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Willingness to change compulsory trips to bicycle: Role of habit, perceptions and the built environment

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ABSTRACT

We study the roles of habit, the perception of insecurity, and the built environment in the willingness to change to cycling for compulsory trips in Santiago, Chile. Data from an innovative stated choice survey to current non-users of the bicycle (who had previously declared that they might change to bicycle on their regular trips) allowed us to estimate a hybrid latent class discrete choice model incorporating *habit*, *insecurity* and having a *pro-environment attitude* as latent constructs. The approach allowed us to detect significant heterogeneity in behaviour depending on the city's location and the participant's income level. Our results confirm that trip distance plays a preponderant role in potential bicycle choice but also affects the perception of insecurity and the habit strength; in the case of shorter trips, it seems more feasible to break the habit associated with the current mode used, increasing the willingness to switch to bicycle for regular trips. Our results also confirm the importance of having cycleways available to increase the potential switch to bicycles and show the importance of having a *pro-environmental* attitude. Unlike previous studies, we succeeded in associating trip attributes and built environment variables among the factors explaining *habit* and *insecurity*, allowing us to examine the effects of these intangible attributes in mode switching. Finally, we estimate subjective values of time (SVT), finding significant variations by class and type of infrastructure. In particular, there is a consistently higher perceived disutility of cycling time for higher-income individuals. However, having cycling infrastructure available reduces the SVT for both classes significantly.

1. Introduction

In the last decade it has been proven that cycling offers great advantages over traditional transport modes in highly congested cities, i.e., shorter travel times (Hamilton and Wichman, 2017; Rodríguez-Valencia et al., 2021), improvements in both the physical (Oja et al., 2011; Teschke et al., 2012; Mueller et al., 2015; Clockston and Rojas-Rueda, 2021) and mental health of users (Ma et al., 2021), economic savings, due to lower costs, and social benefits such as zero emission or noise, among others (Pucher and Buehler, 2012).

Among the factors examined to explain the growth in bicycle use, subjective variables, such as attitudes and perceptions, have been

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shown to affect the intention of use of bicycles by different types of users (Dill et al., 2014; Maldonado-Hinarejos et al., 2014; Paige-Willis et al., 2013; Muñoz et al., 2016). In particular, it has been found that individuals with a pro-environmental attitude find cycling more attractive and that this may be determinant in explaining a shift towards this mode (Heinen et al., 2011; Fernández-Heredia et al., 2016; Wang et al., 2018; Clark et al., 2021).

However, studies in psychology and human behaviour highlight that neither soft nor hard measures to encourage changes are effective if they are not accompanied by triggers that encourage a change in individual habits (Wood et al., 2005; Verplanken and Wood, 2006; Verplanken et al., 2008; Janke and Handy, 2019). On the other hand, many studies have shown a relationship between the *habit* associated with cycling and more continuity in cycling, as well as in having a positive attitude towards cycling (Heinen et al., 2011; Gatersleben and Haddad 2010; Ducheyne et al. 2012).

In this research, we show that intangible variables – such as a multidimensional perception of *insecurity* towards cycling, the *habit* associated with the mode of transport used and having a *pro-environment* attitude – can indeed affect the potential demand for cycling in a large city. Unlike previous research, however, we succeeded in incorporating trip attributes among the variables that explain the strength of *habit* and built environment variables among the factors that explain the perception of *insecurity,* allowing us to analyse the effect of these intangible elements in designing policies to encourage bicycle use.

The remaining of the paper is organised as follows. In section 2 we review the literature related with the impact of habit and the general perception of insecurity on bicycle demand. Section 3 explains in certain depth our data collection exercise. In section 4 we discuss our modelling effort. In section 5 we apply the results of our models to examine the design of public policies that could help achieving a shift from motorised transport to bicycle in the case of compulsory trips in Santiago. Finally, in section 6 we present our main conclusions.

2. Literature review

2.1. Factors influencing bicycle demand

Many studies have found evidence of substantial barriers to choosing a bicycle as a regular mode of transport. These barriers may be associated with the trip's inherent characteristics and perceptions or attitudes of potential users towards this mode. For example, depending on the city location and personal characteristics of the traveller, the literature mentions barriers such as the weather (Motoaki and Daziano, 2015), hilliness or the need to transport cargo or accompany children (Pearson et al., 2022).

One important barrier is the perception of risk (safety and security) associated with using a bicycle. People who perceive a bicycle route as unsafe (i.e., sharing road space with motor vehicles, fearing for their safety, or even having their bicycle stolen) are less likely to use a bicycle for their regular trips (Titze et al., 2008; Winters et al., 2011; Gutierrez et al., 2020; Boufouset al., 2021). Another important barrier is trip distance. For example, Heinen et al. (2011) found that distance was a decisive factor in choosing cycling for work trips and that regular users' attitudes towards this mode tended to be more positive. In the same vein, Winters et al. (2011), Titze et al. (2007) and Goel et al. (2022), concluded that trips of less than 5 km were attractive for cycling, especially in the case of infrequent cycle users (and these references pertain to different countries). Indeed, in the context of Santiago de Chile, Karner and Sagaris (2016) proposed using a distance of 5 km as a rule of thumb. Other researchers have found smaller distance thresholds, such as trips between 2 and 4 km (Keijer and Rietveld, 2000; Pucher and Buehler, 2008; Akar and Clifton, 2009; Mandic et al., 2020) but also more extensive, up to 10 km (Heinen et al., 2011).

As enticements to choose cycling for regular trips, we can highlight certain built environment variables, such as the availability of cycle-inclusive infrastructure in good conditions, the existence of devices to reduce the speed of motor vehicles, direct routes between origin–destination pairs, safe bicycle parking, and showers and lockers at the destination (Akar and Clifton, 2009; Kamargianni and Polydoropoulou, 2013; Habib et al., 2014; Gutiérrez et al., 2020; Márquez et al., 2021). It has also been found that certain land use compositions may induce people to cycle more, such as mixed land uses, green areas, and a higher density of commerce (Titze et al., 2008; Cervero et al., 2009; Handy et al., 2010; Winters et al., 2010; Oliva et al., 2018).

2.2. Impact of habit strength and safety perception on bicycle demand

The study of bicycle travel demand in recent years has included sociodemographic variables, environmental and geographic variables, determinants of cycling-friendly infrastructure, and latent factors such as user's perceptions and attitudes (Muñoz et al., 2016). In particular, the incorporation of latent factors has been mostly done through hybrid discrete choice models (HDC), which allow estimating jointly and robustly the effect of observable and intangible variables. For example, Motoaki and Daziano (2015) estimated a HDC model to analyse the effect of climate on bicycle use. Kamargianni and Polydoropoulou (2013) found that the willingness to walk, or to use bicycle by the teenagers in their sample, had a positive effect on the choice of both modes, and a negative effect on the choice of car. Echiburú et al. (2021) studied the satisfaction associated with frequent trips by bicycle as a function of the built environment and trip length.

