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Sustainable Mobility Policy Analysis Using Hybrid Choice Models: Is It the Right Choice?

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Abstract: In recent years, sustainable mobility policy analysis has used Hybrid Choice Models (HCM) by incorporating latent variables in the mode choice models. However, the impact on policy analysis outcomes has not yet been determined with certainty. This paper aims to measure the effect of HCM on sustainable mobility policy analysis compared to traditional models without latent variables. To this end, we performed mode choice research in the city of Santander, Spain. We identified two latent variables—Safety and Comfort—and incorporated them as explanatory variables in the HCM. Later, we conducted a sensitivity study for sustainable mobility policy analysis by simulating different policy scenarios. We found that the HCM amplified the impact of sustainable mobility policies on the modal shares, and provided an excessive reaction in the individuals' travel behavior. Thus, the HCM overrated the impact of sustainable mobility policies on the modal switch. Likewise, for all of the mode choice models, policies that promoted public transportation were more effective in increasing bus modal shares than those that penalized private vehicles. In short, we concluded that sustainable mobility policy analysis should use HCM prudently, and should not set them as the best models beforehand.

Keywords: sustainable mobility; policy analysis; hybrid choice models; latent variables; mode choice

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1. Introduction

In recent years, mode choice modeling has employed Hybrid Choice Models (HCM) by incorporating latent variables [1]. Among other uses, HCM have been utilized to simulate sustainable mobility policies and derive implications from their hypothetical implementation [2]. However, the impact of including latent variables in mode choice models, especially on the outcomes of the sustainable mobility policy analysis, has not yet been determined with certainty.

Mobility policy simulation has been instrumentalized in different ways. Some researchers have used the variation in latent variables values (the attitude toward sociability, attitude toward cars, attitude toward privacy, and attitude toward technology) [3]. Others have used the variation in the attributes of the alternatives, i.e., time and cost [2,4]. Despite this, some authors have claimed the impossibility of deriving transport policy implications from HCM when the simulation utilizes the variation in latent variables' values. On the contrary, these criticisms have not been applied when the simulation uses the variation in other explanatory variables [5]. Ultimately, there has been no criticism when the simulation employs the variation in the attributes of the alternatives. Nevertheless, there is no evidence of whether there is an impact on the outcomes of the sustainable mobility policy analysis derived from the use of HCM.

Therefore, this paper aims to measure the impact of HCMs on the outcomes of the sustainable mobility policy analysis, compared to more traditional models without latent variables, by using the variation of the attributes of the alternatives. We performed mode choice research in Santander, a medium-sized northern town in Spain. In the beginning, we defined the perception indicators and identified two latent variables (safety and comfort). Then, we incorporated the latent variables as explanatory variables in the HCM. Subsequently, we considered two traditional discrete choice models: multinomial logit and mixed logit. Finally, we carried out a sensitivity study for sustainable mobility policy analysis by simulating different policy scenarios.

This paper is structured as follows. The following section summarizes the literature review on HCM, focusing on the studies related to mode choice. Section 3 provides the methodology used for the HCM estimation related to MIMIC (Multiple Indicators and Multiple Causes) models and discrete choice models. Section 4 describes the action framework followed in order to identify the latent variables and the perception indicators associated with them. Besides this, this section includes the design, implementation, and analysis of the survey. Section 5 presents the results obtained for all of the estimations, the subjective value of time (SVT), elasticities, and discussion. Section 6 offers the outcomes for sustainable mobility policy simulation, as well as their discussion. Finally, the last section introduces the main conclusions.

2. Literature Review

The inclusion of subjective psychological factors (attitudes and perceptions) in discrete choice models, through latent variables, has experienced an enormous boom recently. This fact was caused by overcoming the theoretical and methodological limitations to its empirical application [6]. Furthermore, HCM also have been utilized because they are a valid method for the correction of endogeneity in discrete choice models [7].

HCM have been applied in areas pursuing the modeling of individual choices, such as marketing and the economy [8–10]. However, most research using HCM has been in the individual mobility area. Some studies have taken place on the adoption of electric vehicles, including latent variables related to vehicle ownership or leasing and their convenience [11], or related to environmental, economic, battery, technological, and innovation aspects [12]. Other articles have been conducted on the acceptability of inter-urban road pricing, considering a latent variable related to fairness [13]. Some authors have also focused on the weekly use frequency of a shared taxi service, contemplating two latent variables associated with the attitudes towards the shared taxi and ridesharing [14]. Other authors have considered the pedestrian crossing behavior at signalized intersections, using five latent variables associated with safety, conformity, comfort, flexibility, and rapidity [15].

Besides this, several studies on route choice have been identified: for bicyclists, assuming three latent variables related to the bicyclist's status, external restrictions, and physical condition [16]; and for commuters, using five latent variables associated with memory, habit, familiarity, spatial ability, and time-saving skills [17]. Likewise, there have been several studies on the willingness to use carsharing or ridehailing, using different latent variables: a latent variable associated with the satisfaction about current travel patterns [18]; two latent variables related to the satisfaction with current mobility options and the uncertainty underlying carsharing decisions [19]; four latent variables associated with the intrinsic preference for driving, pro-environmental attitudes, the symbolic value of cars, and privacy-seeking [20]; two latent variables associated with pro-environment attitudes and neo-urban lifestyle propensity [21]; four latent variables related to privacy–sensitivity, technological-savviness, variety-seeking lifestyle propensity, and green lifestyle propensity [22].

Mode choice modeling has also used HCM extensively. Table 1 identifies the authors, data types, discrete choice models, latent variables, and results for every relevant piece of research. These papers have used mostly urban revealed preferences surveys, just like in this article. Besides this, Multinomial Logit and Mixed Logit models have been the most frequently utilized discrete choice models, and they are applied in this paper as well. Additionally, the latent variables have not been pure at times, as they have been a combination of two pure latent variables, such as comfort/safety. Likewise, there has been a dominant latent variables group: safety and comfort. Table 1 also identifies that safety and comfort are the latent variables commonly used in public transit mode choice [1,23–30].

Table 1. Mode choice papers using HCM [1].

