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Modelling bicycle use intention: the role of perceptions

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Abstract Users' perceptions are identified as key elements to understand bicycle use, whose election cannot be explained with usual mobility variables and socio-economic characteristics. A hybrid model is proposed to model the intention of bicycle use; it combines a structural equations model that captures intentions and a choice model. The framework is applied to a case of a university campus in Madrid that is studying a new internal bike system. Results show that four latent variables (convenience, pro-bike, physical determinants and external restrictions) help explaining intention to use bike, representing a number of factors that are linked to individual perceptions.

Keywords Bicycle use models · Cyclist perceptions · Hybrid models · Latent variables

Introduction

Cycling is recognised as a clean mode of transport and an essential part of an inter-modal plan for sustainable urban travel (OECD 2004); it is also considered as part of a good strategy for healthy cities (Saelens et al. 2003). Transportation planning efforts nowadays include increasing the levels of walking and bicycling. It counterbalances urban sedentary

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life and could replace motorized vehicle trips with all its legacy of negative externalities, especially if its use for utilitarian purposes increases besides recreational ones. Policies of cycling promotion are usually focused on transport demand management and on factors affecting bicycle use (Pucher et al. 2010). Therefore it is necessary to move forward in learning more about the factors that affect the willingness to use the bike.

In most cases travel time and travel cost are the single most important variables when modelling mode choice. In many urban areas, however, the bicycle is a notable exception. Experiments regarding travel time involving other usual modes—car, bus, subway or tramway—and the bicycle have shown that for usual urban distances the bicycle dominates the others in both time and cost (Petritsch et al. 2008). However, in those same areas the bicycle is very far from being the dominant mode: in spite of an average speed than can be comparable or even superior to motorized modes at a very low cost, it is seldom chosen. One might think that the physical effort required (as in walking) and the risk taken to acquire that speed could well explain the reluctance to use it but, as we discuss below, there is evidence that suggests that choosing the bicycle as a mode of transport is a very special process and that there is a need to understand well the motives behind this particular mode choice or its rejection (Eash 1999; Landis et al. 1997; Pinjari et al. 2008).

Besides mobility variables, there are other types of factors identified in the literature which are linked to bicycle use, as individual socio-demographic characteristics, urban environment and users' perceptions. Regarding these latter, bicycle users tend to consider a larger than usual number of variables when making a choice (Pucher et al. 2010; Emond et al. 2009). It is necessary to identify and quantify rigorously these variables and to understand the form they are perceived in order to model bicycle choice properly. This induces two problems to be faced and solved: to improve on the identification of those factors that play a role in the decision to use the bicycle and to design a way to introduce these factors effectively towards their future operational use in choice models. In this paper we propose a methodology to identify these types of variables and to incorporate them into a choice model using a hybrid approach. While the methodology can be replicated, the validity of results themselves is limited to the case where the method is applied, i.e. a model of intention to use the bike within a university campus area in a city with low cyclist culture.

During the last decade many authors have aimed at introducing users' perceptions to enrich the specification of mode choice models and improve their performance (Karash et al. 2008; Cao and Mokhtarian 2005; Heath and Gifford 2006; Duarte et al. 2009; Sener et al. 2009; Bolduc and Álvarez-Daziano 2010). The development of hybrid models (Walker 2001) permits the introduction of indices representing groups of perception variables into traditional econometric choice models: the latent variables. Knowing these perception variables and the associated indices that represent their influence in the decision regarding bicycle use is indeed a useful way to understand and model bicycle use. This requires the identification of those aspects that users take into account when deciding to include the bicycle as an alternative in the mode choice set. Knowing these potential factors, assessing their relative importance, capturing the potential user's decision process and deciding how to make them operational for modelling is the essence of the approach presented in this paper. Although some factors can be deduced through direct observation and others could be detected through traditional mobility surveys, we believe that capturing and using the psycho-social elements behind our perceptions regarding potential bicycle use requires an ad-hoc exploration.

In the following section we review the specification and variables of models that have been aimed at understanding the use of the bicycle. In Sect. 3 we show the characteristics and advantages of the hybrid approach to capture and introduce perceptions when modelling the intention of bicycle use. Then the data collected to construct the real case is presented in Sect. 4. Models and results are shown in Sect. 5 and the main conclusions are synthesized in the closing section.

Explanatory variables from bicycle models regarding use

The elements that influence bicycle use can be grouped into users' characteristics, trip characteristics, environmental context, facilities and subjective perceptions. Here we extract those elements from studies originated both in countries with low cyclist culture as Australia and the United States, and in European countries.

Personal characteristics are understood as the diversity of profiles that can be described using demographic categories (Kemperman and Timmermans 2009). The most important are age (Dill 2003; Rietveld and Daniel 2004; Sener et al. 2009; Baltes 1996; Moudon et al. 2005; Ortúzar et al. 2000), income (Petritsch et al. 2008; Pucher and Buehler 2008; Dill and Voros 2007), gender (Pucher and Buehler 2008; Emond et al. 2009; Moudon et al. 2005; Akar and Clifton 2009; Pucher et al. 2011; Garrard et al. 2008; Harris and Glaser 2006; Krizek et al. 2005; Emond et al. 2009), ethnic origin (Moudon et al. 2005; Pucher and Buehler 2008; Pucher et al. 2011), car ownership and use (Ortúzar et al. 2000; Taylor and Mahmassani 1996, Dill and Voros 2007; Pucher et al. 2011; Xing et al. 2008) and bicycle ownership (Pinjari et al. 2008; Rietveld 2000). Age plays a role mostly in places with incipient bicycle culture, where people between 18 and 45 years old favour its use. Bike use seems more intensive in groups with income above the mean, but correlation with age makes it difficult to isolate its effect. Gender seems relevant only when the bike share is low; male users roughly doubles female users possibly due to female risk aversion and a larger number of home-based and family related trips than men. White non-hispanic people present larger proportions of bike use than black people in the USA. Car ownership and use affect negatively the use of bikes, while bicycle ownership works in favour, although price and operational costs are not a strong barrier.