On the other hand, the incorporation of variables such as the perception of insecurity, a pro-cyclist attitude, and the convenience of using bicycle, have also been incorporated in HDC models (Habib et al., 2014; Fernández-Heredia et al., 2014; Maldonado-Hinarejos et al., 2014; Sottile et al., 2019; Gutiérrez et al., 2020; Gutiérrez et al., 2021; Márquez et al., 2021). In particular, the way in which most of these studies model the risk (or insecurity) variable, considers the presence of cycling infrastructure and socioeconomic variables. However, few incorporate the effect of distance on the perception of perceived insecurity when travelling by bicycle, particularly in cities with little cycling-friendly infrastructure.

In turn, few studies have considered the habit associated with the chosen mode as a latent variable that contributes to explaining the choice or willingness to switch to cycling (Gutiérrez et al., 2020). In general, studies incorporate habit by associating it with the number of times people choose a given mode to make a specific trip (Liao et al., 2023; Gatersleben and Appleton, 2007; Domarchi et al., 2008; Légal et al., 2016; Lizana et al., 2021), and it has commonly been concluded that habit is closely related to a positive attitude towards cycling, and to the willingness to choose cycling (de Bruijn et al., 2009; Heinen et al., 2011, Biassoni et al., 2023).

To measure habit strength, some studies have incorporated the *Self-Report Habit Index* developed by Verplanken and Orbell (2003), or an associated subscale to measure automaticity (Gardner et al., 2012; Haggar et al., 2019; Fu, 2020). In particular, de Bruijn et al. (2009) found that a strong predictor of bicycle use is habit strength. Similarly, Muñoz *et al*. (2013) concluded that, for cyclists … "*with every unit of increase in habit, the increase in the likelihood of that person being a cycling commuter is multiplied by 5.68*".

Based on the review of the cited literature, we would like to highlight two contributions of this research to the study of the effect of habit on cycling: (i) we incorporate habit as a latent variable in a latent class hybrid mode choice model; (ii) we incorporate observable trip attributes (such as distance) as explanatory variables of habit, complementing the classical socioeconomic variables used in previous studies.

3. Data collection

To study the effect of built environment variables, attitudes, and perceptions on bicycle choice in a large city such as Santiago de Chile, we conducted a comprehensive travel and attitudinal survey, ending with a stated choice (SC) experiment. Apart from its size (over 6.5 million inhabitants in an area of over 900 km2), Santiago is characterised by its extreme socio-spatial segregation (Otero et al., 2022), featuring an *eastern high-income cone*, the facilities of which are no different from those of any developed country and the rest of the conurbation, much closer in services and appearance to the typical countries in the Global South (see Fig. 1).

Considering that the focus of this research was on the shift from motorised modes to cycling, our target population considered non-bicycle users, that is, people who primarily used cars and public transport. Furthermore, considering that the morning rush hour is the most congested and polluted time of the day in the conurbation, we focused on compulsory trips (e.g., to work or study on a workday), that is, those that take place at the same time of day, every day, and usually by the same mode of transport.

3.1. Survey design

Based on the literature review and the experience of similar research in the country (Ortúzar et al., 2000; Waintrub et al., 2016; Oliva et al., 2018; Rosetti et al., 2018), we designed a first draft of the questionnaire and of the psychometric indicators required to measure the latent variables. These instruments were tested in a focus group led by expert psychologists and included individuals with

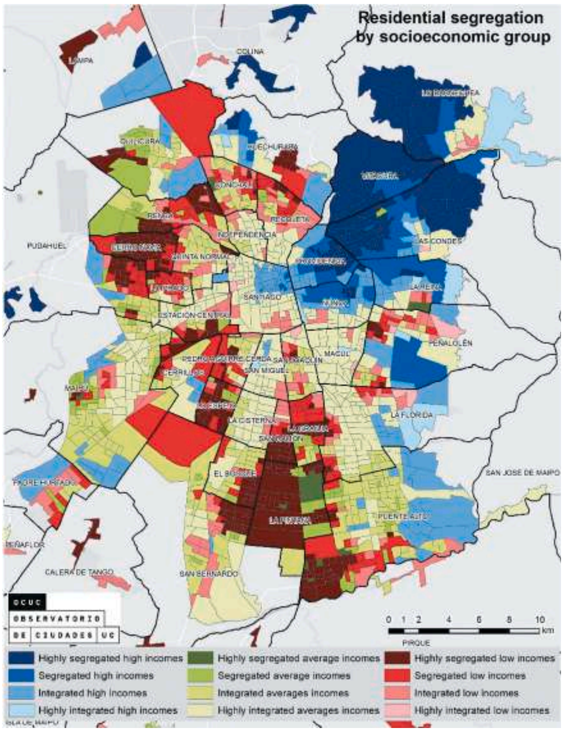

Fig. 1. Residential segregation by socio-economic status in Santiago.
Source: Observatorio de Ciudades UC (observatoriodeciudades.com)

similar characteristics to those of our target population. Our main finding was that the most relevant attributes that hindered the use of bicycles in the case of Santiago residents, were the lack of friendly infrastructure for cyclists (such as exclusive roads and secure bicycle parking to avoid theft), and the perceived risk of accidents or crime against cyclists; this result is consistent with the international literature. Based on the focus group results, we designed the final survey and conducted two pilot tests, to evaluate the clarity of the questions and, above all, that the flow of the survey (taken online using Qualtrics) worked correctly. The design of the instrument was complex, as it pivoted on the information provided by the respondents depending on certain filter questions, such as mode of transport used, whether or not they had a bicycle available, and whether or not they were willing to use a bicycle on their reported trips.

We implemented the final survey between March and May 2018 through a web-based instrument, initially sent to academics and administrative staff of the four campuses of Pontificia Universidad Católica de Chile in Santiago through an invitation from the various faculty deans; this allowed us to obtain 25 % of our complete sample. The remaining 75 % of observations were collected online through social media platforms like Twitter, Facebook, and Instagram. This approach sought to increase variability in terms of socioeconomic level and travel location while acknowledging the potential bias associated with the fact that only people with access to these networks would respond to the survey. Although relatively long, the survey took approximately 10 min on average. To encourage participation, respondents who completed the survey and provided their email addresses entered into a raffle for three 50 USD gift cards (for more details, see Gutierrez *et al.*, 2020).

3.1.1. Attributes used and characteristics of the survey

The survey was divided into four stages. The first considered questions about the respondents and their household (mainly socioeconomic questions, such as age, income level, household size, number of cars in the household, number of bicycles in the household, number of employees and students, among others), and also included the first filter question of the survey: whether or not the individual knew how to ride a bicycle; if not, the survey was terminated and respondents were thanked for their participation.

The second stage considered questions about a regular trip to work or study, made by the individuals during the morning rush hour of a workday. To begin with, the respondents had to select the origin and destination points of their trip on a map displayed in the survey form (associated with a Google API, which allowed us to collect their coordinates; these, in turn, were subsequently used to compute the values of several built environment variables). Then, respondents had to record their time of departure from their home and the time of arrival at their destination, which allowed us to determine the duration of the entire trip.

Additionally, respondents were asked about the modes of transport used, characterising each one (i.e., bus, subway lines, use or not of tolled urban motorways), whether they travelled accompanied or not (or made intermediate stops), walking and waiting times, cost of the trip or fare, whether they made any transfers (change of mode/vehicle), and how many times a week they made the trip in the same way.

