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Modelling individual perception of barriers to bike use

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Abstract

People face different barriers when choosing to commute by bike. The predominance of these barriers in users' perceptions could explain the low cyclability rates present in many cities. An investigation of cyclists' perceptions is developed using the data set obtained through a survey made to individuals from Quito, Ecuador. This study is aimed to evaluate the perception of barriers to bike use, in particular, assesses how perception varies according to the available information and the different profiles of individuals. Using ordered probit models, the study compares the overall evaluation of bike acceptance before and after making individuals reflect on the importance of certain variables (e.g. lack of bike infrastructure). The main results show that to improve bike use acceptance, enhancing multimodality or providing facilities like electric bikes must be considered. The results also demonstrated a high heterogeneity of individuals' perceptions caused by their sociodemographic and travel characteristics.

Keywords: bike use perception; barriers to cycling; urban cycling; ordered probit models

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1. Introduction

Cities face major environmental, socioeconomic, and transport challenges, whereby, the importance of promoting non-motorized modes such as the bike is recognized. Bike transportation offers many benefits at environmental, health, and urban mobility levels. However, despite its advantages, regular bike use is still not broadly accepted in many cities. The unconcern in integrating the bike in urban mobility has created several dares including identifying the most effective ways to spend the usually limited resources allocated to its promotion (Keeling, 2013). Commonly, bike mobility planning is focused primarily on solving the service from a technical perspective (e.g. proposing the fastest routes). However, evidence suggests that to achieve a positive bike use assessment and its acceptance among users, the system must also comply with other subjective aspects that respond to individuals' needs (Cepeda Zorrilla et al., 2018; Heinen et al., 2011). From this perspective, in contexts with low rates of bike use, it seems reasonable to focus on identifying the system's weakest points to reduce the risk of solving other aspects that will not necessarily motivate people to commute by bike (Dell'Olio et al., 2010).

This study aims to identify the barriers that influence individuals around bike use, as well as to obtain the comparative weights of each of them. Previous studies have proven that *Ordered Probit Models* are satisfactory in analyzing categorized or non-quantitative ordered choices and replies (dell'Olio et al., 2018a). The contribution is a model that identifies and ranks the perceived barriers of bike use, better understanding citizens' needs to enrich bike mobility planning. This paper begins with a brief contextualization of the problem. Afterward, the methodology, the collected data, and some results are discussed. Finally, the main conclusions are presented.

1.1. Choice to commute or not by bicycle

Studies conclude that bike commute decision is highly complex since it can be influenced by both objective and subjective factors (Konstantinidou and Spyropoulou, 2017). The psychological factors affecting bike commute, such as attitudes and perception towards cycling, are related among others to environmental, journey, and socioeconomic characteristics (Cepeda Zorrilla et al., 2018; Majumdar and Mitra, 2013). Evidence suggests that these aspects are not necessarily equally perceived by all individuals or have the same weight in the overall perception of the service (Dell'Olio et al., 2010). Therefore, the importance of understanding the relationship between bike use individuals' perception and their different profiles is recognized (dell'Olio et al., 2018b; Garrido et al., 2014).

Several authors agree that aspects such as the *weather conditions*, the *long travel distances*, a *lack of efficient cycling networks*, the *perception of risk* against *traffic and crime*, *city topography*, *physical abilities*, and the *personal appearance* are factors affecting bike commutes and reducing trips' frequency (Fernández-Heredia et al., 2014; Gutiérrez et al., 2020; Iwińska et al., 2018; Majumdar and Mitra, 2013; Muñoz et al., 2013). Wide studies investigate barriers to cycling; however, this number is limited when identifying the weight of each variable in individuals' perception (Handy et al., 2014). Focusing mainly on public transport (PT) service quality, Dell'Olio (2010) among other authors have estimated the different influence that has users' perception of each attribute in the system's overall assessment (Dell'Olio et al., 2010; Garrido et al., 2014).

