). Correcting for nonresponse is therefore crucial when using survey data in estimating travel choice models, such as mode choice models, since the bias resulting from nonresponse may lead to less accurate parameter estimates and over- or underestimation of probabilities. The aforementioned may lead to a less accurate insight into the contribution of various factors in travel choice behaviour and may possibly lead to less accurate conclusions with regard to the efficacy of policy measures, such as road pricing.

Aim of this study is to investigate if the inclusion of initial nonresponse in a travel choice model using cross-sectional or panel data leads to a more externally valid prediction of travel choice behaviour. In order to determine whether the inclusion of nonresponse in travel choice models leads to improved predictions, we developed a hybrid choice model (HCM) and compared this model to a more traditional nested logit model (NLM). In the HCM, a latent variable is included representing the willingness to participate in a cross-sectional or panel survey.

For the purpose of developing and estimating the HCM and the NLM, we used data from the first wave of the Netherlands Mobility Panel (MPN), consisting of 3,996 respondents (Hoogendoorn-Lanser et al., 2015). The MPN is a state-of-the-art household panel, designed to establish the long- and short-term dynamics in travel behaviour of households and household members. Starting from 2013, members from more than 2,000 households annually record their travel behaviour using a three-day location-based trip diary. The MPN offers unique opportunities for nonresponse research. When households are recruited for the MPN, both at the beginning of the MPN and between waves to account for attrition, they are asked to fill in a short screening questionnaire. In this screening questionnaire respondents were not only asked whether they wanted to participate in the panel but were also asked a few simple questions on their household characteristics and travel behaviour (number of cars in the household, total travelled distance per year with these cars and frequency use of different modalities such as car, bicycle and public transport) . Therefore, mode use is known for respondents who indicated to be willing to participate in the panel as well as respondents who indicated not to be willing. In this paper it is therefore investigated whether the inclusion of initial nonresponse in a mode choice model leads to more externally valid predictions. Furthermore, since an existing online access panel is used to recruit households for the MPN, a number of personal- and household characteristics are known of respondents who did not respond to the screening questionnaire.

The paper is organized as follows. In the next section we provide a brief state-of-the-art on nonresponse in travel surveys. In the following section we discuss the research method. In this section the modelling approach is discussed and a description of the data is presented. In the results section we present the results of the model estimations and approximate the effect of using the HCM through a comparison with a more traditional nested logit model. In the discussion section we discuss the results and formulate recommendations for future research.

2. State-of-the-art in mode choice modelling and nonresponse

2.1. Mode choice modelling and determinants

Accurate estimation of changes in modal shares requires the development of models which include policy-sensitive variables and which capture individual preferences and differences in sensitivity to changes in level-of-service characteristics of the various travel modes.

Travel mode choice models are generally based on utility maximization or regret minimization. These theories are based on the assumption that an individual's mode choice is a reflection of underlying preferences for each of the available alternatives and that the individual selects the alternative with the highest utility or the least regret.

These individual utilities come forth from various determinants. Research on determinants of travel mode choice focuses, for a large part, on commuting behaviour (Abrahamse et al., 2009; Asensio, 2002; Commins & Nolan, 2011; Kuppam et al., 1999; Kuppam & Pendyala, 2001; Olde Kalter et al., 2014; Schwanen & Mokhtarian, 2005) . Other studies focus on shopping trips (Feng et al., 2014), school trips (Müller et al., 2008) or mobility in general (Bai et al., 2017; Paulssen et al., 2014). From literature we know that there is a large overlap in terms of the determinants which are identified. In sum, most studies identify age, gender, education, occupation and household composition as relevant personal characteristics, whereas they identify travel time, travel cost and distance as relevant level-of-service characteristics.

2.2. Nonresponse in cross-sectional and panel surveys

It is important to study the patterns of missing data before applying the available (and sometimes very advanced) correction methods. In this sense we need to address the terms Missing Completely At Random (MCAR), Missing At Random (MAR) and Missing Not At Random (MNAR). Already in 1976, Rubin classified missing data problems into these three categories (Rubin, 1976) . In Rubin's theory, every data point has some probability of being missing, governed by a response mechanism. If the probability of being missing is the same for all cases, then the data is MCAR. In other words: causes of the missing data are not related to the data itself. It can easily be seen that the assumption of MCAR is often unrealistic. If MCAR is present, a nonresponse bias in the data is highly unlikely.