The third stage of the survey began by asking whether or not respondents owned a bicycle and if they would be willing to use it for the trip described; the possible answers in this case were *No*, *Yes*, and *Maybe*. People who used a car (driver or passenger), bus and subway (or a combination of them) and who answered *Yes* or *Maybe* (i.e., would be willing to make that trip by bicycle), were asked to participate in the SC experiment, where they had to choose between their current mode and bicycle. In this part, images were shown about the characteristics that cycling-friendly infrastructure could have (i.e., different types of bicycle lanes, or bicycle parking) and, also, if their current mode was public transport, images about three levels of crowding within the vehicles. The SC survey had a different design depending on whether the respondent had reported owning a bicycle or not; in the latter case, the survey referred to using public bicycles and asked whether the respondent was aware of any of the services of this nature available in Santiago.

The fourth section of the survey referred to the following set of psychometric indicators designed to measure the latent variables; the response to these indicators was in a 5-point Likert scale (where 1 represented complete disagreement and 5 complete agreement with the statement presented) as shown in Table 1:

(i) Indicators to measure pro-environmental attitudes (Li et al., 2013).
(ii) Indicators measuring incentives and barriers to cycling (Akar and Clifton, 2009).
(iii) Habit indicators, based on a subscale of the *Self-Report Habit Index* developed by Verplanken and Orbell (2003); this subscale is called *Self-Report Behavioural Automaticity Index*, and was developed by Gardner et al (2012); the validity and reliability of these scales has been tested in several studies (Verplanken and Orbell, 2003; Verplanken and Melkevik, 2008, Lally and Gardner, 2013).

Following a confirmatory factor analysis (CFA), we created four factors that we named: *habit*, *insecurity*, *pro-environmental attitude*, and *availability of cycling-inclusive infrastructure*; these were explained by the subset of indicators shown in Table 2. However, when testing these factors in the HDC model described in section 4, we finally excluded the latent construct *cycling-inclusive infrastructure* for lacking statistical significance.

3.1.2. SC experiment

We designed ten SC experiments, one for each type of user (i.e., based on their current mode and whether the person owned a bike or not). Respondents had to choose between bicycle and their current mode (car-driver, car-passenger, bus, subway, bus-subway combination); for respondents who did not own a bicycle, the alternative was to use one of the public bicycle services available in the city. Each experiment consisted of three blocks, where six choice situations were presented to each individual (see Online Appendix A).

The SC experiments considered an efficient design pivoted on the respondents' current trip values (Rose and Bliemer, 2009). We

Table 1
Indicators for perceptions, attitudes and habit strength.

Indicator
Greater use of public transport could improve air quality in Santiago
Car use is a major cause of air pollution in urban areas
I am willing to change my transport mode if it helps to improve the environment.
I prefer to use motorised vehicles for my trips because I get less tired
I prefer to use car/subway/bus instead of walking or cycling on very cold or rainy days.
I would not mind paying more for my trip if it would help to improve the environment
If you think about your daily trip to work/study, what encourages you, or would encourage you to make this trip by bike?
Bicycle-only lanes throughout my trip
Reduced maximum speed of motorised traffic
Bicycle parking closer to my work/study site
Guarded or covered bike racks
Showers/lockers available at my work/study location
Being able to take my bike on the bus or subway
Seeing more cyclists on the streets
Feeling fitter because I get around by bike
Living closer to my work/study location
What prevents/would prevent you from making this trip by bicycle?
I would need to change clothes
I live too far away
Lack of safe parking for my bicycle
I am concerned about the possibility of an accident
I am worried about getting mugged
I am worried about having a technical malfunction and not knowing what to do
Lack of bike lanes on my usual route
I have health problems
I must carry children or cargo
*Using my *Current Mode* in my daily trips to work or study, is something that:*
I do automatically
I do without thinking
I start doing before I realise that I am doing it
I do it without having to consciously remember

Table 2
Latent variables created from the CFA.

Indicator	Latent Variable
Greater use of public transport could improve air quality in Santiago	Pro-Environmental Attitude
Car use is a major cause of air pollution in urban areas	
I am willing to change my transport mode if it helps to improve the environment	
I am concerned about the possibility of an accident	Perception of Insecurity
I am worried about getting mugged	
I am worried about having a technical malfunction and not knowing what to do	
Reduced maximum speed of motorised traffic.	Cycling Inclusive Infrastructure
Being able to take my bike on the bus or subway	
Guarded or covered bike racks	
Showers/lockers available at my work/study location	
I do automatically	
I start doing before I realise that I am doing it	Habit
I do it without having to consciously remember	

used parameter values taken from research conducted in the context of using bicycles in Santiago as priors (Ortúzar et al., 2000; Oliva et al., 2018; Rosetti *et al.*, 2019).

The relevant attributes and their respective levels were as follows:

(a) *Total travel time in the current mode* (three levels): current time (reported) and two increments of 20 % each.
(b) *Total travel time by bicycle* (three levels): the values were estimated as the average trip distance, divided by three possible travel speeds: 12 km/h, 15 km/h and 18 km/h.
(c) *Public transport waiting time* (three levels): current time (reported), and two increments of 15 % each.
(d) *Number of blocks walked to access the mode or go to the destination* (three levels): reported value and two increments of one block each.

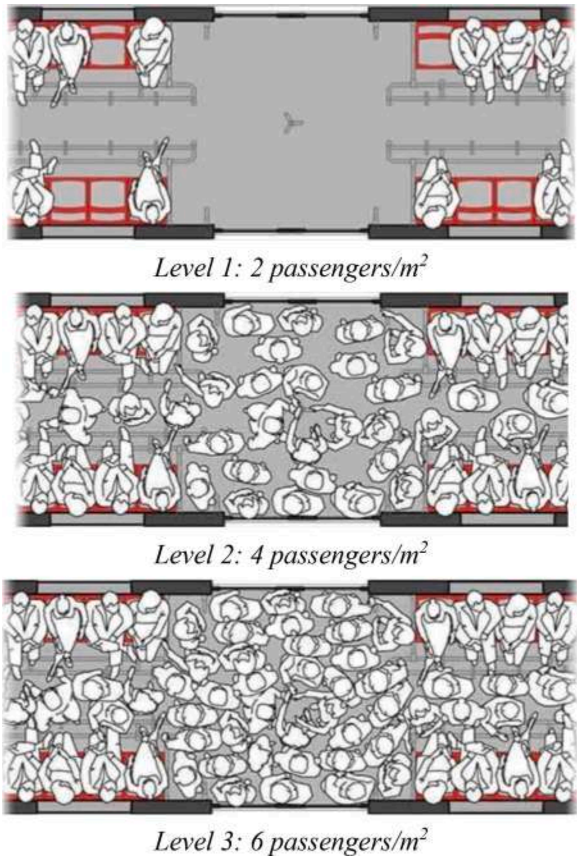

Fig. 2. Representation of crowding level, based on Tirachini et al. (2017).

