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Modeling travel mode choice under social influence for the brazilian context

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ABSTRACT
This study aims to define a behavioral model to verify whether there is social influence on the travel mode choice made in the Brazilian context. To achieve this goal, a survey was carried out at the Darcy Ribeiro campus of the University of Brasilia, via which travel and social data were collected, and which were analyzed by a multinomial logit model. The results of the research reveal that there is social influence on the travel mode choice made by the students commuting to the University of Brasilia, especially when considering sustainable modes (biking and walking) and carpooling: the odds of an *ego* using a sustainable mode are 76% higher if there is an increase of 10% in the proportion of *alters* who use sustainable modes. The odds of an *ego* carpooling are 27% higher when their *alter*'s carpooling increases by 10%. Knowledge of social influence allows a better perception of relevant factors for the decision-making process. Smart urban mobility policies must consider this perspective, especially those policies that aim to promote sustainable and shared travel modes as alternatives to high levels of automobile use.

RESUMO
Busca-se neste trabalho a definição de um modelo comportamental para verificar a existência da influência social na escolha do modo de viagem no contexto brasileiro. Para isso, realizou-se uma pesquisa no campus Darcy Ribeiro da Universidade de Brasília (UnB) com coleta e modelagem logit multinomial de dados sociais e de viagem. Verificou-se, como resultado, a existência da influência social por conformidade na escolha do modo de viagem para a universidade quando se consideram os modos sustentáveis (bicicleta e caminhada) e a carona: a probabilidade de um indivíduo utilizar modos sustentáveis em detrimento do automóvel é 76% maior quando a quantidade de contatos sociais usuários destes modos aumenta em 10%. Para a carona este aumento é de 27%. A consideração da influência social permite a percepção mais abrangente dos fatores relevantes no processo decisório individual, sendo referência para a formulação de políticas públicas de mobilidade, com destaque para aquelas que buscam promover alternativas sustentáveis e compartilhadas.

1. INTRODUCTION

Social aspects are a powerful issue as regards travel behavior research and, in the last decade, it has been a constant on the research agenda (Axhausen, 2008). When trying to understand how the characteristics of an individual's social network influence their transportation choices, this approach is added to other approaches of the travel behavior research for a better understanding of urban trips. Therefore, we have more elements for planning urban mobility policies focused on the concepts of "smart cities".

Traditionally, travel behavior research considers, in addition to an individual's personal, psychosocial, sociodemographic and household characteristics, spatial and temporal constraints imposed by the urban environment on the individual's daily schedule (Hackney and Marchal, 2011; Takano, 2018). When someone is considered to be in your social network, another dimension is included in the urban trip phenomena. There is a shift from understanding "where people are going", "when people are going" and "what activities people are doing" towards "who they are interacting with" (Dubernet and Axhausen, 2015; Ronald *et al.*, 2012; Hackney and Marchal, 2011; Carrasco and Miller, 2009; Axhausen, 2008).

One of the perspectives allowed in this field is social influence. Through their social network, it is possible to evaluate how (and whether) an individual's decision-making process is influenced by the behavior of others with whom they maintain a relationship (their social contacts called *alters*). Social influence occurs by conformity when individuals attempt to match the behavior of others, and compliance, when individuals adjust their behavior to fit the commands, advice, and social norms, prevailing in the group (Maness *et al*., 2015).

Among the existing travel decision-making processes, there is the travel mode choice, which is the object of our research. Travel mode choices are important (Ortúzar and Willumsen, 2008) because current travel behavior research aims at elements that allow individuals to make sustainable trips, cycling or walking, by public transportation, or sharable modes, *e.g.* carpooling (rideshare). Thus, the aim is to reduce dependence on automobiles (Okushima, 2015; Long *et al*., 2015; Feitosa, 2018).

There are consolidated researches that discuss the social influence on an individual's travel mode choice (Vinayak *et al*., 2018; Krueger *et al*., 2018; Feygin and Pozdnoukhov 2018; Lin *et al*., 2018; Marek, 2018; Pike and Lubell, 2018). However, we do not see this topic being explored in travel behavior research in developing countries such as Brazil (Mota, 2019) that has high automobile and public transportation (which is inefficient in most cases) dependency rates (Mota *et al*., 2014). In addition to verifying the existence of social influence in the Brazilian context, we also understand that it is necessary to bring, to Brazilian research, the concept of considering Social Networks in Travel Behavior research. Therefore, the objective of this study is to develop a behavioral model to verify the existence of social influence on the travel mode choice within the Brazilian context.

