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The influence of information-based Transport Demand Management measures on commuting mode choice. Comparing web vs. face-to-face surveys

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Abstract

We test the effect of different contextualization, scaling, framing and formatting of environmental impacts and health benefits information on commuting mode choice. For this, a stated preference (SP) survey was designed. To also test survey mode effect, the survey was administrated both online and face-to-face. We find statistical differences across the two samples in terms of transport preferences, attitudes and perceptions towards the environment, health and social norms. These could be attributed both to differences in the levels of education and professional occupation and self-selection bias. The results in the models estimated from the SP hint the existence of irrational answers in the web-based sample. Information about global CO_2 emissions appears to be ineffective in influencing mode choice whereas self-centric information about calories consumption is effective.

Keywords: Information-based TDM measures; health benefits; CO_2 emissions; mode choice modelling; web-based surveys; face to face surveys

1. Introduction & Scope

Urban mobility depends heavily on the car, with widely known negative impacts. Yet, supply-side approaches cannot be relied upon solely to reverse or even halt these trends (European Commission, 2014). Travel Demand Management (TDM) measures which include soft measures e.g. information, communication & service and activity coordination, have been recently suggested as potential effective actions (Bamberg et al., 2011). Travel behavior advances have borrowed theories from social psychology and behavioral economics, which are aligned with TDM concepts and measures - and in particular information-based TDM. In fact, to encourage the use of less polluting modes, cognitive factors could be used to influence mobility choices using theoretical inputs taken from prospect theory (Kahneman & Tversky, 1979). The way information is framed also impacts on behavior. In his

typology of models for information framing, Hallahan (1999) explains the extent to which conveying information in a certain way e.g. accentuating certain items instead of others or making intervening uncertainty can lead to different public reactions and decision outcomes. Clear links have also been identified between perceived general health, perceived psychological wellbeing, a healthy body weight and the use of active travel modes (e.g. Scheepers et al. (2015)). Peer pressure/support and social networks are found to play actively on individual attitudes, beliefs and travel behavior in particular, as found by Ampt (2003).

Gaker et al. (2011) found that the environmental attributes of transport alternatives or "green value" are of higher importance in mode choice, than in car ownership or route choice. Transforming raw information into an easily identifiable context allows respondents to better understand the measures presented to them into something meaningful (Waygood & Avineri, 2012). Using pounds, kilos or tons as the dominant metric for carbon emissions is one possible way of introducing identifiable environmental information into choice experiments (Gaker et al., 2011). One can also refer to carbon budgets, which increase the effectiveness of environmental measures, when compared with the simple measurement of CO_2 mass (Avineri & Waygood, 2013). Besides scaling (expressing the information per trip, day, month, etc.), framing information with respect to a specific reference point is also determinant (Avineri & Waygood, 2013). Negative framing is found to be more effective than positive framing (Avineri & Waygood, 2013). Information formats that trigger emotions (e.g. tree equivalent and earth equivalent for CO_2 emissions) produce the strongest responses and increase respondents' intention to travel more sustainably (Waygood & Avineri, 2012). The number of studies focused on the effects of CO_2 emissions information on mode choice is relatively short (Choudhury et al., 2008; Gaker et al., 2010, 2011; Gaker & Walker, 2013; Achtnicht, 2011; Waygood & Avineri, 2012; Avineri & Waygood, 2013). Of these only Waygood & Avineri, (2012) and Avineri & Waygood (2013) considered specifically the effects of framing and compared different ways of measuring CO_2. Gaker et al. (2010) consider the effects of peer influence, and Gaker & Walker (2013), analyse the effect of information about consumed calories on the top of CO_2 emissions information on mode choice.

To assess the effect of information-based TDM measures on travel behavior, surveys, and web-based ones in particular, have become increasingly popular among researchers, most likely due to the fact that they could be very cost effective. Bayart & Bonnel (2015) underline the complementarity of each survey mode to increase the response rate and produce more reliable results. Yet, the number of works in the transportation literature explicitly comparing the results obtained in web-based and face-to-face surveys seems to be small. Web-based surveys have also several shortcomings (de Abreu e Silva & Davis, 2015). They may compromise model accuracy due to problems of data comparability (Stopher & Jones, 2003) and lead to "primacy effect" in responses (Dillman & Browker, 2001), as respondents tend to choose the firstly proposed choice alternative. Face-to-face surveys, often reported to be more burdensome but also more reliable, could lead to 'social compliance' effects (response orientation in the presence of the surveyor), and to the 'recency effect' (Dillman & Browker, 2001), increasing the tendency of the respondent to opt for the latest heard option.

