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Attribute non-attendance in choosing the bike as a transport mode in Belgium

Abolghassem Jandari[1]
Faculty of Economics and Business, KU Leuven, B-3000 Leuven, Belgium.

Michel Meulders[2]
Faculty of Economics and Business, KU Leuven, B-3000 Leuven, Belgium.

Saskia Desplenter
Faculty of Economics and Business, KU Leuven, B-3000 Leuven, Belgium.

Martina Vandebroek[3]
Faculty of Economics and Business, KU Leuven, B-3000 Leuven, Belgium
Leuven Statistics Research Centre, KU Leuven, B-3001 Leuven, Belgium

Cycling is an important pillar of the global endeavor to have a more sustainable transportation system. Many papers have studied how trip and person characteristics affect selecting the bike as a transport mode but unlike other researchers, we model the probability of cycling using a binary item response model where the choice is modelled as a trade-off between the individuals' tendency to cycle and the threshold related to each cycling situation.

We distinguish between frequent and occasional cyclists. The results show that occasional cyclists are more affected by adverse weather situations, darkness, and uphill slopes. Contrary to the previous studies, a separate bike path turned out a stronger motivator for the group of frequent cyclists.

The model fit can substantially be improved by accounting for attribute non-attendance. The results show that weather and wind speed have the highest probability to be taken into account, and the bike path had the lowest probability of being considered by the respondents.

Employing the attribute non-attendance model made it possible to make accurate and trustworthy conclusions about the attributes by focusing on the people who take into account the attributes. More specifically, it was found that the presence of a separate bike path and a 100% asphalt route can increase the average probability of taking the bike by up to 55 and 40 percentage points, respectively.

Keywords: *attribute non-attendance, cycling, choice modelling.*

[1] A: Naamsestraat 69, 3000 Leuven, Belgium T: +32 16 37 74 94 E: abolghassem.jandari@kuleuven.be
[2] A: Warmoesberg 26, 1000 Brussels, Belgium T: +32 2 210 16 11 E: michel.meulders@kuleuven.be
[3] A: Naamsestraat 69, 3000 Leuven, Belgium T: +32 16 32 69 75 E: martina.vandebroek@kuleuven.be

1. Introduction

Increasing the share of cycling among transport modes has a pivotal role in improving public health, and diminishing the environmental predicaments caused by vehicles (De Nazelle *et al.*, 2011; Rabl and de Nazelle, 2012). A notable benefit of cycling is the overall amount of physical activity that it will add to the individuals' activity (Donaire-Gonzalez *et al.*, 2015). Research in Flanders, Belgium, showed that using the bike for work trips has a positive impact on coronary heart disease risk factors and generally can improve the user's health (De Geus *et al.*, 2007). Bassett *et al.* (2008) also suggest that the higher usage level of active transports in Europe might be one of the factors resulting in lower rates of obesity compared to countries like the USA, Canada, and Australia. Concerning environmental issues, cycling has many apparent benefits if it replaces driving a car. Those benefits include: reducing air and noise pollution as well as the benefits derived from reduced fuel consumption. Cycling will have considerable economic benefits for cities and individuals (Krizec, 2007). Reduced health care costs, savings from transport costs, saving money on infrastructure costs, and cycling-based tourism are some of the economic benefits (Handy, van Wee and Kroesen, 2014).

Because of all these benefits, researchers and policymakers are highly interested in finding ways to promote cycling. However, cycling is a physical activity that some people may find troublesome, or that they have safety concerns about (Rodríguez and Joo, 2004). Therefore, in addition to the usual variables used in classic transport mode choice models (e.g. travel time and travel cost), more variables are needed to explain the probability of choosing the bike.

Many studies attempted to address people's propensity towards cycling using different types of variables. Heinen, van Wee and Maat (2010) introduced five groups of variables that affect cycling: the built environment, the natural environment (e.g., weather, landscape), socio-economic variables, psychological factors, and aspects related to the cost, time, effort, and safety. There is a significant amount of information available in the literature regarding the effect of the variables in each group and comprehensive literature reviews are provided in Heinen et al. (2010), Pucher, Dill, & Handy (2010), Fernández-Heredia, Monzón, & Jara-Díaz (2014), Handy et al. (2014), and Buehler & Dill (2016).

In this paper, we use a binary item response model to estimate the probability that a person will select the bike in a certain situation. In our model, the choice is explained by a trade-off between the individuals' tendency to cycle and the threshold related to the cycling situation. Based on the results of a binary choice experiment, we analyze the effects of rain, wind, bike path, slope, light, and distance on the probability of taking the bike. Furthermore, we assess which attributes are taken into account while deciding to cycle or not. Accounting for attribute non-attendance (ANA) when modelling choice behavior is important for two reasons. First, if individuals are ignoring attributes, it means that they have a non-compensatory choice behavior. So, any improvement in the ignored attribute will not compensate individuals for the negative effect of another attribute level and therefore utility should not be represented in the usual way (Lagarde, 2013). Second, ignoring ANA could lead to biased coefficients and in turn to biased policy recommendations (Lagarde, 2013). Many studies tried to understand cycling behavior, but none has investigated the role of heuristic rules in choosing the bike as a transport mode.

Cycling behavior has not been studied before in the context of item response models. Our main contribution is proposing a modelling framework, building on basic models that are commonly employed by practitioners. In our modeling framework, the item response model gets more complex at each step, first by adding the latent classes, and then by accounting for attribute non-attendance. Accounting for attribute non-attendance enables us to mainly focus on the people who consider an attribute when analyzing the effects of that attribute. This will be specifically beneficial for the policymakers since we can be sure that our conclusions about an attribute are based on the responses of the people who care about that attribute. So in the end we will have more accurate and trustworthy results.

We study cycling in Belgium, a country ranked top five in the EU regarding bike usage (Vandenbulcke *et al.*, 2011). However, the share of cycling is still small compared to countries like the Netherlands, Denmark, and Germany (Pucher and Buehler, 2008; European Union, 2017). Based on the "FOD Mobiliteit en Vervoer" (Federal Public Service, Mobility, and Transport) report, in 2014 9.5% of the commuting work trips in Belgium were done by bicycle. This number is 3% in Brussels, 1.5% in Wallonia (French-speaking region), and 14.9% in Flanders (Dutch-speaking region) (FODMobiliteit, 2017). More than half of the Belgians who live within 5 km of their workplace commute by private cars while only 19% of them use the bike (Vandenbulcke *et al.*, 2011). So, there is a lot of potentials to increase the share of cycling.

The remainder of the paper proceeds as follows. In Section 2 we will review the literature and explore the current information available on the effects of each group of variables. Section 3 describes the survey and the data collection and the methodology used in the study. In sections 4 we report and discuss the estimated latent class model and the attribute non-attendance model, respectively. Finally, the fifth section presents the conclusions together with the potential policy implications of the study.

2. Literature review

2.1 Trip characteristics

As with any other transport mode, cycling is directly influenced by trip characteristics. Travel time is one of the main trip characteristics with a critical role in transport mode choice and normally has a negative effect on a mode's attractiveness. However, studies have shown that cyclists are eager to increase their travel time slightly in exchange for a better bike path (Tilahun, Levinson, and Krizek 2007). Travel distance is another factor playing a key role. Longer distances take more effort which might lead to choosing other transport modes over the bicycle. This is especially true for commuters, whereas, for recreational cyclists, the distance might not be a real issue (Heinen, van Wee, and Maat 2010). Travel cost is the trip factor on which the bicycle has a great advantage compared to other transport modes (Bergström and Magnusson 2003). Trip cost for other transport modes can also affect bike usage. For instance, in regions with low gas prices or free public transit, cycling has a low share (Heinen, van Wee, and Maat 2010).

2.2 Cycling infrastructure

The cycling infrastructure is one of the most widely studied groups of variables in the cycling literature. The comfort and safety of cyclists are directly affected by the cycling infrastructure (Heinen, van Wee and Maat, 2010; Khan, Kockelman and Xiong, 2014). Cycling infrastructure variables gained much attention in previous studies because they can be modified and improved to change people's behavior toward active transport modes. In all countries where the share of cycling has increased substantially, this was preceded by a massive increase in the length of the cycling network (Pucher and Dijkstra, 2003; Pucher and Buehler, 2008; Harms, Bertolini and Brömmelstroet, 2016). As an example, the share of cycling in Seville, Spain, increased with a factor of 6 in the period 2000-2015 after adding a fully segregated network of cycle paths (Marqués *et al.*, 2015; Pucher and Buehler, 2017). However, previous studies have shown that adding more bike paths to the city's traffic network will not suffice, and other policies such as making the use of a private car less attractive and more expensive are also needed (Pucher, Dill and Handy, 2010; Harms, Bertolini and Brömmelstroet, 2016). However, adding more bike paths has been the main intervention in most of the successful countries. Pucher & Buehler (2008) indicate that providing a separate bike path was a "cornerstone" for the Netherlands, Denmark, and Germany in making cycling safe and attractive.