In order to do this, we present a multinomial logit model created with travel and social data collected from a sample of users of the Darcy Ribeiro campus of the University of Brasilia (UnB), in the Federal District, Brazil. In the model, we included social influence, the individual's and the urban environment's characteristics as explanatory variables.

The following section presents a review of the literature on social networks and travel behavior. Section 3 describes the data sets and research methods used. Section 4 discusses the modeling results, and Section 5 presents an analysis and policy implications. In the last section, Section 6, there is a summary of the study results and guidelines for future research.

2. BACKGROUND

The theoretical framework of this study is mainly based on social networks and travel behavior. Despite the advances made in travel behavior research in the Brazilian context in recent years (Feitosa, 2018; Takano, 2018; Silva, 2013), the incorporation of social networks has not yet been seen (Mota, 2019).

A social network can be defined as a structure of relationships, in which individuals are represented by nodes (or vertices) and relationships between individuals by a link (or edges) (Carrasco and Miller, 2009; Carrasco *et al*., 2008). Nodes represent entities such as groups, organizations, nations, and people. Edges represent resource flows, dependence, cooperation, friendships, information, support, and competition (Carrasco *et al*., 2008; Wasserman and Faust, 2009).

Social networks are primarily studied in sociology and have applications in other fields. In general, social networking is used to understand how social structures facilitate or prevent behaviors and opportunities (Carrasco *et al*., 2008). Thus, social networks allow us to study how an individual's decision-making process is modified by other people's actions, behaviors, attitudes, and beliefs, as well as the individual's perception of other people's actions, behaviors, attitudes, and beliefs (Kim *et al*., 2017; Maness *et al*., 2015; Aronson *et al*., 2002).

Including social networks in travel behavior research allows three perspectives (Kim *et al*., 2017; Pike, 2015; Van Den Berg *et al*., 2013). The first perspective is the study of social activities-travel (Moore *et al*., 2013; Carrasco and Miller, 2006), which starts from the understanding that "individuals travel to socialize and to meet other people". In the second perspective, an individual's social network is understood as a social capital resource. Consequently, the more extensive an individual's social network is, the more transportation resources this individual will have access to (Shin, 2017). In the third one, social networks are a source of influence: people tend to behave the same way their social contacts do.

The third perspective allows the study of the transportation mode choice or other related travel choices, as, for example, choosing the place of residence (Li, 2018), departure time (Xiao and Lo, 2016), and shopping location (Han *et al.*, 2011). We use the social influence perspective in this study, which was mainly based on the research carried out by Susan Pike (Pike, 2014; Pike, 2015; Pike and Lubell, 2016; Pike and Lubell, 2018) and Maness *et al.* (2015).

Pike (2015) extensively studied social influence on transportation mode choices for university trips in Davis (USA). The main conclusion was the confirmation of social influence on the mode choice, mainly regarding the cycling mode. Wang *et al.* (2015), Sherwin *et al.* (2014), and Long *et al.* (2015) had similar results for cycling, and Morrison and Lawell (2016) for carpooling.

In the study by Maness *et al*. (2015), a broad review of the literature on social influence can be found, from which the "*Generalized behavioral conceptual model of social influence on transportation choices*" is proposed. This model assumes that an individual (n) makes choices according to a decision rule that depends on evaluating payoffs (P_{ni}), in which *i* is the alternative evaluated. The payoff function is as follows:

$$P_{ni} = \beta_i x_{ni} + \theta_i s_{ni}\big(G_n(w), m_{ni}(N), m^*{}_{ni}(N)\big) + \mu_i E_n + \varepsilon_{ni} \quad (1)$$

where

x_{ni}: personal characteristics of an individual *n* for alternative *i*.

$s_{ni}(\dots)$: social influence mechanisms for individual *n* for alternative *i* due to endogenous and contextual factors;

$G_n(w)$: individual *n*'s social contacts and the strength of these relationships, modeled through weighting function (w);

$m_{ni}(N)$: the population's compliance social influence sources on individual *n* for alternative *i*;

$m^{*}{}_{ni}(N)$: the population's conformity social influence sources on individual n for alternative i;

N: group with all individuals;

E_n: environmental factors on individual n;

ε_{ni}: unobserved effects on the individual for alternative i;

β_i, θ_i, μ_i : model parameters.

Personal characteristics (x_{ni}) and environmental factors are inherent to individuals. They are traditionally incorporated into behavioral transportation model choices (Takano, 2018; Silva, 2013). Social aspects are represented by the social mechanism function (s_{ni}) that relates social network characteristics (G_n), compliance $m_{ni}(N)$, and conformity $m^{*}_{ni}(N)$ social influence. Compliance social influence includes advice, commands, and norms that trigger specific behaviors from contextual social factors. Conformity social influence occurs via information obtained from social contacts and by observing other people's behavior.