In addition, certain survey modes can also have a stronger (positive) influence on the outcome of the survey than others depending on the profile of the respondent. In their study, Susilo et al. (2017) compared results obtained via paper-and-pencil surveys, online and real-time questionnaires, embedded in route navigation app or in a dedicated Android Game app, and focus groups, administrated to respondents upon request and based on socio-demographics. They found that paper-based methods reported the highest travel satisfaction among respondents, whilst game app and focus groups methods reported the lowest satisfaction. Interestingly, their conclusion differed depending on the sociodemographic profile that was considered. Bayart & Bonnel (2008) found that although internet users tend to spend more time outside home they travel less, and mostly using non-motorized modes. Liu & Wang (2015) found that face-to-face respondents provide warmer and more favorable feelings. Gosling et al. (2004) argue that internet users do not differ from other people in some specific psychological traits, and both Marta-Pedroso et al. (2007) and Fleming & Bowden (2009) found no significant differences between web-based surveys, mail and personal interviews in the context of contingent valuation studies.

Hence to disentangle these findings, the purpose of our paper is twofold. First we aim to compare the results obtained both in web-based vs. face-to-face surveys, particularly in aspects related with perceptions and attitudinal constructs. Secondly we aim to study the effects of information based TDM related with societal benefits (CO_2

emissions) and individual health related benefits (consumed calories) on the choice of different travelling options (commuting trips only). Related with the second objective, we also aim to identify how different are the results about the effectiveness of information based TDM, obtained from the web-based vs. the face-to-face ones. Led by the reported findings, the experimental design applied here considers different competing ways of presenting CO_2 emissions and calories consumption. We refer the reader to the work of Oliveira & Pinho (2010) and de Abreu e Silva et al. (2012) for a thorough description of our studied city, Lisbon, its Metropolitan Area (LMA) and transportation system. Our main contribution is the simultaneous comparison of a wider range of different information formats in a Stated Preference (SP) context than the state-of-the-art literature, where regular attributes like travel times and costs are also present.

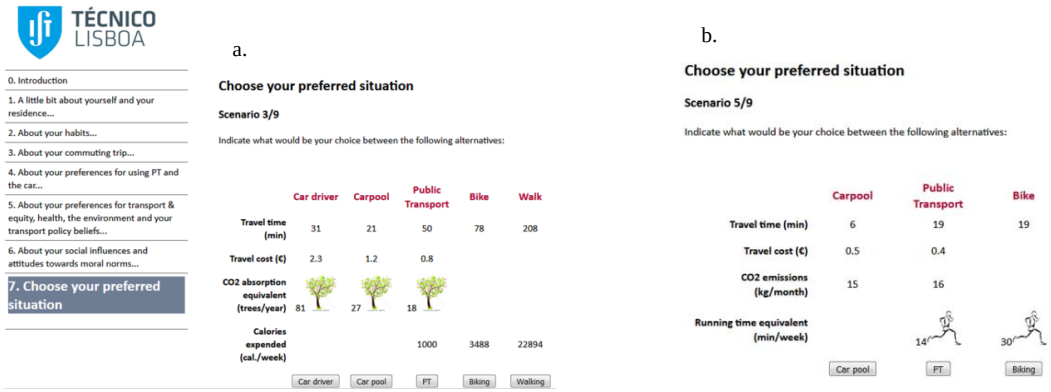
The remainder of this paper is organized as follows. In the following section, the survey organization is briefly described. On the third section, results of the different analyses are presented and discussed. The final section presents the main conclusions and discusses future developments of the present work.

2. Survey design

The survey application – identical across both survey media – focuses on commuting behavior and commuting choices. It is organized in three main parts. The first one focuses on the respondent socioeconomic characteristics and its revealed commuting behavior. The second part includes a series of questions, using Likert scales, about attitudes and perceptions on transport modes, transport policy, equity, environmental and health impacts of transport, and social influences and norms. Attitudinal questions related with health perceptions and physical exercise were based on the work of Korn et al. (2013) and Marsh et al. (2010), whereas perceptions about environmental risk and public attitudes towards injunctive and descriptive social norms were based on the work of Linden (2015) and Allcott (2011). Finally a third part includes a SP exercise with 9 scenarios for commuting mode choice, which were based on the revealed commuting behavior.