Safety for cyclists can be examined both subjectively and objectively. Subjective or perceived safety has a clear connection to the availability of separate bike paths (Van Goeverden *et al.*, 2015). In particular, cyclists, especially inexperienced ones, do not feel safe close to vehicular traffic and usually rank the existence of a separate bike path as the most encouraging factor for cycling (Akar and Clifton, 2009). Also, a separate bike path can reduce the risk of cycling accidents significantly (Marqués and Hernández-Herrador, 2017). Comfort is another factor that is linked to the cycling infrastructure, and generally, it has been proven that a separate bike path will lead to a more comfortable trip for cyclists. However, Li, Wang, Liu, & Ragland (2012) showed that this is not true in all cases and that it will depend on the level of cycling traffic. In addition to all other benefits of a separate bike path, it can also decrease the exposure of cyclists to air pollution even with only a small separation distance from the emission source (Int Panis *et al.*, 2010).

Having uphill slopes in the cycling path is another influencing factor. Similar to cycling long distances, cycling uphill also means more effort for cyclists and will have a negative effect on the probability of taking the bike (Motoaki and Daziano, 2015). However, for recreational cyclists, this might not be a negative effect as they usually do not object against more effort and physical activity (Moudon *et al.*, 2005).

2.3 Environment

Cools, Moons, Creemers, & Wets (2010) showed that weather conditions may change travel behavior. Cyclists are much more affected by the weather compared to other transport modes, and previous studies have shown the importance of the weather on cycling demand (Saneinejad, Roorda and Kennedy, 2012; Motoaki and Daziano, 2015). People use the bike less frequently and for shorter distances in poor weather conditions (Bergström and Magnusson, 2003) and this is not only because of a lower temperature, but also because of stronger winds, less daylight, and more rain and snow. Saneinejad et al. (2012) showed that rain and wind could negatively affect cyclists more than any other transportation mode, including pedestrians. Light and road illumination has received less attention in previous studies, but research indicates that there can be a negative relationship between darkness and cycling too (Gatersleben and Appleton, 2007).

2.4 Individual characteristics

Research findings support the idea that people with different cycling skills, income level, age, and other demographic variables will have different perceptions and preferences regarding cycling infrastructures and policies (Li *et al.*, 2013; Fernández-Heredia, Monzón and Jara-Díaz, 2014; Damant-Sirois and El-Geneidy, 2015). Older people are less likely to choose the bike because doing physical activity might be troublesome for them. Income level has a significant effect on cycling in the regions where cycling is not very popular. Konstantinidou & Spyropoulou (2017) argue that in those regions individuals with higher income levels might contempt cycling.

The effect of any other factor discussed before, can be directly influenced by the individual's cycling skill. People with different cycling skills will have different sensitivities toward the cycling facilities, distance, weather, or any other barriers in choosing the bike (Muñoz, Monzon and López, 2016; Barberan, De Abreu E Silva and Monzon, 2017). Therefore, it is crucial to consider these variables when attempting to understand how and why people choose the bike as a transport mode (Willis, Manaugh and El-Geneidy, 2015). In addition to cycling skills, habits also play an important role in choosing the mode of transport. People who are used to a particular mode of transport will most likely continue to use it, without critically reviewing all other options (Willis, Manaugh and El-Geneidy, 2015). Gender can influence the cycling behaviour and also affect the importance of other factors; men and women can have different motivators and barriers to use the bike (Heesch, Sahlqvist and Garrard, 2012). Apart from the role of the bike path for motivating inexperienced cyclists, it also has more effect in encouraging women than men since women generally have a higher risk aversion and a separated bike path can motivate them more than men (Garrard, Rose and Lo, 2008). Particularly, women attach more importance to daylight than men (Bergström and Magnusson, 2003).

3. Method

3.1 Selection of attributes and levels

Through a preliminary study, the importance of the attributes, described in section 2, was investigated. Based on the results of this preliminary study, the most important attributes were selected to be included in the survey design. The preliminary study was prepared in Qualtrics in both national languages (Dutch and French) and was sent via social media and e-mail to people who were easily accessible to the researcher.

A total of 22 people completed the preliminary survey, of which 12 were living in Flanders, 3 in Brussels, and 7 in Wallonia. Respondents were presented with a list of cycling situation attributes and were asked to list the five most encouraging and the five most discouraging factors from that list. In addition, to determine the importance of each attribute level, the respondents had to rank the attribute levels in order of importance, with '1' indicating the most important factor. Each attribute was formulated both positively and negatively. For example, the attribute 'distance' was formulated both as 'short distance' and as 'long distance'.

Based on the results of the preliminary study, it was decided to include the following attributes in the survey design: weather, bike path, road surface, distance, light, slope, and wind. Little is known about the road surface and wind in the literature so it makes it more interesting to further investigate these two factors. Table 1 shows the attributes used in the survey and their levels.

Table 1. Trajectory attributes and their levels in the survey design.

Attribute	Levels
Weather	Rain Dry and sunny Dry and cloudy
Bike path	None Separate bike path Marking on the road
Road surface	100% asphalt 50% asphalt, 25% clinkers, 25% cobblestones 25% asphalt, 50% clinkers, 25% cobblestones
Distance	15km 10km 5km
Light	Daylight Dark
Slope	Completely flat path Two slopes of 500 meters uphill at 10%
Wind	Powerful (10.8 to 13.8 m/s) Weak (1.6 to 3.3 m/s)

3.2 The experimental design

With the seven attributes shown in Table 1, a local optimal design was constructed using the SAS macros developed by Kuhfeld (2010). The survey consists of 24 hypothetical biking situations in which people were asked whether they would use the bike or not. The question asked with each situation was: “Would you take the bike to complete the following route given the circumstances?”

No details about the context of the trip (e.g. trip purpose) or the availability of other transport modes were given. In this way, only the characteristics of the presented situation and the respondent are assumed to determine the response. Figure 1 shows an example of a cycling situation in the survey.

Would you take the bike to complete the following route given the circumstances?

Weather	Rain
Bike path	Separate bike path
Road surface	100% asphalt
Distance	5 km
Light	Daylight
Slope	2 slopes of 500 meters uphill at 10%
Wind	Powerful

- Yes
- No

Figure 1. An example of the cycling situation in the survey

3.3 Survey

The survey was conducted in Dutch and French with Qualtrics and consisted of three parts. The introduction contained information about the investigator and the investigation. In addition, the anonymity of the respondents was assured, and the emphasis was placed that only fully completed surveys are useful for the study.

The first part of the survey was about cycling behaviour. In this section, questions were asked about owning a bike, how frequently the respondent used the bike, for what purpose the bike is used, whether the bike was the only means of transport, how the respondent estimates his/her cycling skill, whether they combined the bike with other transport modes and whether the respondent used to the bike to commute to school. This was followed by the 24 cycling situations, in which the respondents had to indicate whether they would take the bike in each situation or not, given the circumstances. The third part consisted of some questions about socio-demographic characteristics such as gender, place of residence (region), place of birth (region), education, occupation, marital status, and children.

The survey was distributed through the intranet of a federal government agency in Belgium. People were asked to share the survey link with their friends and family too. As a result, the sample was a convenience sample rather than a random sample and the majority of the respondents in the analyzed sample are employees of the federal government agency. However, using a convenience sample made the data collection both time-efficient and cost-efficient.

A total of 794 people participated in the survey. Persons who did not complete the survey were omitted from the analysis. It was also decided to remove persons who do not own a bike and persons who use no other transport mode than the bike. It follows that the data analysis is based on the answers of 562 respondents.

Table 2 and Table 3 show the distribution of the socio-demographic variables and the variables about the cycling background of the respondents. Concerning the frequency, individuals who use the bike daily are the largest group with 33 percent of the sample. Work, relaxation, and recreation are the main purposes of cycling. The low share of bike use for school comes from the low number of students in the sample. Sixty-three percent of the respondents in the sample consider themselves to be advanced cyclists which seems consistent with the frequency of cycling in the sample and the assumption that those who cycle more, are more advanced cyclists.