(e) *Public transport fare* (three levels): reported value and two increments of 20 % each.
(f) *Level of crowding in public transport* (three levels): 2 passengers/m^2, 4 passengers/m^2, and 6 passengers/m^2 as shown in Fig. 2; these levels were interpreted as *empty*, *full* and *crowded*, respectively (Batarce et al., 2016; Tirachini et al., 2017).
(g) *Cost of car trip* (three levels): base value calculated according to the trip distance and adding the reported cost of parking (current value), and two increments of 20 % each.
(h) *Type of bikeway* (four levels): we presented images of the four options as shown in the example in Fig. 3: (i) no bikeway (i.e., sharing the street with other vehicles); (ii) sidewalk bikeway; (iii) painted bikeway on the street, and (iv) segregated bikeway on the street.
(i) *Type of bicycle parking* (three levels): we presented images of the three options as shown in the example in Fig. 4: (i) none, that is, you should use your own lock and secure the bicycle anywhere, (ii) cage type parking, and (iii) cage type parking with a security guard.
(j) Cost *of bicycle parking* (two levels), only in the case of cage parking: CLP 300/day or CLP 500/day[1]; and zero in other cases.

Fig. 5 shows, as an example, a choice situation presented to subway users.[2] As can be seen, in addition to the alternatives, e.g., the current mode and bicycle, the individual could also respond that both options seemed equal in terms of their attractiveness (indifference option).

As the situations included the alternative currently used by the respondent, there was no need to include a non-purchase option (Olsen and Swait, 1998). Examples of all choice situations are given in the Online Appendix A.

3.2. Main survey results

The data collection stage finished up with a total of 1,398 surveys completed by individuals over 18 years of age who made morning rush hour trips to work or school (27 % of which were academics or administrative staff at Pontificia Universidad Católica de Chile). Of

[1] At the time of the survey, 1 US$ = CLP 680.
[2] This figure represents a real survey scenario but has been translated into English for better comprehension.

this total, 28 % travelled by bike, 9 % walked and 5.4 % used modes other than car or public transport. Thus, according to the methodology explained above, only 57.6 % (805 people) were eligible to participate in the third stage of the survey, that is, to respond whether they were willing to switch to cycling for their reported trip. Of this subtotal, 327 responded Not willing, 175 said Yes, they would be willing and 303 Maybe, they would be willing to switch to bicycling, resulting in an initial sample of 478 individuals for the SC survey.

After a thorough debugging process, the SC experiment was initially presented to 478 individuals. However, following the application of specific elimination criteria,[3] the final modelling sample comprised 419 individuals, each responding to six choice situations, rendering a total of 2,514 observations. A summary of the main characteristics of this sample is presented in Table 3 and compared with statistics from the city's most recent travel survey (Encuesta de Movilidad de Santiago – EMS2024, Hurtubia et al., 2024).

From the coordinates of each origin and destination reported by the respondents, we calculated a set of variables related to the built environment, within a radius of 500 m around each point. For this purpose, we used information from the Internal Revenue Service, the Ministry of Transport and Google API, as shown in Table 4. All the variables representing distances between points, including the distance between the origin and destination of the respondent, were calculated as Euclidean distances, that is, the straight-line distance between each pair of points.

The Alameda-Providencia axis, which runs from west to east in Santiago, is the most important avenue in the city and concentrates the highest density of jobs in it. This makes the area around it the largest concentrator of forced commuting destinations during the morning rush hour.

Fig. 6 shows that the trip destinations of our sample are concentrated relatively close to the Alameda-Providencia axis, while the origins are more dispersed in relation to this axis. The figure also shows, at a macro-zone level, the differences in income according to the origin of the travellers.

4. Model estimation results

To model the choice between the reported current mode and bicycle in a usual morning rush hour trip, we estimated models with five choice alternatives: car-driver, bus, subway, bus-subway combination, and bicycle, but only two alternatives were available to each individual, their current mode and bicycle. At the beginning of our specification searches, we also had car-passenger as an alternative; however, as only ten individuals were car passengers initially, we decided to add these observations to the car driver alternative for modelling purposes.

The search for the best specification began with the estimation of multinomial logit (MNL) models, to define initial parameters for each attribute. Subsequently, a mixed logit (ML) model was estimated, including an error component to capture the *pseudo-panel* effect associated with the fact that the six responses given by each individual are not independent of each other (Ortúzar and Willumsen, 2024, Chap 8). It is important to note that our specification also accounted for an *indifferent* alternative within the choice set (see Fig. 5). To treat this, we followed the methodology proposed by Bahamonde-Birke et al. (2017). Finally, to estimate the models, we used the specialised software Apollo[4] (Hess and Palma, 2019).

We also estimated a latent class model after finding that the cost parameter had relatively low significance, causing frequent sign changes throughout the modelling process. We could detect the existence of two distinct latent classes, namely *residents of the higher-income eastern cone* (Class 1) and *residents of the rest of the city* (Class 2), recall Fig. 1.

The allocation of classes was determined by the socioeconomic characteristics of the individual and their household, as follows:

$$f^1 = ASC^1 + \gamma^1_{Grad} Graduate + \gamma^1_{cars} Cars + \gamma^1_{East} East$$

$$f^2 = 0$$

where ASC^1 corresponds to the Class 1-specific constant, and the explanatory variables for this class are: whether the individual holds a professional or postgraduate degree (*Graduate*), the number of cars in the household (*Cars*), and whether the individual resides in the city's highest-income district (*East*).

We finally estimated a latent class – hybrid discrete choice (HDC) model including three latent variables (see Fig. 7). The first one, *habit*, is associated with the current mode of transport and was measured using the indicators described in Table 2. The second is related to the perception of *insecurity* towards the bicycle (i.e., with the risks of having an accident, being mugged, or experiencing some mechanical failure in the bicycle and not knowing how to solve it). The third latent variable, *pro-environmental attitude*, reflects an individual's positive attitude towards the environment. It captures people's willingness to change their behaviour to favour an environmental improvement. The indicators suggest a concern for air pollution in urban areas and an openness to changing transport habits to improve the environment.

The specification of these latent variables was derived from a principal components analysis (PCA), in which the three latent

[3] The process considered the following elimination criteria: (i) individuals who consistently chose the "indifference" option in all choice situations (5 individuals); (ii) individuals with reported travel times greater than 90 min (as it was improbable that they could use a bike, 14 individuals); (iii) individuals with costs higher than CLP 20,000 (5 individuals); (iv) individuals with zero or negative travel times (caused by errors in the estimation of their travel distance and time when programming the survey in Qualtrics, 35 individuals).

[4] The models were estimated using 800 inter-individual draws, employing modified Latin hypercube sampling (MLHS).

Fig. 3. Example of SC survey images: 4 types of bicycle lanes, based on Rossetti et al. (2018).

Fig. 4. Types of bicycle parking presented in the SC experiment.

Subway

Travel time	12 minutes
Trip fare	CLP$740
Walking distance	2 blocks
Waiting time	5 minutes
Occupancy	Overcrowded

Either one is indifferent to me

Bicycle

Travel time	27 minutes
Parking fare	CLP$200/daily
Walking distance to parking	0 blocks
Type of parking	Guarded
Type of bike path	None

Fig. 5. Example of a computer screen with an option of the SC survey.

Table 3
Modelling sample statistics.

	Category	Sample (%)	EMS2024 (%)
Gender	Male	59	49
	Female	41	51
Income	<USD 463	19	15
	Between USD 463 and USD 926	27	24
	Between USD 926 and USD 1852	28	29
	>USD 1852	26	32
Cars in the household	0	23	38
	1	72	43
	2 or more	5	19
Household size	1 to 2 persons	36	34
	3 to 4 persons	47	46
	5 or more persons	17	20
Own bicycle	Yes	76	62
	No	23	38
Transport mode used	Car-user	31	38
	Bus	15	11
	Subway	27	9
	Bus – subway combination	27	8

Table 4
Description of built environment variables around the origin and destination of each traveller.