In the existing literature, several different terms have been used to define compliance and conformity concepts, and they refer to the phenomenon in which individuals tend to mimic other people's behavior, either to adjust to the social norms in force in the group, to be accepted, or to maintain a positive self-image (Kim *et al.*, 2018; Aronson *et al.*, 2009). Among the terms used are spill-over effect, peer effect, social multiplier, bandwagon effect, imitation, contagion and herd behavior (Kim *et al*, 2018). In this study, social influence is called "conformity" and "compliance", following the classification found in Maness *et al.* (2015).

3. METHOD AND DATA

The method we used has two steps: travel and social data collection procedures and analysis procedures. We chose the University of Brasilia to carry out the research due to its convenience and because of the dependence its community has on automobiles and public transportation. The travel mode share of the university is: public transportation 53.1%; automobiles (driving alone) 24.6%; carpooling 11.5%; cycling and walking 7.6%; other modes 3.2% (Mota, 2019). Furthermore, the university is mostly a place of youth (every six months about 4,000 new students enroll in the university), where people in training are acquiring new habits and behaviors, which will be replicated in the future in the students' professional and family lives.

3.1. Data collection

Data were collected through an online survey that was applied to the community of UnB's Darcy Ribeiro campus. The campus has a population of 53,657 (DPO, 2018), including undergraduate and graduate students, professors, researchers, and employees. The survey was based on Pike (2015), Aruwajoye (2016), Silveira (2013), and on the Campus Travel Survey of the University of California, in Davis (Wei, 2018). More information about the survey can be found in Mota (2019).

Data were collected via a link that directed volunteer respondents to the survey. We sought answers from people from different departments, groups, and profiles. Therefore, the link was shared through Facebook in several groups linked to the university. We also publicized the link by randomly handing out pamphlets at strategic places at the university, such as the Central Library, the University Restaurant, and in classroom buildings. For our convenience, the survey was interrupted when the link reached a total of 955 accesses which resulted in 407 complete answers.

The social data were included in the survey through an egocentric approach (Pike, 2015; Van Den Berg *et al.*, 2013; Haustein *et al.*, 2009; Carrasco *et al.*, 2008; Wasserman and Faust, 2009;). This approach allows the sample collection of an individual's social network. The individual, called *ego*, shares information about their social contacts, called *alters*, and information on their relationships too (Kim *et al.*, 2017).

Seeking to facilitate the respondent's understanding, we chose to register information on the *alters* with whom the *ego* had interacted in the previous six months, as done by Pike (2015). Respondents could list five *alters*, at the most, to obtain their core reference group (Pike, 2015; Axhausen, 2008; Mota, 2019). The command was: "For this question, think about all the people who have been part of your social circle in the past six months; this includes people with whom you live, work, attend class, socialize, or participate in activities, etc. or people you speak with on the phone or the Internet. List the first names of the five contacts you have had the most frequent and regular interaction with over the past six months." For each *alter* the *ego* listed the travel mode for work/study, home location, time, and closeness of the relationship.

3.2. Survey Variables

Following the objective of the analysis, the dependent variable of the model was defined as the respondent's travel mode choice, a categorical variable. The options outlined were cars (driving alone); carpooling (rideshare); public transportation (buses and the subway); and a sustainable mode (walking and cycling).

The independent variables were divided into three groups, which are shown in Table 1. The first group consists of the variables that allow assessing social influence by conformity and compliance, respectively, the *alters*' travel mode choice ($m^*_{ni}(N)$), calculated as a percentage, and the agreement with statements that reflect social norms (compliance) ($m_{ni}(N)$). Other variables characterize the individual's social network $G_n(w)$.

Table 1 – Independent Variables

SOCIAL
Alter's Travel Mode Choice - conformity ($m^*_{ni}(N)$)
Social Norms - compliance ($m_{ni}(N)$)[a]
Social network Characteristics ($G_n(w)$) (Closeness and time of relationship, *ego-alter* home distance)
PERSONAL/HOUSEHOLD (x_{ni})
Attitudes[a]
Preferences[a]
Sociodemographic data (Gender, ethnicity, household income, location and type, age, number of adults, child, and cars in the household)
TRAVEL AND BUILT ENVIRONMENT (E_n)
Urban Density (inhabit./ha)
Mobility Resources available (*Carona Phone* use and bicycle sharing system use)
Travel Time
Travel Distance

[a] Statements described in Table 2.