Regarding trip characteristics time, cost and distance have lost importance (Rietveld and Daniel 2004; Hunt and Abraham 2007; Petritsch et al. 2008), particularly relative to better and safer infrastructure (Hopkinson and Wardman 1996; Hyodo et al. 2000; Eash 1999) up to fifteen kilometers trips in urban areas, which seems particularly relevant under work schedule flexibility (Akar and Clifton 2009) although walking dominates for very short distances. Feeder distance becomes relevant when bike is combined with public transport (Rietveld 2000) or as an extension to a long car trip (Taylor and Mahmassani, 1996). Recreation or sport seems more relevant than commuting as bike trip purpose (Sener et al. 2009; Moudon et al. 2005; Burbidge and Goulias 2009), influenced by overall cyclist culture (Pucher and Buehler 2008), hours at work, clothing, location of the workplace, availability of public transport, facilities at the workplace, displacements needed during work and image with the colleagues (Rondinella et al. 2012; Heinen et al. 2010a, b; Wardman et al. 2007).

Environmental context plays a role in bicycle use, including climate, topography and urban design (Moudon et al. 2005). Temperature, rain, snow or humidity might reduce up to 20 % of cyclists volume (Dill 2003; Aultman-Hall 2009; Nankervis 1999; Shiva Nagendra and Khare 2003; Bergström and Magnusson 2003), but this depends on the period of variability (seasonal or daily), on the trip purpose and on place (Nankervis 1999; Aultman-Hall 2009; Rietveld and Daniel 2004; Thomas et al. 2009). High slopes reduce bicycle use (Rietveld and Daniel 2004; Parkin et al. 2008; Cervero and Duncan 2003; Stinson and Bhat 2003; Sener et al. 2009) but this is linked with other factors as urban density, accessibility, type of interaction with the car regarding traffic level, the existence of bike ways (Pucher and Buehler 2008; Moudon et al., 2005; McCahil and Garrick 2008). The urban setting in general indeed plays a role in bicycle use (Kemperman and Timmermans 2009; Sener et al. 2009; Cervero and Duncan 2003; Zahran et al. 2008).

In principle, *facilities* as a bicycle network seems relevant in bicycle choice (Moudon et al. 2005; Akar and Clifton 2009; Hunt and Abraham 2007; Pucher et al. 2011; Titze et al. 2008; McClintock and Cleary 1996; Cour Lund 2009), but experience diminishes risk and safety fears (Taylor and Mahmassani 1996; Hunt and Abraham 2007; Rondinella et al. 2012). Some authors point out that bikeways induce relaxation (Alves 2006; Carré 1999) and a reduction in pedestrians' safety (Hunt and Abraham 2007). Friendly exclusive networks for bicycles indeed favours bike use particularly where the mode share is low (Moudon et al. 2005), which in turn induces further developments of these types of facilities (Faghri and Egyháziová 1999; Barnes and Krizek 2005). Safe parking places has emerged as the most important infrastructural element for bike users everywhere (Hunt and Abraham 2007), linked to the reduction of theft risk (Taylor and Mahmassani 1996) and with the unavailability of space at home. Lockers to keep clothes, showers or toilettes seem to contribute to solve daily conflicts between the cyclists and the colleagues (Sener et al. 2009) which makes the perception of non-users important (Rondinella et al. 2012); these facilities are valued differently by men and women (Taylor and Mahmassani 1996).

According to the theory of planned behaviour (Ajzen, 1991), beyond the objective factors mentioned above there are *perceptions* which are subjective representations of these factors that depend on many personal characteristics and experiences (Sener et al. 2009). These are relevant under changes in the travel conditions (Bamberg et al. 2003), so capturing attitudes and perceptions is necessary to induce the use of the bicycle in urban contexts where the bike culture is absent (Teich 2009). Perception of accident risk is a most important factor (Rietveld and Daniel 2004, Sener et al. 2009; Pucher and Buehler 2008; Wardman et al. 2007; Parkin et al. 2008, Hopkinson and Wardman 1996, Noland and Kunreuther 1995; Molino and Emo 2009; Carter et al. 2007; Natarajan and Demetsky 2009; Danya et al. 2009). The probability of accidents for cyclists increases with high speed of motorized vehicles, poor visibility of the facilities and the cyclists, restricted mobility and accessibility for bikes, high volumes of motorized vehicles, high level of interaction between cyclists and motorized vehicles, ignorance of traffic rules. Other factors increase risk, as alcohol consumption in the population, number of vehicles per household and other socio-geographical factors (Noland and Quddus 2004). Eash (1999) and Allen-Munley et al. (2004) have concluded that choosing safe routes is particularly valued by cyclists. Also important is roads' quality, segregation from cars and traffic intensity (Petritsch et al. 2006). These objective variables related with risk-exposure reinforce the need to dig deeper into the perception of safety and its (latent) causes (Taylor and Mahmassani 1996). The objective elements behind the subjective relation between bike use and health have not been studied as much as those related with risk (Akar and Clifton 2009; and Zahran et al. 2008).

Although modelling exercises are context dependent, those factors that persistently have appeared in behavioural studies are summarized in Table 1, which suggests that there is a variety of elements that should not be overlooked and that searching for variables that capture perceptions, intentions and pre-dispositions is a relevant task.

Table 1 Relevance of different variables in bicycle use models

Factors	Authors	1	2	3	4	5	6
Subjective factors							
Trip distance		+		+++			
Perceived risk			+		++		
Bike tracks and lanes		+++			+++		
Convenience			++				
Cost					+++		+
Travel time			+		++	+++	+
Opportunity of physical exercise					+++		+
Flexibility			++		++		
Comfort			+				
Vandalism					++		
Ecological					++		
Observable factors							
Topography		+				+	
Bike facilities					+++		+++
Bike parking available			+				+++
Public Transport accessibility				+			+
Shower available in working places					++		+
Age				+++			
Gender		++	+	+			
Car availability		+	+	+			
Income		++		++			
Percentage of students							
Socioeconomic class		+++					
Level of studies				+			
Ethnics		+					
Bike experience				++			++
Bike availability				+++			+

The number of marks indicates importance of the variable in the model

(1) Parkin et al. (2008) [UK]; (2) Noland and Kunreuther (1995) [USA]; (3) Ortúzar et al. (2000) [Chile]; (4) Hopkinson and Wardman (1996) [England]; (5) Stinson and Bhat (2003) [USA]; (6) Taylor and Mahmassani (1996) [USA]

Capturing perceptions to model bicycle use

The black box representing the system of preferences is too black to understand the user' motives behind the choice of the bike (Barnes and Krizek 2005); the main basic factors behind other modes' choices are of limited explanatory power in this case (Pinjari et al. 2008; Eash 1999; Schossberg and Brehm 2009). There is a need to go beyond what is directly observable in order to capture emotions, feelings and perceptions (Heinen et al. 2010b).