1.2. Service Quality and user satisfaction

Service Quality (SQ) has been widely studied since Parasuraman et al., (1985) first introduced it, defining SQ as the difference between both the expected and the perceived quality of service. Perceived quality has shown to have a positive effect on user's satisfaction with transport services (De Oña et al., 2016). However, evidence suggests that although users perceive a good SQ, taking this indicator as a criterion of success could be precarious, hence, it cannot be used as the only reference when planning policies aimed at retaining customers or attracting new ones (Fernández-Heredia et al., 2014). Parasuraman et al. (1988) suggested that for studying the SQ of transport services, their defining variables have to be established, proposing a generic list of 22 attributes and dimensions applicable to any type of service. However, many authors criticized this list stating that the attributes must respond to each specific case (Babakus and Boller, 1992). Likewise, other evidence proved that the predictive value of the model developed by Parasuraman increased when the items were adapted to the study context (Carrillat et al., 2007). The key then is to enlist generic attributes but adding other aspects own of each context and service.

Several methodologies and tools have been developed to evaluate SQ variation according to users' profiles. For instance, satisfaction surveys allow researchers to associate quality perception to a type of user classifying them accordingly to their socioeconomic and journey characteristics (Alonso et al., 2018; Branion-Calles et al., 2019). Others studies establish this relationship using methodologies based on structural equations (de Oña et al., 2013) or the application of decision trees (De Oña and De Oña, 2015). Likewise, other not model-based methods have provided interesting results, such as descriptive statistics (Eboli and Mazzulla, 2011) or neural networks (Garrido et al., 2014).

Ordered probit models have proven to be a highly efficient and useful tool for modeling perceived quality. This particular methodology allows ordered qualitative responses to be modeled, meaning that the non-linearity existing between the different replies can be considered (Alonso et al., 2018; dell'Olio et al., 2018a; Dell'Olio et al., 2010). Another model's key feature is its ability to use interactions to incorporate systematic variations resulting from users' socioeconomic characteristics, assuming that these factors follow a statistical distribution (Bordagaray et al., 2012).

2. Methodology

2.1. Data collection and survey design

Data collection was conducted in Quito, Ecuador. A city of 372 km2 and nearly 1.7 million people (INEC, 2017). In 2011, inhabitants' mobility rate was 3.4 million daily trips, mostly made by PT (62%) and private car (20%), and just 0.3% by bike (Metro de Quito, 2012). After a literature review aimed to identify psychological, socioeconomic, environmental, and travel-related factors that could affect bike use, a first draft of the survey was presented to specific groups of people from the study area. Afterward, considering the first stage's feedback, a second draft was tested to verify the clarity of the questionnaire and the right capture of the information needed for the model estimation. The final survey was carried out via the web in the last week of January of 2021 and collected 422 completed forms. Figure 1 presents a flow chart of the process.

Fig. 1. Methodology flow chart.

The questionnaire consisted of two segments. The first collected information about individuals' sociodemographic and journey characteristics (see Table 2), information which permitted respondents' stratification into different profiles. The second part consisted of three questions and enclosed bike use perception. It resided in asking individuals to score a subjective aspect related to bike use (a barrier). The first question got a first evaluation of bike use, representing individuals' initial opinion based on the information they have, ergo, their understanding of the service through the personal experience. The second got separate values for each barrier. The third question, asked right after individuals valued each barrier, consisted of a second score of the overall perception of bike use (see Table 1). This second score is required to analyze any changes on bike's global score once individuals had the opportunity to analyze every aspect of the system (dell'Olio et al., 2018b; Dell'Olio et al., 2010).

The set of selected barriers was city slopes (CS), lack of adequate bike infrastructure (LBI), road insecurity (RI), crime insecurity (CI), city temperature (CT), long travel distances (TD), difficulty in maintaining the personal appearance (PA), and insufficient physical conditions and cycling skills (PHC).

Using a five-point Likert scale, participants were asked to rate the variables (see Table 1).

Table 1. Survey segment 2: Perception of bike use.

Question 1	***Do you agree that biking, in your city; is a good option to commute?***		Strongly disagree	1	→	5	Totally agree
Question 2	***The following aspects could DEMOTIVATE bike use, how much do you think they influence?***						
	Variable		Very influential	1	→	5	Not influential
	CS	The city slopes					
	LBI	Lack of adequate bicycle lanes and parking slots					
	RI	Fear of having a traffic accident					
	CI	Insecurity against crime					
	CT	The temperature of the city (too cold, too hot)					
	TD	Travel distances					
	PA	Difficulty maintaining the personal appearance					
	PHC	Low physical conditions and abilities to bike use					
Question 3	***Do you consider the bike as a good option to commute in your city?***		Strongly disagree	1	→	5	Totally agree