The second independent variable group is the personal/household characteristics (x_{ni}), and the third group is the travel and built environment characteristics (E_n). Personal/household characteristics are sociodemographic characteristics, individual attitudes, and preferences. Characteristics of the built environment are external features to the individuals and represent the spatial and temporal constraints of the urban environment: urban form through urban density; the mobility resources available for the university community, the "*Carona Phone*" (Taco *et al.*, 2016) ride app and the bicycle sharing system; travel distance and time.

The urban density, travel distance, and vehicle ownership variables were not obtained directly from the survey. The density, measured by the number of inhabitants per hectare (inhabit./ha), was obtained for the Administrative Regions (Jatobá, 2017) and for the cities (IBGE, 2017) that make up Brasilia's Metropolitan Area (Mota *et al.*, 2014). We also used urban population density in an aggregated way for each region and city. The travel distance between the person's place of residence and the university was calculated in kilometers. To do this, we used Google Maps and considered the shortest route between the university and the region/city center where *ego* lives. Vehicle ownership was calculated considering the number of cars and people in each *ego*'s household (household motorization rate).

3.3. Analysis Procedures

After collecting the data, we started the data analysis. First, we did a sample characterization, an exploratory analysis of social influence on the travel mode choice and prepared the database for the modeling. For the exploratory analysis of social influence on the travel mode choice, we calculated the average percentage of the *alters*' mode choice for each *ego*'s mode reported. The preparation of the database consisted of the removal of all answers that would not be relevant to the model, either because they did not fit the research's delimitation or because they had incomplete answers. Answers from 350 respondents (*egos*) remained, and they shared information about 1,571 *alters*.

Then, we excluded some of the qualitative variables initially found in the survey answers. This procedure was necessary to avoid the estimation of infinite parameters, failure in convergence, or complete separation of data during the modeling (Field, 2018; Ortúzar and Willumsen, 2008). This may be due to the concentration of answers in some of the variable categories. On the whole, during the modeling, we observed that these problems did not occur for the variables that presented categories with more than 10% of the respondents. Thus, it was not possible to insert the following variables into the models: "Time it takes to make the trip", "Safety and Commuting at the time I prefer", shown in Table 2. It is important to emphasize that all qualitative variables were included in the model as three-level variables (low, medium and high), converted from the Likert scale. Hence, we reduced the concentration of answers on certain categories.

The correlation between quantitative variables was verified in order to detect possible collinearities between them. As expected, a strong correlation ($\rho = 0.81$, measured by Pearson's coefficient) was found between the variables "Distance between the campus and home" and "Travel Time". For modeling purposes, the distance between the campus and home was chosen rather than the travel time because it presents models with better significance values with regard to social influence. In Pike's research (2015), data are modeled from travel distance because distance is an important variable to define how social influence acts, as shown by Pike and Lubell (2018). Furthermore, choosing the distance variable can rule out possible errors that can be brought to the model, since, on average, cars, rides, bikes, and walking modes have similar travel times, but different distances.

Given the qualitative nature of the dependent variable in this research, the multiplicity of explanatory variables, the inferential interest, and the search for the dependency relationship between the variables, the multinomial logistic regression was selected. As a result, there is an alignment between this study and the research developed by Ji *et al.* (2018), Heinen (2016), Pike (2015), Takano (2010), among others.

3.3.1. Model and hypotheses

We created three multinomial logit models, which were linked to three hypotheses:

- Model 1: we verified the hypotheses "there is social influence on the travel mode choice for the Brazilian context". We created a base model of travel mode choices under social influence using the entire database.
- Model 2: we verified the hypotheses "social influence on the travel mode choice is not dependent on the social influence within the *ego*'s home". We created a travel mode choice model for *egos-alters* from different households, which only considered the social contacts that do not live in the same household as the respondent's (Pike and Lubell, 2016). "Excluding household members minimizes the overlap of and similarities in the choice environments of each *ego* and their social contact" (Pike and Lubell, 2016).
- Model 3: we verified the hypotheses "closeness of the *ego-alter* relationship affects the social influence dimension on the travel mode choice". We created a travel mode choice and social influence model by weighing the *ego*'s network data by social link strength. We expect that the closest social contacts will have a greater influence on the travel mode choice.

4. RESULTS

4.1. Sample Characterization and Exploratory Analysis

Among the 407 respondents (called *egos*), 334 (82%) were undergraduate students, 56 (14%) graduate students, 4 (1%) professors/researchers, 13 (3%) administrative and other technical staff. Their gender and ethnicity are detailed in (Mota, 2019) and were compatible with other studies done on campus (DPO, 2018; Aruwajoye, 2016; Silveira, 2013). A predominantly young sample was obtained (the mean was 23.6 years of age) and the average per capita monthly family income was R$ 2,298.77.