The traditional discrete choice paradigm establishes that the utility that underlies individual decisions has two components: one that the observer-analyst can replicate (the so-called systematic component) and another that captures the unknown errors and other (presumably unobservable) factors. Among the options to capture complex structures of decision when studying mode choice, mixed models were labelled as “the models of the future” (Ortúzar and Willumsen 1990) because of their flexibility to deal with unknown phenomena that contribute to the unobserved part of utility. This has been viewed as a conformist approach involving the resignation to understand and incorporate those unknown factors as the psycho-social or latent variables that cannot be observed but can be indirectly treated (Golob 2001; Vredin Johansson et al. 2006; Daziano and Bolduc 2013; Yáñez et al. 2010). Models with latent variables represent an improvement.

Along these lines Ben-Akiva et al. (1999) proposed an expanded framework to model choice behaviour, which originated the dynamic hybrid models characterized by a sub-model of latent variables that produces a set of indices that can be incorporated to a traditional discrete choice model (Ben-Akiva et al. 2002; Raveau et al. 2010; Correia et al. 2010; Bolduc and Álvarez-Daziano 2010). Hybrid models have been used in areas as freight transport demand (Ben-Akiva et al. 2008), mode choice (Vredin Johansson et al. 2006; Bolduc et al. 2008; Daziano and Bolduc 2013; Raveau et al. 2010; Yáñez et al. 2010; Correia et al. 2010; Fleischer et al. 2012) or land use—mobility relations (Mokhtarian and Cao 2008).

The need to include perceptions in a quantitative way to allow for qualitative conclusions has been advocated for all the so-called active modes as walking and cycling (Burbidge and Goulias 2009; Schossberg and Brehm 2009), latent variables and the models that contained them provide an adequate framework to explain their choice (Golob 2003; Golob 2001; Raveau et al. 2010). The added complexity is worth only if the problem that is faced receives a clear contribution from the new variables (which is unknown before the model is actually built and estimated) or is very strongly supported by the analysis of previous models and results; the key question is whether the addition of latent variables would provide a more solid explanation for bicycle use.

An approach that has been particularly useful to work with latent variables is the Structural Equation Model System (SEM; Keesling 1972, Jöreskog 1973; Wiley 1973; Bentler 1980). It has been applied to transport beginning in the eighties (Golob 2003). Combining random utility models within the discrete choice paradigm with a latent variables model poses a relevant econometric challenge. Walker (2001) proposed the joint or integrated estimation of the two sub-models, which can be described as the simultaneous estimation of a system of structural equations using maximum likelihood with complete information. The system would consist of a discrete choice model with endogenous explanatory latent variables and a model for these latter with four equations; two of measure and two structural (Walker and Ben-Akiva 2002; Bolduc et al. 2008; Bolduc and Álvarez-Daziano 2010; Raveau et al. 2010). This is the optimal methodology although very complex to solve. It has been applied satisfactorily using both classical (Ben-Akiva et al. 2008; Bolduc et al. 2008) and Bayesian methods (Bolduc and Álvarez-Daziano 2010; Daziano and Bolduc 2013). An experimental prototype exists (Bolduc and Giroux 2005) and there is no available software for more than three alternatives (Yáñez et al. 2010). As the integrated estimation of the system to obtain the parameters requires the manipulation of complex multidimensional integrals such that solutions cannot be achieved always, some authors have proposed alternative procedures: the simulated maximum likelihood with a mixed logit nucleus for the discrete choice sub-model (Bolduc et al. 2005); the simultaneous treatment of Latent Variables and discrete indicators (Bolduc and Álvarez-Daziano 2010); the use of Bayesian methods that could simplify the integration problems that the classic methods have; and the inclusion of Latent Variables with random parameters (Yáñez et al. 2010).

There are many ways to obtain the parameters of the psycho-social model and those associated to the utility of the discrete choice model. One is to use the discrete choice model approach with indicators included directly in utility as done by Koppelman and Hauser (1978); Green (1984) and Harris and Keane (1998), among others; a variation is to include directly latent attributes in utility as done by Elrod et al. (1995). This procedure is not recommended since these indicators are not causal and can generate multicollinearity issues (Walker 2001). A second possibility is to use a sequential method in two stages, beginning with an Exploratory Factorial Analysis (EFA) to represent the latent variables, which are later included directly in the discrete choice model as a second stage (Prashker 1979). A third approach is to use the two stages using MIMIC (Multiple Indices and Multiple Causes) as the first stage; then the latent variables are incorporated to a discrete choice model where they are treated jointly with the rest of the explanatory variables (Ashok et al. 2002; Vredin Johansson et al. 2006, Raveau et al. 2010). Finally, there is the possibility of integration over a range of variation of the latent variables (Walker and Ben-Akiva 2002), or by including the latent variables with random parameters within the framework of a mixed Logit model. Sequential methods have the disadvantage of not using all the information simultaneously, but its application is quite intuitive which is why most researches use this approach (Raveau et al. 2010). In order to understand bicycle use with attitudinal variables we will make a compromise and use the best of the sequential methods, which is the combination of MIMIC and discrete choices.

Data and context

The hybrid-modelling framework chosen was applied using the information from a dedicated survey in the City of Madrid, Spain. The city of Madrid has a population of some 3.2 million inhabitants. The main university campus –*Ciudad Universitaria*– is located in its western part and host more than 150,000 students, academics and personnel in a wide green area of 5.5 square kilometres. It includes three public universities with 144 centres, over 30 halls of residence, institutional buildings, research institutes, three sports centres and a botanical garden, all mixed throughout the campus. Only 60 % of persons come from Madrid City, while the rest come regularly from the suburbs and even further from neighbour provinces (less than one percent of students live in the campus' residences). The campus has good public transport facilities with 3 metro stations and 6 bus lines, as shown in Fig. 1.

There are 324,000 trips per working day arriving to the campus, 42 % by metro, 26 % by car, 16 % by bus, 12 % walking and 4 % ride their own bike. Those arriving by public transport access their final destination within *Ciudad Universitaria* by foot (87 %) and by bus (13 %).

The university campus is part of the city of Madrid without any access restriction. Therefore, there is an intensive use of cars which cause pollution, noise and accidents. To reduce these problems, the three universities, in collaboration with the City Council and the Public Transport Authority, have developed a Sustainable Mobility Plan to improve sustainability levels of the campus. Some of the agreed main actions are to restrict car access and car traffic and to foster cycling, particularly for internal trips. Environmental conditions can be considered favourable for bicycles—Mediterranean climate, relatively flat and quality of landscape with some isolated slopes—but the high traffic flow makes cycling unpleasant. To improve internal mobility a study called UNIBICI was carried out.