Table 2. Personal cycling history among the respondents

Variable	Levels	Percentage
Frequency of cycling	Approximately daily	33%
	Only on weekends	8%
	Several times a week	17%
	Several times a month	10%
	Several times a year	23%
	Never	7%
Purpose of cycling	Work	34%
	School	1%
	Leisure	47%
	Shopping	8%
	Other	10%
Self-assessment of cycling skill	Not cyclist	20%
	Beginner	17%
	Advanced	63%
Using/used bike commuting to school	Yes	64%
	No	36%
Combine bike with other transportation modes	Yes	32%
	No	68%

Regarding socio-demographic variables, 65 percent of the respondents live in Flanders, 31 percent live in Wallonia, and 4 percent live in Brussels. Ninety-eight percent of the respondents have a high school or a higher education diploma, and 72 percent are government employees. Except for government employees and private company employees, other types of employment have a relatively low share in the sample. The majority of the respondents in the sample are married and have kids, and 57 percent are female. The average age among the respondents in the sample was 48 years.

Table 3. Socio-demographic characteristics of respondents.

Variable	Levels	Percentage
Gender	Male	43%
	Female	57%
Region of residence	Brussels	4%
	Flanders	65%
	Wallonia	31%
Birthplace	Brussels	4%
	Flanders	66%
	Wallonia	26%
	Abroad	4%
Education	None/Primary	2%
	Secondary	56%
	Bachelor	24%
	Master	19%
Occupation	Student	1%
	Unemployed	1%

	Laborer	1%
	Private company employee	17%
	Government employee	72%
	Self-employed	3%
	Retired	4%
Marital status	Single/Widow	23%
	Married	77%
Have kids	Yes	74%
	No	26%

3.4 *The latent class model*

Figure 2 shows how many respondents selected the bike in a particular number of situations. We can see that there is a considerable amount of heterogeneity in the data and that people have very different attitudes towards using the bike. Also, there is a spike at 24 which shows that a large proportion of the individuals always takes the bike. We tried to capture this heterogeneity by using a random intercept and two latent classes in our model.

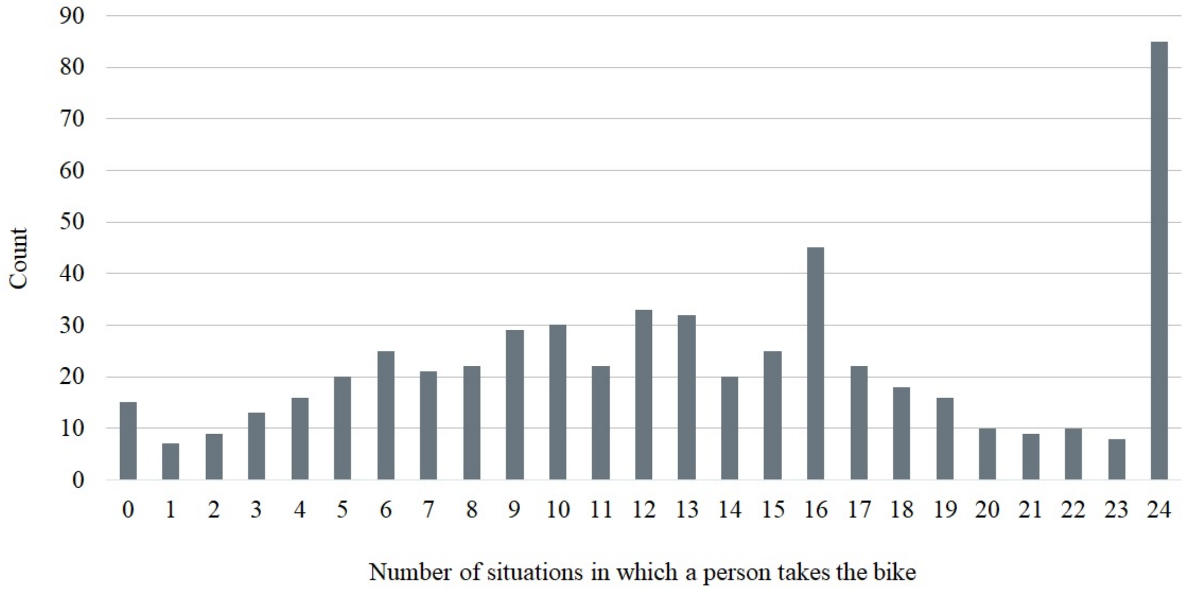

Figure 2. Number of people who chose the bike in a certain number of situations.

The response variable, Y_{pi}, is a binary variable which equals 1 if person p indicated that he/she would use the bike in situation i and 0 otherwise. In a first step, a random intercept logistic regression including all the trajectory attributes as fixed effects was estimated. Equation 1 shows the individual linear predictor for the corresponding logistic regression model and Equation 2 shows the corresponding probability of taking the bike for person p in situation i:

$$\eta_{pi} = \theta_p - \delta_i. \tag{1}$$

$$\mathrm{P}\big(Y_{pi} = 1\big) = \frac{\exp(\theta_p - \delta_i)}{1 + \exp(\theta_p - \delta_i)}. \tag{2}$$

The proposed model belongs to the family of explanatory item response models (De Boeck and Wilson, 2004). In Equation 1, θ_p can be interpreted as the tendency to choose the bike for individual p, and δ_i is the threshold for situation i. We model the threshold as a linear function of the M

discrete situation attributes. Assuming N_m attribute levels for attribute m and using $X_{imk}, k = 1, \dots, N_m - 1$ for the corresponding effects coded variables, the threshold is modelled by

$$\delta_i = \sum_{m=1}^{M} \sum_{k=1}^{N_m - 1} \beta_{mk} X_{imk}. \tag{3}$$

The individual tendency to bike θ_p was similarly modelled as a linear function of $L + 1$ individual characteristics where age was mean-centered and treated as a continuous variable and the L discrete variables were effects coded by the variables $Z_{plj}, l = 1, \dots, L, j = 1, \dots, N_l$:

$$\theta_p = \mu_p + \gamma_{age} age_p + \sum_{l=1}^{L} \sum_{j=1}^{N_l - 1} \gamma_{lj} Z_{plj}, \tag{4}$$

$$\mu_p = \mu + \nu_p \qquad \nu_p \sim N(0, \sigma_\nu^2)$$

To decide on the variables to include in the model, we estimated a mixed logistic regression assuming only a normal distribution for θ_p with mean μ and variance σ_θ^2. Then we regressed these individual-level estimates for θ_p on the individual characteristics. Using a stepwise variable selection approach in both directions (Ripley *et al.*, 2013) we selected the group of $L + 1$ individual characteristics with the best AIC value for the regression model.

A graphical representation of this model is shown in Figure 3. Dotted ellipses represent random variables and elements that are a function of these, and the squares contain observed variables.

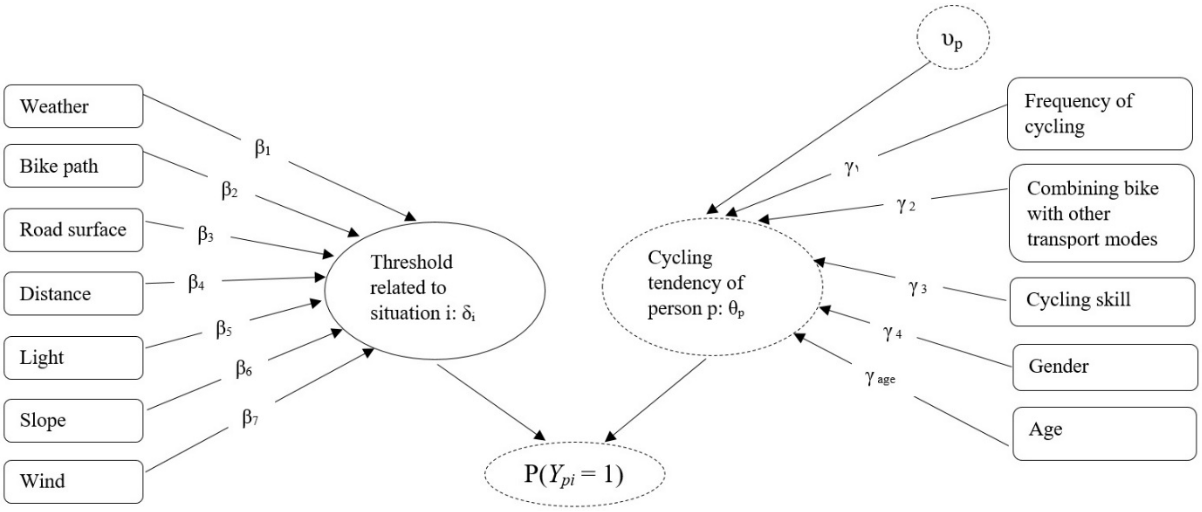

Figure 3. Graphical representation of the latent class model.

