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Modelling observed and unobserved factors in cycling to railway stations: application to transit-oriented-developments in the Netherlands

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Typically, mode choice behaviour is studied as a function of observed travel factors. Given the importance of unobservable factors on choice behaviour, this paper deviates from this approach. We analysed cycling as mode choice to access railway stations, incorporating latent variables and psychometric data to capture relatively intangible factors that influence mode choice. Such factors are not observable, but can manifest themselves through adjustable indicators. The database used for this paper contains 12000 observations of journeys carried out in the Rotterdam – The Hague area in the Netherlands, covering thirty-five railway stations. In addition to using a traditional binary logit model, we estimated three hybrid choice models for access mode choice. These hybrid choice models represented observed and unobserved factors simultaneously, including the train users' perception of connectivity, attitude towards station environment and perceived quality of bicycle facilities. The results show that both attitudes and observable travel-related elements are important in the decision to cycle to the station or not. Variations in these perceptions and attitudes significantly affect the bicycle-train share. At the same time, improvements in unguarded bicycle parking facilities may increase the number of people who cycle to the train station more than improvements in guarded bicycle parking would. Moreover, the availability of the parking facilities is crucial during rush hours. Another conclusion is that transport strategies to encourage bicycle-train use must be implemented by station type, i.e. measures to encourage bicycle access at larger stations. Further research would develop a hybrid choice model for egress, and a stated choice experiment would compare these results.

Keywords: *bicycle use, train stations, public transport use, Netherlands, hybrid choice model*

1. Introduction

Many European cities - mostly in the Netherlands, Denmark and Germany - have integrated the bicycle into public transport, recognising the important role of the bicycle as feeder mode. International studies show that the provision of abundant bicycle parking at metro stations, as well as at suburban and regional train stations, is probably the most important form of multimodal coordination by cities (Pucher and Buehler, 2007, 2008).

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In the Netherlands, the bicycle is a very important mode for accessing train stations; it has a 38% share in the modal split for those people who live up to 3 km from a train station (Givoni and Rietveld, 2007). In Germany and the UK, 40% of bicycle users only cycle up to 2 km to a train station (Martens, 2004). The bicycle also plays an important role in the multimodal chain within public transport in North American cities, the demand for bike-and-ride far exceeding the supply of facilities in some of those cities (Pucher and Buehler, 2009). At the same time, both multimodal trips and the use of soft modes are important objectives of transit oriented developments (TOD), in which pedestrian and cyclist provisions take part in 'Design' objectives of the 3 Ds (Cervero and Kockelman, 1997) or 7 Ds (Banister and Hickman, 2006).

Any behavioural process is informed by perceptions and beliefs based on available information, and influenced by affect, attitudes, motives and preferences (Ben-Akiva *et al.*, 1999b). The information about the alternatives constitutes the observable elements, whereas the attitudes, motives and preferences form the unobservable or *latent* elements. Latent means potentially existing but not evident or realised. As explained by Ben-Akiva *et al.* (1999b): *perceptions* refer to the cognition of sensation, and *attitudes* are stable psychological tendencies to evaluate particular outcomes or activities with favour or disfavour.

Both observable and latent elements have a verified effect on cycling as main mode. Previous studies have proven the influence of the observable elements on cycling as main mode, such as availability and type of cyclist infrastructure (Hunt and Abraham, 2007), gradient (Menghini et al., 2010), delays and continuity (Stinson and Bhat, 2004), weather, nature of facilities for cycling, existence and/or improvement of parking bicycle at destination (Krizek, 2006), and existence of showers and other facilities (Heinen et al., 2010; Hunt and Abraham, 2007; Tilahun et al., 2007). The Dutch centre for expertise on infrastructure developed a succinct approach, by defining five elements of quality in a cyclist network safety, directness, attractiveness and comfort (CROW, 2007).

Latent elements influencing the choice to commute by bicycle have also demonstrated to be important. Examples are direct effect, long term awareness and safety (Heinen et al., 2010), the safety perception of mixed traffic infrastructure (Chataway et al., 2014), and the contemplation of cycling (Gatersleben and Appleton, 2007) as well as the 'image' of cycling (Daley and Rissel, 2011).

To explain and forecast mode choice in train station access, mode choice is typically modelled as a function of observable factors such as provision of good bike parking (Martens, 2007; Rietveld, 2000), the availability of bicycle lockers (Taylor and Mahmassani, 1996), travel distance (Keijer and Rietveld, 2000; Taylor, 1996), short (egress) distances (Martens, 2007), journey purpose, travel in rush hour, type of discount travel card used, and weather (Givoni and Rietveld, 2007), car ownership (Debrezion *et al.*, 2009; Martens, 2004) and distance to city centre (Krizek and Stonebraker, 2011). Furthermore, Heinen and Bohte (2014) studied the effect of attitudes on the decision to commute by public transport and bicycle. They tested three types of attitudes (towards car use, public transport and bicycle use) and found that beliefs about public transport are more positive for public transport-bicycle commuters. However, the problem with incorporating psychometric data as fitted variables in a discrete choice model is that these fitted variables contain a measurement error. Therefore, to obtain consistent estimates, the choice probability must be integrated over the distribution of the latent variables, obtaining the distribution from the factor analysis model (Morikawa *et al.*, 1990; Walker, 2001).

Ben-Akiva *et al.* (1999a) and Walker (2001) developed a methodological framework for hybrid choice models (HCMs). It requires three structural equations, namely the latent variable equation, the measurement equation and the utility equation (DCM or discrete choice model). In the latent variable equation, the latent variable is contrasted with the measurement model and estimated with the utility equation. One of the main advantages of integrating DCM and latent variables via HCM is the control of error measurements by integrating the latent variable over the distribution of the factors. Furthermore, previous works proved that HCM are clearly superior to even highly flexible traditional models because the latter ignore the effect of subjective attitudes and perceptions over mode choice or transport related decisions. s Various studies confirm this added value for forecasting decision processes as the HCM was able to produce significant latent variables that lead to superior fitting measures (Raveau *et al.*, 2010; Yáñez *et al.*, 2009; Yáñez *et al.*, 2010).

Chataway *et al.* (2014) developed a structural equation model to analyse safety perceptions of cycling in mixed traffic. However, they addressed the latent constructs, but without considering the effect on choice behaviour (i.e. mode choice). In the context of transit-oriented developments, Olaru *et al.* (2011) analysed the residential location choice via latent variables and choice models. Thus, to the author's knowledge, no hybrid choice model for cycling to the station has been developed yet. The aim of this analysis is to draw robust conclusions about the influence of attitudes and perceptions in the access journey to the train station. The image of both station and trains service could play an important role in access mode split, but this has not yet been demonstrated.