The UNIBICI project was design to study the potential impact of a public-bike lending system inside the campus connecting the main nodal points with the end destinations. This

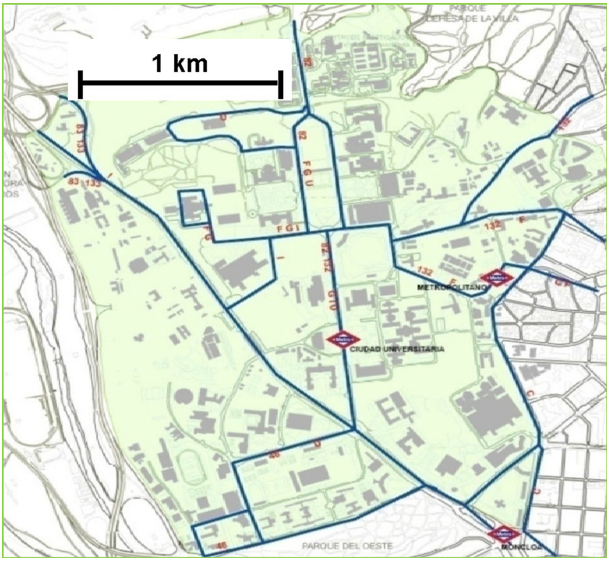

Fig. 1 Madrid University main campus: buildings, bus lines and metro stations

extends the number of public transport modes available and also offers a new and sustainable mode of transport that helps internal mobility. The system proposed was fully automatic. When analysing the potential demand, it was very important to understand the motives behind the intention to use the bike. To this end a detailed analysis was carried out to identify the main barriers that prevent users riding bicycles and to establish the main factors that could promote bicycle use.

The data required for the study was obtained conducting an on-line survey on campus. The first step was to identify the relevant key factors to be surveyed. Following the literature discussion presented in Sect. 2, the factors behind the perceptions related with bicycle use—subjective by definition—can be classified grossly in two groups: those that promote use and those that are a barrier to use. The pro-use factors identified are: efficiency (avoids congestion, no serious parking problems, door to door, competitive with others below certain distances), always available, not expensive, non-pollutant and nearly noiseless, active (promotes healthy life) and joyful. Regarding those factors that inhibit use, we have: long distances, risk of accidents, adverse topography, unfitness, adverse climate, fear of stealing, unavailable complementary facilities, relatively uncomfortable. Note that the availability of bikeways was not included in the pro-use factors because of the close interrelation with risk perception, as previously documented.

The initial survey contained questions regarding the perception of the factors mentioned above plus others that were considered case-specific, in addition to socio-economic characteristics and mobility patterns. Then we run two focus groups that included individuals who use bicycles in Ciudad Universitaria (students and workers) in order to confirm, reject or change the key factors identified. We conducted the focus group only among these users (no focus groups for no-users) because it is a minority group whose preferences and specificities could be difficult to capture by other methods such as surveys. Using this information, a questionnaire was prepared, which was tested by conducting a face to face pilot survey on 233 users at different locations within Ciudad Universitaria.

Lastly, the definitive questionnaire was prepared including four sections: socio-demographic information, mobility, bicycle use combined with the subjective evaluation of different factors (*perception questionnaire)* and willingness to use the future UNIBICI system under various scenarios. These are

- Scenario 0: bike points up to 250 metres, with the first half hour free of charge and the next half hour 0.50€;
- scenario 1: scenario 0 with bike-lane network;
- scenario 2: scenario 0 with traffic calming and car restriction;
- scenario 3: scenario 0 with bike points closer;
- scenario 4: scenario 1 plus scenario 3;
- scenario 5: scenario 2 plus scenario 3;
- scenario 6: scenario 0 with the second half hour priced at 1€;
- scenario 7: scenario 0 with the first half hour priced at 0.50€.

The final survey was conducted on-line through a dedicated website, from April to July 2008. There was no risk of a technological bias due to the computer friendly attitude prevailing in the campus. To contact the target population, an e-mail was sent to all email accounts provided by the different universities on campus. As a reward, and to encourage participation in the survey, approximately 1,000 reflective bands were given away and there was a prize draw for ten foldable bicycles. Total respondents ascended to 3,908 but only 78 % completed the questionnaire. The final representative sample gathered comprised 3,048 people representing 2.9 % of the universe. For a 95 % confidence interval, the sampling error was 1.78 % considering the most unfavourable assumption of maximum indeterminacy. A stratified analysis according to activities (students, faculty, administrative), schools and age showed that the sample was indeed representative.

According to the survey outputs, 76 % of people accessing the campus on a daily basis are students, the remainder are employees. The number of people surveyed who had an employment was 57 %. Consequently, it is possible to conclude that the target population of the study does not eminently comprise students but rather there are also a high number of employees and people who combine employment with study.

Figure 2 shows that more than half of the respondents have a bike available. However, only 15 % use a bike regularly and another 30 % use it occasionally. They use bikes mainly for sport of leisure trips and only 19 % use it for their trip to the university (work + study).

A *perception questionnaire* covered questions about the factors that promote and factors that inhibit bicycle use. The questions in each case were:

- promote bicycle use: "*Assess the reasons that led you to not use the bike or use it less than desired*"
- inhibit bicycle use: "*How do you value this factor when you decide whether to use the bicycle as a mode of transport?*".

A *Likert scale* graded in a numeric and semantic way was used: 1 (not important), 2 (very little importance), 3 (little importance), 4 (some importance), 5 (very important) and 6 (fundamental). An even scale was used to prevent possible centrality bias (Lapietra 2007). Figure 3 shows the average valuations obtained.