2.2. Statistical approach

The type of model was selected after collecting and treating the data. Since the dependent variables (initial and final overall bike use perception) are ordinal by nature, ordered probit models seemed to be suitable. Following the belief that latent and continuous variables cannot be measured discretely, thus the variable (bike use perception) is intended to be segmented into several options associating each one of them with a range value of the latent variable (in this case from 1 to 5) (see Table 1). This method's key idea is that allows transforming a continuous latent variable into an ordered, observed, and discrete reply. So when individuals select an option, they are in fact selecting not a discrete value but rather the closest answer to their true perception, of bike use in this case (Alonso et al., 2018; Dell'Olio et al., 2010; Echaniz et al., 2019).

Two types of models were estimated for the different respondents' profiles. Both the initial bike use overall evaluation (V_i) and the second bike use overall evaluation (V_f) were related separately to the barriers to bike commute (see Tables 1 and 5). The first model aims to identify which variables are unconsciously relevant when an individual decides not to commute by bike, and the second, which variables would individuals consider as important after having more information about the service. According to literature, an *ordered probit model* entails a direct relationship between the dependent variable, in this case, initial (V_i) and final (V_f) bike use perception scores, and the independent variables (barriers) V_{ik}. A constant β_0, and an estimation error ε_i associated with individuals' heterogeneity, complements the model (dell'Olio et al., 2018a).

The models are based on the following mathematical expression:

$$Q_i^* = \beta_0 + \sum_{k=1}^{N} \beta_k \cdot V_{ik} + \varepsilon_i \qquad \text{with } k \in [1, 2, \dots, N] \tag{1}$$

Q_i represents a person i general evaluation; β_0 the model constant; N the number of evaluated bike use aspects (barriers); β_k the coefficient of the variable *k (barrier)*; V_{ik} the evaluation made by each person *i* of each variable *k*.

To fit the models Log Likelihood function was used:

$$\log L = \sum_{i=0}^{n} \quad \sum_{j=0}^{J} m_{ij} \, log\left[F\left(\mu_j - \beta'_{V_i}\right) - F\left(\mu_{j-1} - \beta'_{V_i}\right)\right] \tag{2}$$

3. Results and discussion

3.1. Initial data analysis

First, the data set composed of 422 observations were analyzed to characterize individuals' profiles (see Table 2).

As explained in subsection 2.2, bike use overall evaluation was asked twice (see Table 1). Therefore, the difference between V_f and V_i will show any changes in people's opinion concerning the first evaluation. The results showed that around 60% of individuals changed their score, either positively or negatively (see Figure 2).

Table 2. Profile of respondents.

Variable	Category	Frequency	Percent	Variable	Category	Frequency	Percent
Sample		**422**	100%				
Gender	Female	186	44%	**Household income**	< 400 USD	75	18%
	Male	236	56%		400 - 800 USD	166	39%
Age (years)	< 24	121	29%		800 - 1.200 USD	135	32%
	25 to 44	142	34%		> 1.200 USD	46	11%
	45 to 64	132	31%				
	> 65	27	6%	**Mode of transport**	Walking	43	10%
Main occupation	Student	104	25%		Bicycle	23	5%
	Dependent worker	87	21%		Public Transport (bus, BRT)	186	44%
	Self-employed / independent worker	57	14%		Private car	31	7%
	Home care	62	15%		Motorcycle	14	3%
	Unemployed	91	22%		Taxi / Service on demand	27	6%
	Retired/pensioner/other	21	5%		Teleworking / No commute	98	23%

In all categories, V_f had a higher score, generally double, except for two: *bike users* and private *car users* (see Figure 2). These results show that people tend to be more critical than they would be if they had more knowledge about the service, that is, ignorance or misinformation prevents them from evaluating the system impartially. Seem to be that, at the beginning, individuals tend to perceive more negatively the barriers. These results can be explained by the lack of familiarity with bike use present in the city of study (see Table 1). With what, in other contexts where bike use is more positioned, the results could be different since previous findings suggest that an individual is more positive towards modes that are included in the daily mobility patterns compared to the modes that are not (Ton et al., 2020). About the positive variation of PT users, this result is not surprising, previous studies suggest the clear tendency to shift from PT to bike. This may be because users may find PT as an inflexible or unreliable mode, therefore they would choose more flexible options such as the bike (Thorhauge et al., 2020). Furthermore, in many cities, PT service quality is poorly perceived, so the bike can be seen as a better choice. This knowledge is important, since policies aimed at improving certain factors may have little effect on people's opinion if aspects with an apparently greater weight than they actually have, are prioritized. Therefore, any strategy seeking to increase bike use must first focus on knowing which aspects truly influence people's perception. The difference between V_f and V_i is denoted by δ_{value}. Given that V_f trending was to change positively, this paper presents the *ordered probit models* estimated for the two categories that did so negatively: *bike users* and *car users* (see Figure 2).