Previous studies have shown that people can differ substantially with respect to considering using the bike (Heinen, Maat and Van Wee, 2011; Li *et al.*, 2013; Motoaki and Daziano, 2015). Classifying people into groups and studying each group separately, has gained much attention in recent years (Dill and McNeil, 2013). We added latent classes to explain the possible heterogeneity. In a latent class model, each class can have different parameter estimates. In our model, U_p is a latent variable which equals q if person p belongs to the latent class q ($q = 1, \dots, Q$). We denote the probability that person p belongs to the latent class q by ξ_q:

$$\mathrm{P}(U_p = q) = \xi_q \quad \text{with} \quad \sum_q \xi_q = 1. \tag{5}$$

Equation 6 to Equation 8 respectively show the linear predictor for $\delta_{i|q}$, $\theta_{p|q}$, and the probability of taking the bike in situation i for person p, given that the person p belongs to class q:

$$\delta_{i|q} = \sum_{m=1}^{M} \sum_{k=1}^{N_m - 1} \beta_{mkq} X_{imk}. \tag{6}$$

$$\theta_{p|q} = \mu_q + \nu_p + \gamma_{age}^{q} age_p + \sum_{l=1}^{L} \sum_{j=1}^{N_l - 1} \gamma_{qlj} Z_{plj} \qquad \nu_p \sim N(0, \sigma_\nu^2). \tag{7}$$

$$\mathrm{P}\left(Y_{pi} = 1 | U_p = q\right) = \frac{\exp(\theta_{p|q} - \delta_{i|q})}{1 + \exp(\theta_{p|q} - \delta_{i|q})}. \tag{8}$$

Notice that in Equation 7, the average tendency to select the bike can differ across classes, whereas the variance of the latent distribution is assumed to be constant across classes.

3.5 *Accounting for attribute non-attendance*

There are two different approaches to study attribute non-attendance: the stated and inferred attribute non-attendance approach (Mariel, Hoyos and Meyerhoff, 2013). In the stated ANA approach the respondents are asked to state the ANA rules they applied to make their choice. However, Campbell & Lorimer (2009) showed that the respondents' declarations about their ANA rules might be unreliable. Contrary to the stated ANA approach, the inferred ANA approach uses analytical methods to infer the rules used by respondents. In this approach, the ANA patterns are explored using a latent class model where each class represents a certain non-attendance decision rule (Hess and Rose, 2007; Scarpa *et al.*, 2009; Hensher and Greene, 2010).

The attribute non-attendance is modelled using the equality-constrained latent class (ECLC) approach (Scarpa *et al.*, 2009). In this method, ANA will be modelled by assigning each individual to a latent class in which some of the attributes will have zero weights in the linear predictor, and the non-zero attributes will have the same parameter across the classes. With M attributes, there will be 2^M latent classes, each represented with a vector of weights with the length M. Each element of the vector represents one attribute and equals 1 if that attribute is considered in that ANA pattern and 0 otherwise. In our case, with 7 attributes in the linear predictor of the situation threshold we have 128 latent classes representing the ANA patterns:

(0, 0, 0, 0, 0, 0, 0)

(1, 0, 0, 0, 0, 0, 0)

(0, 1, 0, 0, 0, 0, 0)

(0, 0, 1, 0, 0, 0, 0)

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(1, 1, 1, 1, 0, 1, 1)

(1, 1, 1, 1, 1, 0, 1)

(1, 1, 1, 1, 1, 1, 0)

(1, 1, 1, 1, 1, 1, 1)

Here, the respondents who belong to the first class do not consider any of the presented attributes and will answer randomly. On the other end of the spectrum, the individuals in the last class will respond considering all the attributes and based on all the information provided. The remaining respondents belong to a class for which at least one attribute will have the weight 0 in the linear predictor.

As mentioned before, the ANA class membership probability of the individuals will be inferred from the collected data. To do that, we define H_{pm} as a binary latent variable which equals 1 if person p considers situation attribute m and 0 otherwise. H_{pm} is assumed to have a Bernoulli distribution with probability ζ_m. Then the probability that person p has the ANA pattern $\boldsymbol{H}_p = \boldsymbol{h}_p$ equals (Hole, 2011):

$$\mathrm{P}\left(\boldsymbol{H}_p = \boldsymbol{h}_p | \boldsymbol{\zeta}\right) = \prod_{m}^{M} (\zeta_m)^{h_{pm}} (1 - \zeta_m)^{1-h_{pm}}. \tag{9}$$

The linear predictor of the threshold related to situation i then becomes:

$$\delta_{i|q,\boldsymbol{h}_p} = \sum_{m=1}^{M} h_{pm} \sum_{k=1}^{N_m - 1} \beta_{mkq} X_{imk}. \tag{10}$$

The linear predictor of the cycling tendency of person p will be the same as Equation 4, and the probability of taking the bike for person p in situation i will be:

$$\mathrm{P}\left(Y_{pi} = 1 | q, \boldsymbol{H}_p = \boldsymbol{h}_p\right) = \frac{\exp(\theta_{p|q} - \delta_{i|q,\boldsymbol{h}_p})}{1 + \exp(\theta_{p|q} - \delta_{i|q,\boldsymbol{h}_p})}. \tag{11}$$

In the model shown in Equation 9, it is assumed that latent non-attendance variables are independent across attributes. Collins, Rose, & Hensher (2013) show that releasing this assumption can improve the model fit though it requires many more parameters. Therefore, we will compare the fit of the model in Equation 11 with that of a model including interactions between each pair of the latent non-attendance variables.

4. Results

4.1 Ignoring attribute non-attendance

Latent class logistic regression models with 1 up to 6 classes were estimated using the LatentGOLD software (Vermunt and Magidson, 2016). The estimation of each model was done with 100 random starting points to avoid local maxima. A summary of AIC and BIC values for the models with 1 to 6 classes with/without a random intercept is shown in Figure 4. Red lines show the AIC and BIC values for the models that have a fixed intercept and Blue lines show the AIC and BIC values for the models that include a random intercept. Full lines show the AIC values and dashed lines show the BIC values.

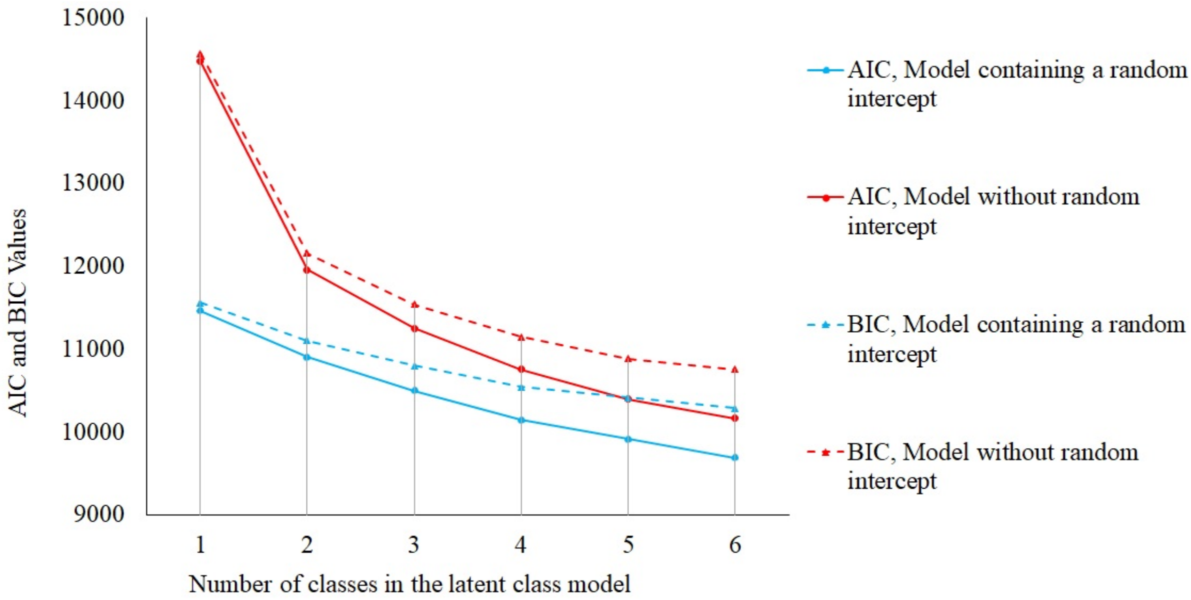

Figure 4. AIC and BIC values of the latent class models.

In Figure 4, it can be seen that adding a random intercept improves the model fit considerably. This means that persons with the same individual characteristics still have different tendencies to select the bike in a certain situation. Also in the models without a random intercept, going from 1 class to 2 classes has a significant impact on the model fit.

The model with two latent classes including a random intercept was selected for the analysis. As shown in Figure 5, if we check the area under the curve (AUC) values of the ROC curves for each model, we can see that the AUC values increase as a function of the number of classes, but the main increase happens up to the model with two classes and a random intercept and after that, adding more classes does not increase AUC much. Moreover, the model with two latent classes had a straightforward interpretation and, the main conclusions about people's attitudes toward cycling do not really change by having more classes in the model. So it was decided to continue with the model that has two latent classes and a random intercept.