Results show that the deterrent factors are perceived as less important than positive ones. The most negative factors appear to be the lack of adequate facilities (changing rooms, place to park safely, etc.) and the sense of danger. The following in negative importance are some factors that could be considered as external, such as climate, topography and distance. The

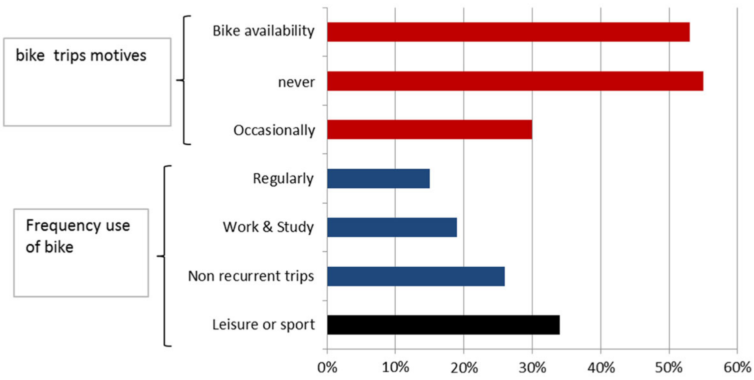

Fig. 2 Use of bicycle among UNIBICI survey respondents

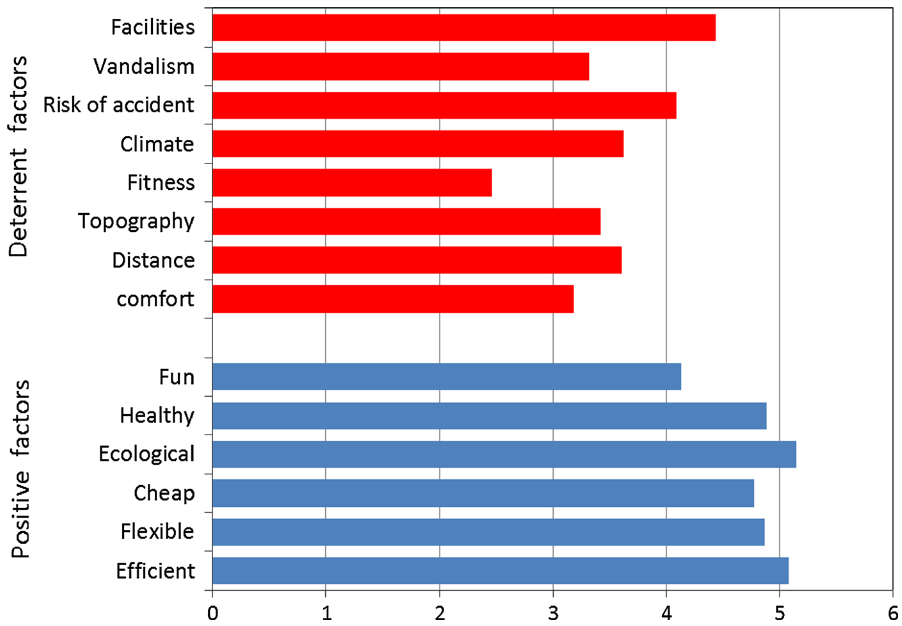

Fig. 3 Average valuation of positive and deterrent factors

third group of importance within the deterrent factors are related to the personal circumstances like the perception of comfort, risk of accident, fear of theft, and lack of fitness (the least important). The positive factors received higher and more homogeneous importance rates. Marked as very important are efficiency and the consideration of biking as an ecological mode of transport. Then other rather important factors are flexibility, healthy and cheap. Finally the bike is considered as fun with average importance of 4.1.

Related to the future use of the UNIBICI system, 74 % of those surveyed stated that they would be willing to use it (i.e. would choose bike in the intention model) and half of those said they would do so regularly once the system would be in operation.

The hybrid model for bike use intention

The modelling process of the intention of use of the UNIBICI public bike system is summarized in Fig. 4. In the first phase, we explored the existence of latent variables and the interdependence between them using Structural Equations Model techniques. Once identified, a Multiple Indicator Multiple Causes (MIMIC) Model was formulated to measure its value in relation with observable variables within the context of UNIBICI. In the third phase, we estimated a discrete choice intention model incorporating these latent variables.

The analytical structure of the model is synthesized in Eqs. (1)–(3) below with two components: a model of choice and a latent variable model (Ashok et al.2002; Vredin and Johansson et al. 2006; Raveau et al. 2010). In this scheme the indirect utility is expressed as a binomial logit (Greene 1990):

$$\begin{aligned} u_i &= as_i + bz_i + c\eta_i + \varepsilon \\ q_i &= 1 \quad \text{if} \;\; u_i > 0 \\ q_i &= 0 \quad \text{if} \;\; u_i \leq 0 \end{aligned} \tag{1}$$

where u_i is the conditional indirect utility representing individual i's willingness to use the bike, z_i is the vector of observable trip specific attributes, s_i is the vector of observable individual specific attributes, η_i is the vector of individual specific latent variables, *a, b,* y *c* is the vectors of unknown parameters to be estimated, q_i is the declared use intention (1: positive intention, 0: negative intention).

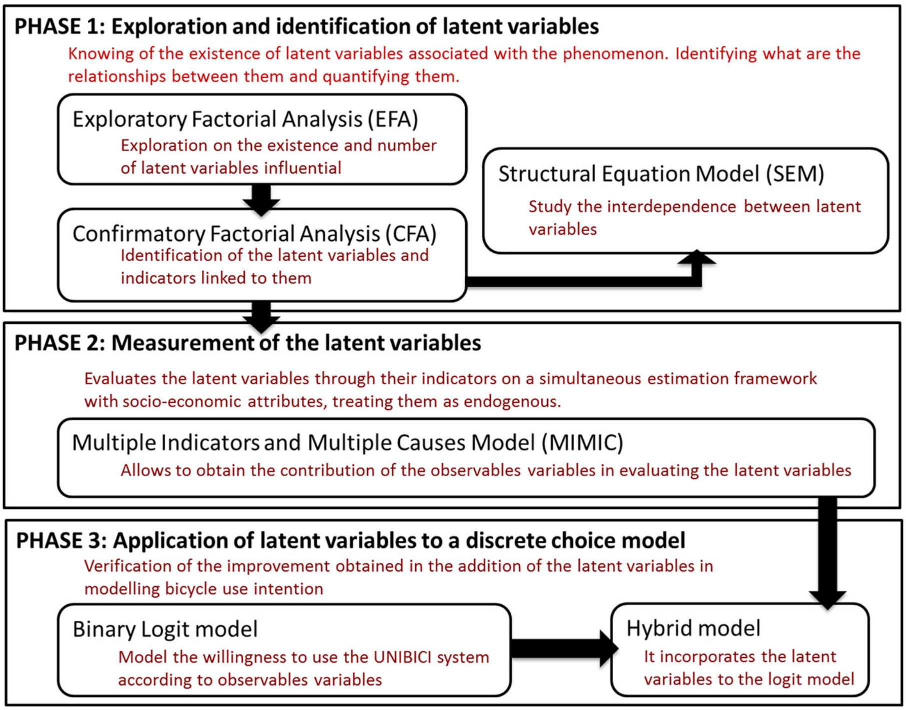

Fig. 4 Synthesis of the modeling process

The structural relations to the latent variables are:

$$\eta = \Gamma x + \varsigma \tag{2}$$

And the measurement equations are:

$$y = \Lambda \eta + \xi \tag{3}$$

where:

- x: vector of exogenous observable variables that causes η (observable individual and trip specific attributes)
- y: vector of observable indicators of η (efficient, flexibility, etc.)
- Λ y Γ: matrices of unknown parameters to be estimated and ς, ξ y ε_j are independent measurement errors.