Built Environment Variables	Mean	Standard Deviation
Euclidean distance (km)	7.5	4.8
Linear meters of cycleway at origin (m)	631	666
Linear meters of cycleway at destination (m)	533	619
Distance to subway at origin (m)	1519	2420
Distance to subway at destination (m)	843	1355
Distance to Alameda-Providencia axis from origin (m)	4507	4210
Distance to Alameda-Providencia axis from destination (m)	3541	3517
Number of bus-stops at the origin	15	7
Distance to nearest cycleway from origin (m)	808	1649
Distance to nearest cycleway from destination (m)	624	708

variables were able to explain about 74 % of the variance of the data. The reliability of these constructs was assessed using the Cronbach's α coefficient, with values ranging from 0.71 (*pro-environmental* and *insecurity*) to 0.85 (*habit*). These values exceed the recommended threshold of 0.70 (Fornell and Larcker, 1981). Similarly, their validity was evaluated through the average variance extracted (AVE), which ranged between 0.50 and 0.54, meeting recommended thresholds (Hair et al., 2010).

The LC-HDC model was estimated using the simultaneous estimation approach, to ensure consistent and unbiased parameters (Bahamonde-Birke and Ortúzar, 2014). That is, the *Multiple Indicator Multiple Causal Indicator* (MIMIC) model associated with the measurement equations and the structural equations, and the discrete choice model, were estimated simultaneously.

After testing different specifications of the utility function for each mode, we found the following functional form as having the best statistical fit and microeconomic consistency[5]:

$$U_{CarUsers} = \theta_C + \theta_{TTCar} \bullet TravelTime_{Car} + \theta^s_{cost} \bullet Cost_{Car}$$

$$U_{Bus} = \theta_B + (\theta_{TTPT} + \theta_{Crowded} \bullet Crowded_B + \theta_{Overcrowded} \bullet Overcrowded_B) \bullet TravelTime_B + \theta_{Access} \bullet AccessTime_B + \theta^s_{cost} \bullet Cost_B + \theta_{DistA} \bullet AlamedaDistance_B + \theta_{BStop} \bullet NumberBusStops_B$$

[5] Following the suggestion of one referee, we tested a model specification following the suggestion of Vij and Walker (2016) but found it clearly inferior to our best specification.

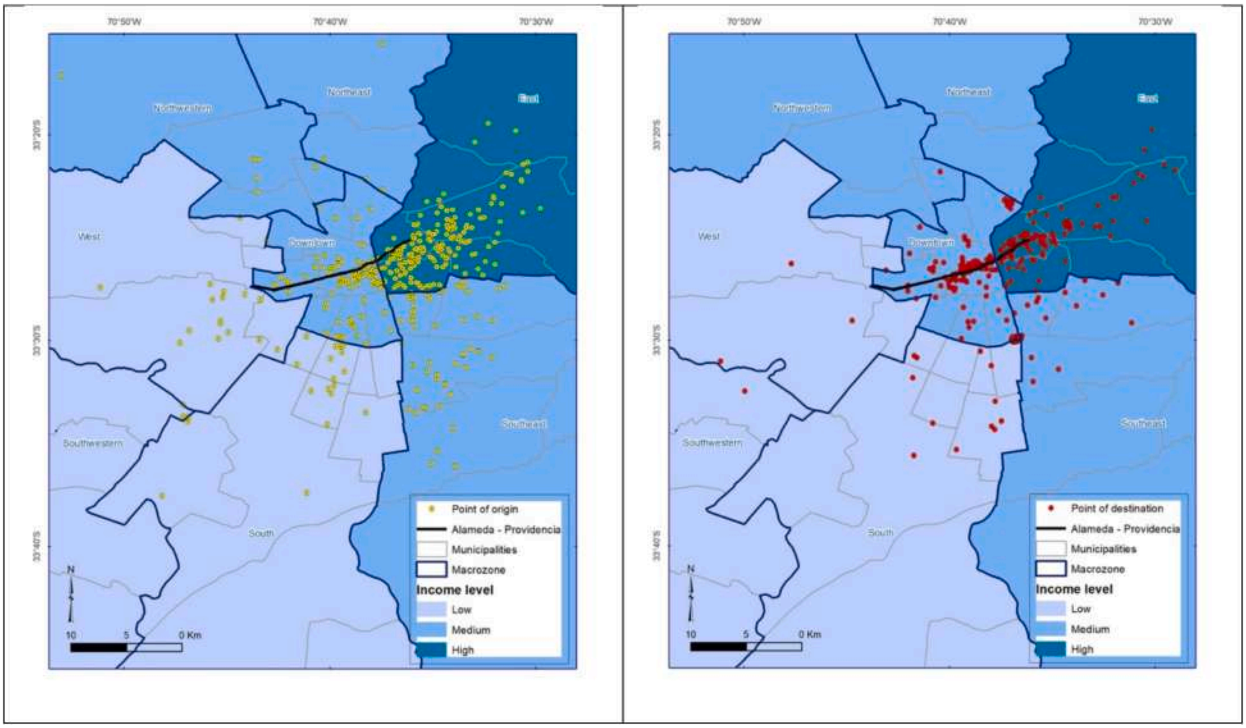

Fig. 6. Points of origin (left) and destination (right) of work or study trips in the modelling sample.

$$U_{Subway} = \theta_S + (\theta_{TTPT} + \theta_{Crowded} \bullet Crowded_S + \theta_{Overcrowded} \bullet Overcrowded_S) \bullet TravelTime_S + \theta_{Access} \bullet AccessTime_S + \theta^s_{cost} \bullet Cost_S + \theta_{DistS} \bullet SubwayDistance_S$$

$$U_{BSubway} = \theta_{BS} + (\theta_{TTPT} + \theta_{Crowded} \bullet Crowded_{BS} + \theta_{Overcrowded} \bullet Overcrowded_{BS}) \bullet TravelTime_{BS} + \theta_{Access} \bullet AccessTime_{BS} + \theta^s_{cost} \bullet Cost_{BS} + \theta_{DistS} \bullet SubwayDistance_{BS}$$

$$U_{Bicycle} = (\theta_{TBike} + \theta_{OS} \bullet Onsidewalk + \theta_P \bullet PaintedBikelane + \theta_S \bullet SeparatedBikelane) \bullet TravelTime_{Bike} + \theta^s_{cost} \bullet Cost_{Bike} + \theta_{Cage} \bullet Cage + \theta_{WalkingBike} \bullet Walking + \theta_{LenghtBike} \bullet LenghtBikelane_D + \beta^s_1 \bullet Habit + \beta_2 \bullet Insecurity + \beta_3 \bullet Pro - Environmental$$

The utility functions considered level-of-service attributes, built environment variables and the three latent variables, *pro-environmental*, *habit* and *insecurity*, with four and three indicators, respectively. The habitual variable, associated with the current mode, was incorporated in the bicycle utility, to capture the impact of *habit* strength on the likelihood of selecting the alternative mode. So, we hypothesized that this variable should have a negative coefficient, as an individual habituated to using a given transport mode should have reduced propensity to change to cycling.