$$\delta_{value} = V_f - V_i \tag{3}$$

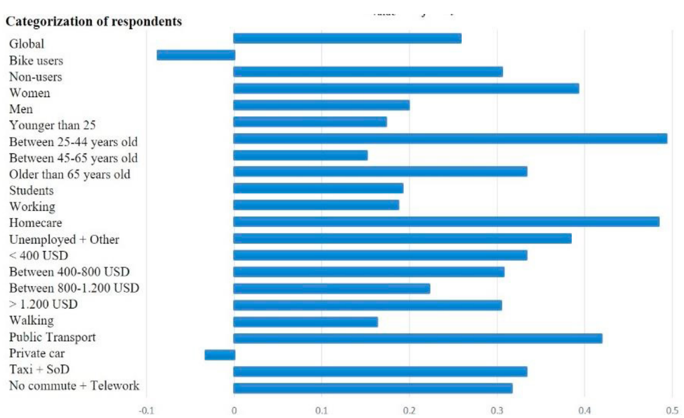

Fig. 2. Variations on δ_{value} according to respondents' categorization.

The negative change in bike users can be because in contexts with poor cycling facilities and lack of incentives, people who decide to commute by bike do so out of beliefs and not out of any kind of incentives (Iwińska et al., 2018; Jakovcevic et al., 2016). In other words, they are bike commuters 'no matter what', with which the reflection process may have made them focus on the weakest aspects of the system and therefore have been more critical. This agrees with previous studies that show that bike use incentives work in a first stage, as a hitch for new users. However, if the aspects initially identified as barriers are not improved, users will no longer find benefits from cycling once incentives are removed and will consequently stop doing so (Jakovcevic et al., 2016).

3.2. Estimated models

Statistical software STATA (StataCorp, 2013) was used to estimate the four models, one for each dependent variables V_i and V_f for each profile (*bike users* and *car users*). The final data set enclosed 54 observations (see Table 3). First, to track any data error, descriptive statics was performed. Said *data cleaning* examined mean, minimum, and maximum values of the variables (see Table 3).

Table 3. Descriptive analysis of the variables.

	Bike users					**Private car users**				
Variable	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**
Bike_V*i*	4.3043	1.1455	1	5	23	3.4194	1.1482	1	5	31
CS	3.3043	1.5502	1	5	23	4.1290	1.2039	1	5	31
LBI	3.9565	1.2239	1	5	23	4.0323	1.1397	2	5	31
RI	4.1739	1.3702	1	5	23	4.5161	1.0286	1	5	31
CI	3.5652	1.3425	1	5	23	3.4839	1.1796	1	5	31
CT	4.0435	1.1862	1	5	23	4.2581	0.9650	1	5	31
TD	3.1304	1.4555	1	5	23	4.0645	0.8920	2	5	31
PA	2.8261	1.3702	1	5	23	2.7419	1.3655	1	5	31
PHC	3.3478	1.5843	1	5	23	3.1935	1.4473	1	5	31
Bike_V*f*	4.2174	1.0853	1	5	23	3.3871	1.1159	1	5	31

Table 4. Ordered probit models for bike users and car users.