If the probability of being missing is the same only within groups defined by the observed data, then the data is MAR. Although the data is missing at random, a bias may be present in the data. If neither MCAR or MAR hold, the data is MNAR. This means that the probability of being missing varies for unknown reasons. This is a strong indication that a bias is present in the data.

The aforementioned distinction between MCAR, MAR and MNAR is important since it provides us with understanding why certain weighting or imputation methods will not work(Cheng & Trivedi, 2015; Rubin, 1976). For example, very simple fixes, such as list wise deletion, work only under the assumption of MCAR (Pigott, 2001). However, when this assumption is violated, biased estimates may be the result. A possible solution when data is MAR is applying inverse probability weighting. This method involves calculating the probability of response as a function of observed characteristics, as shown by Jones et al. (2006). To correct for attrition when data is MNAR becomes more complicated. To correct for attrition in the case of MNAR, often untestable assumptions have to be made since true values of the variables of interest in the population are often not known (Cheng & Trivedi, 2015)This is also the case in the determination of the bias in travel diary data obtained through mobility panels and cross-sectional surveys. Kitamura and Bovy (1987) state that the main reason for this is that the number and characteristics of the 'true' mobility is not known. According to Meurs et al. (1989) it is however possible, under various assumptions, to attain insights into this 'true' mobility on an aggregate level. In this context they conclude that a bias in a multi-day panel data can be assumed to be present. This bias has a within as well as a between wave component and a non-random attrition component. The latter even exists after controlling for personal- and household characteristics. La Paix Puello et al. (2017) also show the presence of a bias in the reporting of trips due to panel attrition in the MPN.

In this regard, it can be assumed that unit nonresponse in surveys and panels is almost always non-random. This was for example shown for between wave attrition in various mobility panels (Meurs et al., 1989). In this context, it was shown that attrition can be, for instance, related to household income, educational level and trip rates (Kitamura & Bovy, 1987).

In the current paper we aim to correct for initial nonresponse through the incorporation of a latent variable representing the willingness to participate in a panel or cross-sectional survey in a transport mode choice model. We hypothesize that this method of correcting for nonresponse may be a good alternative to correction methods such as weighting and imputation. Here, we need to stress that in the current study we only take the initial nonresponse into account. We do not aim to quantify the bias due to attrition and item nonresponse

3. Research method

3.1. Data collection method and sample description

The Netherlands Mobility Panel is a new data source which has been available in the Netherlands since 2013 (Hoogendoorn-Lanser et al., 2015) . The MPN consists of several elements, namely a screening-, personal- and household questionnaire and a three-day location-based trip diary. The screening questionnaire is only filled out when a household is recruited to the panel, whereas the personal- and household questionnaires are filled in every year. In the location-based trip diary respondents report their travel activities for three consecutive days once per year. The screening- and household questionnaires are filled out by the so-called gatekeeper (an adult household member), while the individual questionnaire and the location-based trip diary are filled out by the individual household members.

Approximately 2,000 complete households participate in the MPN, resulting in a fairly representative sample of the Dutch population. Since the MPN is a mobility panel, multiple waves are available. However, in the current study we only made use of data from the first wave. Table 1 shows the sample composition of the first wave of MPN and the distribution of variables among the Dutch population, according to the Gold Standard (MOA, 2017). This sample consists of 3,996 respondents who completed both the questionnaires and the three-day travel diary.

Table 1. MPN sample composition

		Gold Standard	Wave 1			Gold Standard	Wave 1
Gender	Male	49,4%	46,5%	**Work situation**	Employed	50,3%	56,9%
	Female	50,6%	53,5%		Does household/volunteer	7,7%	6,3%
					Student	13,1%	10,9%
					Jobless/disabled	8,4%	7,8%
					Retired	20,6%	18,1%
Age	<24 yo	18,4%	14,2%	**Household size**	1	19,4%	22,6%
	25 - 34 yo	14,0%	16,1%		2	34,2%	36,9%
	35-44 yo	15,5%	18,1%		3	16,3%	13,6%
	45-54 yo	17,6%	17,7%		4	19,8%	18,7%
	55-64 yo	15,2%	17,0%		5	7,4%	6,4%
	>65 yo	19,3%	17,0%		6 or more	2,9%	1,7%
Education level	Low	37,1%	30,5%	**Household situation**	Single household	19,3%	22,6%
	Medium	39,9%	37,7%		Adult household	44,7%	42,8%
	High	22,9%	31,7%		Youngest child <12 yo	23,6%	19,3%
					Youngest child 12-17 yo	11,4%	14,7%