Regarding the mobility resources available on campus, we discovered that 31% of the sample had already used the shared bike system. The "*Carona Phone*", a ride app, was used by 4% of those in the sample, but the app was unknown to 51% of the respondents. Concerning the attitude and preference indicators, shown in Table 2, it became clear that, in general, the respondents consider travel times, safety and perceived control (the independence to commute whenever they want to) to be extremely/very important. Perceived control is linked to individual transportation, bicycle users and pedestrians. As for preference, we found out that the sample agrees with the statement "travel time is wasted time", with a high willingness to ride a bicycle and a low willingness to use public transportation.

For the exploratory analysis of social influence on the choice of the travel mode, we obtained Table 3. We discovered that *ego* users of sustainable modes are those with the highest proportion of social contacts (*alters*) who use sustainable modes.

Table 2 – Frequency of answers to Compliance, Attitudes, and Preferences

COMPLIANCE					
Statement	Extremely important	Very important	Indifferent	Of little importance	Not important
The opinion of people I know	15 (3.7)	53 (13)	114 (28)	69 (17)	156 (38.3)
Things I learn on the news or other sources	31 (7.6)	77 (18.9)	118 (29)	74 (18.2)	107 (26.3)
Using the same means of transportation as other people I know	22 (5.4)	42 (10.3)	89 (21.9)	78 (19.2)	176 (43.2)
Information about transportation I learn from people I know	42 (10.3)	120 (29.5)	95 (23.3)	79 (19.4)	71 (17.4)
Getting to school or to work with others (by any means of transportation)	36 (8.8)	59 (14.5)	110 (27)	80 (19.7)	122 (30)
Using a means of transportation that is socially acceptable	30 (7.4)	49 (12)	86 (21.1)	74 (18.2)	168 (41.3)
ATTITUDES					
Statement	Extremely important	Very important	Indifferent	Of little importance	Not important
Time it takes to make the trip*	236 (58)	119 (29.2)	30 (7.4)	12 (2.9)	10 (2.5)
Safety*	214 (52.6)	126 (31)	40 (9.8)	17 (4.2)	10 (2.5)
Environmental Impacts	74 (18.2)	110 (27)	120 (29.5)	59 (14.5)	44 (10.8)
Transportation Costs	193 (47.4)	89 (21.9)	58 (14.3)	25 (6.1)	42 (10.3)
Getting physical exercise during my commute	27 (6.6)	52 (12.8)	103 (25.3)	83 (20.4)	142 (34.9)
The cost of owning a car or other vehicles	166 (40.8)	113 (27.8)	64 (15.7)	34 (8.4)	30 (7.4)
Commuting at the time I prefer (perceived control - time)*	208 (51.1)	131 (32.2)	32 (7.9)	17 (4.2)	19 (4.7)
Going other places before, during or after work (perceived control - trip chaining)	159 (39.1)	125 (30.7)	63 (15.5)	37 (9.1)	23 (5.7)
Comfort	113 (27.8)	151 (37.1)	92 (22.6)	36 (8.8)	15 (3.7)
PREFERENCES					
Statement	Strongly agree	Agree	Indifferent	Disagree	Strongly disagree
I like cycling	150 (36.9)	86 (21.1)	84 (20.6)	39 (9.6)	48 (11.8)
I like using transportation	49 (12)	94 (23.1)	77 (18.9)	67 (16.5)	120 (29.5)
I need a car to do my activities	109 (26.8)	83 (20.4)	67 (16.5)	58 (14.3)	90 (22.1)
Travel time is wasted time	198 (48.6)	112 (27.5)	42 (10.3)	36 (8.8)	19 (4.7)

Number of respondents and (percentage); N = 407; * variables not inserted in the model

Table 3 – Exploratory analysis of conformity social influence

Ego's Mode Choice	Average Percentage of *Alters*' Mode Choice			
	Carpooling	Driving alone	Sustainable	Public transportation
Carpooling (N=40)	**30%**	26%	3%	39%
Driving alone (N=91)	16%	**49%**	4%	28%
Sustainable (N=27)	4%	35%	**27%**	32%
Public transportation (N=192)	10%	27%	2%	**57%**

4.2. Modeling

Model 1 consists of the base modeling and was designed to verify the existence or not of social influence on the transportation mode choice in the sample. To do this, after the database preparation procedures, all respondents' answers were considered, with a sample of 350 *egos* (respondents) and 1,571 *alters* (respondents' social contacts).