At the same time, the effect of attitudes towards station environment (related to bicycle accessibility) has barely been approached. For example, Debrezion et al. (2009) jointly analysed access mode and choice of departure station , but only three stations were included in the case study. Nevertheless, station facilities could have a key effect on the access mode, and as a consequence, on satisfaction with travelling by train (Givoni and Rietveld, 2007). Brons et al. (2009) concluded that in many parts of the rail network, improvements in access services to the railway station can accomplish the same effects as expansion of the railway network. Furthermore, the quality of the total chain from residence to place of activity might influence the railway market potential (Rietveld, 2000).

This paper develops an explicit representation of the effects of *perceptions* and *attitudes* on the access to railway stations. We examine the link between three latent constructs: *attitudes towards station environment*, *perception of connectivity and perceived quality of bicycle facilities*. The aim of our study is to cover the substantial knowledge gap of explaining the behaviour of train-bicycle users via hybrid choice models. As described in the literature review, hybrid choice models have demonstrated superior explanation of individuals' behaviour than traditional choice models. Our study adds to the existing body of knowledge the following contributions: (1) the development of hybrid choice models for bicycle as access mode, (2) the estimation of latent constructs via both psychometric and observable elements, which enrich the estimation, and (3) the estimation of more consistent parameters of latent variables.

Finally, earlier studies demonstrated the influence of the built environment in the modal split; for example, people in settlements with the largest populations tend to travel shorter distances by car (ECOTEC, 1993), higher densities increase the use of public transport (Banister *et al.*, 1997) and diversity of services and facilities alters the modal split (Banister, 1996). Also, shorter distances to train stations increase the probability of train use (Cervero, 2007). Therefore, we added built environment variables to the latent construct, following the traditional analysis of mode choice. The model estimation is done over the distribution of the latent variable; this leads to a more reliable estimation of travel behaviour.

In this section, we discussed our motivation for developing an HCM for bicycle-train users. The next section presents the case study of this research, the metropolitan area Rotterdam – The Hague in the Netherlands. Section 3 describes the analytical framework of the HCM, whereas Section 5 covers the model results. Finally, Section 6 contains the conclusions, and discusses policy recommendations.

2. Case study and data collection

The case study relates to the StedenbaanPlus project, called 'Transit Oriented Development (TOD) in the Randstad South Wing'. In the implementation of the StedenbaanPlus project, local and regional governments, Netherlands Railways (NS, which is the principal passenger railway operator in the Netherlands) and Prorail (the national rail network manager) have been working together since 2006. The project covers the South Wing of the Randstad area, which includes Rotterdam and The Hague (Figure 1), and is one of the most densely populated areas in Europe with over 3.2 million inhabitants (Zuidvleugelbureau, 2011). StedenbaanPlus aims to densify urbanisation around more than thirty railway stations and improve the accessibility of station areas to increase rail ridership.

The TOD concept is based on the five Ds, namely density, diversity, design, distance to transit, and destination accessibility, as defined by Ewing and Cervero (2010). We used the TOD concept as a framework for the characteristics of the built environment and tested the effect of the TOD dimensions by adding those as explanatory variables. Subsections 2.1.1 to 2.1.5 describe those variables. Table 1 shows which variables constitute each TOD dimension. Figure 3 shows the framework of the model estimation.

2.1 Data collection

The database used for this paper combines information from *KTO* data (acronym in Dutch for the Customer Satisfaction Survey)s (Brons *et al.*, 2009), a Dutch cyclist route planner (Fietsersbond, 2011) and a database of firms in the Netherlands (LISA, 2012). The *KTO* survey is the national data collection and analysis conducted by NS every year among train users. The survey collects information about journey (origin/destination, purpose), assessment of station facilities (bicycle parking, safety, service at the station), on-board service, assessment of train service (i.e. frequency, punctuality and intermodality), cleanliness, and so on.

The study in the present paper is based on data for thirty-five departure stations in our study area. In order to obtain a sufficiently large number of completed surveys, we merged the results of the *KTO* survey for the years 2009, 2010 and 2011, so that we had a sample size with of 12,000 observations. Merging three different years could produce a representative bias. However, in this case such bias is not possible because the respondents were different each year.

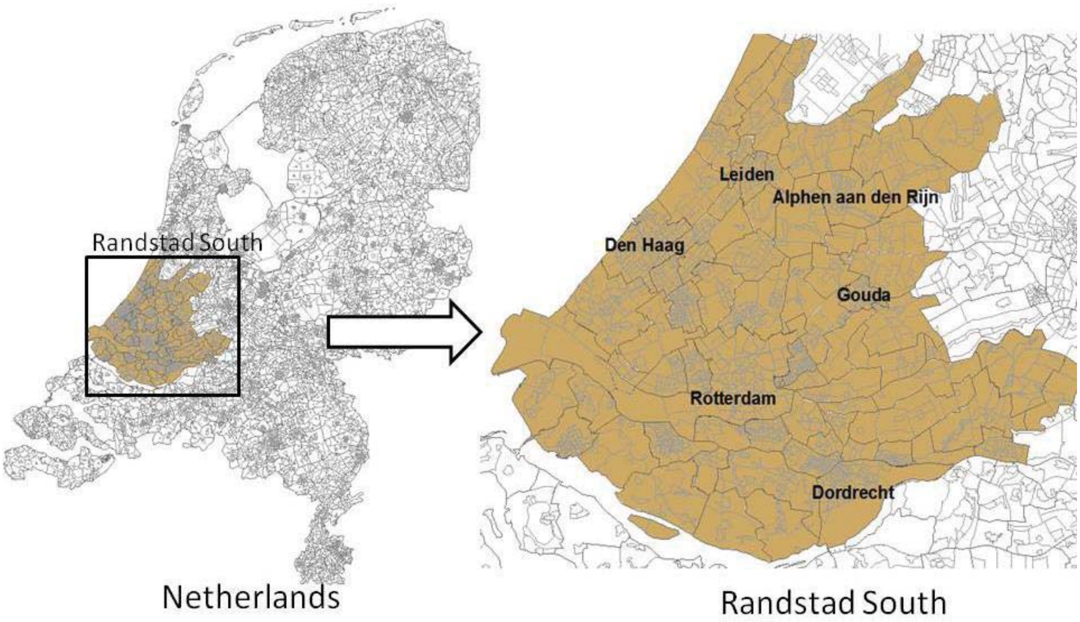

Figure 1. Study area Randstad South Wing

2.2 *Density*

In a TOD, understanding the characteristics of the built environment and urban form land use is important to produce higher levels of transit use, walking, and cycling in station precincts (Renne, 2009). The built environment can be represented as number of street links, number of intersections, block dimensions and housing density (Renne (2009). Accordingly, in the present paper, density is measured within the station precinct as residential density (number of dwellings per square kilometre), population density (number of inhabitants per square kilometre) and density of bicycle network (km of bicycle infrastructure per square kilometre).