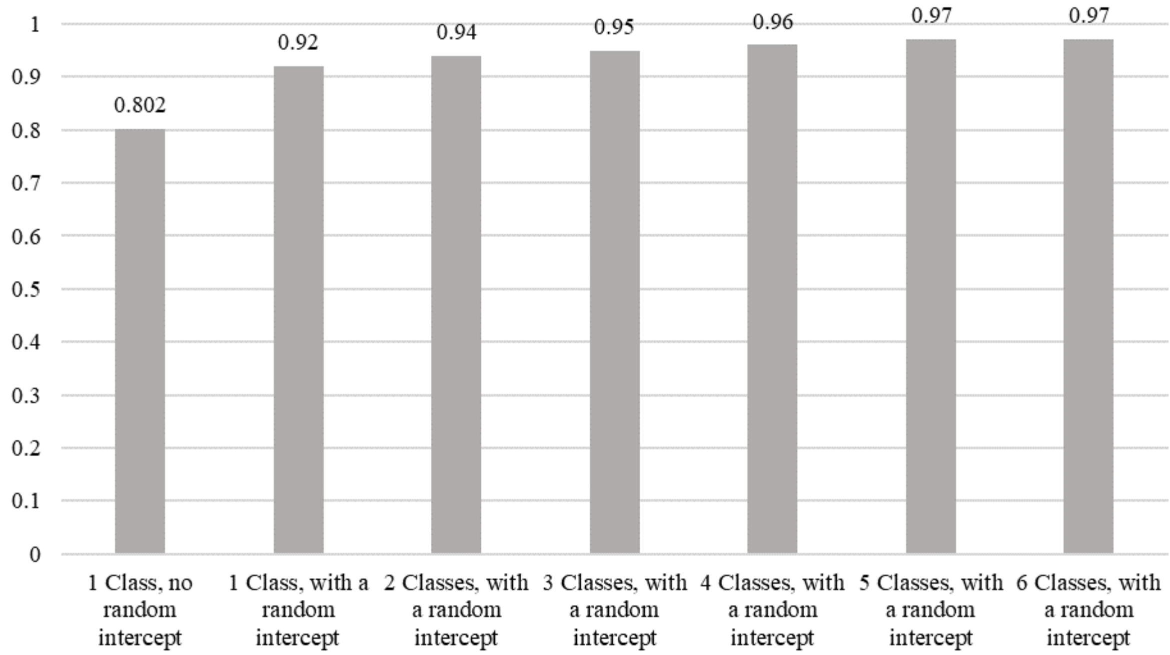

Figure 5. AUC values for the ROC curves of the models with a different number of latent classes.

The estimation results are shown in Table 4. Notice that 66.7% of the sample was classified in class 1 and 33.3% in class 2.

As effect coding was used for categorical variables and as the coefficients of situation attributes have a negative sign in our linear model, a larger value for these parameters means a greater barrier for cycling. The last column of Table 4 shows the p-values for testing whether the parameters in the two classes are significantly different. We can reject the $H_0: \mu_1 \leq \mu_2$ against the $H_a: \mu_1 > \mu_2$. This is a one-sided test with p-value: $^{0.02}/_{2} = 0.01$. Therefore, we can say that class 1 consists of persons who have on average a stronger tendency to use the bike. This class will further be called "frequent cyclists". On the other hand, persons of class 2 will be referred to as "occasional cyclists".

Table 4. Estimation results for the latent class model with 2 classes and a random intercept.

Variable	Levels	Class 1	Class 2	p-value: test the difference between classes
Intercept	μ	1.67*	-0.65	0.02
	σ^2	2.17*	2.17*	
Weather	Rain	0.79*	4.26*	0.00
	Dry and sunny	-0.44*	-2.50*	
	Dry and cloudy	-0.35*	-1.76*	
Bike path	None	0.52*	0.16	0.01
	Separate bike path	-0.54*	-0.32*	
	Marking on the road	0.02	0.16	
Road surface	100% asphalt	-0.18*	-0.34*	0.29
	50% asphalt, 25% clinkers, 25% cobblestones	0.06	0.06	
	25% asphalt, 50% clinkers, 25% cobblestones	0.12*	0.28*	
Distance	15km	0.46*	0.64*	0.15
	10km	0.04	0.09	

	5km	-0.5*	-0.73*	
Light	Daylight	-0.6*	-0.85*	0.01
	Dark	0.6*	0.85*	
Slope	Completely flat path	-0.39*	-0.61*	0.01
	Two slopes of 500 meters uphill at 10%	0.39*	0.61*	
Wind	Powerful (10.8 to 13.8 m/s)	0.48*	0.93*	0.00
	Weak (1.6 to 3.3 m/s)	-0.48*	-0.93*	
Cycling frequency	Approximately daily	2.08*	1.86*	0.03
	Only on weekends	-0.02	0.23	
	Several times a week	1.15*	-0.18	
	Several times a month	0.38	-0.23	
	Several times a year	-0.63*	-1.12*	
	Never	-2.96*	-0.56	
Cycling skill	Not cyclist	-0.8*	-0.32	0.21
	Beginner	0.24	-0.5	
	Advanced	0.56*	0.82*	
Combine bike with other transport modes	Yes	-0.47*	0.10	0.06
	No	0.47*	-0.10	
Gender	Male	0.54*	0.24	0.26
	Female	-0.54*	-0.24	
Age		-0.04*	0.01	0.05

AIC = 10903, BIC = 11102, Number of parameters = 46, Log-likelihood = -5405, Number of observations = 562

*: significantly different from 0, given an alpha level of 0.05

Almost all of the previous studies have shown that a separate bike path is much more critical for inexperienced cyclists and that the absence of a separate bike path will not affect experienced cyclists significantly. However, we found that frequent cyclists give more weight to a separate bike path and that the absence of any bike path is a greater barrier for them. A possible explanation is that, compared to other studies, there are no very inexperienced cyclists in our sample.

The road surface and distance effects did not significantly differ across the two classes, and as expected, the routes with shorter distances and more asphalt surface are more favorable.

Light has received less attention in previous studies, but it has significant parameters for both classes in our analysis. Also, the parameters of "light" are significantly different in the two classes. Darkness is a higher threshold for occasional cyclists than for frequent cyclists. The two classes have also statistically different sensitivities to a slope in the route: occasional cyclists find an uphill slope a little more bothersome than frequent cyclists.

Our results indicate that the wind level also has a significant effect on the probability of choosing the bike and that this effect is different for the two classes. Strong wind has a more negative effect on occasional cyclists than on frequent cyclists.

Figures 6 to 10 depict detailed comparisons of how situation attribute levels affect the probability of taking the bike for persons in each class. The results for distance and road surface are not shown in these figures because the effects of these variables do not differ across the two classes. In these figures, the occasional cyclists are shown with dashed-lines and frequent cyclists with full-lines. The minimum tendency to choose the bike in class 1 is -0.796 and the maximum in class 2 is 1.447. The lines are only drawn for those tendency values that occur for both classes in the dataset. Notice that in Figure 6 the estimates for "dry and sunny", and "dry and cloudy" in class 1 are almost equal and therefore their lines overlap. Also in Figure 7, the estimates for “mark on the road” and “no bike path” in class 2 are equal, and so these lines overlap.

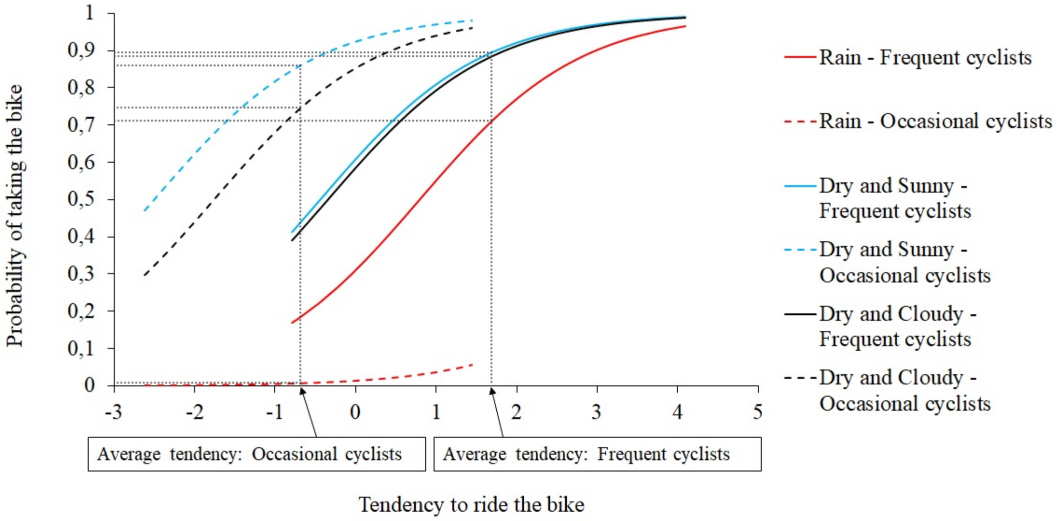

Figure 6. Probability of taking the bike in different weather conditions.