We created a dummy variable for the trip distance: *Distance < 2.5 km*, which takes the value of 1 for trips less than 2.5 km and 0 otherwise. This variable appeared in the structural equation of *habit*. Another variable used to explain *habit* was *frequency*, measured as the number of times per week that the person made the trip in the same mode and at the same time. Finally, we included a dummy variable indicating the respondent's willingness to use bicycle, which takes the value of 1 if the person initially responded *Yes* to being willing to use it, and 0 if they responded *Maybe*. This variable was introduced to capture the difference between those surely open to cycling and those that are not sure about it.

Table 5 shows the estimated parameters for our best two models, the LC model and the LC-HDC model. The signs of the parameters are consistent with microeconomic theory; in addition, most are significant at more than 90 % confidence. As for most variables (e.g., meters of cycleway at the origin) the expected sign of the parameter is known in advance, we need to apply a one-tailed hypothesis (Ortúzar & Willumsen, 2024, p 144). In this case, the critical t-ratio for 90 % significance is 1.282. The alternative-specific constants (ASC) of subway and car were not significantly different from the ASC for bicycle, which was taken as a reference.

Analysing the specific travel time parameters across Car, Public transport, and Bicycle we can observe that car users exhibit a higher sensitivity to time, penalizing it more significantly than users of the other two modes. In the case of public transport, the parameter for access time is about 1.1 times higher than that for travel time. The same is true for the variable bicycle walking distance, which is penalised more than travel time.

The cost, along with habit strength, are attributes which have parameters that vary by class. Examining the *cost* parameter across the two latent classes reveals distinct differences in the subjective value of time (SVT). For Class 1 (individuals living in the high-

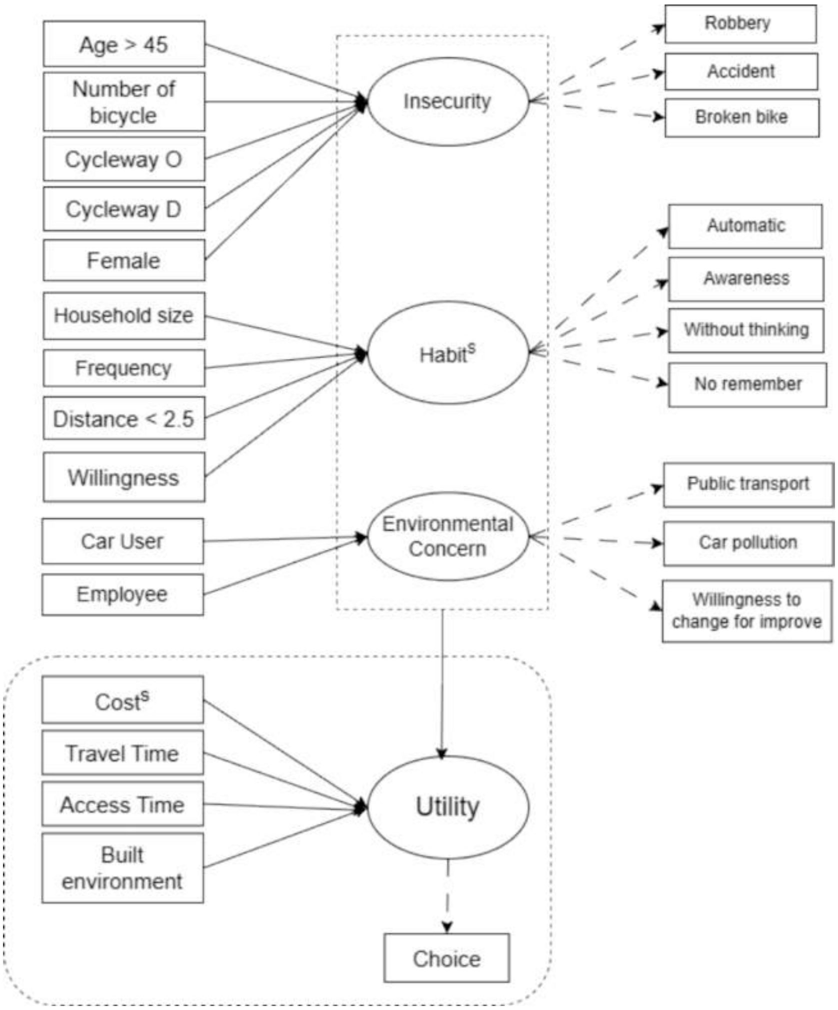

Fig. 7. Hybrid Latent Class choice model structure.

income eastern cone), the *cost* parameter has a smaller magnitude (and is also less significant), indicating a lower sensitivity to cost and, consequently, a higher SVT. In contrast, Class 2 (individuals living in the rest of the city) has a more negative *cost* parameter, reflecting a higher sensitivity to cost and a lower SVT. This difference suggests that individuals in Class 1 may prioritize time savings over monetary savings, while those in Class 2 are more inclined to prioritize cost savings in their transportation choices.

Public transport users feel more uncomfortable as the density of passengers inside the vehicle increases (i.e., crowding level). Specifically, as crowding intensifies from 4 to 6 pass/m^2, the negative impact of travel time on perceived utility grows. This is interesting, given the increased relevance of this attribute after the COVID-19 phenomenon, where in-vehicle crowding became a key issue (Arellana et al., 2020; de Vos, 2020; Dong et al., 2021). On the other hand, the subway correctly loses attractiveness as its stations are farther away from the destination; similarly, the bus becomes more attractive as there are more access stops in the surroundings of the origin and when the location of the destination is closer to the central axis of the city (Alameda-Providencia); this was to be expected, since many bus routes circulate along this axis coming from different districts of the city, even travelling fairly long distances.

Following Oliva et al., (2018), we included the linear meters of bikeway available in a 500 m buffer around the destination point in the bicycle utility. The positive coefficient of this attribute indicates that an increased length of cycleway at the destination increase the utility of choosing the bicycle, highlighting the favourable impact of improved cycling infrastructure on mode choice.

Finally, analysing the cycling infrastructure variables, such as type of parking and type of cycleway, the model allows inferring that compared to not having a secure place to leave the bicycle parked (i.e., leaving it with a lock anywhere), having cages or secure parking is preferable, which is consistent with the literature (Chen et al., 2017; Jonkerena and Kager, 2020).

On the other hand, regarding the type of cycleway, the model indicates that the presence of any form of cycling infrastructure is perceived to improve travel time compared to the absence of such amenities (e.g., cycling on the road without dedicated lanes). Having a bikeway on the sidewalk is the least preferred option, and this is contrary to what was found in a study about bicycle users' behaviour in Santiago, using images similar to those used in this research (Rossetti et al., 2019). This may be due, at least in part, to the fact that in the last years the number of cyclists in the city has grown a lot and their circulation on sidewalks has received strong criticism, in the

Table 5
Model estimation results.