2.3 *Diversity*

This set includes variables relating to the spatial area around the station, such as the spatial mix of land use functions and type of companies. Land use diversity is represented in this study as number of employees by three different economic sectors. The number of companies and employees was determined within the station precinct, which is demarcated within a radius of 3 km around the station. In total, 21 economic sectors were tested; three turned out to be relevant in the cycling access namely public, health and retail. The source of these data is the LISA database, which contains employment details on all individual firms in the Netherlands (LISA, 2012).

2.4 *Design*

In this paper, design is represented by the station facilities and design of bicycle route.

- *Design of the station:*

The design of the station was analysed by the availability and status of station facilities. This group includes all variables related to the direct station environment, station type, service provided at the station (i.e. quality of bicycle parking spaces), etc. We used the station types as defined by NS: (1) Very large station in city centre, (2) Large station in medium-sized city, (3) Suburban station with hub function, (4) Medium-size station in centre of small town or village, (5) Suburban station without node function, (6) Station in rural small town or village. These data were obtained from Progammabureau Stedenbaan (2012).

The station type does not explain the aesthetic design, but it is related to the availability of certain facilities. For example, restaurants, stores (number of), places to sit and talk. *Figure 2* shows that according to the research undertaken as part of this research project (La Paix and Geurs, 2014a, 2014b), the smaller stations (Type 6) are usually endowed with good cyclist facilities but scarce place to sit and talk. By contrast, the larger stations (type 1) are endowed with good station features but poor cyclist facilities.

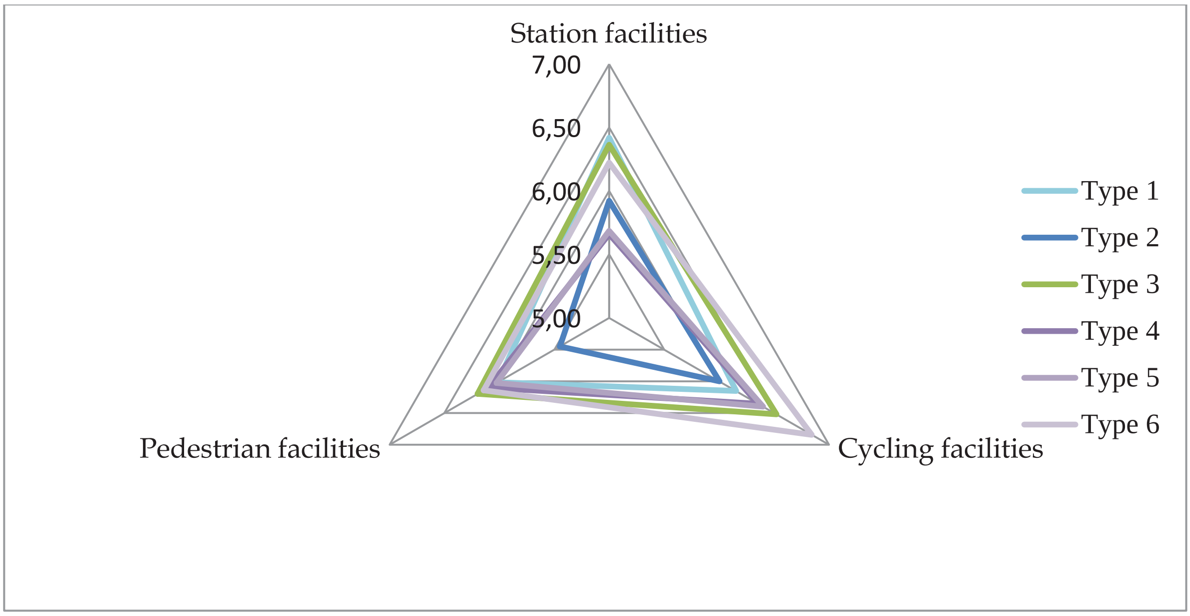

Figure 2. Assessment by station type

- *Design of bicycle route:*

The design of bicycle route includes the variables that influence the route taken from the origin to the destination, the train station. We used a detailed bicycle network database of the *Fietsersbond*, the Dutch Cyclists' Union (Fietsersbond, 2011). The indicators for 'road surface quality', 'traffic nuisance' and 'lighting' were retrieved from the evaluation by users who are members of *Fietsersbond*. In this database, each link is assessed by a set of users who know the link. Average values of road quality, traffic nuisance, and lighting level are calculated for the access routes of each train station. *Fietsersbond* defines the levels of each indicator as follows:

a. Road surface quality: the quality of road surface depends on the maintenance condition and affects the level of vibration caused by the road surface. The following four possible quality levels were distinguished: good, reasonable, bad and unknown. When the quality level is unknown, the average value in the station area is used.
b. Traffic nuisance: this indicator is defined as the disturbance caused by the presence of motorised traffic. The *Fietsersbond* distinguishes five possible quality levels of traffic nuisance, which we used: very little, little, reasonable, much and very much. As in the quality assessment, unknown values are replaced with the average value in the station area.
c. Lighting: this was defined as the level of lighting on the road during night-time. Three possible values were defined: partially present or present (depending on whether there are light posts every 60 to 80 metres or at closer distances), or not present.

2.5 Distance to transit

The effect of route length by bicycle to the train station was tested. The shortest routes from the postcode (4-digit postcode level) to the station were calculated and filtered by a length of 5 km or less.

2.6 Access to destinations

The access to destinations is represented by the connectivity of the station: with other public transport modes and access/egress modes, such as bicycle. In this case, the connectivity is represented as the number of bus-tram-metro (BTM) lines, number of high-speed (HS) Intercity (IC), and Sprinter trains stopping at the station and availability of bicycle parking spaces.

2.7 *Socioeconomic characteristics*

The socioeconomic variables account for various demographic and socioeconomic variables of the bicycle user. In this study, they cover age, gender, occupation based on *KTO* data. Additionally, we included an average value of income level to the model specifications, based on the first four digits of the six-digit alphanumeric postcode. The source of this income level is Statistics Netherlands (CBS). Since the individual income level was not available in the survey, this generic income by postcode level served as proxy.

2.8 *Travel-related variables*

The travel-related attributes include journey characteristics (travel time, rush hour, etc.), Given the relevancy of travel-related variables as reported in the literature, we also included characteristics of the journey in the study, such as journey purpose (work, business, study, school, etc.), travel in rush hour (Givoni and Rietveld, 2007), type of travel card used (such as discount or student card), weather (raining or not). This information is available in the *KTO* database.