Author	Data	Model	Latent Variables	SVT	Elasticity	Simulation
Gutiérrez et al. [1]	Urban SP	ML	Convenience Unsafety/Insecurity	√	√	-
La Paix et al. [2]	Urban RP/SP	ML	Infrastructure quality Connectivity Pro-bicycle	-	√	√
Tarabay & Abou-Zeid [4]	Urban RP/SP	BL	Pro-ridesourcing	√	-	√
Hess et al. [3]	Intercity SP	ML	Sociability Pro-car Privacy Pro-technology	√	√	√
Márquez et al. [26]	Urban SP	MNL/ML	Comfort Safety	-	-	-
Sarkar & Mallikarjuna [27]	Urban RP	MNL	Comfort Flexibility	-	-	-
Cheng et al. [23]	Urban RP	MNL	Comfort Convenience Reliability Flexibility Safety Pro-environment	-	√	-
Fernández-Antolín et al. [7]	Urban RP	MNL	Car loving	√	√	-
Daziano & Rizzi [24]	Intercity RP	ML	Comfort Security/Safety	-	√	-
Kamargianni et al. [31]	Urban SP	MNP	Safety Green lifestyle Pro-activity	√	-	-
Glerum et al. [25]	Intercity RP	LM	Public transportation comfort	√	√	-
Paulssen et al. [28]	Urban RP	ML	Comfort-convenience Flexibility Ownership	-	-	-
Atasoy et al. [32]	Intercity RP	LM	Pro-car Environmental concern	√	√	-
Raveau et al. [29]	Urban RP	ML	Reliability Accessibility-Comfort Safety	-	-	-
Yáñez et al. [30]	Urban RP	ML	Reliability Comfort/Safety Accessibility	√	-	√

RP: Revealed Preferences; SP: Stated Preferences; MNL: Multinomial Logit; ML: Mixed Logit; MNP: Multinomial Probit; BL: Binary Logit; LM: Logit Model.

Lastly, the outcomes provided in those papers were unalike. They predominantly presented model estimations, although Table 1 gathers those that included complementary results (SVT, elasticities, mobility policy simulation). Besides this, they have used the mobility policy simulation scarcely to measure the impact on individuals' travel behavior. There has been no discussion in the literature on mode choice to evaluate the effects on the outcomes of the sustainable mobility policy analysis caused by HCM compared to traditional models without latent variables. The contribution of this paper is to satisfy this discussion.

3. Methodology

We used the methodological framework of HCM to incorporate explicitly the psychological factors that influenced the choice process. HCM incorporates tangible elements (the attributes of the alternatives and individuals' socioeconomic characteristics) and intangible elements (latent variables). The latent variables are associated with individual attitudes (for example, being prone to use cars or prone to use technology) and perceptions (for example, the comfort or safety you feel in public transit). They cannot be quantified, but they can be measured through the indicators in individual surveys.

The methodology combined latent variables models and discrete choice models [33]. On the one hand, the latent variables model included structural and measurement equations. We employed a MIMIC model to obtain the individuals' latent variables values for each alternative [34]. The structural and measurement equations are, respectively:

$$\eta_{ilq} = \Sigma_r \, \alpha_{ilr} \times s_{iqr} + \upsilon_{ilq} \tag{1}$$

$$y_{ipq} = \Sigma_l \, \gamma_{ilp} \times \eta_{ilq} + \zeta_{ipq} \tag{2}$$

where η_{ilq} are latent variables, s_{iqr} are the individuals' socioeconomic characteristics, and y_{ipq} are perception indicators. Likewise, the indexes i, l, q, r, and p denote alternatives, latent variables, individuals, explanatory variables, and perception indicators, respectively. Equally, α_{ilr} and γ_{ilp} are the parameters to be estimated, and υ_{ilq} and ζ_{ipq} are the error terms with a zero mean and an estimated standard deviation.

On the other hand, the discrete choice models incorporated the latent variables, like any other explanatory variable. The utility function is as follows:

$$U_{iq} = \Sigma_r \, \theta_{ir} \times X_{irq} + \Sigma_l \, \beta_{il} \times \eta_{ilq} + \varepsilon_{iq} \tag{3}$$

where ε_{iq} is an error component. The parameters to be estimated are θ_{ir} and β_{il}, which are associated with tangible variables—the attributes of the alternatives and individuals' socioeconomic characteristics—and latent variables, respectively. We used a sequential estimation to reduce the computational cost, as in previous papers [35].

Besides this, we utilized the most popular discrete choice models in the literature: Multinomial Logit and Mixed Logit. The Multinomial Logit assumes that the error component distributes IID Gumbel. The Mixed Logit is a very flexible model [36] because the parameters vary randomly in the population, allowing us to incorporate random heterogeneity into the modeling [37]. Additionally, the Mixed Logit enables us to overcome the two main limitations of the Multinomial Logit: the independence of irrelevant alternatives assumption (non-correlated alternatives) and the non-variation in preferences among individuals [37].

4. Data

The survey design required a mixed social investigation strategy combining participative workshops and focus groups. The methodology was based on previous studies related to the optimization and improvement of public transportation systems [38]. However, in this case, the goal was to determine the existing latent variables in urban mobility and the perception indicators associated with them.

Once we analyzed all of the information collected through the citizen participation strategy, we designed the preliminary version of the survey. We conducted 50 pilot surveys, which allowed us to evaluate and redesign them. They were not included in the final analysis. Then, we reformulated the expression of some of the perception indicators. Table 2 shows the perception indicators that we ultimately used. Every perception indicator was rated between 1 (unsatisfactory) and 10 (very satisfactory). Finally, the survey comprised three sections: a typical one-day travel diary, the individuals' socioeconomic characteristics, and the perception indicators. The survey was self-explanatory, in order to make the process easier.

Table 2. Perception indicators.

Rate between 1 (Unsatisfactory) and 10 (Very Satisfactory)
1—Adequacy of the scheduling
2—Comfort during the trip (seats, space)
3—Ease of access
4—Availability of information
5—Reliability in the waiting time
6—Reliability in the travel time
7—Safety regarding accidents
8—Safety regarding trip

Next, we carried out revealed preferences household surveys in Santander, a northern, medium-sized town in Spain. We obtained a representative sample from the household census (by simple random sampling, at a 95% confidence level and a 5% error level). Then, we sent mail to those addresses informing them about the survey and requesting their participation. A week later, the interviewers went to those addresses to deliver the surveys on paper. A few days later, they came back to pick up the surveys. They also resolved any doubt related to the survey in order to increase the number of valid surveys (roughly 90%). The survey interviewers were students from the University of Cantabria, and we trained them before visiting the households. Lastly, we obtained 1179 valid surveys and 3359 trips.