The dependent variable was the travel mode choice, with the alternatives: carpooling, sustainable mode (bikes and walking), public transportation and individual cars, which was used as a basis for comparison. It is worth mentioning that the stepwise-forward criterion for selecting variables was used in the modeling through the "Likelihood Ratio" statistic. Hence, it was possible to obtain the model presented in Table 4, which best suited (Field, 2018) the data collected.

Table 4 also shows Model 2. Model 3 was not significant for social influence and, therefore, it is not presented here. Additional information about the models can be found in Mota (2019).

Regarding social influence, in Model 1, we found out that at a significance level of up to 0.05, social influence by conformity in the sustainable mode (*p*-value = 0.041) and in carpooling (*p*-

value = 0.036) was significant (Table 4). The variables of social influence measurement by compliance were not selected in the stepwise-forward procedure. The variable social influence by conformity for public transportation and individual automobile did not improve the likelihood ratio of the model, so it was not considered.

Table 4 – Frequency of answers to Compliance, Attitudes, and Preferences

Variables	Model Parameters (B)[a]					
	Model 1 (N=350)			Model 2 (N=340)		
	Carpooling	Sustainable	Public transportation	Carpooling	Sustainable	Public transportation
Intercept	3.826**	0.428	3.484***	3.252*	4.532*	3.642**
Proportion of *alters* users of sustainable modes (%)	0.008	0.056**	-0.019	0.638	3.691	-3.063
Proportion of *alters* users of carpooling (%)	0.024**	-0.056**	-0.017	2.526**	-5.977*	-2.241*
Household motorization rate (car/person)	-2.587***	-7.061***	-5.445***	-2.418***	-7.692***	-5.135***
Travel distance (km)	-0.011	-0.181**	0.064**	-0.012	-0.181**	0.065**
Urban pop. density (inhabit./ha)	0.013**	0.022*	0.013**	0.013**	0.021*	0.014**
Age (years)	-0.194***	0.003	-0.101***	-0.186***	-0.007	-0.1***
Shared bicycle system						
already used	0.227	2.466**	0.483	-	-	-
never used[b]						
Comfort *not important*	2.717**	1.879	2.721**	2.925**	3.236*	3.131**
moderately importante	0.084	-0.215	1.42**	0.333	0.342	1.726**
very important[b]						
Needing the car for daily activities *not important*	1.847***	3.86***	2.874***	1.755**	3.094***	2.694***
moderately important	1.078	2.649*	1.368**	1.182	1.753	1.576**
very important[b]						
Public transportation costs *not important*	-1.461**	-3.445	-3.766***	-1.482**	-3.945**	-3.617***
moderately important	0.228	0.548	-0.572	0.225	0.169	-0.401
very important[b]						
Doing physical exercises during travel *not important*	-	-	-	0.236	-3.17***	-1.011
moderately important	-	-	-	0.217	-1.823*	-0.454
very important[b]						
a. Base alternative is an automobile (driving alone)	Log likelihood*(-2): 354.037			Log likelihood *(-2): 337.311		
b. Base range	Qui-squared: 433.576			Qui-squared: 424.674		
*, ** and *** respectively mean a significance level of 0.100; 0.050 and 0.010	*p*-value 0.000 McFadden: 0.550			*p*-value 0.000 McFadden: 0.557		

5. ANALYSIS OF RESULTS

5.1. Model 1

From Model 1 (Table 4), it can be stated that an *ego*, who has a higher percentage of *alters* using a sustainable mode, is more likely to use a sustainable mode than an individual automobile (B > 0). Considering that the proportion of contacts that chose a certain mode was given as a percentage and keeping the other variables constant, it can be said, from Equation 2 obtained from Model 1, that: a variation of 10 percentage points in the number of *alters* that use a sustainable mode increases the chance of an *ego* using a sustainable mode and not using their own car by 76%.

$$\frac{P_s}{P_a} = 0{,}0203\mathrm{e}^{0{,}0564 a_s} \tag{2}$$

where $\frac{P_s}{P_a}$: odds ratio of sustainable mode choice (s) over individual automobiles (a);

a_s: proportion of *alters* that use sustainable modes (%).

Evidence of the existence of conformity social influence on the travel mode choice at the University of Brasilia was like Pike's (2015) findings at the University of California highlighting the use of bicycles. Other studies have found congruous results: Wang *et al.* (2015) used a spatial probit model to assess the social influence on bicycle use in a university community in the United States, concluding that "the more cyclists there are, the more people will become cyclists". Cyclists' social influence was demonstrated by Sherwin *et al.* (2014) through qualitative research in England and by Long *et al.* (2015) in New Zealand.