2.9 *Psychometric indicators*

The aforementioned *KTO* survey contains information about the valuation of train journeys and station facilities from the perspective of the traveller. This survey takes place every year to monitor customer satisfaction levels among Dutch train travellers. The individual replies on a 10-point Likert scale, in which zero means 'cannot be worse' and 10 means 'excellent'. These statements try to capture the individual's impression, positive or negative. Similarly to what Brons *et al.* (2009) did, we selected several psychometric indicators from this survey to indicate perceptions.

Table 1 presents the descriptive statistics of both the explanatory variables and indicators incorporated in the models.

Table 1. Descriptive statistics

Variables	Notation parameter	5D's	N	Minimum	Maximum	Mean	St. dev.
Sociodemographic variables							
Gender (male=1)	β_{male}			0.00	1.00		
Age	β_{age}		11976	15	94	34.10	15.26
Occupation: student (dummy based on Student OV chip-card)	$\beta_{student\ card}$		11190	0.00	1.00	0.24	0.43
Car availability	β_{car}		12288	0	1	0.34	0.47
Average income in thousands (per year) within 3 km station precinct	In β_{value_time2}		11974	14.30	78.80	33.05	10.06

Variables	Notation parameter	5D's	N	Minimum	Maximum	Mean	St. dev.
Travel-related attributes							
Discount	$\beta_{discount}$		12288	0.00	1.00	0.26	0.44
Work purpose	β_{work_motive}		11209	0.00	1.00	0.34	0.48
Business purpose	$\beta_{business}$		11209	0.00	1.00	0.08	0.27
School purpose	β_{School_study}		11209	0.00	1.00	0.16	0.37
Rush hour dummy based on departure time	$\beta_{Rush\ hour}$		12288	0.00	1.00	0.34	0.47
In-vehicle travel time	In β_{value_time2}		12288	10.00	99.00	34.97	11.64
Denominator of average income							
TOD - land use variables							
Length of access route by bicycle. Dummy variable equal to 1 if length > 3 km, zero if otherwise	$\beta_{length3km}$	Distance to transit	12288	193	4992	1889	1254
Number of dwellings	$\beta_{dwellings}$	Density	12288	*15557*	*28000*	*17093*	*7444*
Jobs per inhabitant	β_{jobs}	Density	12288	*0.12*	*3.47*	*1.19*	*1.08*
Population density (2011)	$\beta_{population}$	Density	12288	*6000*	*58800*	*33975*	*14151*
Ratio of job types: positions over total number of jobs within station precinct							
- related to health (hospitals, clinics, etc.)	β_{WP_Health}	Diversity	12288	*0.03*	*0.51*	*0.17*	*0.11*
- related to public works	$\beta_{WP_{public}}$	Diversity	12288	*0.00*	*0.45*	*0.15*	*0.15*
- related to retail	β_{WP_retail}	Diversity	12288	*0.06*	*0.35*	*0.08*	*0.04*
Average assessment of traffic nuisance in the route from 1 to 5	$\beta_{Averagetraffic\ nu}$	Design	12288	*-0.35*	*0.71*	*0.14*	*0.19*
Density of bicycle network	$\beta_{density\ bicycle}$	Density	12288	15557	64803	44082	9196
TOD - Station characteristics							
Number of high speed trains (HST)	λ_{HST_trains}	Access to destinati ons	12288	0.00	3.00	0.75	1.22
Number of InterCity trains (IC)	$\lambda_{IC_{trains}}$	Access to destinati ons	12288	0.00	12.00	5.85	3.96

Variables	Notation parameter	5D's	N	Minimum	Maximum	Mean	St. dev.
Number of Sprinter trains	$\lambda_{Sprintertrains}$	Access to destinations	12288	1.00	7.00	4.64	1.87
Number of BTM lines			12288	0.00	31.00	18.15	8.66
NSStationType1	$\lambda 2_{NSstationType1}$ $\beta_{station\_Type\_1}$	Destinations	12288	0.00	1.00	0.39	0.49
NSStationType2			12288	0.00	1.00	0.37	0.48
NSStationType3	Reference category		12288	0.00	1.00	0.08	0.28
NSStationType4			12288	0.00	1.00	0.06	0.24
NSStationType5			12288	0.00	1.00	0.08	0.28
NSStationType6			12288	0.00	1.00	0.02	0.13
Assessment of easiness to find travel information (from 1 to 10)	$\lambda_{easytofindtravelin}$	Design	12288	6.3	7.5	7.09	0.24
Assessment of lighting (from 1 to 10)	$\lambda_{lightingstationenv}$	Design	12288	6.0	7.1	6.78	0.20
Number of bicycle parking spaces at departure station	$\lambda_{Bicycleparking}$ $\beta_{Bicycle\ parking\ sp}$	Design, access to destinations	12288	80.00	13485	5058	3979
Psychometric indicators (evaluation from 1 to 10)							
Punctuality of the trains	$\sigma_{punctuality}$, LV indicator	Design	11920	1.00	10.00	6.40	1.44
Connection train to train at departure station	In Factor analysis	Access to destinations	9849	1.00	10.00	6.49	1.30
Quality of lighting at the departure station	σ_{light}, LV indicator	Design	10959	1.00	10.00	6.84	1.32
Shelter on platform at departure station		Design	10880	1.00	10.00	6.04	1.67
Frequency of trains at departure station	$\sigma_{frequency}$, LV indicator	Access to destinations	10591	1.00	10.00	6.78	1.18
Social safety at departure station during the day	In Factor analysis	Design	11734	1.00	10.00	7.65	1.04
Social Safety at departure station during the night	$\sigma_{safety\ night}$, $\alpha_{safety\ night}$ LV indicator	Design	11236	1.00	10.00	6.70	1.47

Variables	Notation parameter	5D's	N	Minimum	Maximum	Mean	St. dev.
Quality guarded bicycle parking at departure station	$\sigma_{guarded}$, $\sigma_{quality\ guarded}$ $\alpha_{quality\ guarded}$ LV indicator $\lambda_{qualityguarded\ pa}$	Design	4373	1.00	10.00	6.77	1.71
Quality unguarded bicycle parking at departure station	$\sigma_{unguarded}$ $\lambda_{qualityunguarded}$	Design	6709	1.00	10.00	5.64	1.75
General judgment of the departure station	$\sigma_{station}$, LV indicator	Design	10797	1.00	10.00	6.70	1.21
Connection of other public transport by train	In Factor analysis	Access to destinati ons	8579	1.00	10.00	6.82	1.51
Quality of roads to access the departure station	$\beta_{Averageroad\ quali}$	Design	11839	4.70	7.70	5.77	0.82

3. Modelling framework

Following the methodology generalised by Walker (2001) for incorporating latent variables in discrete choice modelling, Figure 3 shows the general framework of the integrated choice and latent variable model. The latent variable model includes socioeconomic and neighbourhood attributes. However, we used a discrete choice model to estimate the probability of each alternative given by travel attributes, some socioeconomic attributes and neighbourhood attributes.