Parameters	In Utility for	LC model	LC-HDC Model
		Coefficient (t-ratio)	Coefficient (t-ratio)
θ_{Car} (ASC)	Car User	0.845 (3.71)	0.949 (2.26)
θ_{Bus} (ASC)	Bus	−0.278 (−0.67)	−1.104 (−1.40)
θ_{Subway} (ASC)	Subway	0.600 (3.49)	0.673 (1.44)
$\theta_{BSubway}$ (ASC)	Bus-Subway	0.336 (1.59)	0.249 (0.51)
θ_{1Cost} (Cost)	Class 1	0.013 (0.24)	−0.115 (−1.64)
θ_{2Cost} (Cost)	Class 2	−0.706 (−8.05)	−0.607 (−3.40)
θ_{TTC} (Travel time)	Car User	−0.030 (−4.21)	−0.045 (−6.19)
θ_{TTC} (Travel time)	Public transport	−0.013 (2.58)	−0.021 (−3.13)
θ_{Crowd} (Occupation, 4 pass/m^2)	Public transport	−0.006 (−1.60)	−0.007 (−1.62)
θ_{Overc} (Occupation, 6 pass/m^2)	Public transport	−0.013 (−3.42)	−0.019 (−4.16)
θ_{AT} (Access time)	Public transport	−0.039 (−3.51)	−0.036 (−1.94)
θ_{TTBK} (Travel time)	Bicycle	−0.040 (−10.46)	−0.051 (−11.30)
θ_{OS} (On the sidewalk)	Bicycle	0.011 (4.12)	0.015 (5.06)
θ_{P} (Painted)	Bicycle	0.015 (5.35)	0.018 (6.21)
θ_{S} (Separated)	Bicycle	0.017 (6.26)	0.020 (6.70)
θ_{Cage} (Cage without guard)	Bicycle	0.340 (0.58)	1.069 (1.42)
$\theta_{alkingBike}$ (Walking distance)	Bicycle	−0.064 (−1.63)	−0.075 (−1.70)
θ_{DistS} (Distance from subway to destination)	Subway	−0.298 (−3.26)	−0.277 (−1.85)
$\theta_{BusStops}$ (N° bus stops)	Bus	0.059 (2.80)	0.097 (2.65)
$\theta_{Alameda}$ (Distance to Alameda)	Bus	−0.165 (−4.03)	−0.158 (−2.36)
$\theta_{LenghtBike}$ (Length of cycleway at destination)	Bicycle	0.364 (4.58)	0.339 (2.46)
γ_{panel} (pseudo-panel)	All	0.911 (12.13)	2.258 (7.20)
β^{1}_{1} (Habit)	Bicycle – Class 1	–	−0.545 (−1.72)
β^{2}_{1} (Habit)	Bicycle – Class 2	–	1.502 (2.15)
β_{2} (Insecurity)	Bicycle	–	−0.872 (−2.74)
β_{3} (Pro-environmental)	Bicycle	–	2.024 (5.08)
Class − Membership			
ASC	Class 1	−1.601 (−1.25)	−0.495 (−0.76)
$\gamma_{Graduate}$ (Graduate)	Class 1	3.097 (2.39)	1.314 (2.44)
γ_{East} (East Origin)	Class 1	1.618 (1.21)	1.401 (1.73)
$\gamma_{1more\ car}$ (1 or more cars)	Class 1	–	0.677 (1.39)
Structural Equation			
Z1: Habit	Bicycle		
λ_{HH_size} (N° of people in the household)		–	0.026 (2.45)
λ_{F} (Frequency)		–	0.067 (4.53)
$\lambda_{DIST2.5}$ (Trip distance less than 2.5 km)		–	−0.117 (−2.398)
λ_{DIST5} (Willingness to change to bike)		–	−0.078 (−2.82)
Z2: Insecurity	Bicycle		
λ_{Sex} (Female)		–	0.186 (4.99)
λ_{age3} (Age >45 years)		–	0.122 (2.50)
λ_{Bk} (N° of bicycles in the household)		–	−0.058 (−3.94)
$\lambda_{LinearMetersO}$ (Linear meters of cycleways at origin)		–	−0.041 (−1.60)
$\lambda_{LinearMetersD}$ (Linear meters of cycleways at destination)		–	−0.058 (−2.25)
Z3: Pro-environmental	Bicycle		
λ_{Car} (Car user)		–	−0.122 (−2.83)
$\lambda_{Employee}$ (Employee)		–	−0.064 (−1.53)
ρ^2 *adjusted*		*0.1743*	*0.1793*
AIC		*3033.41*	*3069.6*
Sample size		*419*	*419*

press and public platforms, both by pedestrians and seasoned cyclists.

The differing signs of the *habit* parameter across the two classes reveal distinct behavioural patterns in their transport choices. For Class 1 (individuals living in the high-income eastern cone), the negative coefficient of the habit variable indicates that a stronger habit in their usual mode decreases the willingness to switch to the bicycle. This result aligns with findings that a familiar mode reduces cognitive load by eliminating the need to consider alternatives; a habitual trigger, such as trip timing or purpose, often leads to an automatic choice of mode (Gardner, 2009; Orbell and Verplanken, 2015). In contrast, for Class 2 (lower-middle-income individuals living in the rest of the city), the positive coefficient suggests that stronger habituation to their usual mode would, counterintuitively, increase the perceived utility of switching to the bicycle.

A possible explanation for these contrasting signs lies in the different motivations behind habit formation: necessity versus choice. Habits often form out of necessity when decisions are taken within consistent contexts, as seen in individuals with limited transport accessibility. For Class 2, where lower income and urban constraints may require the use of specific modes (akin to captivity), the positive habit coefficient may indicate that familiarity (or weariness?) with their current mode fosters openness to alternative options like cycling, especially if these options provide practical benefits, such as cost savings or reduced travel time (Ebert and Lin, 2024). Conversely, for Class 1, whose members enjoy greater accessibility to a variety of transport options, habits are more likely formed by the privilege of being able to choose their actual preferences. Research suggests that such preference-driven habits are more resistant to change, as individuals perceive their selected mode as optimised for comfort or convenience, thus decreasing the likelihood of switching to alternatives (Bartle et al., 2019; Hodgson, 2010).

Unlike previous studies that have analysed the role of habit in mode choice, in our model trip length plays a relevant role. Trip distance, as an explanatory variable of *habit*, allows us to infer that the shorter the trip (less than 2.5 km), the lower the habit associated with the chosen transport mode. This can be explained by the fact that the shorter the trip, the more modes are available to the individual to make it, including walking in trips of 2.5 km or less.

On the other hand, the more frequent the trip (days per week on which the same trip is made) and the more people in the household, the more accustomed the individual is to his/her usual transport mode. Frequency may go some way to explaining the repetitive nature of mode choice behaviour, while household size suggests that travel decisions may depend on several family members.

To use these results in recommending pro-bicycling public policies, it is interesting to analyse the *insecurity* variable. The effect of sociodemographic attributes, allows us to conclude that: (i) in the case of adults, older than 46 years old, there is more perception of insecurity when using a bicycle compared to the younger ages' range; (ii) women feel more insecure when using a bicycle than men, and this may be the reason why they appear less willing to use bicycles in different investigations in this field (Krizek et al., 2005; Garrard et al., 2008; Pucher et al., 2010; Akar et al., 2013; Abasahl et al., 2018; Gutiérrez et al., 2020); (iii) those with more bicycles in the household, have a lower perception of insecurity, probably because they are familiar with its use.