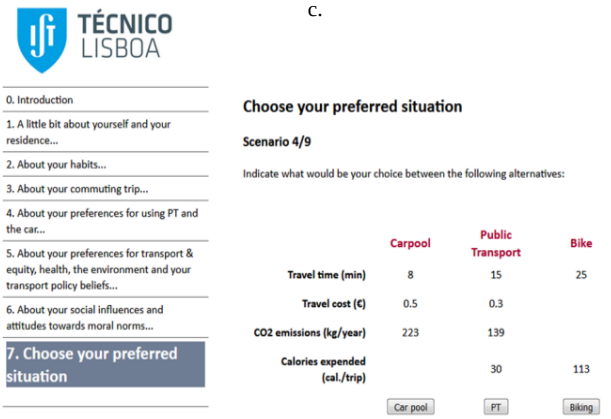
As showed in Figure 1, the SP scenarios include up to five alternatives: ‘car driver’, ‘car pool’ ‘public transport’, ‘walk’ and ‘bike’. The attributes in the SP exercise cover travel costs and travel times, CO_2 emissions (societal costs) and calories consumption (individual benefits) associated with the use of each mode. The information about CO_2 emissions and calories is presented to the respondents in ways aimed at capturing framing effects and emotional responses. Thus CO_2 emissions information was presented in five different ways, ‘trip emissions’, ‘monthly emissions’, ‘yearly emissions’ (e.g. Fig. 1c), ‘amount of equivalent trees to offset the yearly emissions’ (e.g. Fig. 1a), and ‘percentage of the yearly average carbon budget’ (e.g. Fig. 1d). Calories consumption information was presented in three different ways, ‘calories consumed by trip’, ‘weekly calories consumption’ and the ‘equivalent weekly minutes of running’ to consume the same amounts of calories (e.g. Fig. 1b).

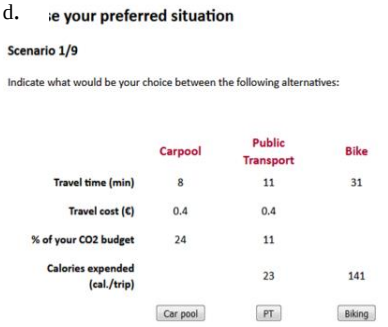
Figure 1 SP scenarios captions



(a. with trees equivalent to offset yearly CO_2 emissions and ***b.*** with min/week running time

equivalent per week)





(***c.*** with yearly CO_2 emissions and ***d.*** with CO_2 emissions expressed as the national yearly budget average per capita)

3. Results

The survey was first disseminated through a list of residents in the Lisbon Metropolitan Area (MA) who had previously agreed to answer to surveys related with transportation research initiatives. It resulted in 160 online surveys in July 2016, which after data cleaning were reduced to 146 surveys with a valid RP component, of which 129 had a valid SP component. These were complemented 3 months later with 266 face-to-face surveys (aimed at having a global sample similar to the LMA socio-demographics) using the exact same information, which were later reduced to 259 surveys with a valid RP component and 240 with a valid SP component. Globally the obtained commuting modal shares are similar to the ones collected for the LMA in the 2011 Census (www.ine.pt). Both samples were tested for differences in terms of socioeconomic characteristics, behavior and attitudinal aspects, using statistical tests and ordered probit models. Although the complementary sample intended to reduce the web-based survey sample bias, there was enough overlap (in terms of gender and age) to allow a direct comparison between face-to-face and web-based responses, in what concerns attitudinal constructs. Comparison about attitudinal constructs was made using confirmatory factor analysis and multi-group analysis. In order to reduce possible effects due to sample size and different socioeconomic characteristics of both samples in multi-group analysis, a randomly chosen subsample of the face-to-face survey with the same distribution between gender and age brackets (20-29, 30-39, 40-49 and 50-65 years old) as in the web-based sample was built.

3.1. Differences in revealed modal preferences between the face-to-face and web surveys

The comparison of the main socioeconomic characteristics and modal shares between the face-to-face sample (259 observations), face-to-face subsample (146 observations), and the web-based sample is presented in Table 1 below.