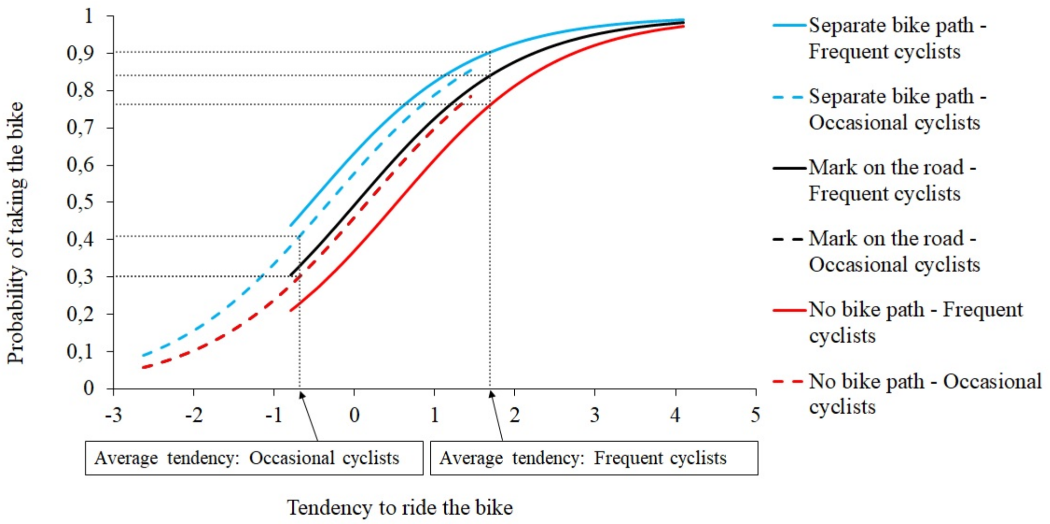

Figure 7. Probability of taking the bike for different types of bike paths.

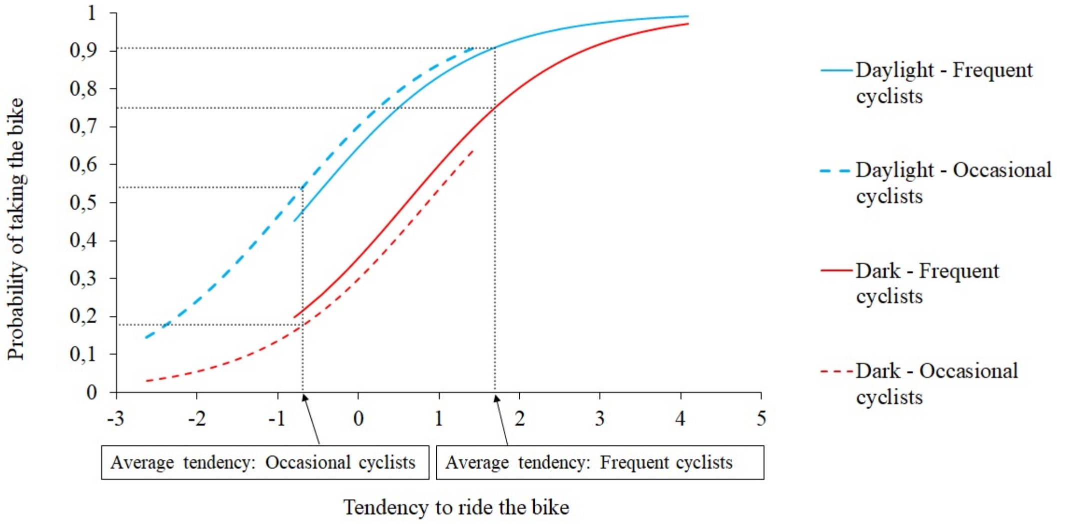

Figure 8. *Probability of taking the bike for different levels of light.*

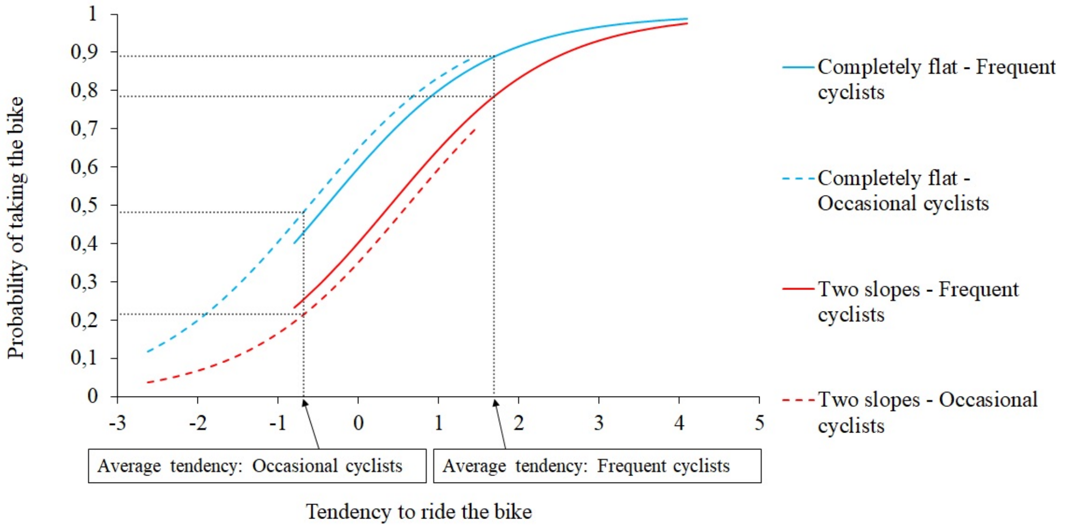

Figure 9. *Probability of taking the bike for different levels of slope.*

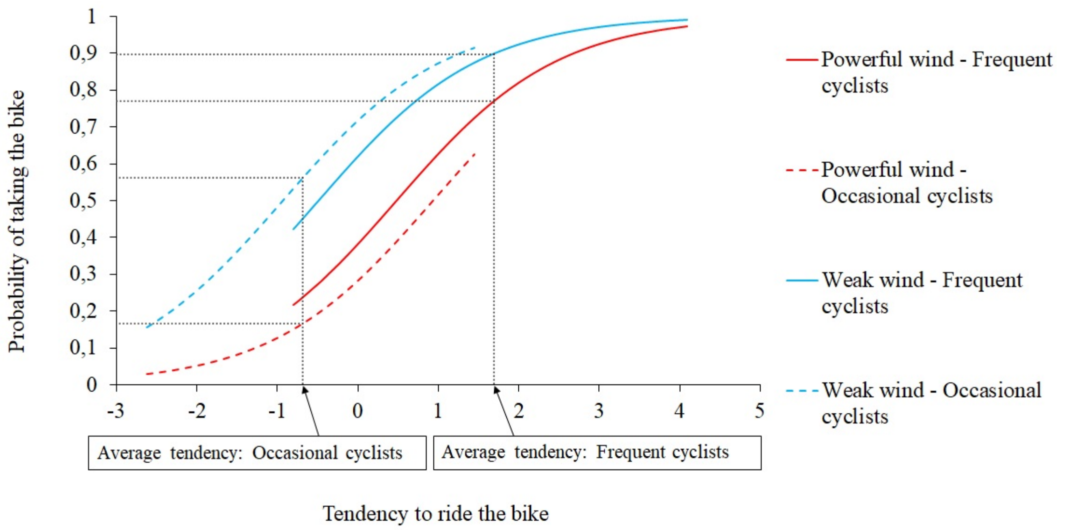

Figure 10. *Probability of taking the bike for different levels of wind.*

In Figures 6 to 10, the tendency to ride the bike for the average person in both classes, and their corresponding probabilities of taking the bike are shown using dotted lines. For every situation attribute level, except "weather: dry and sunny", the probability of taking the bike is substantially higher for an average frequent cyclist than an average occasional cyclist. When weather is dry and sunny, the probability of taking the bike is still higher for an average frequent cyclist, but the difference is not as extreme as it is for the other situation attribute levels.

In Figure 6 we can see that rain has a very different effect on the probability of taking the bike between the two classes. The probability of cycling for occasional cyclists is very low (close to zero) when it is raining. The "dry and cloudy" and the "dry and sunny" weather have almost the same effect for frequent cyclists. But, occasional cyclists have a higher probability of taking the bike when it is dry and sunny than when it is dry and cloudy.