From the diary data of the first wave of the MPN (n=3,996 respondents) it can be observed that most of the individuals choose the transport mode ‘Car as driver’ (39.3%), followed by ‘Bicycle’ (26,0%), ‘Walking’ (15.6%), and ‘Car as passenger’ (10.4%). The train is used for 2.8% of all trips, while bus, tram and metro are used for 2.3% of trips. Except for the car, these share are similar to shares observed from the National Travel Survey (Kennisinstituut voor Mobiliteitsbeleid, 2016). In the MPN a higher share is found for car as driver (39% vs 32%) and a lower share for car as passenger (10% vs 15%). This can be explained by the fact that children below the age of 12 years are not included in the MPN. In the MPN the average travelled distance per trip amounts to 11.8 km (SD=24.8), while the average travel time amounts to 23.1 minutes (SD=43.57).

As indicated in section 1, when respondents are recruited they are asked to fill in a screening questionnaire. From analysis of this information it followed that 46.7% of the individuals indicated that they were willing to participate, while respectively 27.6% and 25.7% were not willing to participate or did not react at all. From analyses performed through chi-square tests it followed that several characteristics of the individuals were significantly related to willingness to participate, such as gender, age, education and working situation ($p<.05$).

3.2. Formulation of the nested logit mode choice model

The developed HCM as well as the NLM have a nested structure. We chose a nested structure since it can be assumed that in a transport mode choice model the error terms between certain alternatives are correlated. This can for example easily be imagined for the alternatives ’bicycle’ and ‘e-bike’.

A nested structure allows for interdependence between pairs of alternatives in a common group (McFadden, 1978). The NLM and the HCM consist of 6 alternatives. These are respectively: car as driver, car as passenger, public transport, bicycle, e-bike and walking. Due to correlation of the error terms between several alternatives, we implemented the following nests in the model:

- a nest with the alternatives ‘car as driver’ and ‘car as passenger’;
- a degenerate nest with the alternative ‘public transport’;
- a nest with the alternatives ‘bicycle’ and ‘e-bike’;
- a degenerate nest with the alternative ‘walking’.

There is a vast body of literature on which determinants of travel mode choice should be included in travel mode choice models, see section 2.1. With regard to the determinants of travel mode choice in the developed model we chose to use the distinction into three different components as proposed by Bhat (1998):

- observable level-of-service characteristics offered by the travel mode for the individual's trip (travel time and departure time);
- intrinsic observed (e.g., personal characteristics) individual-specific bias (gender, age, educational level, work situation, car ownership and household situation);
- a mean-zero random term.

In terms of the included factors to determine the probability of choosing alternative *i,* the NLM and the HCM are similar. The difference between the two models is that in the HCM a latent variable, representing the willingness to participate in a cross-sectional or panel survey is included as a representation of an unobserved individual-specific bias. This latent variable will be discussed in the next subsection.

In the current models we only use a limited set of variables. Reason for this is that the aim of the paper is to investigate whether the inclusion of the willingness to participate in a cross-sectional or panel survey in a transport mode choice model leads to an improvement of the model. It is therefore explicitly not the objective of the current study to develop a new transport mode choice model. Furthermore, the fact that only data from the first wave of the MPN are used in the models leads to limitations in the number of variables that can be included (limited number of respondents available). Therefore, determinants such as income, parking facilities and mode preferences are not included.

3.3. Formulation latent variable model

The latent variable in the HCM consists of the willingness to participate in a cross-sectional survey or panel. In order to attain this willingness, we developed a nested logit model of the willingness to participate in the MPN. The model consists of three behavioural alternatives: Willing, Not Willing and No Reaction. These three categories are observed from the screening questionnaire. In this questionnaire respondents were asked to indicate whether they were willing or not willing to participate to the MPN. If respondents did not respond to the questionnaire they are treated as choosing the alternative No Reaction. Preliminary analyses showed that the error term of the alternatives Not Willing and No Reaction are correlated. Therefore in the model two nests are implemented; a degenerate nest with only the alternative Willing and a nest with the alternatives Not Willing and No Reaction.