In Figure 3, terms in ellipses represent unobservable (latent) constructs, whereas those in rectangles represent observable variables. The right portion of Figure 3 is the latent variable model. The latent variable is denoted by X_n^* for individual n. X_n^* is unobservable, but the observable variable indicator (I_n) is the materialisation of the latent variable. The dashed arrow from the latent variable to the indicator is the measurement model. The indicator is only used to test the estimation of the latent variable; it is not used in the model estimation itself. Thus, the indicator is used to identify the latent variable, and is introduced as unobserved construct in the discrete choice model by the structural equation, represented by the solid arrow from X_n^* to choice model.

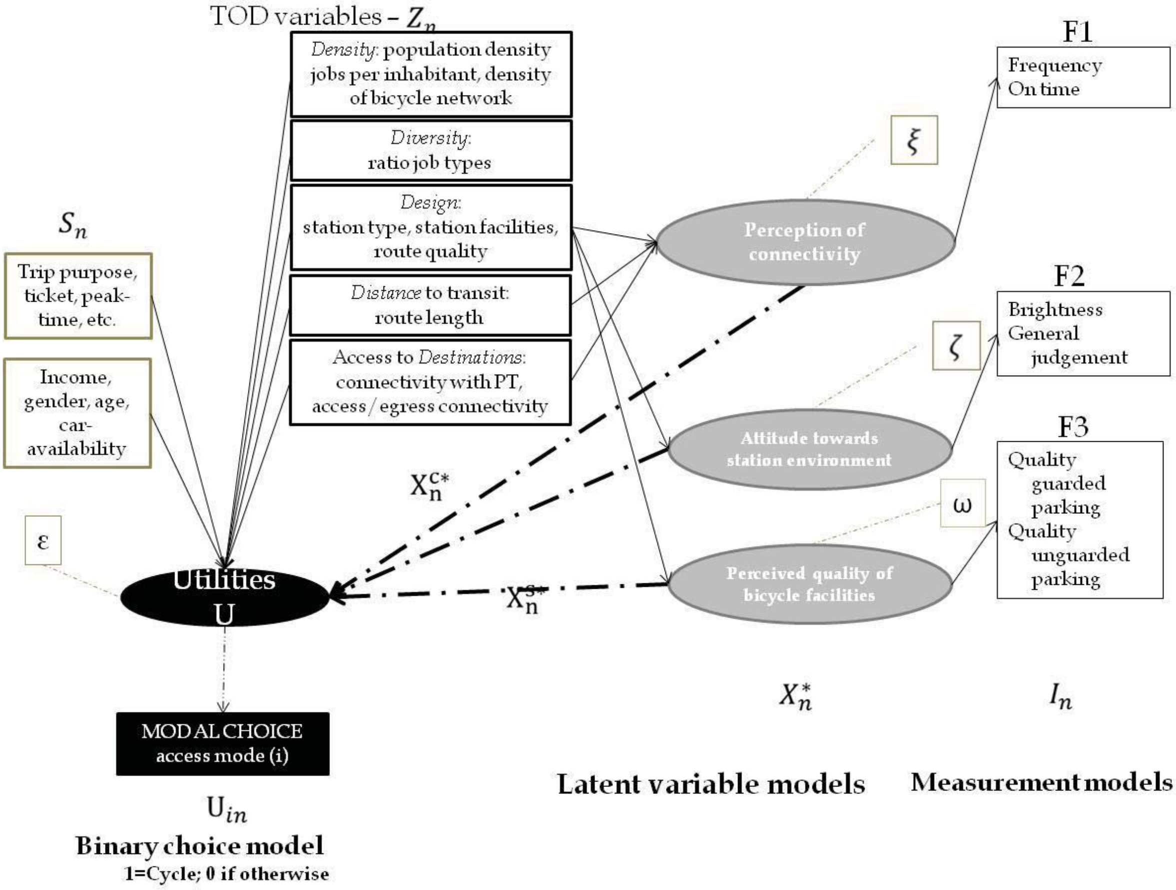

Figure 3. General framework of the hybrid choice model.

3.1 Model specifications

For the latent variable model, the distribution of the indicators is conditional on the values of the latent variable $f_I(I_n\,|X_n^*\,;\alpha,\sigma_\vartheta)$. The indicator is given by $I_n = m(\,X_n^*\,;\alpha\,) + \upsilon_n$. Then, the indicator I_n of the latent variable X_n^* is estimated via the parameter α, which is an unknown parameter to be estimated, and υ_n is the error term. The estimation is done via the following equation:

$$I_n = \alpha X_n^* + \upsilon_n \tag{1}$$

For the latent variable model, we need the distribution of the latent variables given the observed variables X_n. $f_{LV}\,(X_n^*|X_n;\,\lambda\,,\sigma_\omega)$. The latent variable is given by the formula:

$$X_n^* = h(\,Z_n;\lambda) + \,\omega_n \tag{2}$$

Here, X_n^* is the generic expression of both perceived connectivity (X_n^c) and quality of station environment (X_n^s), the latent variable. λ is the unknown parameter to be estimated and ω is the random disturbance term, normally distributed, with variance σ_ω. Z_n is the vector explanatory variables containing 2Ds (design and access to destination) properties.

In this case, there are the latent variables, namely (1) *attitude towards station environment* (X_n^s), which is a linear function of both technical aspects and satisfaction statements, (2) *perception of connectivity* (X_n^c), and (3) *perceived quality of bicycle facilities*(X_n^{b}). These latent variables are linear functions of both observable (quantitative) and qualitative elements associated with user's perception and attitudes.

The utility for choosing alternative i is a function of the explanatory variables (S_n, Z_{sn}), the attributes of the alternative (X_i) and the latent variable (X_n^*). $f_T\,(U_n\,|S_n, Z_{ns}\,, Z_i, X_n^*\,;\,\beta)$. Z means the 5Ds variables, and S means the sociodemographic and travel related characteristics. The choice *i* by the individual n is expressed as the following structural equation:

$$U_{in} = v\left(\,S_n, Z_n\,, X_i, X_n^* \quad ;\, \beta_i\right) + \,E_{in} \tag{3}$$

U_{in} is the utility for individual n for alternative i. Utility is decomposed into systematic and random disturbance, and the systematic utility is a function of both observable and latent variables. β is a set of unknown parameters (to be estimated), and ε is the random disturbance term with variance σ_ε.

The measurement equation of the probability of the individual n choosing the alternative i can be written as follows:

$$P(i|S_n, Z_n\,, X_i, x_n^*\,;\,\beta, \sigma_\varepsilon) = prob\,\left[u_{in} \geq U_{jn}, \forall\, j\, \in c_n\right] \tag{3}$$

In this equation, C_n is the binary choice set of the individual n. In our case, all alternatives are available.