As regards carpooling, we found an increase in the probability of carpooling (B > 0) in relation to the use of individual cars when the number of *alters* who carpool increases. Considering that the proportion of social contacts that choose a mode was given as a percentage and keeping the other variables constant, it can be said, from Equation 3 obtained from Model 1, that: a variation of 10 percentage points in the number of *alters* who carpool increases the probability of an *ego* carpooling by 27% over the use of individual cars.

$$\frac{P_c}{P_a} = 0{,}0293\mathrm{e}^{0{,}0240 a_c} \quad (3)$$

where $\frac{P_c}{P_a}$: odds ratio of the carpooling mode choice (s) over individual automobiles (a);

a_c: proportion of *alters* that carpool (%).

Carpooling was not a research object for Pike (2015), but it was considered by other authors. Morrison and Lawell (2016) demonstrated social influence by conformity in the decision of carpooling for military work trips. The main conclusion reached by the authors was that a 10% increase in the number of colleagues who carpool increases by 5.14% the probability of an *ego* carpooling. We observed that the influence measured by the authors was lower than the proportion of 10% to 27% found in the community sample of the University of Brasilia. This may be evidence of a higher tendency of the researched student groups to carpool by social influence since they are younger than the ones in the Morrison and Lawell (2016) sample.

Other variables included in the model that, along with social influence, were significant are Household Motorization Rate, Urban Density, Age, Travel Distance, Shared Bike System Use and Behavioral Variables. We discovered that choosing to carpool was related to lower importance given to comfort, lower household motorization rates, and higher urban densities. These results can be related to research done by Kowal *et al.* (2013), which demonstrates that places where car use is lower and regions with higher density positively influence the number of social contacts that an individual has. Since the individual has a wider network of contacts, they will have more access to transportation resources such as rideshare (Shin, 2017). This phenomenon does not consist of social influence but can be explained by the social capital aspect. Higher urban population densities may also be related to the shorter distances and travel time individuals need to deviate from their route to give a passenger a ride, or for the passenger to get to a driver. These are key issues for the success of carpooling (Silveira, 2013; Silveira *et al*. 2014).

Regarding public transportation, we found out that families with lower motorization rates, households located in denser areas, younger people, who attribute low importance to comfort, who report having little need for a car to carry out their activities, and who give great importance to the cost of public transportation, were more likely to use public transportation than cars. These results are in line with the research done by Feitosa (2018), who researched the conscious and unconscious motivations for the use of individual transportation modes.

5.2. Model 2

Model 2 was designed to verify whether social influence on the travel mode choice is not dependent on the social influence within the *ego*'s home. This analysis was performed by Pike and Lubell (2016). To this end, we excluded 10 respondents from the database, the ones who had reported all contacts living in the same household, leaving 340 *egos*. We also excluded *alters* living in the same household as the respondent's, leaving us with information on 1,024 *alters*. By removing such social contacts, the proportion of *alters* who used each mode was recalculated for each *ego*.

As seen in Table 4, we observed that when contacts from the same household are excluded, the proportion of carpooling contacts remains a significant variable in the model at a level of 0.05. We may conclude that by increasing the percentage of social contacts who carpool, the likelihood of the *ego* carpooling rather than using their own car increases. Based on this, it can be said that social influence is different from social household influence, and exists between individuals from different households, which is similar to Pike and Lubell's (2016) findings.

The proportion of contacts who use sustainable modes was not significant (p-value > 0.05). This may have been caused by the decrease in the number of individuals in the database since the number of users of sustainable means was already restricted. It is important to mention that for Model 2, to obtain the best fit for the data, the variable "importance of exercising" was selected during the stepwise-forward method and the variable "shared bicycle use" was not selected.

5.3. Model 3

Model 3 was built to verify whether the strength of the *ego-alter* link (or closeness of the relationship) impacts the social influence dimension on the travel mode choice by evaluating the weight (w) of the function created by Maness et al. (2015). We tried to observe if people who are closer have greater social influence by conformity. Closeness of the relationship, obtained by using the egocentric approach, was classified into five levels ranging from very close to not close. Thus, social conformity, represented by the percentage of *alters* using each mode, was calculated using the weighting factor (w) given by the strength of the *ego-alter* link. We expect that the closest social contacts will have greater influence on the travel mode choice. In the model, it would be represented by the change in the model coefficients.