Table 3 compares the individuals' socioeconomic characteristics in the sample and the population census in 2011 (censuses are carried out by the National Statistics Institute every ten years, and the year 2011 is the closest to the year of the survey, i.e., 2012). The percentage distribution in the sample and the census, according to the gender and age criteria, was practically the same, reassuring us that the sample was representative. The sample also offers a similar percentage of individuals according to the education and occupational criteria. Likewise, the individuals' income levels in the sample mostly belonged to the low and medium levels (≤1000 €/month, 25.96%; 1000–2500 €/month, 52.00%; 2500–5000 €/month, 18.21%; ≥5000 €/month, 3.83%).

Table 3. Sample vs. census.

Category	Sample Observations	Sample %	Census %
Male	548	46.48%	46.41%
Female	631	53.52%	53.59%
≤24	138	11.70%	21.32%
25–34	165	13.99%	13.72%
35–44	186	15.78%	14.78%
45–54	262	22.22%	15.61%
55–64	187	15.86%	13.80%
≥65	241	20.44%	20.77%
No studies	75	6.36%	18.16%
Secondary School	332	28.16%	27.51%
High School	202	17.13%	15.80%
Technical institute	203	17.22%	14.81%
University	367	31.13%	23.72%
Employed	500	42.41%	37.99%
Unemployed	123	10.43%	13.52%
Retired	267	22.65%	24.07%
Student	133	11.28%	16.34%
Other	156	13.23%	8.08%

Finally, Table 4 reveals the composition of the essential variables associated with all of the trips. Most of the trip durations were less than 30 min. Regarding the modal share, the car had the most relevant modal share, and there was a high percentage of trips made by walking.

Table 4. Overall trip variables.

Variable	Categories	%
Travel duration	Equal to or less than 15 min	54%
	Between 15 and 30 min	32%
	Between 30 and 45 min	5%
	Between 45 and 60 min	3%
	More than 60 min	6%
Modal share	Walking	36.32%
	Bus	19.17%
	Car	40.04%
	Other	4.47%

5. Estimation and Results

The approach used to estimate the latent variables model (the MIMIC model) and the discrete choice models (the Multinomial Logit and Mixed Logit) is explained in detail in this section. Additionally, we provide the results of the model estimations, SVT, and elasticities. Lastly, we present the discussion of all of the outcomes included in this section.

Firstly, we started the estimation process with the latent variables model. We estimated the MIMIC model using the AMOS© software and the data collected through household surveys. We considered all of the available explanatory variables and eight perception indicators. Only two transportation modes were considered for the estimation of these models: bus and car. Our latent variables on walking were not relevant, as was also concluded in Yáñez et al. [30]. In the beginning, we estimated many MIMIC models, including different explanatory variables. The estimation process determined that only two latent variables existed, as they explained all of the perception indicators. We called them Safety and Comfort. Likewise, we used—for the final model—several dichotomic variables created from the original continuous explanatory variables. In the end, the structural equations included four dichotomic explanatory variables (Sex, Medium-low age, Medium income, and Low income). Figure 1 illustrates the relationships existing in the MIMIC model. On the one hand, the Safety latent variable was explained by two variables: belonging to the low-income level (<1000 €/month) and belonging to the medium-income group (1000–2500 €/month). Safety explained two perception indicators: safety regarding accidents and safety regarding trips. On the other hand, the Comfort latent variable was defined by three variables: sex (1 if woman, 0 otherwise), belonging to medium-low age range (35–44 years), and belonging to low-income level (<1000 €/month). Comfort explained six perception indicators: adequacy of the scheduling, comfort during the trip, ease of access, availability of information, reliability in the waiting time, reliability in the travel time.

Table 5 provides the results for the structural equations in the MIMIC model. All of the parameters showed a statistical significance of at least 95%, which indicated that the model specification was correct. Regarding the Safety latent variable, medium-income individuals rated Safety negatively in both transportation modes, but to a greater extent in the car. Besides this, low-income individuals evaluated bus Safety positively and car Safety negatively. Concerning Comfort, women valued bus Comfort positively and car Comfort negatively. Similarly, medium-low age individuals, as opposed to low-income, rated bus Comfort negatively and car Comfort positively.