Table 1 Descriptive statistics

Samples characteristics

	Face-to-face sample (259 obs.)(a)		Face-to-face subsample (146 obs) (b)		Web sample (146 obs.) (c)			
	Mean	C.V.	Mean	C.V.	Mean	C.V.	p-value (a) versus(c)	p-value (b) versus (c)
Age	39	0.32	43.58	0.22	43.37	0.21	0.00	0.85
% men	44.01%		48.63%		48.63%		0.27	0.39
HH size	2.93	0.42	2.86	0.43	2.51	0.49	0.01	0.01
% college educated	36.68%		34.25%		84.93%		0.00	0.00
% student	10.42%		1.37%		4.11%		0.03	0.14

% managerial occupation	16.60%		19.18%		50.00%		0.00	0.00
Monthly income (€)	2 461.12	0.72	2 534.12	0.72	3 197.90	0.77	0.00	0.01
Revealed modal shares for commuting								
Car (driver)	45.56%		50.69%		48.63%		0.33	0.38
Car (passenger)	12.36%		15.07%		3.43%		0.00	0.00
Motorcycle	1.93%		2.06%		4.80%		0.11	0.17
Public transport	27.03%		17.81%		29.45%		0.35	0.03
Car + Public transport	2.70%		2.06%		2.06%		0.37	0.40
Walking	9.65%		10.96%		9.59%		0.40	0.37
Bicycle	0.77%		1.37%		2.06%		0.21	0.36
Chi square (likelihood ratio)							0.03	0.07

It can be seen that the percentage of college educated and managerial professionals is the highest in the web-based sample. This has implications in terms of the household monthly income which is significantly different between the face-to-face samples and the web-based sample. These differences don´t result in markedly different modal shares. Although the chi-square test rejects the hypothesis of equality, the shares of the different modes tend not to be significantly different, with the exception of car (passenger) and public transport (only for the face-to-face subsample).

3.2 Differences in attitudes across both survey media

The following comparison reports several questions asking for attitudes about perceptions on transport modes, transport policy, health and environmental concerns, transport impacts on health and climate change, and social concerns. Since attitudinal data was built using Likert scales, ordered probit models were built for each one of the statements to assess the role of survey mode on responses. The variables used include gender, age segments, education attainment, professional occupation and survey mode. Table 2 presents for each of the Likert scale question the coefficient relative to the survey mode (1 if web-survey) and its significance level.

Table 2 Comparison between web-based and face-to-face Likert scale statements

	Mean value web-based (146 obs.)	Mean value face-to-face (259 obs.)	Web-based survey coefficient
Nothing will make me stop using the car	2.89	4.07	-0.64**
The car offers me the flexibility I need for my schedule	5.26	5.00	-0.12
The car gets me to my destination quickly	5.08	5.09	-0.20
The car provides me with the privacy, liberty and comfort I need	5.23	5.39	-0.29*
Older, poorer people and students should have specific discounts in public transport fares	6.34	5.22	0.70**
Using the car has a strong impact on climate change	5.89	5.63	0.24
Cycling and walking have strong health benefits and are good for the environment	6.42	6.05	0.30*
Cycling and walking regularly help reducing weight	6.23	6.08	0.08
Keeping myself in good health all year round is very important	6.43	6.01	0.15
Keeping myself fit even if it takes some extra effort is very important	5.71	4.93	0.31*
I pay a lot of attention to ensure that my diet is healthy	5.26	5.33	-0.22
Transport policy should aim to establish equity in transportation by subsidizing more vulnerable groups of people	5.53	4.43	0.42**
Car users don´t pay for the total environment and socioeconomic costs of driving	3.96	3.46	0.15
Transport policy should promote more cycling and walking	5.60	5.05	0.26
Car users should pay for using the car in congested areas (by introducing congestion tolls)	4.12	3.70	0.22
Public transport should be financially sustainable	4.03	4.90	-0.25
Parking illegally is a major offence	5.81	5.53	0.01
My friends and family think that climate change is a real threat	5.28	4.07	0.39**
My friends and family travel by car because they think it is cool	2.11	1.72	0.08
My friends and family think that car expresses a better social status than using public transport	2.27	1.65	0.31*
My friends and family travel frequently by bicycle and they think it is cool	2.01	1.32	0.36**