In the developed model we included several personal and household characteristics, namely: gender, age (in classes), education, employment status and household situation. Furthermore, an interaction between gender and age was included in the model. This interaction was used in the model since the correlation matrices showed that these are strongly correlated.

4. Results

4.1. Modelling the willingness to participate

In this subsection we present the results of the parameter estimation of the nested logit model of willingness to participate in the MPN. Data from the screening questionnaire of the first wave of the MPN are used. This screening questionnaire was filled in by the breadwinner of the household. Therefore, all respondents who filled in the screening questionnaire are 18 years and older. From the analysis it followed that the nest elasticity was significant ($p<.05$). The coefficient is however difficult to interpret since the current nested logit model contains a degenerate nest (only one alternative in a nest). In Table 2 the results of the parameter estimation are displayed for the main variables.

Since the dataset can be regarded as a so-called labelled experiment, we chose to implement two Alternative Specific Constants (ASC's). From the table, it can be observed that only the ASC for Willing is significant ($p<.05$). No Reaction is the reference category. The parameter estimates therefore show the relative utility of that specific variable for Willing or Not Willing, compared to No Reaction. From the table it can be observed that men have a relative higher utility for Willing and Not Willing compared to No Reaction than women. It can also be seen that the relative utility of Willing and Not Willing compared to No Reaction is lower for all age groups compared to respondents of 65 years and older. Furthermore, having no, low or a medium education leads to a significantly lower relative utility for Willing (p<.05) compared to No Reaction than being high educated. From the parameter values it can also be concluded that respondents from single households have a higher relative utility for both Willing and Not Willing compared to No Reaction than respondents from large household with only adults.

Table 2. Parameter estimates and standard errors for the main variables of the nested logit model (the significant parameter values are displayed in bold (p < 0.05))

Variable		Estimate Willing	Estimate Not Willing	Estimate No Reaction	Std. error Willing	Std. error Not Willing
ASC		**0.688**	0.102	ref.	**0.111**	0.178
Gender	**Male (ref. female)**	**0.715**	**1.050**	ref.	**0.087**	**0.129**
Age	**18-24 (ref. 65ao)**	-0.167	**-0.477**	ref.	0.121	**0.232**
	25-34 (ref. 65ao)	**-0.377**	**-0.990**	**ref.**	**0.098**	**0.173**
	35-44 (ref. 65ao)	**-0.277**	**-0.863**	**ref.**	**0.098**	**0.173**
	45-54 (ref. 65ao)	**-0.273**	**-0.802**	**ref.**	**0.099**	**0.176**
	55-64 (ref. 65ao)	-0.029	-0.220	**ref.**	0.102	0.173
Education	**No – Low (ref. high)**	**-0.138**	-0.093	ref.	**0.040**	0.058
	Medium (ref. high)	**-0.090**	**-0.125**	**ref.**	**0.030**	**0.050**
Employment	**Paid (ref. unemployed)**	**-0.154**	-0.181	**ref.**	**0.056**	0.098
	Disabled (ref. unemployed)	-0.089	-0.158	**ref.**	0.076	0.135
	Retired (ref. unemployed)	-0.094	-0.151	ref.	0.104	0.159
	Student (ref. unemployed)	**-0.327**	**-0.524**	**ref.**	**0.097**	**0.210**
	Other (ref. unemployed)	**-0.357**	**-0.530**	**ref.**	**0.077**	**0.145**
HH situation	**Single (ref. other)**	**0.316**	**0.476**	**ref.**	**0.043**	**0.064**
	Youngest child 0-13 (ref. other)	**-0.188**	**-0.480**	**ref.**	**0.041**	**0.081**
	Youngest child 13-17 (ref. other)	**-0.198**	**-0.293**	**ref.**	**0.052**	**0.084**

Interactions between gender and age were included in the model as well. The results of the parameter estimations for these interactions are displayed in Table 3. From the table it can be observed that a substantial number of significant parameter estimates are present. They are, however, difficult to interpret since the reference category is different for every interaction. From the tables it can be concluded that a significant relationship exists between various household and personal characteristics as well as interactions with gender and the willingness to participate in the MPN.