Figure 7 illustrates the probability of taking the bike in each class for different types of bike paths. Having a mark on the road or no bike path at all has the same effect for occasional cyclists but for frequent cyclists these two types of paths have a significantly different effect. This means that only a separate bike path can motivate the occasional cyclists, but for frequent cyclists, even a mark on the road can make a difference compared to having no bike path. Also here we can see the substantial role of the separate bike path for frequent cyclists and the difference it can make in the probability of cycling for this group. The predicted probability of taking the bike for an average frequent cyclist in the presence of a separate bike path is 0.9 while this number is 0.41 for an average occasional cyclist.

In Figures 6 to 10, positive levels of attributes cause a larger increase in the probability of cycling for the occasional cyclist. Also, the negative levels of attributes decrease the probability of cycling for occasional cyclists more than the other class. So we can say that occasional cyclists are generally more sensitive to the situation thresholds compared to frequent cyclists.

4.2 *Attribute non-attendance model*

We extended the model discussed in the previous section to account for ANA. Relation of ANA and person characteristics was studied in a post-hoc way, because including the person covariates in the model was not feasible due to the increase in run-time. The post-hoc analysis did not show any significant relations between the ANA patterns and personal characteristics.

The AIC value for the ANA model was 9727, and the BIC value was 9870. The AIC and BIC values for our previous model (which did not account for ANA) were 10903 and 11102. So there has been a significant improvement in the model fit after accounting for the ANA in the model showing that persons ignore part of the attributes when deciding on choosing the bike. It is interesting to notice that the ANA model (Table 5) does not include the individual characteristics and, achieves a better model fit than the model which uses individual characteristics to account for heterogeneity (Table 4) but ignores the heuristic decision-making rules.

Another check for the usefulness of accounting for ANA was obtained by estimating the frequency of taking the bike for each model. Figure 11 shows the observed frequency of taking the bike and the 95% bootstrapped confidence intervals for the model ignoring and the model accounting for ANA. As it is shown in Figure 11, the ANA model performs better in reproducing the frequencies.

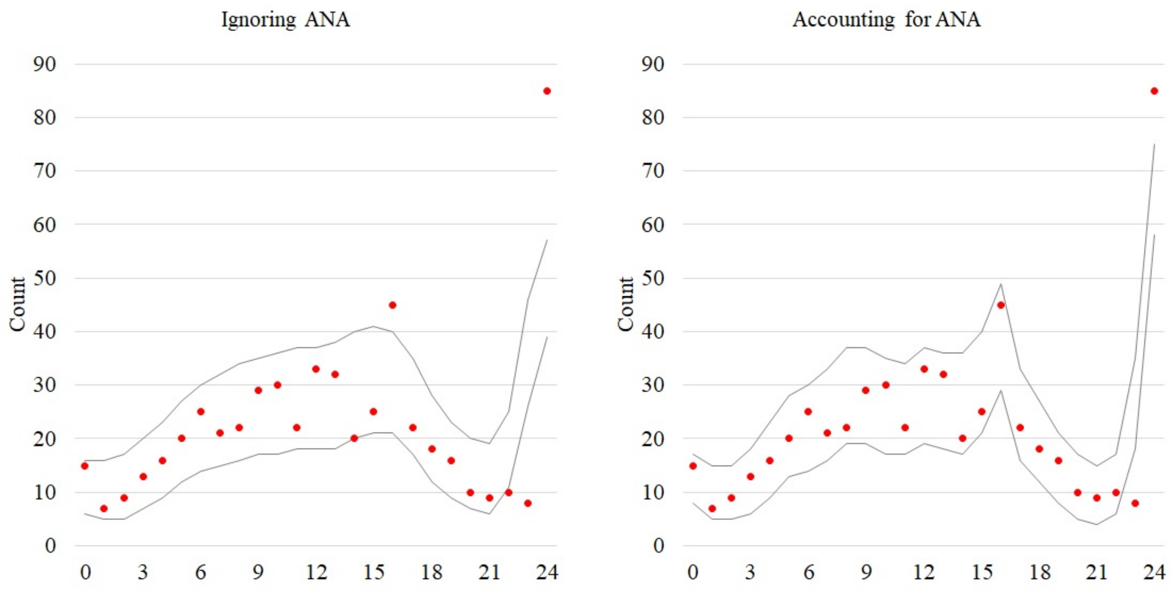

Figure 11. The estimated 95% bootstrapped confidence intervals for the frequency of taking the bike.

Another possible model that can be an appropriate candidate to model the data is the mixed item response model where in addition to the intercept, some or all of the parameters are random across persons. This model has been used widely in the literature because of its ability to capture the heterogeneity among persons. We estimated the full mixed model with independent random parameters using the "gmnl" package in R (Sarrias and Daziano, 2017). The resulting AIC and BIC values were 10870 and 11050 respectively. The random-intercept ANA model with two latent classes has a better fit both in terms of AIC and BIC. Furthermore, it should also be noted that estimating the ANA model was much faster than estimating the full mixed model.

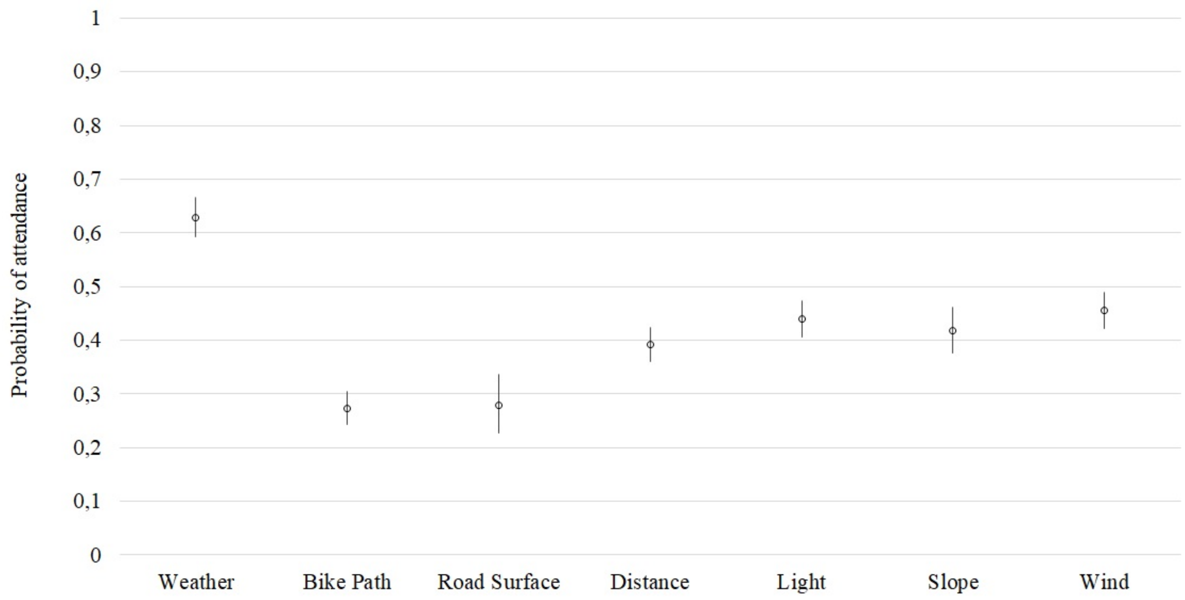

Figure 12. The estimated probability of attendance and the 95% confidence interval per situation attribute.

The estimated probability of attendance for each situation attribute and its 95% confidence interval is shown in Figure 11. The ANA rates shown in Figure 11 are not class-specific. The probabilities of attendance do not differ between the occasional and the frequent cyclists. We also estimated an

ANA model with class-specific ANA rates but the AIC and BIC values indicated that this did not improve the model.

The weather has the highest probability to be taken into account when choosing the bike. Except for the weather, all other attributes have an attendance probability lower than 0.5. It is striking that only 27% in the sample considered the bike path. Many of the previous studies have introduced the bike path as the most important factor to increase the share of cycling but, our results showed that 73% of the sample ignored the bike path.

We hypothesized that the low probabilities of attendance could be due to the relatively high share of respondents who chose the bike in almost every situation (see Figure 2). As 15% of the sample selected the bike in all 24 situations, this means that the situation's thresholds were not high enough to overcome their tendency to ride the bike. So they selected the bike always without really making a trade-off between situation attributes. However, re-estimating the model without those people who selected the bike in all situations yielded very similar estimated probabilities of attendance.

Table 5 shows the estimated parameters for the situation characteristics in the ANA model. The model has again two latent classes; 58.5% of the respondents are in class 1, and 41.5% are classified in class 2.

Table 5. Estimation results for the ANA model.