My friends and family travel frequently by public transport because they think it is convenient	3.84	3.30	0.14
My friends and family travel frequently by public transport because they think it is affordable	2.87	3.12	-0.16
My friends and family think that public transport expresses a better social status than using the bicycle	1.36	1.27	0.12
My friends and family are personally taking action to slow climate change	3.17	2.46	0.16
People whose opinion I value advocate that everyone should take action to reduce climate change	4.80	2.82	0.65**
My friends and family would support me if I decided to change my behavior in order to reduce climate change	4.71	4.08	0.24
It is not expected of me to change my behavior in order to help tackle climate change	2.86	2.93	0.11
I make an effort to change my behavior to reduce my impact on climate change	4.97	3.67	0.56**
If others don´t do their part it is indifferent if I do anything to slow climate change	2.27	2.34	0.22

** - p-value < 1%, * - p-value < 5%

For 19 of the 30 attitudinal statements it can be concluded that survey mode doesn't condition the answers. But respondents of the web-based survey seem to be more aware and concerned about transportation policy issues and transportation environmental impacts. These results point to the existence of self-selection from the web-survey respondents, since these were part of a panel of people who volunteered before to answer research related transport surveys.

A confirmatory factor model followed by a multi-group analysis were then made, based on an exploratory factor analysis of the face-to-face and web-based surveys for which 3 factors showed some similarities between the combined sample (292 observations) analysis and both the face-to-face and web-based samples. The 3 factors, considered in the confirmatory factor model and presented in Table 3, were the following:

- A first factor that relates with the opinions and behaviors of the respondent social network as well a as relevant alters, named *Perceived social influence on climate change*
- A second factor about exercise and health habits and perceptions of mobility options on health - named *Health concerns*
- A third factor related with perceptions about the effects and support to change behavior – called *Behavioral change.*

The confirmatory factor analysis indicates that the model has a moderately good fit. Multi-group analysis shows that the same model estimated with the two subsamples is different both in terms of measurement weights and structural covariances. The model based on the web subsample has a better fit. An interesting result is that the factor *Perceived social influence on climate change* is the most similar one between both subsamples, since only one statement has measurement weights that are statistically different.

Table 3 Confirmatory factor and multi-group analysis

Measurement model

Statements		Factors	Global sample		Face to face survey sub-sample		Web survey sample		p-value equality of coef.
			Coef.	p-value	Coef.	p-value	Coef.	p-value	
I make an effort to change my behavior to reduce my impact on climate change	<	Perceived social influence on climate change	1.00		1.00		1.00		
My friends and family would support me if I decided to change my behavior in order to reduce climate change	<	Perceived social influence on climate change	1.00	0.00	0.96	0.00	1.44	0.00	0.00
People whose opinion I value advocate that everyone should take action to reduce climate change	<	Perceived social influence on climate change	1.55	0.00	1.59	0.00	1.58	0.00	0.51
My friends and family are personally taking action to slow climate change	<	Perceived social influence on climate change	1.15	0.00	1.33	0.00	1.35	0.00	0.43

My friends and family think that climate change is a real threat	<	Perceived social influence on climate change	1.04	0.00	1.06	0.00	1.08	0.00	0.34
I pay a lot of attention to ensure that my diet is healthy	<	Health Concerns	1.00		1.00		1.00		
Keeping myself fit even if it takes some extra effort is very important	<	Health Concerns	1.72	0.00	1.41	0.00	2.06	0.00	0.00
Keeping myself in good health all year round is very important	<	Health Concerns	1.25	0.00	1.41	0.00	0.89	0.00	0.00
Cycling and walking regularly help reducing weight	<	Health Concerns	1.15	0.00	1.38	0.00	0.69	0.00	0.00
Cycling and walking have strong health benefits and are good for the environment	<	Health Concerns	1.17	0.00	1.37	0.00	0.72	0.00	0.00
If others don´t do their part it is indifferent if I do anything to slow climate change	<	Behavioral change	1.00		1.00		1.00		
It is not expected of me to change my behavior in order to help tackle climate change	<	Behavioral change	1.88	0.00	1.80	0.00	1.44	0.18	0.00
My friends and family would support me if I decided to change my behavior in order to reduce climate change	<	Behavioral change	1.00	0.00	1.29	0.00	0.15	0.69	0.00
Covariances									
Perceived social influence on climate change	<	Health Concerns	0.41	0.00	0.35	0.00	0.10	0.10	0.00
Perceived social influence on climate change	<	Behavioral change	0.22	0.04	0.24	0.13	0.23	0.15	0.71