Since the model is composed of the choice i and the latent variable, we have to estimate the joint probability of observing choice i and latent variable X_n^*. The latent variable is a function of the distribution of its error term. Next, the latent variable is fitted over the integral of the distribution of ω. The indicators are the manifestation of the latent variables, and addition of the indicators leads to the following expression:

$$\begin{aligned} &P(i, I_n|S_n, Z_n\,, X_i\,;\,\beta, \alpha, \lambda, \sigma_\varepsilon, \sigma_v, \sigma_\omega)\; = \\ &\int_{X^*} P(i|S_n, Z_n\,, X_i, X_n^*\,;\,\beta, \sigma_\varepsilon)\, f_I(I_n\,|X_n^*\,; \alpha, \sigma_v)\, f_{LV}(X^*|S_n, Z_n, \lambda\,, \sigma_\omega)\, dX^* \end{aligned} \tag{5}$$

3.2 *Likelihood function*

The maximum likelihood was obtained from maximising the logarithm of the likelihood function L over the unknown parameters:

$$\boldsymbol{L} = \sum_n \sum_{i \in C_n} \boldsymbol{d_{in} log\, P(i, I\,|S_n, Z_n, X_i;\; \beta, \lambda, \alpha, \sigma_\varepsilon, \sigma_v, \sigma_\omega}) \tag{4}$$

The binary variable d_{in} characterises the individual decisions, taking values according to Equation 7:

$$\boldsymbol{d_{in}} = \begin{cases} \boldsymbol{1\; if\; U_{in} > U_{jn}, \forall\, j \in C_n} \\ \quad \boldsymbol{0\; in\; other\; case} \end{cases} \tag{5}$$

The structural and measurement equations are assumed to be normally and independently distributed. The indicators depend on the latent variable and observed variables X_n.and X_n^*, respectively. Then, the densities are given by the standard normal density function ϕ, and the standard deviation of the errors term in the latent variable (σ_ω). The density function for the latent variable is given by:

$$\boldsymbol{f_{LV}\,(X_n^*|\,S_n, Z_n;\;, \sigma_v) = \frac{1}{\sigma_\omega}\phi\left(\frac{X_n^* - S_n\lambda_s - Z_n\lambda_z}{\sigma_\omega}\right)} \tag{6}$$

Since there is one indicator, the function of that indicator is conditional on the latent variable, explanatory variables, and standard deviation of the error terms:

$$\boldsymbol{f_I(I_n|\, X_n^*;\ \alpha, \sigma_v)} = \frac{1}{\sigma_v}\boldsymbol{\phi}\left(\frac{I_n - X_n^*\alpha}{\sigma_v}\right) \tag{7}$$

3.3 *Factor analysis*

We conducted a factor analysis to identify the underlying constructs of perceived station environment and passenger's perception of network connectivity at the departure station. Finally, these items were reduced to three factors: Factor 1 represents the latent variable '*perception of connectivity*'; while factor 2 represents the '*attitude towards station environment*'. Factor 3 is called '*perceived quality of bicycle facilities at station'*.

Based on the communalities, we selected a list of eleven statements from the database. The communality measures the level of variance explained by one variable. We discarded variables with communalities smaller than 0.40. The factor analysis elicits how these statements are associated to explain a specific attitude or impression. In this case, based on the eigenvalues, we limited the factor analysis to three factors, which explain the 52% of the variance. The extraction method was *principal component analysis*. The rotation method was *Varimax* with *Kaiser* normalization (Kaiser, 1959). Table 2 shows the factor loadings.

In the measurement model of the latent variable, the indicators are based on psychometric questions selected from the factor analysis. Those questions ask the respondents to evaluate specific characteristics of train service and station. Examples of these characteristics as taken from the *KTO* Survey are '*quality of lighting at the station*', '*connection with other public transport modes', 'frequency' and 'punctuality'* of the trains of the train.

In order to select the best indicators for each latent variable (factors), we estimated a linear regression model in which the dependent variable is the indicator and the explanatory variables are socioeconomic and travel-related characteristics. Hence, the selection of indicators is based on two criteria, namely factor loadings and consistent results between regression models. As can be observed, the variables '*connection of other public transport by train*', '*punctuality of the train*', '*frequency of the train*' and '*connection train to train*' present the higher load in factor 1. Accordingly, we selected '*connection of other public transport by train*' and '*frequency of the train*'.

Four variables scored higher in factor 2. However, after estimating regression models for each variable to select the best, two of them were selected as the best indicators of *attitude towards station environment*. Those indicators are '*brightness at the station*' and '*general judgement of this station*'. Similarly, two variables are used as indicators of factor 3 (*quality guarded bicycle parking and quality unguarded bicycle parking*).

Table 2. Factor loadings, with significant variables in bold

Variables	Component		
	Factor 1: *perception of connectivity*	**Factor 2:** *attitude towards station environment*	**Factor 3:** *perceived quality of bicycle facilities at station*
What is your opinion about the following characteristics of the departure station? (scale from 1 to 10)			
Connection to other public transport by train	**0.442**	0.168	0.259
Social safety during the day at station	0.309	**0.674**	-0.011
Social safety during the night at the station	0.311	**0.650**	0.043
Punctuality of the trains	**0.813**	0.122	0.092
Frequency of the train	**0.748**	0.184	0.117
Quality of lighting at the station	-0.004	**0.735**	0.160
Shelter on platform	0.234	0.455	0.213
Quality guarded bicycle parking	0.152	0.183	**0.803**
Quality unguarded bicycle parking	0.160	0.137	**0.829**
Connection train to train	**0.847**	0.159	0.102
General judgement of this station	0.049	**0.776**	0.217

4. Results

This section discusses the most relevant findings from the model results. Table 3 shows the results for three discrete choice models: one traditional binary logit model, in which the dependent variable is '*use of bicycle in the access to the station*' (1 if yes, 0 if otherwise) and two hybrid choice models (HCMs), which include latent variables describing *perception of connectivity* or *attitude towards station environment*. The results are consistent with the expected signs. The results show that both latent variables are significant and positive. Thus, attitudes towards station environment and perception of connectivity are important in the choice of cycling to the railway station. This means that improvements in perceptions about both station and connectivity would lead to increased bicycle use. The standard deviation of the latent variables is significant, with $\sigma_{connectivity}$ and $\sigma_{station}$ indicating a relevant sensitivity among the population with respect to these unobserved effects.