The built environment variables incorporated in the structural equation of the perception of *insecurity*, allow to infer that the availability of dedicated cycling infrastructure decreases this perception. This finding aligns with those of other recent studies, which highlight the need for continuous, well-connected infrastructure not only around origin and destination but also along the routes themselves to improve safety perceptions and encourage bicycle usage (Rérat and Schmassmann, 2024; Le Gouais et al., 2021).

Finally, a *pro-environmental* attitude has a positive effect on the utility of cycling, indicating, as expected, that individuals with this orientation are more willing to shift to bicycle use. Our model suggests that, within our sample, individuals who are car users, and people that are employees are less likely to exhibit a *pro-environmental* attitude. Consequently, these individuals show lower willingness to transition to the bicycle as a mode of transport.

5. Discussion and policy implications

In this research we explored the effect of perceptions on the potential demand for using bicycle for commuting trips in the morning rush hour in the city of Santiago. Our LC-HDC model incorporated variables associated with the environment, both at the origin and at the destination of the journey, within a radius of 500 m around each point. These variables were included both in the utility functions of the various modes and in the structural equations of the latent variables.

The subjective value of travel time (SVT) was calculated using the estimated parameters for time and cost for each mode and class. For Class 1 (individuals living in the high-income eastern cone of the city), the SVT for car is approximately 395 CLP/min, while for public transport it is 179 CLP/min. In contrast, Class 2 (lower-middle-income individuals living in the rest of the city) exhibits an SVT for car of 75 CLP/min and for public transport of 34 CLP/min, indicating a higher sensitivity to cost in transportation decisions.

For bicycles, the SVT also varies significantly by class and type of infrastructure. In Class 1, the SVT is 446 CLP/min without cycling infrastructure, while in Class 2 it is 85 CLP/min, indicating a consistently higher perceived disutility of cycling time for higher-income individuals. However, for both classes, the provision of cycling infrastructure significantly reduces the SVT:

- For cycleways on sidewalks, the SVT decreases to 316 CLP/min for Class 1 and 60 CLP/min for Class 2.
- For painted cycle lanes on roads, the SVT is 290 CLP/min for Class 1 and 55 CLP/min for Class 2.
- For separated cycle lanes on roads, the SVT is 272 CLP/min for Class 1 and 52 CLP/min for Class 2.

These results highlight that while higher-income individuals in Class 1 perceive a greater disutility in cycling overall, they also experience the most substantial reductions in the perceived cost of travel time when provided with high-quality cycling infrastructure. This finding is consistent with recent results from an extensive travel survey (Hurtubia et al., 2024), showing that during the last decade, cycling increased mainly in the high-income zones of the city, where most high-quality infrastructure has been built during the same period. For Class 2, the reductions are smaller in absolute terms but remain significant, suggesting that improving cycling infrastructure can also improve this mode's attractiveness for lower-middle-income individuals.

The subjective values of time obtained in this study reflect the specific characteristics of the sample, particularly their heterogeneity in income levels and modal preferences, and confirm the importance of considering socio-economic and contextual factors when designing targeted transport policies.

We analysed the impact on mode choice probabilities of adding 1 km of cycleway at the origin and destination of every individual across the two classes. For Class 1, the probability of choosing a bicycle increases from 30.37 % to 38.17 %, while car use slightly decreases from 27.79 % to 25.22 %. In Class 2, where there is a higher initial preference for cycling, the probability of choosing the bicycle increases significantly from 55.17 % to 63.40 %, with car use dropping from 14.29 % to 11.48 %. These results suggest that adding cycleways could be particularly effective in encouraging bicycle use, especially among lower-middle-income individuals living in those parts of the city (Class 2) where the quantity and quality of cycling infrastructure are lower than in the high-income eastern area.

This finding also highlights the social equity implications of expanding cycling infrastructure. Providing equal access to high-quality cycling facilities not only encourages bicycling overall but also reduces existing disparities in transport accessibility and safety. Lower-income individuals often reside in areas with very scarce or inadequate infrastructure, limiting their mobility options (Mora et al., 2021; Tiznado-Aitken et al., 2022). Policies prioritising cycling infrastructure in underserved areas could significantly improve social equity by enabling these populations to access affordable, sustainable transport options.

From our model, it is possible to infer that the *habit* associated with the current mode is more significant on longer trips. Although it is difficult to alter this variable in the short term through public policies, the location of social housing should consider this result and take advantage of the higher valuation of high-accessibility locations by lower-income individuals (Valenzuela-Levi et al., 2021).

Shifting now to analyse the *habit* effect, let us first note that habit develops with the frequency of use of a transport mode and is a variable that affects the decision to use the mode. Regarding policy implications, we know that habit is not easy to break. According to the behavioural theories underpinning this phenomenon, we need triggers to force a change in individual habits; in this sense, the shock due to the quarantine (mandatory or optional) that affected people's lives for several months since 2020 was undoubtedly an opportunity. Our results show the convenience of focusing campaigns aimed at breaking the habit (and switching to a more sustainable mode) on individuals who make relatively short trips to work, i.e., less than 2.5 km, given that they are less likely to have developed a strong habit with their current mode of transport.

6. Conclusions

This paper aimed to show that the willingness to use the bicycle for commuting depends not only on trip and individual attributes, but also on non-observable factors such as attitudes and perceptions. The habit associated with the mode of transport used in daily commuting to work or study plays an important role in the decision, and both trip and household characteristics of the individual serve as explanatory variables of this phenomenon. The results of our model allow us to infer that for short trips, of less than 5 km, habit tends to be less influential in mode choice; therefore, these trips may be susceptible to change or become less habitual.

As expected, the perception of insecurity when using a bicycle discourages its use. Our model results indicate that individuals with more cycling-friendly infrastructure available in their environment have a greater perception of security. Once again distance, as an explanatory variable for this factor, allows us to deduce that the longer the trip, the more insecure it is perceived to be, as it is exposed to traffic or the possibility of robbery for longer periods of time. Environmental concern was also modelled, with car users being less likely to report an environmentally conscious attitude.

In addition to the three latent variables described above, bicycle choice is affected by level-of-service variables such as travel time and cost, parking availability, type of cycleway available, and length of cycleway available near the origin. Further, for trips longer than 2.5 km, commuting by bicycle is significantly less attractive for our sample members, who are not habitual users of this mode. Nevertheless, it is worth noting that, in Santiago, nearly one third of all trips made by car are shorter than this distance (Sectra, 2015; Hurtubia et al., 2024).

We would need a more equitable availability of cycling-friendly infrastructure to encourage bicycle use in the city. This requirement is particularly relevant for the lower-income municipalities in Santiago so that their inhabitants may have access to this mode in the same conditions as in higher-income municipalities, where currently the majority and the best cycleways in Santiago are located. In addition to the availability of infrastructure to encourage different travel patterns, behavioural change measures are also needed to break the habit associated with the current modes and reduce the perception of insecurity towards cycling.

Finally, as a continuation of this research, in future work, we would like to study whether there have been changes in travel patterns in recent years due to the social problems brought on by the COVID-19 pandemic through further contact with the respondents who participated in this survey.

CRediT authorship contribution statement

Margareth Gutiérrez: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft. **Ricardo Hurtubia:** Data curation, Funding acquisition, Methodology, Resources, Supervision, Validation, Visualization, Writing – review & editing. **Juan de Dios Ortúzar:** Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2025.104395.

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