Table 3. Parameter estimates and standard errors for the interactions of the nested logit model (the significant parameter values are displayed in bold)

Variable	Estimate Reaction	Estimate Not Willing	Estimate No Reaction	Std. error Reaction	Std. error Not Willing
Age:Gender					
18-24:Male	**-0.585**	**-0.783**	ref.	**0.148**	**0.308**
25-34:Male	0.136	**0.483**	ref.	0.119	**0.200**
35-44:Male	0.153	0.575	ref.	0.110	**0.186**
45-54:Male	**0.409**	**0.876**	ref.	**0.117**	**0.190**
55-64:Male	0.155	0.267	ref.	0.128	0.199

4.2. Probability estimates of the nested logit model

In the previous subsection we presented the parameter estimates of the nested logit model of willingness to participate in the MPN. This does however not yet inform us on how well the model performs in terms of predicting the willingness to participate in the panel. In this context we ran simulations using the data from the MPN and calculated the probabilities for Willing, Not Willing and No Reaction. Next, we calculated the descriptive statistics with regard to the estimated probabilities.

Table 4. Descriptive statistics for the estimated probabilities of Reaction, Not Willing and No Reaction in the panel derived from the nested logit model

Willingness	N	Mean	Std	Min	Max
Willing	8,980	0.467	0.112	0.100	0.734
Not Willing	8,980	0.276	0.101	0.101	0.542
No Reaction	8,980	0.257	0.163	0.079	0.792

The descriptive statistics for the model are displayed in Table 4. When comparing these statistics to the empirical mean as presented in subsection 3.1, it can be observed that the probabilities displayed in Table 6 closely resemble these. For instance, the observed willingness to participate in the MPN was 46.7% while the estimated willingness to participate amounts to 0.467. It can therefore be concluded that the nested logit model, in terms of the estimated probabilities, performs relatively well.

4.3. Parameter estimations of the mode choice models

In this subsection we start with a presentation of the parameter estimates of the developed NLM and HCM. From the analyses of both models it follows that the nest elasticities are significant ($p<.05$). The coefficients are however difficult to interpret since both models contain two degenerate nests (for the alternatives 'Public transport' and 'Walking').

In order to test whether the nested structure we performed a Wald test, a likelihood ratio test as well as a scoretest, in which we compared the NLM to a MNL of the same structure. The three tests did not reject the null hypothesis of no correlation at the 1% level. The nested structure therefore seems to be adequate.

In Table 5 and 6, the parameter estimations are displayed for the NLM and the HCM. From the tables it can be observed that most of the parameter values are significant in the NLM and HCM model. Furthermore, the signs of the parameter values are in the expected direction. For instance, travel time has a negative value which means that higher travel time is accompanied by a lower utility for an alternative. Furthermore, the magnitude of the parameter values are in line with our expectations as well.

When comparing the parameter values of the NLM and the HCM, it can be observed that both models yield, with regard to their magnitude, comparable parameter values. Furthermore, the extent to which the parameter values are significant is quite comparable between the two models. This is in part caused by the fact that both models have the same nested structure and the same factors.

From the parameter values of the HCM it becomes clear that a few of the parameter values for the latent variable 'willingness' are significant. Based on our previous analyses, it was expected to find more significant parameters for the latent variable.

4.4. Comparing the two models

As was mentioned before, the parameter values of the NLM and the HCM are quite comparable in terms of their magnitude and their significance. Furthermore, the r^2 is quite comparable in magnitude between the two models. In order to test whether the the willingness to participate in a cross-sectional survey or panel influences mode choice we performed a Wald test together with a likelihood ratio test and a score test and compared the NLM and the HCM. From the analysis it followed that the null hypothesis of no difference between the two models was rejected. It can therefore be concluded that the inclusion of the willingness to participate has a significant influence on mode choice.

An often used test in order to determine the difference between two discrete choice models is through the use of the estimated probabilities. In this context we calculated the differences in probabilities between the NLM and the HCM. It was found that the differences in the probabilities between the HCM and the NLM are very small. The differences in probabilities between the HCM and NLM showed that not including the willingness to participate leads to a very small underestimation of car use as a driver and e-bike a very small overestimation of car as passenger and bicycle. Although the willingness to participate in a longitudinal travel survey yields a number of significant parameters in the HCM, including this willingness in a mode choice model appears to have very little effect. The largest differences in mode choice between the NLM and HCM model amounts to just over 0.01% and it is therefore questionable whether the effort needed to include willingness in a mode choice model is worth it.

Table 5. Parameter estimates and standard errors for the NLM. The significant parameter values (at a 95% confidence level) are in bold.