Equations 1 form the discrete choice model, while 2 and 3 constitute the MIMIC model for the latent variables that is estimated first in the hybrid model sequence. This methodology has been used with good results in other transport demand analysis (Vredin Johansson et al. 2006; Correia et al. 2010), but this is the first time that it is used to model bike use intention. In MIMIC models, the latent variables are explained by the characteristics of the user and the system using *structural equations*, while the latent variables represent perception indicators detected by measurement equations.

As a result we obtained four latent variables: convenience, pro-bike, physical determinants and external restrictions (Fernández-Heredia et al. 2014). The effects of these variables were captured through thirteen indicators of perception: economical, fun, healthy, ecological, flexibility, efficiency, comfort, long distances, fitness, topography, weather, vandalism and auxiliary facilities. Thirteen explanatory variables were also included in the MIMIC model: age, gender, studies level, income level, car availability, bicycle use, leisure bicycle use, commuting bicycle use, UPM member (Polytechnic University of Madrid, one of the three universities present in the campus), occupation (student or faculty member) and willingness to use UNIBICI. In Fig. 5 we can see the *path diagram*, a graphical representation of the approach: on the left we find the socio-demographic characterization and on the right the user indicators related to the latent variables. The values of the parameters of the structural and measurement equations shown in the path diagram of Fig. 5 are shown in Table 2; they were obtained with the Asymptotically Distribution Free Parameter Method in LISREL software.

Regarding the statistical quality of the estimated system, the Goodness of Fit Index GFI = 0.97 and the Root Mean Square of Approximation, RMSEA = 0.064 indicates an acceptable fit with reasonable errors of approximation. The Comparative Fit Index CFI, takes a value of 0.78 which is low, but reasonable. The Adjusted Goodness of Fit Index which takes into account a correction for the number of variables considered, AGFI = 0.95 is above the recommended value 0.80. These indicate that the final MIMIC model in this study has a good fit. Let us move to the interpretation of the estimated parameters.

The relationships between latent variables and indicators are stronger than between observable variables and latent variables, but the overall pattern of relations is clearly stated. The columns of the measurement equations show that each latent variable is clearly related to specific perception indicators, except for climate which is part of two of them. *Efficiency and flexibility* explain each 89 and 88 % of convenience. The indicators linked to pro-bike also explain high percentages of this latent variable, including *cheap, ecological, healthy and fun* (75–85 %). Smaller values can be observed for the indicators that explain latent variables Physical determinants and External restrictions, with values of 50 % of roaming explanatory

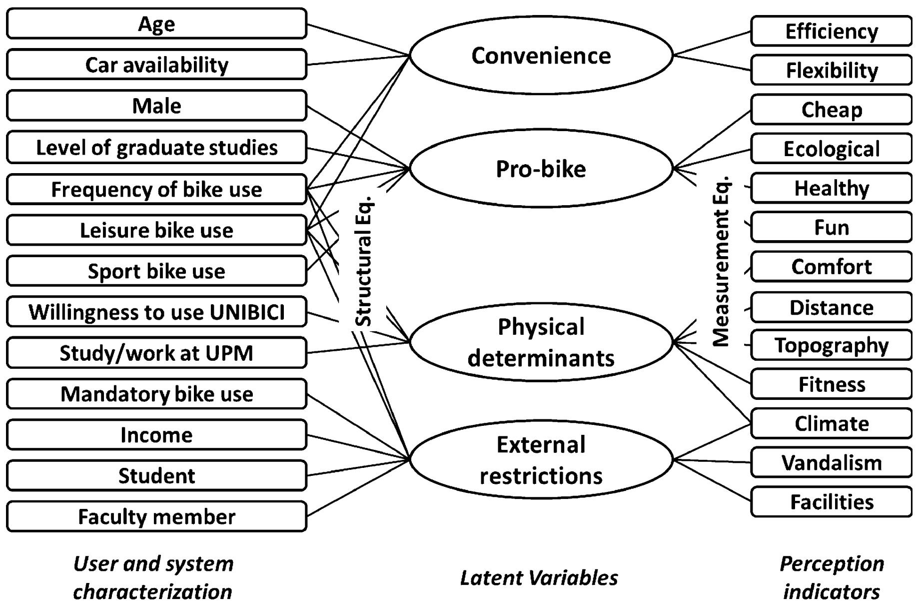

Fig. 5 Relationships in the latent variables model

power. *Climate*, on its turn, is less influential but affects two latent variables: explains 34 and 35 % of Physical restrictions and External restraints respectively.

Looking at the lower part of Table 2, there are two observable socio-demographic variables that are related to the quantification of the four latent variables: *cycling for leisure* and *frequency of cycling*. Leisure trips can be affected by many variables because they can be done in other modes or even cancelled as no necessary trips. The frequency, on its turn, has the greatest weight among the observable variables, which confirms the importance of cycling experience to explain the good disposition towards it. The rest of variables have influence in specific latent variables. Thus, age affect only Convenience while being male or having a university degree affect Pro-bike. The level of income and the status (student or faculty member, which includes both teachers and university staff) are clearly associated to External restrictions.

Regarding the importance of each latent variable for different individuals, one should look at the columns of the Structural Equations. It shows that *convenience* is more important for frequent bike users and less important for elders and for users that bike for recreational purposes. *Pro-bike* is also valued by frequent cyclists, which explain 50 % of the measure, and less valued by males, walker or students. *Physical determinants* are less valued by those who use the bike less and have greater willingness to use the system UNIBICI. Finally, *external restrictions* are most valued by frequent bike users.

The choice intention model formed by Eq. (1) was estimated with and without the latent variables in addition to the relevant variables discussed in Sect. 2.[1] Results are shown in

[1] Several actions were carried out to limit the effect of repeated observations and possible overestimation of certain statistics. A correlation panel analysis was performed among duplicate observations using the test Wooldridge with the software STRATA. The results indicated that the serial correlation levels were low. When assessing the logit model, estimators were applied with a Panel- Corrected Standard Errors (PCSE) to correct the effects of these autocorrelations. In our study data showed no correlation among alternatives nor heteroscedasticity, so we did not go beyond model structure (1)–(3) to keep the analysis simple.