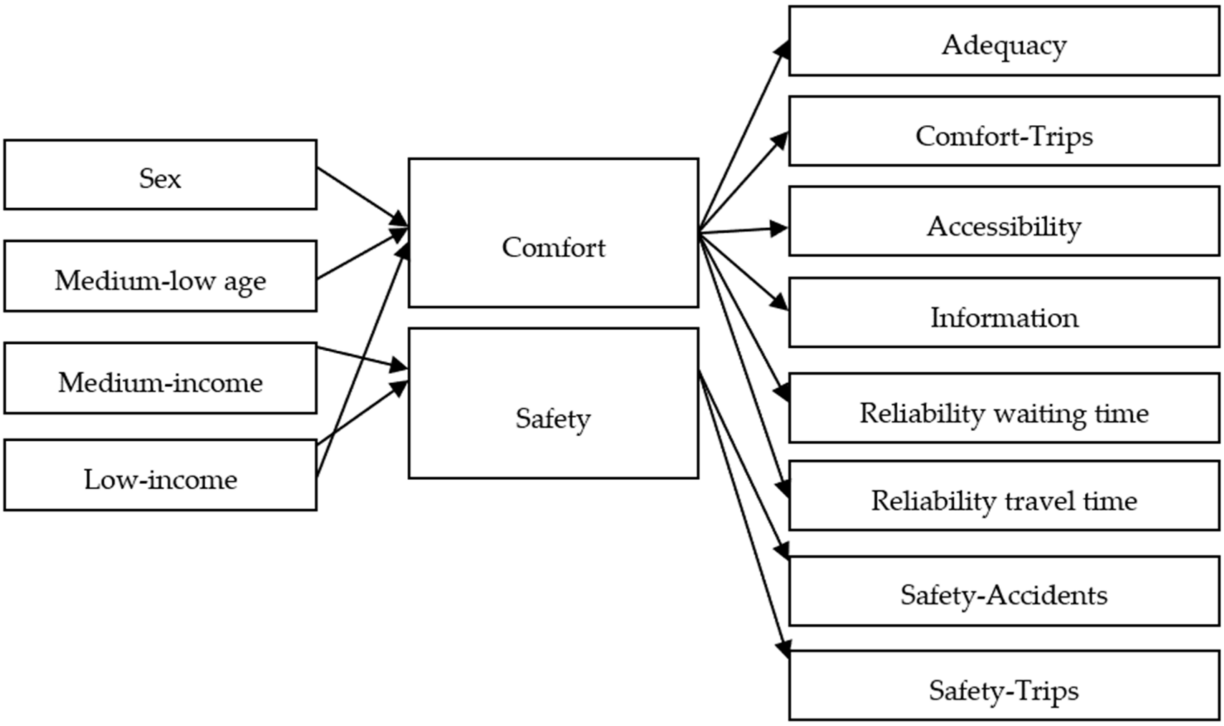

Figure 1. Relationships in the MIMIC model.

Table 5. Structural equation results for the MIMIC model (in parentheses, the t-statistic).

Parameter	Bus	Car
α Medium Income/Safety	−0.191 (−2.651)	−0.225 (−3.206)
α Low Income/Safety	0.172 (2.354)	−0.37 (−4.512)
α Sex/Comfort	0.159 (2.493)	−0.193 (−2.863)
α Medium-low age/Comfort	−0.194 (−2.129)	0.226 (2.403)
α Low income/Comfort	0.162 (2.841)	−0.372 (−4.717)

Ultimately, the MIMIC model allowed us to calculate the parameter values for the structural equations. Then, we calculated the individuals' latent variables values for each alternative. Once we obtained these values, we introduced the latent variables, and the other explanatory variables, into the discrete choice models.

Thus, we started the discrete choice model estimation process using the NLOGIT© software. We considered two models—Multinomial Logit and Mixed Logit—and we estimated them with and without latent variables (Comfort and Safety). Equally, we kept the same econometric specification in order to facilitate the subsequent comparison among the models. Besides this, we included the three dominant transportation modes (walking, bus, and car) into the choice set, like other studies [7,25,32]. However, we only considered the latent variables for buses and cars, because they were not relevant for walking, as in Yáñez et al. [30]. We also introduced the travel time, the waiting time (only for the bus), and the travel cost (for walking, the value is zero) as explanatory variables in the utility functions. All of the parameters associated with the explanatory variables were specific to each alternative, except for the latent variables, for which we assumed generic parameters.

In the end, the econometric specification for HCM (we eliminated the latent variables for the models that are not HCM) was:

$$U_{Walking} = ASC_{Walking} + \theta_{Walking,TT} \times TT_{Walking} + \varepsilon_{Walking} \quad (4)$$

$$U_{Bus} = \theta_{Bus,TT} \times TT_{Bus} + \theta_{Bus,TC} \times TC_{Bus} + \theta_{Bus,WT} \times WT_{Bus} + \theta_{Com} \times Com_{Bus} + \theta_{Saf} \times Saf_{Bus} + \varepsilon_{Bus} \quad (5)$$

$$U_{Car} = \theta_{Car,TT} \times TT_{Car} + \theta_{Car,TC} \times TC_{Car} + \theta_{Com} \times Com_{Car} + \theta_{Saf} \times Saf_{Car} + \varepsilon_{Car} \quad (6)$$

where ASC is the alternative specific constant for walking, TT is travel time, WT is waiting time, TC is travel cost, Com is the Comfort latent variable, and Saf is the Safety latent variable.

Table 6 provides the results obtained for the discrete choice models. We estimated four models: Multinomial Logit without latent variables (MNL), Multinomial Logit with latent variables (HCMMNL), Mixed Logit without latent variables (ML), and Mixed Logit with latent variables (HCMML). Firstly, all of the parameters offered the correct signs in all of the models (negative for time and cost; positive for the latent variables) and were statistically significant at 95%. Secondly, the travel cost parameters in buses and cars were higher than those related to the different times of the alternatives in all of the models, which indicated that they had a more significant impact on choice behavior. Thirdly, the parameters for the latent variables also had a high value, and Safety was always more elevated than Comfort. Besides this, the parameters for the latent variables were higher than those associated with all of the time variables. However, these parameters were consistently lower than those associated with the travel cost, except for the car cost. Fourthly, HCM had higher log-likelihood values, l(θ), because its value was closer to zero. This indicates that they delivered better results in terms of model adjustment, and were more explanatory than more traditional models, which did not incorporate latent variables (only time and cost). Similarly, Mixed Logit models were more explanatory than Multinomial Logit models, both in the models that considered latent variables and those that did not.

Table 6. Discrete choice models result.

	MNL		**HCMMNL**		**ML**		**HCMML**	
Parameter	**Value**	***t*-Test**	**Value**	***t*-Test**	**Value**	***t*-Test**	**Value**	***t*-Test**
$ASC_{Walking}$	−0.360	−2.304	−5.693	−6.388	−0.120	−0.599	−7.250	−6.011
$\theta_{Walking,TT}$	−0.042	−11.19	−0.044	−11.149	−0.051	−8.196	−0.057	−8.034
$\theta_{Car,TT}$	−0.264	−5.042	−0.250	−4.466	−0.283	−5.073	−0.319	−4.311
$\theta_{Bus,TT}$	−0.013	−2.331	−0.023	−3.613	−0.013	−2.268	−0.026	−3.318
$\theta_{Bus,WT}$	−0.091	−3.346	−0.131	−4.149	−0.094	−3.233	−0.175	−4.225
$\theta_{Car,TC}$	−2.031	−3.212	−2.216	−3.192	−1.990	−3.007	−2.895	−3.310
$\theta_{Bus,TC}$	−3.091	−12.77	−4.082	−14.649	−3.228	−12.047	−5.189	−10.608
θ_{Com}	-	-	1.865	10.420	-	-	2.992	5.480
θ_{Saf}	-	-	2.692	5.649	-	-	3.437	5.471
$\theta_{Walking,TT}$ (St. Dev.)	-	-	-	-	0.018	3.040	0.013	1.899
θ_{Com} (St. Dev.)	-	-	-	-	-	-	1.790	2.823
θ_{Saf} (St. Dev.)					-	-	0.743	4.008
l(θ)	−926.18		−823.82		−922.79		−814.74	
Travel SVT (car)	7.80 €/h		6.77 €/h		8.55 €/h		6.61 €/h	
Travel SVT (bus)	0.25 €/h		0.34 €/h		0.24 €/h		0.30 €/h	
Waiting SVT (bus)	1.76 €/h		1.92 €/h		1.74 €/h		2.02 €/h	