	Car as driver		**Car as passenger**		**Public Transport**		**E-bike**		**Bicycle**		**Walking**	
	Est.	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**
ASC	**-4,341**	**0,185**	-0,114	0,075	**-0,720**	**0,108**	**-1,748**	**0,148**	**-0,200**	**0,051**	ref.	ref.
Traveltime (minutes)	**-0,006**	**-0,006**	**0,000**	**-0,006**	**0,000**	**-0,006**	**0,000**	**-0,006**	**0,000**	**-0,006**	**0,000**	ref.

Departure time	Rush hour	**0,118**	**0,016**	**-0,146**	**0,026**	**0,191**	**0,026**	0,089	0,053	**0,055**	**0,016**	ref.	ref.
	No rush hour	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
Gender	Male	**0,147**	**0,016**	**-0,575**	**0,031**	-0,006	0,025	**-0,507**	**0,062**	0,016	0,016	ref.	ref.
	Female	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
Age	<24 yo	0,044	0,064	**0,325**	**0,082**	**0,699**	**0,096**	-3,185	1,760	**0,632**	**0,059**	ref.	ref.
	25-34 yo	**0,235**	**0,043**	-0,045	0,071	**0,224**	**0,086**	**-1,504**	**0,175**	**0,290**	**0,045**	ref.	ref.
	35-44 yo	**0,195**	**0,042**	**-0,353**	**0,075**	**0,182**	**0,087**	**-1,278**	**0,155**	**0,326**	**0,045**	ref.	ref.
	45-54 yo	**0,102**	**0,041**	**-0,293**	**0,069**	0,057	0,087	**-0,517**	**0,123**	**0,172**	**0,045**	ref.	ref.
	55-64 yo	0,049	0,034	**-0,222**	**0,056**	0,013	0,073	**-0,446**	**0,093**	**0,214**	**0,036**	ref.	ref.
	>65 yo	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
Education level	Low	**0,070**	**0,023**	**0,288**	**0,041**	**-0,160**	**0,038**	**0,729**	**0,087**	**-0,101**	**0,023**	ref.	ref.
	Medium	**0,115**	**0,018**	0,071	0,038	**-0,071**	**0,030**	**0,774**	**0,081**	**-0,160**	**0,019**	ref.	ref.
	High	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
Work situation	Employed	**0,370**	**0,039**	**-0,196**	**0,051**	**0,406**	**0,084**	-0,073	0,105	-0,031	0,032	ref.	ref.
	Student	**0,333**	**0,054**	0,101	0,079	-0,106	0,121	**1,130**	**0,113**	**-0,609**	**0,070**	ref.	ref.
	Retired	**0,301**	**0,047**	**-0,172**	**0,056**	**0,326**	**0,097**	-0,120	0,100	0,003	0,043	ref.	ref.
	Disabled	-0,098	0,074	**-0,244**	**0,078**	**0,299**	**0,099**	-0,372	1,730	0,092	0,054	ref.	ref.
	Unemployed	**0,103**	**0,049**	-0,052	0,072	0,054	0,102	**0,385**	**0,122**	**-0,167**	**0,044**	ref.	ref.
	Other	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
Houshold situation	Single household	**0,160**	**0,022**	**-0,498**	**0,045**	**-0,148**	**0,033**	**-0,544**	**0,073**	-0,032	0,023	ref.	ref.
	Youngest child <12 yo	**0,102**	**0,024**	**-0,179**	**0,044**	**-0,378**	**0,046**	**-0,290**	**0,131**	**0,171**	**0,025**	ref.	ref.
	Youngest child 12-17 yo	**0,133**	**0,030**	-0,057	0,047	-0,073	0,044	-0,188	0,121	**0,237**	**0,031**	ref.	ref.
	Other	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
Cars in HH	No cars	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	1 car	**1,119**	**0,059**	0,050	0,047	**-0,175**	**0,035**	-0,119	0,100	**-0,082**	**0,024**	ref.	ref.
	2 cars	**1,304**	**0,065**	-0,040	0,055	**-0,373**	**0,046**	**-0,372**	**0,116**	**-0,259**	**0,030**	ref.	ref.
	3 or more	**1,341**	**0,075**	**-0,204**	**0,087**	**-0,324**	**0,082**	**-0,505**	**0,226**	**-0,274**	**0,050**	ref.	ref.
Driver's license	Yes	**2,532**	**0,158**	**-0,734**	**0,040**	**-0,197**	**0,034**	**0,241**	**0,093**	-0,012	0,024	ref.	ref.
	No	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.