Goodness of fit indicators			
Sample Size	292	146	146
Chi-squared	176.43	152.34	109.56
Degrees of freedom	51	51	51
Chi-squared/Degrees of freedom	3.46	2.99	2.15
GFI	0.91	0.85	0.88
AGFI	0.86	0.78	0.82
RMR	0.19	0.42	0.22
RMSEA	0.09	0.12	0.09
NFI	0.87	0.86	0.76
CFI	0.90	0.85	0.85
PGFI	0.59	0.56	0.58
PNFI	0.67	0.67	0.58

Multi-group analysis (comparison between the web-based and face-to-face surveys), assuming the unconstrained model to be correct

	Df	Chi-square	p-value
Measurement weights	10	39.90	0.00
Structural covariances	10	99.96	0.00

3.3. Differences in the effect of the CO_2 and calories information on commuting mode choices across the surveys

The final step in this analysis consisted in the estimation of logit models to assess the specific effect of information about CO_2 emissions and calories consumed on mode choice. Multinomial and mixed logit specifications were estimated, for the cleaned global sample (369 respondents), which served as the baseline model. This model specification was later applied to the face-to-face (240 respondents) and web-based (129 respondents) subsamples. Several specifications were tested both for the multinomial and mixed models (including different combinations of random parameters, number of draws and distributions). The results, presented in Table 4 for the global model show that the coefficients for the travel time and cost, as well as for the socioeconomic variables present the expected signs. The models for the face-to-face sample are in general in accordance with the model for the global sample, but with a better fit. On the contrary, the model based on the web- survey, presents much different results with some coefficients (e.g. travel cost) with a sign different from what would be expected. Also, in this case the mixed logit

model is not preferred to the multinomial logit model, since the random parameter is not statistically significant. These results point to a strong possibility of survey disengagement and irrationality in the SP answers within the web-respondents (see Petrik et al (2016) for more on a similar conclusion). Therefore, the following interpretation of the model coefficients will be based on the face-to-face survey, and particularly in the mixed logit specification. The implied value of travel time for a household with 1,500 € of monthly income is 13.05 €/hour which is reasonable and with comparable magnitudes of the values found by Choudhury et al. (2017) for commuters in the LMA.

The coefficients for both CO_2 emissions and consumed calories are significant (mixed logit specification) but the signs of the CO_2 coefficients are positive, indicating that the choices tend to be in favor of faster modes, which are the ones associated with more emissions. This is corroborated by an assessment of the relevance and relative importance of different attributes (Table 5) made by the respondents after answering the SP component. Travel time is reported as being the most important attribute, and CO_2 emissions information is considered to be the most important attribute by less than 5% of the face-to-face respondents. The effect of the consumed calories is positive and statistically significant, indicating that respondents (face-to-face survey) value the individual benefits obtained by a more active travel behavior. Comparing the rescaled coefficients for the attributes related with the calories consumed, it is possible to see that the ratio between the weekly calories and trip calories is favorable to the former (with a value of 1.2 in the case of the mixed model for the face-to-face survey). On the contrary, the corresponding ratio between the running time equivalent and the trip consumed calories doesn't indicate a stronger effect for the former (rescaled coefficients ratio 0.92). Hence, the value of the coefficients suggests a positive effect related with framing in terms of scale (presenting values for longer periods, which are necessarily bigger having a stronger effect on individual choices). On the contrary providing information in a more emotional format doesn't appear to be more efficient.