Therefore, all of the models provided correct econometric specifications based on the sign of the parameters and the statistical significance. The magnitude in the latent variables' parameters, their high statistical significance, and their positive sign confirmed their suitability. However, the latent variables did not influence choice behavior equally, with Safety being the most relevant. Likewise, the travel cost was more crucial than time in all of the models. The supremacy of cost was only undermined in the car when we considered HCM, in which case Safety was the most relevant variable to determine choice behavior. Besides this, all of the HCM delivered better results in terms of model adjustment. Thus, the latent variables increased the explanatory capacity in the mode choice models, confirming the results obtained in previous studies [1,2,32].

Table 6 also includes the SVT, which measures the willingness to pay to reduce, by one unit, the time allocated to an activity in terms of €/hour. In this case, we calculated the car travel SVT, the bus travel SVT, and the SVT of waiting for the bus. Firstly, the car travel SVT was higher than the SVT of waiting for the bus in all of the models, and it was always higher than the SVT of bus travel. Secondly, the car travel SVT was lower in the HCM than in the models without latent variables. Likewise, the car travel SVT was lower in the MNL than in the ML, but the value was higher for the HCMMNL than for the HCMML. Thirdly, the bus travel SVT, in all of the models, was small compared to the public transportation ticket (1.3 €). HCM delivered higher values than the models without latent variables, while MNL and ML delivered practically the same value. Fourthly, the SVT of waiting for the bus was higher in the HCM than for the more traditional models, while the MNL and ML models delivered practically the same value.

Therefore, the car travel SVT delivered the highest value in all of the models, and was unaffected by latent variables. This result suggests that users were willing to accept higher costs to reduce travel time in the car, regardless of the mode choice model. The values were lower in the HCM, which matched the results from other studies [25,31,32]. In any case, all of its values were below the mean wage rate of the sample, which we calculated to be around 10 €/hour. However, these values were not far from other studies carried out previously in the same town [39]. On the other hand, the bus travel SVT values were much lower, in all of the models, than the public transportation ticket (1.3 €). This result could explain the low modal share in the bus, meaning that users were not willing to pay such an expensive ticket. The values were practically equal for all of the models, even though HCM delivered higher values than the others. Besides this, the bus waiting SVT was higher than the travel SVT in all of the models, which indicated that individuals perceived the wait as a source of greater disutility than the travel, regardless of the model. The results were consistent with previous studies in urban mode choice [30]. Likewise, just like the bus travel SVT, HCM delivered higher values for the bus waiting SVT. Finally, although the calculation of willingness to pay to increase the latent variables might be tempting, it was not recommended, as they did not have a clear economic interpretation.

Table 7 provides the direct elasticities of the demand concerning cost and times for the bus and car. These values represent the percentage change in the choice probability of a transportation mode by varying an attribute by 1%, for time or cost. Firstly, the signs were correct in all cases (negative) because, when the cost or time of each transportation mode increased, its choice probability decreased. Secondly, the direct elasticity between the cost and the probability of using the bus presented the highest values. Besides this, the HCMML model values were higher than in the others, except in direct elasticity for the car travel time. Finally, the direct elasticity between the travel time and the probability of using the bus, compared to the car, was higher only when we used HCM. Both elasticities were always lower than the elasticities for the bus waiting time.

Table 7. Direct elasticities.

Direct Elasticity	MNL	HCMMNL	ML	HCMML
Cost-demand (bus)	−1.09	−1.44	−1.11	−1.67
Cost-demand (car)	−0.13	−0.14	−0.12	−0.15
Travel time-demand (bus)	−0.14	−0.25	−0.15	−0.27
Travel time-demand (car)	−0.20	−0.19	−0.20	−0.18
Waiting time-demand (bus)	−0.21	−0.30	−0.21	−0.37

Ultimately, we calculated all of the elasticities concerning time and cost variables, and not concerning latent variables, which we found on a previous occasion in the literature [23]. We did so because the interpretation was not feasible from an economic standpoint because it lacked a measurement scale. On the other hand, the bus cost had the highest direct elasticities in all of the models, which indicated that users were susceptible to ticket costs, regardless of the model (with the elasticity being higher than 1, users were very elastic). If we link this result to the low value for the bus travel SVT, we recommend decreasing ticket costs to increase the bus modal share. However, previous studies concluded that the most important value was the elasticity concerning bus time [24,25,32]. Likewise, we obtained the highest values for all elasticities in the HCMML model, except in the direct elasticity for the car travel time. This result indicated that incorporating latent variables in Mixed Logit increased the user's sensitivity, so we must cautiously take these results. Similarly, the highest values in the bus and car travel time elasticities oscillated among the different models, although the time elasticity for the bus was higher in a previous paper [7]. In this case, HCM increased the bus travel time elasticity and decreased the car travel time elasticity. Finally, the travel time elasticities were lower than the bus waiting time elasticities in all of the models. Equally, if we consider that the waiting time SVT was higher than the bus travel SVT, the public transportation promotion policies should be aimed mainly at reducing waiting times.