Table 6. Parameter estimates and standard errors for the HCM. The significant parameter values (at a 95% confidence level) are in bold.

		Car as driver		**Car as passenger**		**Public Transport**		**E-bike**		**Bicycle**		**Walking**	
		Est.	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**	**Est.**	**Std. Err.**
ASC		**-4,293**	**0,186**	0,135	0,104	**-0,733**	**0,120**	**-1,865**	**0,234**	-0,083	0,058	ref.	ref.
Traveltime (minutes)		**-0,006**	**-0,006**	**0,000**	**-0,006**	**0,000**	**-0,006**	**0,000**	**-0,006**	**0,000**	**-0,006**	**0,000**	ref.
Departure time	Rush hour	**0,116**	**0,016**	**-0,143**	**0,026**	**0,187**	**0,025**	0,087	0,052	**0,055**	**0,016**	ref.	ref.
	No rush hour	**0,151**	**0,022**	**-0,471**	**0,040**	-0,002	0,030	**-0,563**	**0,090**	**0,076**	**0,021**	ref.	ref.
Gender	Male	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	Female	0,043	0,063	**0,312**	**0,082**	**0,676**	**0,095**	-3,190	1,688	**0,630**	**0,059**	ref.	ref.
Age	<24 yo	**0,236**	**0,042**	-0,051	0,070	**0,206**	**0,085**	**-1,510**	**0,174**	**0,306**	**0,045**	ref.	ref.
	25-34 yo	**0,199**	**0,042**	**-0,324**	**0,074**	0,165	0,087	**-1,299**	**0,161**	**0,354**	**0,045**	ref.	ref.
	35-44 yo	**0,108**	**0,041**	**-0,267**	**0,069**	0,044	0,087	**-0,544**	**0,124**	**0,207**	**0,045**	ref.	ref.
	45-54 yo	0,058	0,034	**-0,175**	**0,056**	0,000	0,073	**-0,478**	**0,099**	**0,251**	**0,037**	ref.	ref.
	55-64 yo	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	>65 yo	**0,060**	**0,024**	**0,206**	**0,046**	**-0,144**	**0,042**	**0,765**	**0,102**	**-0,145**	**0,025**	ref.	ref.
Education level	Low	**0,112**	**0,018**	0,043	0,038	**-0,067**	**0,030**	**0,779**	**0,082**	**-0,171**	**0,019**	ref.	ref.
	Medium	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	High	**0,374**	**0,040**	**-0,120**	**0,055**	**0,393**	**0,084**	-0,113	0,111	0,019	0,034	ref.	ref.
Work situation	Employed	**0,339**	**0,056**	**0,222**	**0,085**	-0,118	0,122	**1,067**	**0,133**	**-0,531**	**0,070**	ref.	ref.
	Student	**0,307**	**0,048**	-0,095	0,059	**0,304**	**0,096**	-0,163	0,111	0,056	0,044	ref.	ref.
	Retired	-0,088	0,073	**-0,211**	**0,078**	**0,289**	**0,097**	-0,384	1,657	**0,117**	**0,054**	ref.	ref.
	Disabled	**0,119**	**0,052**	0,076	0,079	0,042	0,103	**0,315**	**0,143**	-0,083	0,047	ref.	ref.
	Unemployed	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	Other	**0,162**	**0,023**	**-0,430**	**0,049**	**-0,157**	**0,035**	**-0,579**	**0,084**	0,001	0,023	ref.	ref.
Houshold situation	Single HH	**0,092**	**0,024**	**-0,218**	**0,044**	**-0,372**	**0,046**	**-0,286**	**0,134**	**0,148**	**0,025**	ref.	ref.
	Youngest child <12 yo	**0,119**	**0,031**	**-0,132**	**0,051**	-0,065	0,046	-0,139	0,141	**0,187**	**0,032**	ref.	ref.
	Youngest child 12-17 yo	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	Other	**1,101**	**0,059**	0,030	0,047	**-0,170**	**0,034**	-0,121	0,099	**-0,089**	**0,023**	ref.	ref.
Cars in HH	No cars	**1,282**	**0,065**	-0,063	0,054	**-0,364**	**0,046**	**-0,367**	**0,115**	**-0,266**	**0,030**	ref.	ref.