Table 3. Discrete choice and latent variables in the hybrid model

Name	Binary logit: Bicycle access		HCM Connectivity		HCM Station		HCM bicycle	
	Value	Robust t-test	Value	Robust t-test	Value	Robust t-test	Value	Robust t-test
Variables in binary choice model: 'cycling'								
ASC1	-0.457	-1.43	-3.67	**-17.20**	-1.06	**-2.96**		
$\beta_{attConnectivity}$			0.25	**8.99**				
$\beta_{attstation}$					0.10	**3.76**		
β_{age}	-0.01	**-4.28**	-0.01	**-4.87**	-0.01	**-3.88**	-0.002	-1.13
β_{male}	0.04	0.29	0.02	0.53	0.04	0.97	0.01	0.16
β_{work_motive}	0.48	**8.03**	0.55	**9.78**	0.51	**9.15**	0.64	**9.74**
$\beta_{business}$	0.63	**7.68**	0.61	**7.41**	0.63	**7.59**	0.70	**7.55**
β_{School_study}	0.41	**5.72**	0.27	**5.15**	0.27	**5.17**	0.27	**4.38**
$\beta_{discount}$	0.26	**4.92**	0.44	**6.25**	0.36	**5.04**	0.49	**5.88**
$\beta_{studentcard}$	-0.16	**-2.53**	-0.22	**-3.39**	-0.21	**-3.19**	-0.25	**-3.36**
$\beta_{Rush\ hour}$	0.27	**5.26**	0.27	**5.52**	0.28	**5.67**	0.28	**4.96**
β_{car}	-0.08	-1.86	-0.10	**-2.23**	-0.08	-1.62	-0.10	-1.95
$\beta_{value\_time\_2}$	0.07	1.55	0.00	0.68	0.08	1.55	0.08	1.27

Name	Binary logit: Bicycle access		HCM Connectivity		HCM Station		HCM bicycle	
Density								
$\beta_{bicycle\ density}$	-0.24	**-4.61**	-0.20	**-3.92**	-0.24	**-4.62**	-0.31	**-5.46**
$\beta_{population}$	-0.01	-1.16	-0.03	**-4.05**	-0.01	-1.19	0.042	**5.13**
$\beta_{dwellings}$ *(per squared km)*	-0.01	-1.21	0.002	0.57	-0.52	-1.19	-0.003	-0.9
β_{jobs}	0.40	**3.26**	0.20	**2.51**	0.38	**3.14**	1.23	**11.45**
Diversity								
β_{WP_Health}	-0.21	-0.44	-0.185	-0.38	-0.238	-0.49	-1.3	**-2.29**
β_{WP_public}	-3.23	**-4.98**	-2.95	**-5.02**	-3.32	**-5.08**	-6.41	**-9.02**
β_{WP_retail}	1.18	1.25	0.605	0.66	1.05	1.12	1.61	1.5
Design								
$\beta_{Averageroad\ quality}$	2.40	**6.63**	2.75	**9.15**	2.40	**7.78**	1.20	**3.45**
$\beta_{Averagetraffic\ nuisance}$	-1.04	-0.26	-1.00	**-4.49**	-1.04	**-4.60**	-1.52	**-5.87**
Distance (to public transport)								
$\beta_{length3km}$	-0.35	**-6.21**	-0.33	**-5.97**	-0.35	**-6.12**	-0.37	**-5.68**
Destinations (accessibility)								
β_{BTM_lines}	-0.03	**-5.24**	-0.03	**-6.45**	-0.03	**-6.30**		
$\beta_{station\_Type\_1}$	-0.27	**-4.33**	-0.11	**-2.69**	-0.37	**-8.29**		

Name	Binary logit: Bicycle access		HCM Connectivity		HCM Station		HCM bicycle	
$\beta_{Bicycle\ parking\ spaces)}$	0.002	**9.35**	0.002	**9.67**	0.002	**2.08**		
Variables in latent models								
$\beta_{meanAtt}$			5.87	**42.52**	6.15	**43.83**	1.79	**7.32**
Design								
$\lambda 2_{NSstationType1}$					-0.24	-1.83		
$\lambda_{easytofindtravelinformation}$					0.03	0.37		
$\lambda_{Bicycleparking}$					0.06	**21.03**		
$\lambda_{lightingstationenvironment}$					-0.003	-0.04		
$\lambda_{qualitybikeaccessroads}$			-0.02	-1.26			0.05	1.44
$\lambda_{qualityguarded\ parking}$			0.003	0.79				
$\lambda_{qualityunguarded}$			0.08	**15.29**				
Destinations (accessibility)								
$\lambda_{IC_{trains}}$			-0.01	**-2.10**			-0.02	-1.61
$\lambda_{Sprintertrains}$			0.05	**2.96**			0.25	**8.22**
λ_{HST_trains}					-0.15	**-10.31**		
σ_{LV}			0.23	**11.59**	0.06	**2.98**	0.67	**51.91**

Name	Binary logit: Bicycle access	HCM Connectivity		HCM Station		HCM bicycle	
Measurement model							
$\sigma_{punctuality}$		0.199	**12.71**				
$\sigma_{frequency}$		0.234	**13.14**				
$\alpha_{frequency}$		0.368	**20.14**				
$\sigma_{safety\ night}$				0.805	**72.54**		
$\alpha_{safety\ night}$				0.297	**18.33**		
σ_{light}				0.182	**10.11**		
$\sigma_{gral\ judgment}$				0.241	**11.75**		
$\sigma_{quality\ guarded}$						0.818	**81.06**
$\alpha_{quality\ guarded}$						0.731	**21.12**
$\sigma_{quality\ unguarded}$						1.06	**152.8**
Fit measures							
Number of estimated parameters	24	35		36		33	
Rho-bar	0.157	0.330		0.215		0.155	

LV = latent variable; HCM = hybrid choice model; DCM = discrete choice model

The travel-related variables are the standard explanatory variables that contextualise the results. Analysing these parameters we find that school or study journeys begin more often by bicycle. Both business and work journeys also very often start by bicycle but less frequently. Clearly, a discount for train use would make the train more attractive, but the result shows that train discounts are also associated with more bicycle use. The student card, an indicator of occupation at the same time, is negatively associated with bicycle use because it reduces public transport cost, making public transport more attractive than cycling to the station. This result is in line with findings of Keijer and Rietveld (2000) who highlighted that the share of cycling and walking in the modal split decreased in the years after the introduction of the public transport card for students in 1991 (*OV-studentenkaart,*). The *OV-studentenkaart* allowed students to use public transport at no charge; the OV chip card succeeded it in 2010.

Longer travel time of the main journey is also a deterrent to accessing the train station by bicycle. This could be associated with business journeys and higher incomes, which may facilitate more car use. In fact, the estimated parameter of *value of time* (average income level in the residence area divided by travel time) indicates that people living in relatively affluent neighbourhoods tend to cycle to the station less.