Table 2 MIMIC model parameter estimation

Latent variables:	R^2	Convenience		Pro bike		Physical determinants		External restrictions	
Measurement equations		Coef	t-std	Coef.	t-std	Coef.	t-std	Coef.	t-std
Efficiency	0.80	0.89	*						
Flexibility	0.78	0.88	(44.10)						
Cheap	0.70			0.84	*				
Ecological	0.73			0.85	(45.20)				
Healthy	0.68			0.82	(40.02)				
Fun	0.56			0.75	(35.11)				
Distance	0.37					0.61	*		
Topography	0.49					0.70	(26.04)		
Health fitness	0.54					0.74	(23.36)		
Climate	0.24					0.34	(11.84)	0.35	(11.84)
Comfort	0.39					0.71	(23.60)		
Vandalism	0.48							0.69	*
Facilities	0.38							0.61	(10.91)
Structural Eq.	*(R^2)*	*(0.30)*		*(0.32)*		*(0.44)*		*(0.04)*	
Mandatory bike use								−0.63	(−4.00)
Leisure bike use		−0.19	(−5.49)	−0.19	(−4.66)	0.06	(1.73)	−0.31	(−3.20)
Sport bike use				0.18	(4.17)				
Age		−0.30	(−6.21)						
Male				−0.27	(−8.94)				
Level of Graduate Studies				−0.20	(−6.72)				
Income								−0.29	(−2.17)
Student								−0.47	(−2.58)
Faculty member								−0.31	(−2.30)

Table 2 continued

Structural Eq.	(R^2)	*(0.30)*		*(0.32)*		*(0.44)*		*(0.04)*	
Study/work at UPM						−0.09	(−2.78)		
Car availability		0.10	(1.84)						
Frequency of bike use		0.49	(15.74)	0.50	(14.28)	−0.58	(−15.24)	0.84	(5.12)
Willingness to use UNIBICI						−0.25	(−7.15)		

* Fixed parameter in the estimation

Table 3 Models for bike use intention without and with latent variables

	Logit model		Hybrid	
	Coef	t-student	Coef	t-student
Intercept	1.103	(8.29)	−1.423	(−8.64)
Male	0.131	(4.01)	0.106	(3.06)
Income	**−0.386**	**(−3.99)**	–	–
Level of graduate	0.084	(2.25)	0.080	(2.18)
Student	0.265	(4.90)	0.289	(7.30)
Home with more than 3 members	−0.160	(−4.37)	−0.133	(−3.58)
Spanish nationality	0.232	(2.97)	–	–
Study/work at UPM	−0.254	(−7.23)	−0.199	(−5.55)
Study/work at non university center	−0.203	(−2.60)	−0.144	(−1.79)
Trip				
Car user (travel by car to campus)	−0.199	(−4.42)	−0.094	(−2.06)
Walker (travel on foot to campus)	0.403	(6.52)	0.285	(4.51)
Distance traveled in CU	0.497	(4.94)	0.535	(5.21)
Total travel time	3.720	(5.95)	3.551	(5.58)
Inner trip with origin in CU	0.795	(8.90)	0.752	(8.25)
Inner trip with origin in CU	0.278	(5.37)	0.277	(5.23)
Trip purpose: leisure	−0.872	(−4.05)	−1.201	(−5.49)
UNIBICI system				
Distance among system points	−0.365	(−9.82)	−0.381	(−10.05)
Possibility of Traffic restrictions	−0.558	(−13.28)	−0.585	(−13.59)
Possibility of bike lane	0.114	(2.49)	0.118	(2.55)
Fee	−2.002	(−45.82)	−2.101	(−46.59)
Latent				
Convenience	**–**	**–**	**1.186**	**(9.25)**
Pro-bike	**–**	**–**	**2.157**	**(15.11)**
External restrictions	**–**	**–**	**−1.236**	**(−12.14)**
Physical determinants	**–**	**–**	**0.452**	**(5.32)**
Cyclist experience				
Non bike availability	0.132	(3.53)	0.097	(2.55)
Frequency of bike use	0.892	(8.56)	0.550	(5.13)
Public bike system familiarity	0.204	(6.37)	0.144	(4.40)
Mandatory bike use	−0.294	(−5.09)	−0.344	(−5.84)
Leisure bike use	0.087	(3.34)	0.068	(2.57)

	Logit	Hybrid
Number of observations	22.815	22.816
Log-likelihood	−12.468	−12.002
restricted Log- likelihood	−14.770	−14.770
Chi squared	4.605	5.534
Number of parameters	25	28
AIC	1.095	1.054
Homer-Lemeshow Chi squared	157.07	130.95

Table 3 continued

	Logit	Hybrid
McFadden Pseudo r squared	**0.1559**	**0.1872**
Correct predictions	**0.1559**	**74.63 %**
Normalized index	**0.26**	**0.32**

Bold values signify results explained in the discussion

Table 3. Regarding goodness of fit, comparison between models obtained with different methodologies and different number of variables should be based on their predictive ability. From this viewpoint the most interesting is the normalized index (Ortúzar and Willumsen 1990), which allows direct comparison based on predictive functionality criteria; it increases by 23 % using the proposed hybrid methodology for modelling the bike use intention. Other parameter commonly used is McFadden's pseudo r squared, which increases by 20 %. Generally it can be said that the introduction of latent variables provides better predictive modelling capabilities.

Beyond the improvements in the goodness of fit of the model, the most relevant aspect to discuss is the effect of the introduction of psycho-social latent variables as elements to understand the intentions to use the bicycle in the proposed context and in general. We first note that all four latent variables seem relevant from a statistical viewpoint and have the expected sign. It should be noted, though, that sequential estimation tends to overestimate slightly the weight of the latent variables (Raveau et al. 2010).

To compare the relative weight of the different variables in the explanation of bike use intention, we calculated the product of the mean value and the coefficient obtained in the model (we show this value in brackets in the next discussion followed by the variance of the variable). The most influential variables on the willingness to use the system are:

- *Pro-bike latent variable (1.70, 0.0001):* includes positive attitudes related to the bike, not directly related to the displacement efficiency. According to the scientific literature, these types of factors are valued more in areas where cycling culture is low, so this result is consistent with such studies.
- *Convenience latent variable (1.00, 0.0002):* includes the positive aspects of cycling related to transport mode competitiveness, efficiency and flexibility in use.