	1 car	**1,317**	**0,074**	**-0,224**	**0,086**	**-0,319**	**0,080**	**-0,488**	**0,224**	**-0,284**	**0,050**	ref.	ref.
	2 cars	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	3 or more	**2,531**	**0,157**	**-0,736**	**0,040**	**-0,196**	**0,034**	**0,249**	**0,092**	-0,008	0,024	ref.	ref.
Driver's license	Yes	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.	ref.
	No	-0,087	0,101	**-0,786**	**0,222**	0,096	0,178	0,425	0,575	**-0,454**	**0,102**	ref.	ref.
Willingness		**-4,293**	**0,186**	0,135	0,104	**-0,733**	**0,120**	**-1,865**	**0,234**	-0,083	0,058	ref.	ref.

5. Discussion

Decision-making in transport planning requires prediction of the effect of proposed policies on transport mode choice. In order to acquire these predictions, transport mode choice models can be used. To estimate parameters and probabilities in these models, cross-sectional survey and panel data can be applied. Through cross-sectional surveys and panels the travel behaviour of individual travellers and households can be registered. However, the extent to which these data yield accurate parameter estimations and probabilities is influenced by nonresponse, since nonresponse may lead to a nonresponse bias in the data.

Therefore, in this paper we assessed whether the inclusion of initial nonresponse in a mode choice model yields more accurate parameter estimates. We envisaged that incorporating the probability of the willingness to participate in a cross-sectional survey or panel as a latent variable in a mode choice model would improve the model results.

The results show that overall the latent variable 'willingness' was significant in determining transport mode choice only for the modes 'car as passenger' and 'bicycle'. This means that this unobserved individual-specific bias has a significant influence on this type of travel behaviour. Since preliminary analysis of the screening data showed a significant relationship between the willingness to participate and mode choice, it was expected to find more significant parameters for the latent variable. This might be caused by the overlap in used parameters for determining the willingness to participate and determining mode choice. When overlapping variables are removed from the NLM and HCM models, it was found that more significant parameter estimates are found for willingness. Another explanation could be that initial nonresponse is not so much related to mode use, but more to travelled distances.

In order to establish the added value of using a hybrid choice model through the inclusion of the effect of nonresponse we compared parameter values and the estimated probabilities between the hybrid choice model and a more traditional nested logit model of mode choice. The estimation of probabilities for both the hybrid choice model and the nested logit model show that the transport mode choice of car as driver and e-bike is slightly underestimated in the nested logit model while the choice of car as passenger and bicycle is slightly overestimated in the nested logit model. The found differences are, however, negligibly small.

Although it was expected that including willingness to participate would lead to substantial improvements of the mode choice model, it appears to have very little effect. It should, however, be noted that there are some limitations to the described models. Before being able to truly assess the value of including willingness to correct for initial nonresponse, it is recommended to overcome these limitations in future research.

The first limitation lies in the fact that, as discussed in section 3.2, a very limited set of variables is included in the models. Since the aim of this study was not to develop a new transport mode choice model, but rather to assess whether we could correct for initial nonresponse by including the willingness to participate, only a few variables were included in the model. Adding variables such as income, parking facilities, life events and preferences might significantly benefit the model and would possibly yield different effects of willingness. Also the fact that all trips, regardless of trip purpose, are included in the models is a clear limitation of the model. It is known that mode use is different, dependent on the trip purpose (Kennisinstituut voor Mobiliteitsbeleid, 2016). The model performance could probably be increased by modelling, for instance, only commuting trips. However, since this model is based on data from the first wave of the Netherlands Mobility Panel, not enough observations are present to estimate different nested logit models per trip purpose. It is therefore recommended to include multiple waves of data in the estimation of the model or to estimate a simpler multinomial logit model to assess the impact of willingness on mode choice.

Furthermore, the current study describes the results of the estimations of parameters and probabilities using a hybrid choice model with a nested structure. However, it may well be that a mixed logit model with a latent variable better captures the heterogeneity in mode choice behaviour of individual travellers. Since this was not the aim of the current study, we recommend to perform future research aimed at studying alternative model formulations while correcting for nonresponse. It is also recommended to include the willingness in other travel choice models besides a mode choice model. It could very well be that initial nonresponse produces a large bias on, for instance, travelled distances than on mode choice. Also, in the present study we only corrected for initial nonresponse. At present we did not include attrition. We therefore recommend to perform future research in order to study the effects of extending the model with attrition as well.

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