Dependent variable	**Bike users Bike_Vi**			**Bike_Vf**			**Private car users Bike_Vi**			**Bike_Vf**		
Log likelihood	-19.013			-20.93			-40.47			-36.37		
Pseudo R2	0.17			0.17			0.11			0.20		
LR chi2(8)	8.04			8.51			10.12			18.12		
Prob > chi2	0.09			0.07			0.02			0.00		
Variable	**Coef.**	**z**	**P > | z |**	**Coef.**	**z**	**P > | z |**	**Coef.**	**z**	**P > | z |**	**Coef.**	**z**	**P > | z |**
CS							-0.255	-1.51	0.13			
LBI										-0.489	-2.02	0.043
RI	-0.301	-0.99	0.324	-0.649	-1.92	0.055						
CI	0.349	1.22	0.222							0.729	2.6	0.009
CT							-0.407	-2.33	0.02	-0.769	-3.5	0
TD	-0.701	-2.59	0.010	0.330	1.43	0.154						
PA	0.385	1.44	0.150	-0.672	-1.91	0.057				-0.231	-1.49	0.137
PHC				0.640	1.85	0.065	0.272	1.92	0.055	0.272	1.77	0.076
/cut1	-3.114		-6.383	-3.574		-6.244	-3.391		-5.691	-3.129		-5.750
/cut2	-2.291		-4.929	-2.209		-4.635	-2.494		-4.596	-2.396		-4.899
/cut3	-1.178		-3.683	-1.590		-3.967	-1.765		-3.798	-1.132		-3.526
/cut4							-0.420		-2.466	0.303		-2.148

Comparing the models, conclusions can be drawn about how the mode of transport affects the variables' evaluation (see Table 4). Insecurity against crime (CI), a barrier perceived by *bike users* as important at the beginning, in the second evaluation does not appear. This may be because, as stated above, urban cyclists choose bike use out of beliefs; therefore, CI may not be such an influential factor in their perception. On the other hand, CI went from having null importance to being the most influential barrier to *car users*. These findings are interesting since they suggest that *car users* they perceive CI as the most influential barrier and that is why they decide to commute by car and not by bike.

To *bike users*, the physical conditions and abilities to use the bike (PHC) have significantly higher importance on the second evaluation (in the first did not appear), this could be because the reflection process perhaps made them comprehended the realities they are exposed to when using the bike (e.g. tiredness). Likewise, they introduced travel distances (TD) after the reflection process. This could be perhaps because cyclists thought about the times when they do not use the bike and the reasons for not doing it, identifying TD as an influential barrier. On the other hand, *car users* did not consider TD in either of the two evaluations; this may be because they are not familiar with TD as a barrier, as they commute by car.

4. Conclusions

This paper presents the first findings of a research developed in Quito, Ecuador aimed to identify the aspects of bike use that may be preventing its acceptance. Prior to this study, there was uncertainty about whether if all bike use barriers have the same impact on the overall bike use perception, whereby the method proposed by Dell'Olio et al. (2010) was useful in identifying the *relative importance* of the barriers to bike use.

This research identifies the different bike use perceptions of a group of individuals before and after having reflected on each of the components of the system. According to individuals' categorization, bike use evaluation decreases depending on the mode of transport (bike users and car users). On the one hand, the reflection process causes bike users to reduce the weight they give to aspects such as the importance of maintaining the personal appearance and insecurity against crime. While travel distances and the physical conditions and abilities to use the bike, result having higher importance. Regarding car users, the city temperature fell in the second evaluation, while insecurity against crime, missed in the first evaluation, a posteriori was highly influential. Hence, according to the results, regarding bike users, enhancing multimodality, and the provision of facilities for bike use (e.g. electric bikes) will achieve the greatest impact on bike use perception; whilst for car users should be by focusing on safety.

This study shows the importance of people's needs as a crucial factor to be considered when developing strategies to promote bike use, so that mobility services can be capable of meeting demand requirements to retain existing users or attract new ones, especially from motorized modes. In cities with low bike commute rates, dissemination strategies could focus on promoting the bike as a fast, comfortable and reliable option, presenting it as a mode of transportation and not only for recreation or as a healthy lifestyle (Handy et al., 2014; Savan et al., 2017). This could be a key factor in changing the mindset towards its adoption as a regular mode for commuting. Short-term targeted campaigns can be an effective policy measure to expose the benefits and potentially engage new users in active mobility.

The application of the proposed methodology may provide planners and policymakers with valuable information for developing strategies aimed at different profiles of people; hence, bike mobility planning should be the product of the collaboration between different mobility actors, and not a product developed solely by experts and technicians. Nevertheless, it is important to mention that this study is a first attempt to capture the bike use perception of a group of individuals in a city with a particular size, topography, and climate conditions. Further research should focus on studying the preferences of other sub-groups (e.g. males vs. females, students vs. workers, etc.), as well as in other cities with other characteristics where different results could be obtained.

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