We found out that there was no significant change in the model. There was no variation in the model coefficient B for carpooling. For sustainable modes, despite the change in coefficient B, Model 3 had significance greater than 0.05 (p-value = 0.068). Therefore, the statement that link strength interferes with the social influence was inconclusive, which is why the parameters were not presented in Table 4.

Since the sample for this research was restricted, we recommend that future work should focus on researching the interference of social link strength on social influence. We also suggest that model comparisons be made from sample stratification, in which *alters* and *egos* with a closer relationship are considered in comparison with *alters* and *egos* with a weaker relationship.

5.4. Policy Implications

From a social perspective, the main contribution brought by this paper can be summarized in the so-called Reference Marketing, a term used in business to refer to the advertising of a product or service made by clients based on their own experiences with the product/service. Purchasing products can be analogous to the assimilation of behaviors, such as choosing a travel mode.

Thus, within the scope of mobility policies, one can think about the creation of tools that encourage an individual to share his “mobility experiences” in active and shared travel modes with his social contacts - such as cycling, walking and carpooling - precisely those that presented an inclination to social influence in this research. Sharing these experiences can be enhanced by using social media platforms such as Facebook, Twitter, and Instagram. An example is the event called “May is Bike Month”, mentioned by Pike (2015). The campaign used to increase bicycle commuting uses social tools such as “challenge a friend” and “share your accomplishments” to prompt friendly competition among participants as they log bike travel distances during the event.

Another mechanism may be giving discounts or prizes to individuals who purchase public transportation tickets jointly with others. Prizes and discounts can also be given to those who advertise to their social contacts the use of mobility resources such as ride apps, bike-sharing, and scooters.

As for the use of bicycles, considering that it was associated with shorter travel distances, government officials can invest in policies that promote their integration with other modes such as the subway and buses (Paiva, 2013). Such use can be further enhanced by seeking to invest in higher-density areas.

With regard to carpooling, one can think of promoting them to seek a more rational way of using vehicles (Silveira *et al*. 2014). Rideshare can be used for the whole trip, or also for accessing mass transportation points. However, to achieve this, it is necessary to think about the construction of parking lots at bus or subway access areas, thus reducing the number of vehicles circulating in the urban environment.

As for public transportation, the main result is the need to improve passenger comfort during their journeys. We also discovered that places with higher density increase the probability of people using it. Therefore, it is important to promote mobility policies jointly with urban planning ones.

Finally, it is important to create policies according to people’s ages and lifecycle stages. This idea is linked to the Target Marketing concept, which can be applied to travel behavior (He *et al*., 2016). As it is generally shown, younger people, who have no children and live with their parents, are more prone to carpooling, so it is necessary to create policies for young people, through universities and schools. On the other hand, older people already have the habit of using individual cars and have more restrictions, be them family- or work-related. So, specific policies for this target audience should be sought, such as corporate carpooling programs, which can be incentive instruments in companies by the government.

6. CONCLUSIONS

The main conclusion of this research is that the proposed objective was achieved. The behavioral model that adjusted to the data collected at UnB’s Darcy Ribeiro campus was defined and the existence of social influence on the travel mode choice when considering sustainable modes and carpooling was verified. There was no evidence of social influence on the use of cars and public transportation.

As for Models 2 and 3, we found out that social influence and social household influence are different. Due to the constraints of the research sample, it was not possible to verify if greater proximity in social relationships (close friends, people with strong emotional connections, among others) are associated with greater social influence.

Future papers will require a more extensive data collection, with greater participation of people using sustainable modes and carpooling. From a larger sample, the following research is recommended: to analyze social influence stratified by gender; to model social influence as a function of the travel distance, to limit the profiles of people who are more susceptible to social influence, according to their place of residence, as done by Pike and Lubell (2018); to verify the changes caused in the social influence due to the strength of the *ego-alter* link; to include other social norms (Krueger *et al.*, 2018), attitude and preference indicators; to consider possible endogeneities associated with discrete choice models that include social influence (Pike and Lubell, 2018; Maness *et al.*, 2015).

We recommend that other social data collection approaches be used rather than the egocentric one. By doing that, it will be possible to research social influence on travel mode choices by evaluating specific groups of people similar to what was done by Morrison and Lawell (2016), Kormos *et al.* (2015), or Sunitiyoso *et al.* (2011). This is the starting point for assessing social influence through dense networks or small-world networks.

Despite the limitations, the results obtained are considered satisfactory, as they have the potential to subsidize the creation of public policies for urban mobility. By considering social perspectives, a new dimension is added to the classic research on travel mode choices, which allows a greater understanding of the phenomenon of how people travel in urban areas, to guide urban mobility policies for more sustainable mobility.

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