6. Sustainable Mobility Policy Simulation

This paper aims to measure the effects of using HCM on sustainable mobility policy analysis, compared to traditional models without latent variables, such as Multinomial Logit and Mixed Logit. The outcomes provided in the previous section revealed that including latent variables in the choice models had a substantial impact on the SVT and elasticities. This section offers the simulation of sustainable mobility policies based on the previously estimated discrete choice models, both HCM and traditional choice models. This technique provided the variation in the modal shares derived from the sustainable mobility policies [37]. Thus, this section aims to determine the ways in which the policy scenarios (changes in the values of the alternatives, time and cost, associated with the motorized alternatives, bus and car) impacted the probabilities of the choice of the bus and its modal share, given the latent variables Comfort and Safety. The common goal in the policy scenarios was to increase the public transportation market share:

1. Scenario 1: This scenario considered bus fare reductions (10%, 20%, 30%, 40%, and 50%). We can reach this scenario by increasing the subsidy for public transportation.
2. Scenario 2: This scenario considered bus travel time reductions (10%, 20%, 30%, 40%, and 50%). We can reach this scenario by implementing exclusive bus lanes.
3. Scenario 3: This scenario considered bus waiting time reductions (10%, 20%, 30%, 40%, and 50%). We can reach this scenario by improving compliance with scheduled frequencies, coordinating the bus fleet, or using mobile apps.
4. Scenario 4: This scenario considered increases to the cost of using cars (10%, 20%, 30%, 40%, and 50%). We can reach this scenario by increasing parking costs or taxes on private vehicles.
5. Scenario 5: This scenario considered car travel time increases (10%, 20%, 30%, 40%, and 50%). We can reach this scenario by reducing the number of parking spots, the operational speed, and the number of car lanes.

Ultimately, Scenario 1, Scenario 2, and Scenario 3 promoted public transportation by reducing bus fares and travel and waiting times, respectively. On the other hand, Scenario 4 and Scenario 5 penalized private cars by increasing the cost of using cars and travel times, respectively. In other words, the different scenarios combined measures of bus promotion and car penalization.

Table 8 shows the results for the policy scenario simulations. This table exhibits the percentual variation in the bus modal share, compared to the initial levels, due to the change in the attributes of the alternatives. In general terms, all of the policies simulated in each scenario positively impacted the bus modal share. Similarly, the bus modal share variation increased as the variation in the attributes of the alternatives increased. Moreover, the highest increases in the bus modal share were associated with the HCMML model. Thus, the HCM were more explanatory, as we revealed in the previous section, and provided more significant impacts on the bus modal shares for the same policies. In other words, incorporating latent variables as explanatory variables increased the impact of the policy. Likewise, Scenario 1 presented the most relevant bus modal shares variations (maximum of 13.61%). This result was consistent because the direct elasticity of bus prices was previously the highest (−1.67).

Table 8. Bus modal share variation.

	Variation	MNL	HCMMNL	ML	HCMML
Scenario 1 (Bus fare reduction)	−10%	0.05%	0.14%	0.36%	2.12%
	−20%	0.10%	0.21%	0.79%	4.56%
	−30%	0.16%	0.27%	1.29%	7.32%
	−40%	0.21%	0.40%	1.87%	10.38%
	−50%	0.26%	0.52%	2.52%	13.61%
Scenario 2 (Bus travel time reduction)	−10%	0.06%	0.17%	0.06%	0.35%
	−20%	0.15%	0.32%	0.13%	0.68%
	−30%	0.28%	0.52%	0.19%	1.05%
	−40%	0.49%	0.89%	0.26%	1.44%
	−50%	0.81%	1.41%	0.34%	1.77%
Scenario 3 (Bus waiting time reduction)	−10%	0.00%	0.05%	0.06%	0.40%
	−20%	0.00%	0.05%	0.13%	0.79%
	−30%	0.00%	0.03%	0.20%	1.22%
	−40%	0.00%	0.06%	0.28%	1.68%
	−50%	0.00%	0.09%	0.37%	2.10%
Scenario 4 (Car cost increase)	+10%	0.09%	0.17%	0.40%	0.31%
	+20%	0.18%	0.28%	0.84%	0.60%
	+30%	0.27%	0.39%	1.33%	0.92%
	+40%	0.38%	0.57%	1.84%	1.26%
	+50%	0.50%	0.77%	2.37%	1.54%
Scenario 5 (Car travel time increase)	+10%	0.01%	0.06%	0.03%	0.37%
	+20%	0.02%	0.07%	0.06%	0.72%
	+30%	0.03%	0.05%	0.10%	1.11%
	+40%	0.03%	0.10%	0.13%	1.50%
	+50%	0.04%	0.14%	0.16%	1.83%

In terms of every Scenario, Scenario 1 provided the lowest values for the MNL (0.05%, 0.10%, 0.16%, 0.21%, and 0.26%), while the ML offered values that nearly doubled them (0.14%, 0.21%, 0.27%, 0.40%, and 0.52%). The latent variables increased the effect of bus fare reductions on the modal share for the HCMMNL model (0.36%, 0.79%, 1.29%, 1.87%, and 2.52%), but exceedingly so for the HCMML model (2.12%, 4.56%, 7.32%, 10.38%, and 13.61%). Figure 2 illustrates the bus modal share variations for the bus fare reductions.

Scenario 2 offered the lowest values for the HCMMNL (0.06%, 0.13%, 0.19%, 0.26%, and 0.34%), while the MNL provided slightly higher values that increased to a larger extent as the reductions in bus travel time increased (0.06%, 0.15%, 0.28%, 0.49%, and 0.81%). The ML presented higher values than both models (0.17%, 0.32%, 0.52%, 0.89%, and 1.41%), but the highest values appeared in the HCMML (0.35%, 0.68%, 1.05%, 1.44%, and 1.77%). Figure 3 exhibits the greater magnitude of the variations for the HCMML, but to a lesser extent than in Scenario 1.

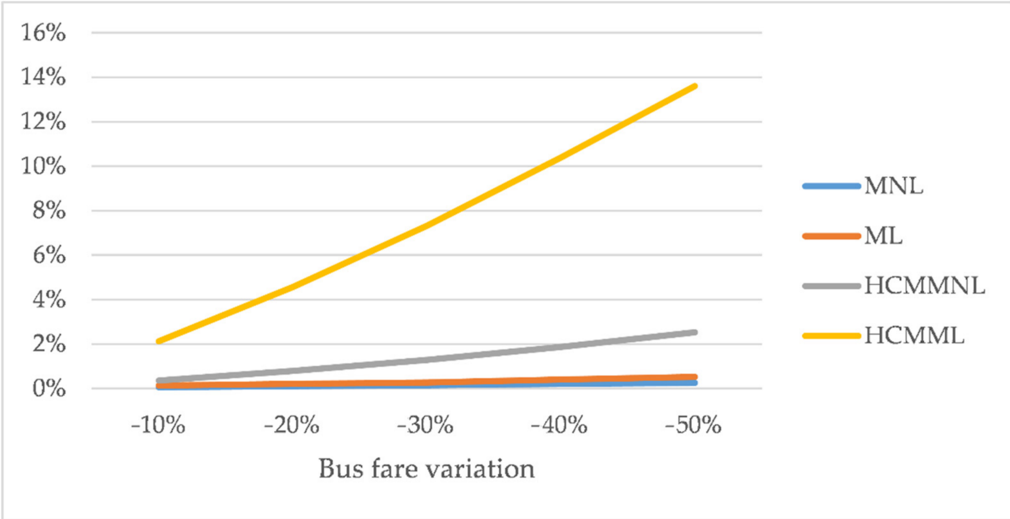

Figure 2. Bus modal share variation (bus fare reduction).