Table 4 Multinomial and mixed mode choice model estimation results

	Global sample				Face to face				Web			
Model parameters	Multinomial coef		Mixed coef		Multinomial Coef		Mixed coef		Multinomial coef		Mixed coef	
Travel time	-0.04	***	-0.05	***	-0.05	***	-0.08	***	-0.04	***	-0.04	***
Travel cost	-0.16	**	-0.19	**	-0.47	***	-0.56	***	0.32	*	0.32	*
CO2/trip	0.59	***	0.64	***	1.07	***	1.21	***	0.47	***	0.47	***
CO2/month	0.02	***	0.02	***	0.02	***	0.03	***	0.01	***	0.01	***
CO2/year	0.00	***	0.00	***	0.00	***	0.00	***	0.00	***	0.00	***
CO2/year Trees eq.	0.04	***	0.04	***	0.06	***	0.06	***	0.03	***	0.03	***
% CO2/year	1.91	***	2.04	***	2.87	***	3.18	***	1.59	***	1.59	***
Kcal/trip	1.2E-04	*	1.9E-04	***	1.9E-04	*	3.1E-04	***	1.8E-04	*	1.8E-04	*
Kcal/week	1.3E-05	**	1.9E-05	***	2.5E-05	**	3.7E-05	***	1.3E-05		1.3E-05	
Kcal/week run min. eq.	3.8E-04	*	3.5E-04		4.5E-04		8.1E-04	***	2.3E-04		2.3E-04	
car as a driver												
Commute trip subsidized	0.44	**	0.45	**	1.30	***	1.34	***	-2.23	***	-2.23	***
Inertia_RP	1.42	***	1.38	***	1.47	***	1.37	***	0.82	***	0.82	***
Gender male	-0.23	*	-0.25	**	0.07		0.03		-0.92	***	-0.92	***
Gym subscription	-0.67	***	-0.71	***	-0.58	***	-0.65	***	-0.62	***	-0.62	***
Carpool												
Inertia_RP	1.97	***	2.02	***	1.86	***	1.99	***	2.83	***	2.83	***
Public transport												
Inertia_RP	1.20	***	1.28	***	1.02	***	1.24	***	1.54	***	1.54	***
Walking												
Inertia_RP			0.87	***	1.12	***	1.39	***	0.48	*	0.48	*
Exercises 4 hours + Bicycle	1.07	***	1.13	***	0.92	**	1.03	**	1.73	***	1.73	***
Exercises 4 hours +	0.91	***	1.03	***	1.53	***	1.76	***	-99.23		-49.23	***
Random parameters			0.02			***	0.04				0.00	
Fit indicators												
Nº observations	3293		3293		2136		2136		1157		1157	
Log Likelihood	-2313.54		-2307.02		-1317.09		-1300.64		-891.61		-891.61	

Log Likelihood (constant only model)	-2951.04	-2951.04	-1722.85	-1722.85	-1144.67	-1144.67
# parameters	19.00	20.00	19.00	20.00	19.00	20.00
Adj rho^2	0.21	0.21	0.22	0.23	0.20	0.20

*** - p-value < 1%, ** - p-value < 5%, * - p-value < 10%

Table 5 Perceived relevance of the different attributes

Most relevant attribute	Face-to-face survey	Web-based survey
Travel time	62.3%	57.5%
Travel cost	21.9%	20.5%
CO2 emissions	4.8%	11.6%
Kcal	8.2%	6.2%
No response	2.7%	4.1%
Chi-square test (p-value)		(0.17)
% CO_2 relevant	36.3%	60.3%
Chi-square test (p-value)		(0.00)
% Kcal relevant	28.8%	32.9%
Chi-square test (p-value)		(0.40)

3. Conclusions

Looking at our main results we conclude that several differences on the distribution of answers in attitudinal questions could be ascribed to differences in the socioeconomic characteristics of both samples, particularly education levels and professional occupation. Nevertheless, it is likely that self-selection exists in the web-based sample, implying that respondents are more motivated and more concerned about transport policy and transportation environmental impacts, when compared with other individuals with similar socioeconomic characteristics. But at the same time these respondents appear to give signs of disengagement in the stated preference component, as evidenced by the SP logit model results for the web-based subsample. These results point to the relevance of using interviewers in stated preference surveys and the risks associated with self-completion of this type of surveys. The logit model results indicate that information about CO_2 appears to be ineffective to guide the choice of commuting modes, but respondents appear to value the health benefits of a more active commuting choice. These results contradict the findings of Gaker & Walker (2013) who found negative coefficients for CO_2 emissions and positive for calories consumption. Our results also point to the existence of framing effects relative to the information on calories consumption, but conveying information in a more emotional format appears to not being more effective.

Our results have several limitations, some of which could be addressed in future work with the same database and others would imply more data collection activities. Sample sizes in both subsamples could preferably be larger and more aligned in terms of sociodemographic attributes other than age and gender distributions, although this would only be possible with more resources. Also the use of different methods to disseminate the web-based survey, other than the used mailing list, could reduce the potential self-selection bias. Regarding the logit model results, these could be improved (at least in their robustness) by testing more sophisticated specifications, including hybrid choice formulations, to explicitly account for attitudinal constructs, and latent class formulations, to take into consideration different decision rules. Other way to improve the models will be to specifically look for irrational answers and eliminate them from the sample, particularly in the case of the web-based sample.

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