Variable	Levels	Class 1	Class 2	p-value: test the difference between classes
Intercept	μ	1.95*	-1.41*	0.00
	σ^2	4.58*	4.58*	
Weather	Rain	1.25*	5.66*	0.00
	Dry and sunny	-0.79*	-3.42	
	Dry and cloudy	-0.47*	-2.24	
Bike path	None	0.81*	2.09*	0.00
	Separate bike path	-1.30*	-1.12*	
	Marking on the road	0.49*	-0.97	
Road surface	100% asphalt	-0.21*	-1.31*	0.00
	50% asphalt, 25% clinkers, 25% cobblestones	-0.07	0.83	
	25% asphalt, 50% clinkers, 25% cobblestones	0.28*	0.48	
Distance	15km	1.03*	1.10*	0.00
	10km	0.05	0.68*	
	5km	-1.08*	-1.78*	
Light	Daylight	-1.41*	-1.50*	0.00
	Dark	1.41	1.50*	
Slope	Completely flat path	-0.55*	-1.44*	0.00
	Two slopes of 500 meters uphill at 10%	0.55*	1.44	
Wind	Powerful (10.8 to 13.8 m/s)	0.67*	1.85*	0.00
	Weak (1.6 to 3.3 m/s)	-0.67*	-1.85	

AIC = 9727, BIC = 9870, Number of parameters = 33, Log-likelihood = -4830, Number of observations = 562

*: significantly different from 0, given an alpha level of 0.05

In Table 5, class 1 has a positive intercept which is significantly different from the intercept for class 2. Class 2 has a negative intercept which can be treated as the average cycling tendency in class 2. As before, class 2 can be labeled as occasional cyclists, and class 1 as frequent cyclists. It should be noted that the class membership of the two latent classes in the ANA model is not the same as the two latent classes that we had in the previous model (the model that ignores ANA). Table 6 shows for each model the number of individuals in each class. The last column of Table 6 shows that a large portion of the individuals in each class overlap between the two models.

Table 6. Number of the individuals in each latent class

	The model that ignores ANA	The model that accounts for ANA	Overlap
Class 1 – Frequent cyclists	375	329	297
Class 2 – Occasional cyclists	187	233	155

There are three major differences with the results that we obtained earlier when ANA was ignored. The first difference is in the parameters for the bike path. Unlike before, here the "no bike path" is a stronger barrier for occasional cyclists. But, the separate bike path is more important to the frequent cyclists as we also had in our previous analysis. The second difference is that generally, parameters are more extreme than in the latent class model without ANA. But, these parameter estimates hold given that a person attends to all attributes. By averaging over all ANA patterns, we obtain the average β parameters that hold for the entire sample. The third difference is the fact that in the ANA model all the parameters differ significantly across the two classes, but in the original latent class model, some parameters were not significantly different.

As mentioned in Section 4.2, having interactions between all pairs of latent non-attendance variables can improve the model fit (Collins, Rose and Hensher, 2013). However, allowing for pairwise interactions resulted in AIC and BIC values of 10936 and 10702 which are higher than for the model with uncorrelated latent non-attendance variables.

4.3 Policy implications

Using the predicted probability of taking the bike in each situation and for each individual, we can draw up some useful conclusions about the impact of the variables which are modifiable by the policymakers. Those variables are the bike path and the road surface. We have reported the average predicted probability of taking the bike for each level of the variables in Table 6. The ANA model (Table 5) was used to compute the average predicted probabilities, but the results of the model that ignores ANA (Table 4) are also reported to have a comparison. When using the ANA model results, to have a more realistic and practical conclusion, only predicted probabilities of the individuals who considered an attribute were included in the analysis of that attribute. This was done because these are the people who truly care about that attribute and therefore, policymakers have a higher chance of influencing these people cycling behavior by modifying the attribute.

Table 7. Average probability of taking the bike for each attribute level.

Variable	**Levels**	**The average probability of taking the bike**			
		Accounting for ANA		**Ignoring ANA**	
		Class 1 Frequent cyclists	**Class 2 Occasional cyclists**	**Class 1 Frequent cyclists**	**Class 2 Occasional cyclists**
Bike path	Separate bike path	83%	68%	62%	45%
	Marking on the road	36%	70%	61%	47%
	None	28%	20%	56%	52%
Road surface	100% asphalt	66%	64%	61%	49%
	50% asphalt, 25% clinkers, 25% cobblestones	64%	24%	61%	46%
	25% asphalt, 50% clinkers, 25% cobblestones	55%	27%	57%	50%

As expected, the average probability of taking the bike is generally higher for class 1 which is reasonable as this class represents the frequent cyclists. Based on the ANA model results, the presence of a separate bike path compared to when there is no bike path increases the average probability of taking the bike by 55 percentage points for frequent cyclists (class 1) and 48 percentage points for occasional cyclists (class 2). Adding marking on the road can also be effective, especially for occasional cyclists as for them it increases the average probability by 50 percentage points compared to the situation where there is no bike path.

Using the ANA model results we see that having a 100% asphalt route compared to a 50% asphalt route results in only 2 percentage points higher average probability of taking the bike for frequent cyclists, but this number is 40 percentage points for the occasional cyclists. Very few information exists in the literature about the role of the road surface in cycling behavior, but here we can see how crucial it can be, especially for the people who use the bike less frequently.

Table 6 shows a considerable difference between the results of the model that accounts for the ANA and the model that ignores it. For instance, in the model that ignores ANA, the average probability of taking the bike in situations with is a separate bike path is lower than in situations without a bike path. This shows how different or probably misleading the results can be if the attribute non-attendance is ignored. This puts even more emphasis on the importance of accounting for attribute non-attendance when studying cycling behavior.

5. Conclusion

This study investigates a new modelling approach to study cycling behavior. First, we modelled the probability of choosing the bike in a particular situation using a latent class binary item response model where the choice is modelled as a trade-off between the individuals' tendency to cycle and the threshold provided by characteristics of the situation. Second, we extended the model by accounting for attribute non-attendance (ANA) to see whether all situation attributes are taken into account while deciding whether or not one would take the bike in a certain situation.

We studied the factors influencing the propensity of cycling in Belgium, one of the top-ranked countries in Europe regarding the bicycle's share among other transport modes. The survey sample data consisted of the respondents who own a bike, and 63% of them have stated that they have advanced cycling skills. Cycling in this context was not studied before. All the previous studies were concentrated on motivating non-cyclists to make a change from the private car to the bicycle. However, in the current study, we tried to explore ways of encouraging people who are already familiar with cycling.

The first model (ignoring ANA) identified a class of frequent cyclists and a class of occasional cyclists. There were significant differences between the sensitivity of the two groups to the situation thresholds. Rain, wind, uphill slope, and darkness were greater barriers for occasional cyclists. No differences between the two classes were observed for the sensitivity to distance and road surface. With respect to weather, uphill slope and darkness our results are in line with findings from previous studies (Heinen, Maat and Van Wee, 2011; Li *et al.*, 2013; Motoaki and Daziano, 2015). But, in contrast to previous studies, our results indicate that frequent cyclists are more concerned about the type of bike path than occasional cyclists and that a separate bike path is more important for the former group.

Allowing for attribute non-attendance (ANA) improved the model fit significantly. We also observed major differences in the interpretation of the results of the two models that account for and ignore ANA and found that ignoring ANA can yield misleading results.

The average predicted probability of taking the bike was computed for three types of bike paths and three types of road surfaces. In the ANA model, the attendance probability of bike path was 0.27. However, for frequent cyclists who account for this attribute having a separate bike path increases the average probability of cycling by 55 percentage points, whereas for occasional cyclists having a separate bike path increases the probability of cycling by 48 percentage points. In contrast, in the model that ignores ANA, a separate bike path increased the average probability of taking the bike by only 6 percentage points for frequent cyclists and decreased it by 7 percentage points for occasional cyclists.

Road surface has an attendance probability of 0.28 in the ANA model and having a complete asphalt road increases the average probability of cycling by up to 40 percentage points for the frequent cyclists and by 11 percentage points for occasional cyclists. In contrast, the results of the model that ignores ANA show that having a complete asphalt route can increase the average probability of taking the bike by only 4 and 3 percentage points for the frequent and occasional cyclists, respectively.

In this study, bike path and road surface are the two main attributes that can be directly modified by policymakers to increase the cycling share among the transport modes. We observed that accounting for ANA or ignoring it, can lead to very different interpretations about the impact of these attributes on cycling behavior. Moreover, road surface has not gained much attention in the previous studies which makes the findings on this variable more interesting for policymakers.

In this study, we asked people whether they would cover a specific route by bike or not without considering the alternative travel mode that the respondent would choose if he/she does not cycle. Future research might elaborate on this and evaluate whether switching from car to bike is determined by the same factors as a switch from other travel modes.

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