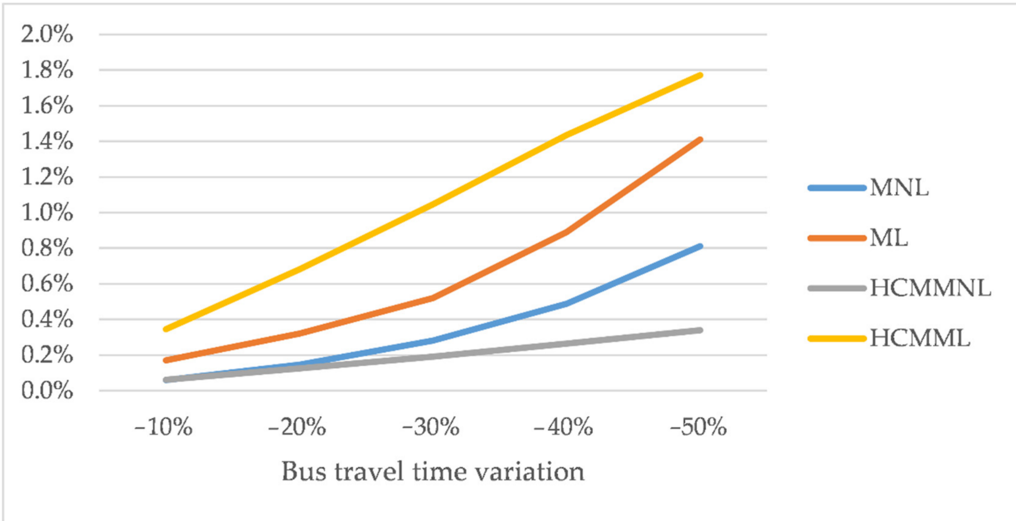

Figure 3. Bus modal share variation (bus travel time reduction).

Scenario 3 presented the lowest values for the MNL, as no bus waiting time reduction affected the bus modal share. The ML provided low values that did not increase sustainably with successive waiting time reductions (0.05%, 0.05%, 0.03%, 0.06%, and 0.09%). The latent variables increased the effect of waiting time reductions on the modal share for the HCMMNL (0.06%, 0.13%, 0.20%, 0.28%, and 0.37%), but exceedingly so for the HCMML (0.40%, 0.79%, 1.22%, 1.68%, and 2.10%). Figure 4 displays the bus modal share variations for the bus waiting time reductions.

Scenario 4 offered the lowest values for the MNL (0.09%, 0.18%, 0.27%, 0.38%, and 0.50%), while the ML provided slightly higher values that increased to a larger extent with higher increases in car costs (0.17%, 0.28%, 0.39%, 0.57%, and 0.77%). The latent variables increased the effect of the rise of car costs on the modal share for the HCMML (0.31%, 0.60%, 0.92%, 1.26%, and 1.54%), but exceedingly so for the HCMMNL (0.40%, 0.84%, 1.33%, 1.84%, and 2.37%). Figure 5 presents the bus modal share variations for the car cost increases.

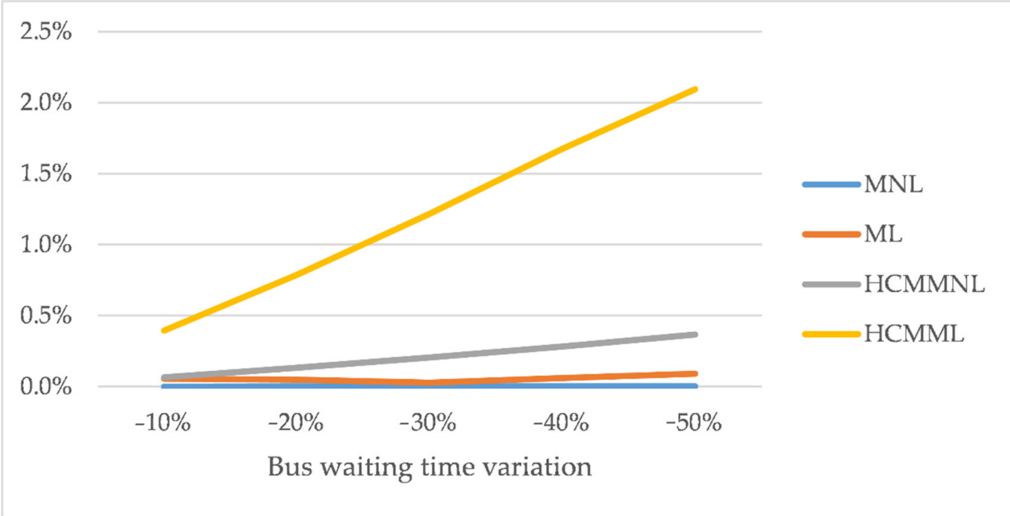

Figure 4. Bus modal share variation (bus waiting time reduction).