The most important variables that inhibit the intention to use of the system are:

- *Fee (−0.50,0.0081):* along with time, cost is a traditionally important variable in transportation decisions. The possibility that the system had a fee for use generates a clear rejection.
- *Physical determinants (−0.70, 0.0002):* measures the assessment of users with personal physical determinants when using the bike in general. Its negative value in the utility function means that users who appreciate the different indicators rely on this latent variable, show a greater lack of interest in the bike system, because of their feeling of inability to use the bike in general.
- *Trip for leisure purpose (−0.30, 0.0007)*[2]: users who travel for leisure, i.e. occasional users, may have less interest in efficient travel or be less willing to pay an annual fee for a system that would be used sporadically.

[2] Leisure purpose was introduced as an attribute or factor because non-commuters trips are residuals, which prevented the estimation of a purpose specific model.

The remaining variables have a weight lower than 0.30. It is especially significant that among these five variables weighting greater than unity, three are latent variables (out of the four latent variables in total). This result is indeed encouraging, as it shows the reward of capturing perceptions adequately.

Regarding the other variables there are three that change substantially when the (highly significant) latent variables are introduced: the constant (change sign), income and Spanish nationality, both of which drop from the model. And there are ten variables whose coefficients remain quite stable, including the four associated to the UNIBICI system. We consider this a clear improvement of the model when latent variables are introduced. The negative constant reflects what has been detected earlier, namely the basic reluctance to use the bicycle in spite of all the advantages according to the usual modal characteristics. Income has been systematically found as a non-factor when deciding on bicycle use, so the disappearance as an explanatory variable is a good sign when latent variables are included; same with nationality. On the stable or robust coefficients, distance, price and time are consistently present with the expected sign.

Conclusions

In this paper we have explored, identified and used latent variables related to psychosocial aspects that contribute to explain the intention of cycling. A methodology based on a structural equation models and a discrete bicycle use intention model was developed and applied to study a new bike sharing system in the main university campus in Madrid. Four variables were detected which we named convenience, pro-bike, external restrictions and physical (internal) determinants. These variables, along with the traditional variables of transport demand, perform well at improving our knowledge regarding the determinants of cycling. When they are introduced in the choice model in order to capture intention of use, the latent variables are shown to be relevant and the rest of the variables appear with coefficients whose sign and size seem to truly unveil their effects. To the best of our knowledge this is the first attempt at capturing intentions, perceptions or attitudes related to the use of the bicycle within the framework of hybrid models, which have been used in other fields of transportation (Bolduc et al. 2008; Correia et al. 2010; Di Ciommo et al. 2013; Daziano and Bolduc 2013).

The results of the MIMIC procedure show that the four identified latent variables capture clearly the information of the indicators which cover all factors affecting the intention of using bicycle. The first two variables—convenience and pro-bike—are associated with the positive aspects that users perceive about cycling and appear to be very relevant. Convenience refers to the bicycle as a competitive and efficient mode of transportation compared to other modes. The pro-bike factors are related to the low cost of the trip (cheap), that it is a healthy and funny activity and reinforces the ecological aspects of mobility. The two remaining latent variables—physical determinants and external restrictions—represent potentially discouraging elements. They group factors based on the user's possibility of acting on them. The physical determinants have two components: the network and the territorial configuration on one side, and the traveller side, which includes personal fitness and trip comfort. Finally there are aspects that the traveller cannot control, as the danger of theft, climate and the provision of facilities for bikers (parking, changing rooms, etc.) which are perceived as external barriers, but their importance is much less than the former factors. It is important to note that, although these four latent variables make sense within the specific case study, they cannot be extrapolated to other systems or cities.

However, the methodology to reach them can be replicated and the identification of these four latent variables can be useful in the initial exploration stage of other similar studies.

When these latent variables representing perceptions and attitudes are incorporated into the choice intention model, they indeed contribute to explain better the intention of use of the proposed lending system. The four variables are shown to be statistically significant, representing the type of perceptions discussed above. Particularly important is the pro-bike variable, whose significant and large coefficient suggests that individuals do appreciate very positively things like environmental friendliness, healthiness and joyfulness when deciding to use the bike lending system. It is quite important to note that two variables actually drop from the intention of use model when the latent variables are included—income and Spanish nationality—confirming previous findings. The four variables related directly with the bike lending system under study are quite robust and remain in the model with practically the same quantitative contribution. For policy purposes, it has been detected that being acquainted with the use of bicycle has an important effect on the degree of acceptance of the new system. Therefore initiatives aimed at "trying" the use of bikes can be really successful because they facilitate the positive perception of cycling, attracting new users.

These results indicate that policy actions to increase bicycle use have to focus primarily on fostering personal motivations, highlighting the benefits of biking through awareness campaigns emphasizing the factors behind the latent variables regarded as positive. The dedicated infrastructures and facilities appear to be also important because they facilitate the trip by bicycle; they also contribute to reinforce awareness, showing the political will to promote not motorized modes. In the specific case of UNIBICI system, our results indicate that the use of the system could be increased if several actions were taken to improve the perception of pro-bike and convenience factors. This could be achieved with a good campaign on the benefits of cycling in general and especially for internal trips in the campus. It is also important to have a system with a cheap access and supporting measures that make the use of bike in the campus friendlier.

Other important finding relates to the differential perception of benefits depending on previous experience, as far as regular bikers are more aware of them, which coincides with the finding by Emond et al. (2009) regarding the role of exposure to bike at earlier stages in life. In addition, several authors as Bergström et al. (2003) or Nkurunziza et al. (2010) have highlighted differences in perceptions depending on the use of the bicycle throughout individuals' life. The lack of experience could be resolved by means of public bicycle schemes or other type of lending systems including—on demand—help and guidance. Once an individual starts using bicycle, the perception of its benefits—for a trip, for the cyclist and for the environment—increases.

In general, our results reinforce one important hypothesis: bicycle users take into account a larger number of factors than those considered by users of other transport modes. To represent properly the preferences of potential bike users, modelers and policy makers have to go beyond modal times, modal costs, facilities, other usual modal factors and socio-economic individual characteristics; they have to pay attention to attitudes and perceptions that we hope we have contributed to detect. Evidently, perceptions and their associated factors could be case-specific, but we believe that a methodology like the one presented here is worth the effort.

Finally the incorporation of the identified latent variables to choice models seems to be a promising way to consider bike trips in modal choice. Although the present case study is rather limited, the improvements achieved indicate that the perceived utility of biking is linked to physiological factors that cannot be avoided.

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