Car availability plays an important role in bicycle modal share. Car availability negatively influences bicycle use as travel model to the train station. The result is consistent among the three estimated models and is also consistent with the results of Givoni and Rietveld (2007). Additionally, we can observe that the effect of car availability is stronger if the latent variables are considered. Since car availability is a sociodemographic variable, its effect could be strengthened by the introduction of the latent variables (individual heterogeneity).

Furthermore, the model results show that access distances greater than 3.6 km are a deterrent for accessing the train station by bicycle. This result is consistent with the findings of Givoni and Rietveld (2007), who found that the main substitute for the car is the bicycle for journeys shorter than 3.6 km (used by 50% of those who do not have access to a car). According to the results, cycling to the station is more frequent in areas with lower residential density. The effect of residential density is negative. This result is consistent with the findings for station type 1, namely that larger stations located in large city centres are less attractive to cyclists. In addition, both findings can be associated with a higher use of BTM in high-density areas.

The fit measures in Table 3 show that the hybrid model of perceived connectivity performs better than the hybrid model of station environment, and includes the rho bar and log-likelihood. Since the estimated models contain a different number of parameters, goodness of fit is compared by way of the rho bar (the larger the rho bar, the better the forecasting). The hybrid model including perceived connectivity has a greater rho-bar value (0.33) than the model of perceived quality of bicycle facilities (0.155); it is also greater than the rho-bar value of the standard logit model (0.157). At the same time, the standard logit model shows a higher rho-bar value than the hybrid model of attitude towards station environment (0.215). A larger rho-bar ensures better forecast of travel behaviour.

The three latent variables (perception of connectivity, attitude towards station environment and perceived quality of bicycle facilities) are positively associated with bicycle use. The estimated parameters for latent variables are significant at the 95% confidence level. Regarding perception of connectivity and bicycle facilities, one of the most important factors is the quality of unguarded bicycle parking. Similarly, the image of bicycle facilities at the station is strengthened by a good quality of bicycle access roads. The results also show that the number of Sprinter trains enhances the perception of connectivity at the station. These results are consistent with the findings by Brons et al. (2009) and Givoni and Rietveld (2007), who found that satisfaction with rail journey is associated with the facilities of the chosen access mode.

The indicators used in the measurement model of latent variable connectivity were '*punctuality of the trains*' and '*frequency*'. Table 3 shows the standard deviation $\sigma_{punctuality}$ and $\sigma_{frequency}$; both are significant which means that these variables adequately explain the latent variables. In other words, from the user's viewpoint, the connectivity of departure station mostly manifests itself in these two elements of service level: punctuality and frequency of train service. The latter point constitutes an important issue when analysing station size; most of the small stations have a low train frequency.

The latent variable '*attitude towards station environment*' shows a positive influence on cycling to the station. The higher the valuation of station environment is, the higher the probability of cycling to the station. The indicator that represents the unobserved effect is '*judgment of the station*'. The standard deviation $\sigma_{gral\ judgment}$ is highly significant, indicating the representativeness of the latent variable through this measure. The analysis of the estimated parameters and the t-test shows that the quality of bicycle parking is one the most relevant elements in the attitude of bicycle users towards station environment. Low quality of lighting in station surroundings discourages train users from accessing the station by bicycle. The availability of high-speed trains at the station also discourages cycling to the station. However, high-speed trains often stop only at larger stations, which can be associated with access by BTM. These two latter conclusions are added findings of the present study.

At the same time, in the identification of the latent effects of '*perceived quality of bicycle facilities*', the assessment of unguarded bicycle is more important than the assessment of unguarded bicycle parking.

With the developed model, we can also make an analysis of the market share of bicycle use. Table 4 presents the average utility and probabilities of cycling according to the three models. The negative disutility is greater for the station model. The probability of cycling is higher in the standard logit model, which means that this latter tends to overestimate the probability of cycling. Hence, missing important unobserved effects may lead to overvaluation of demand solutions in travel behaviour.

Table 4. Average utility and probabilities

	Average utility	Average probability
HCM - LV Connectivity	-0.808	0.324
HCM - LV Station	-1.103	0.268
HCM – LV Bicycle	-0.976	0.296
DCM - Logit	-0.696	0.335

LV = latent variable; HCM = Hybrid Choice Model; DCM = Discrete Choice Model

5. Conclusions and discussion

This paper contributes an analysis of the role unobserved factors play in the choice of access mode to train stations. The main contribution of this paper is the development of hybrid choice models for bicycle choice. Other studies have analysed customer satisfaction data such as satisfaction and assessment (Givoni and Rietveld, 2007), but no published study explains simultaneously how the *perceived connectivity* and *attitude towards station environment* affect cyclist behaviour in the access to the station. Our analysis shows that both observed and unobserved factors are important. For the two hybrid choice models we used, the fit improved after addition of the latent variable. Additionally, the results show that omitting attitudes tends to lead to overestimation of the probabilities of cycling to the train station. Our study also shows that observable factors remain relevant after the addition of unobserved effects.

The purpose of using hybrid choice models with latent variables is to design strategies that target different groups of individuals much better. The policy recommendations derived from our model results relate to both passenger and station levels:

Firstly, variations in perceived connectivity and quality of station environment significantly affect the bicycle-train share, for example through improvements in parking facilities and station attractiveness. More specifically, the results encourage designing specific transport strategies for rush hours; for example, making additional and automatic bicycle racks available in rush hours. Also, this study shows that, as in other bicycling cities in Europe, one of the main problems for bicycle planners and cyclists is the congestion during peak hours (Pucher and Buehler, 2007). In the Netherlands, cyclists (and pedestrians) are hardly affected by traffic congestion, but do require good quality of parking facilities to encourage bicycle use during rush hours.

Secondly, improvements in the quality of unguarded bicycle parking facilities may increase the number of people who cycle to the train station more than improvements in guarded bicycle parking would. For example, as highlighted by Pucher and Buehler (2009), providing sheltered bicycle parking instead of accommodating bicycles on transit vehicles deserves more attention.

Thirdly, the results show that strategies for improving the efficiency of train service in rural stations (with lower train frequencies) would considerably contribute to the positive image of train service. Consequently, more users would use the train and cycle to the station.

Finally, bicycle-train users are not equally flexible with regard to changes in train costs. Therefore, specific strategies must also target groups by income level. For example, a workers' train-bicycle card could allow commuters to park their bicycle at a reduced price, or a weekend card could offer a special price for access journeys during the weekend.

Future research could apply the same model to the egress part of train journeys. Additionally, a stated choice experiment could be conducted to identify differences in choice behaviour, under controlled variation of attributes identified as important in the present paper. Such attributes are namely cost, journey duration and quality of infrastructure for feeder modes. In the same line, an egress experiment would enrich the results, i.e. analysis on the asymmetry between bicycle use for both access and egress.

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