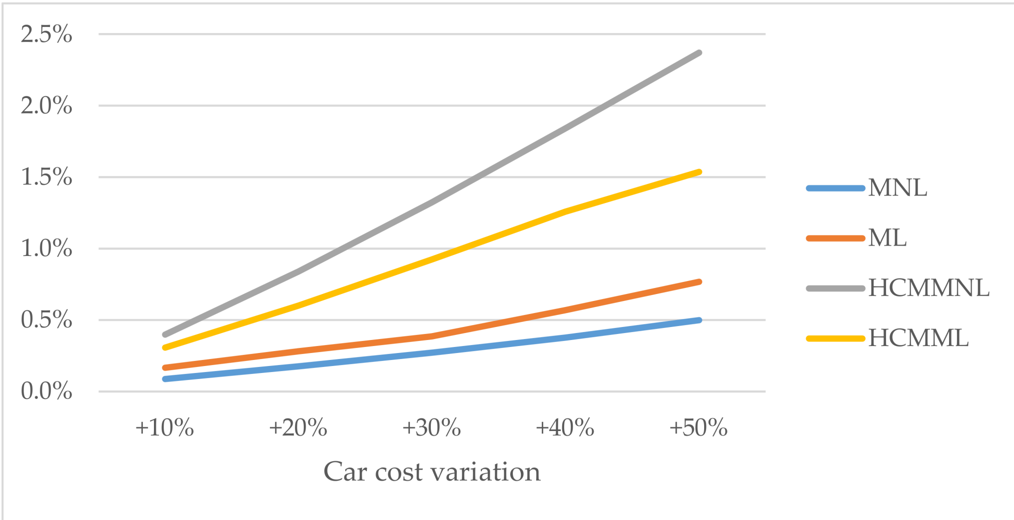

Figure 5. Bus modal share variation (car cost increase).

Scenario 5 presented the lowest values for the MNL (0.01%, 0.02%, 0.03%, 0.03%, and 0.04%). The ML provided low values that did not increase sustainably with successive car travel time increases (0.06%, 0.07%, 0.05%, 0.10%, and 0.14%). The latent variables boosted the effect of car travel time increases on the modal share for the HCMMNL (0.03%, 0.06%, 0.10%, 0.13%, and 0.16%). The highest values appeared for the HCMML (0.37%, 0.72%, 1.11%, 1.50%, and 1.83%). Figure 6 exhibits the bus modal share variations for the car travel time increases:

Despite the amplitude of the analysis carried out in this paper, some limitations persist, allowing us to prompt future research. On the one hand, it is necessary to delve deeper into the implications of the consideration of perception indicators as continuous or ordinal variables, and the complexity associated with the indicators [6]. On the other hand, we used the sequential estimation approach because of its flexibility and lower computational cost. However, it would be interesting to conduct the sensitivity analysis using simultaneous estimation in the future. Besides this, we included perception indicators, but attitudinal data could be incorporated in order to improve the future analysis, including a latent variable related to environmental attitudes.

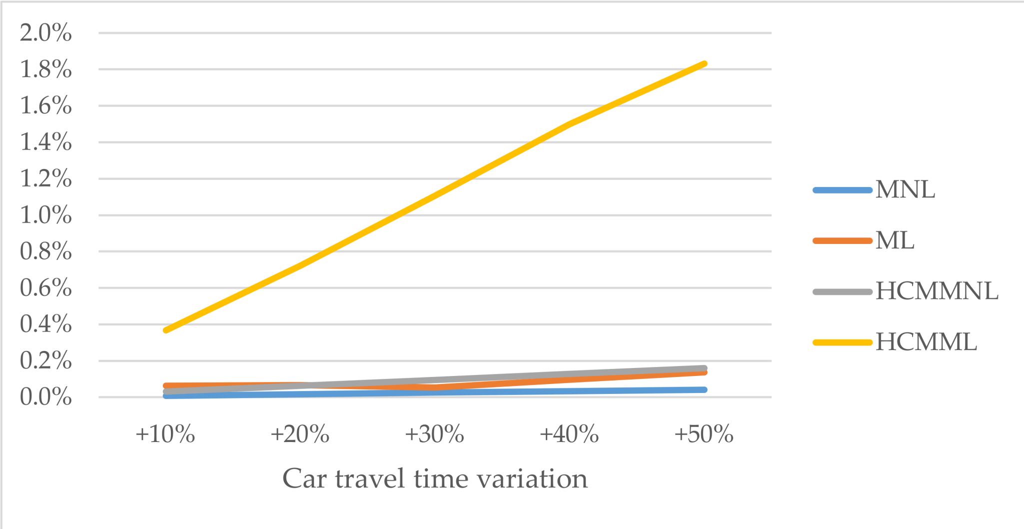

Figure 6. Bus modal share variation (car travel time increase).

In summary, we determined that the impact of incorporating latent variables into the discrete choice models was far-reaching. HCM affected the SVT, elasticities, and sustainable mobility policy analysis. Likewise, the policies to promote the bus, especially bus fare reduction, caused a more significant impact on the bus modal share than those that penalized the car. In other words, policies that promoted public transportation were more effective in increasing the bus modal share than those that penalized private transportation. Besides this, HCM were models that guaranteed better results when the goal was evaluation. On the contrary, when the goal was prediction, the results should be assessed with caution. Ultimately, we concluded that sustainable mobility policy analysis should use HCM prudently, and should not set them as the best models beforehand.

7. Conclusions

This paper aimed to measure the impact of the HCM on the outcomes of the sustainable mobility policy analysis compared to more traditional models without latent variables. To this end, we identified the relevant latent variables for mode choice in the city of Santander, i.e., Safety and Comfort, and estimated Multinomial Logit and Mixed Logit models, with and without latent variables.

We found that HCM impacted the outcomes of the sustainable mobility policy analysis substantially. Firstly, HCM provided a better adjustment for the mode choice models. As such, the latent variables increased the explanatory capacity of choice models. Secondly, HCM offered lower values for car travel SVT and higher values for bus travel and waiting SVT. Thirdly, the highest values for all of the elasticities were obtained in the HCMML model, except for the direct elasticity for car travel time. This result indicated that incorporating latent variables in a Mixed Logit model increased the user's sensitivity, so we must cautiously take these results. Likewise, HCM increased the bus travel time elasticity and decreased the car travel time elasticity. Fourthly, HCM amplified the impact of sustainable mobility policies on the modal shares and overrated the individuals' travel behavior reactions. Thus, HCM overrated the impact of sustainable mobility policies on the modal switch. Similarly, for all of the mode choice models, policies that promoted public transportation were more effective in increasing the bus modal share than those policies which penalized private vehicles.

Ultimately, HCM were models that guaranteed better results when the goal was evaluation. On the contrary, when the goal was prediction, the results should be assessed with caution. Therefore, we conclude that sustainable mobility policy analysis should use HCM prudently, and should not set them as the best models beforehand.

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