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The Relevance of Urban Mobility For Consumer Research: an Interdisciplinary

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Consumer psychology research is said to have a narrow scope but consumer psychologists might extend it by studying urban mobility as a relevant topic of the Transformative Consumer Research. We show an example where decision trees and geo-spatial analyses stand for alternative ways for consumers classification based on their mobility patterns.

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EXTENDED ABSTRACT

How often people combine transportation means for commuting? Is this a relevant question for consumer research? According to Anderson et al. (2013) rethinking the ways transportation services are delivered and consumed in cities is a relevant topic for the consumer research movement known as "Transformative Consumer Research". Such topic entails the study of urban mobility which refers to how individuals move in their city, which in turn is closely related to transportation networks (Chen et al., 2017) and the transportation mode choice of individuals (Aarts, Verplanken, & van Knippenberg, 1997). Several factors affect this choice; from the physical ones related with distances from home to workplace (Gonzalez, Hidalgo, & Barabasi, 2008), to the economic ones related with the perceived advantages of commuting with bicycles (Jakovcevic, Franco, Dalla Pozza, & Ledesma, 2016) or motorcycles (Correa, 2017) rather than using other transportation means. Although urban mobility is an interdisciplinary catching topic, it has been neglected in consumer research, with few recent exceptions (Brembech, Hansson, Lalane, & Vayre, 2015).

More than a decade ago the average one-way commute in cities like Bogotá was 90 minutes (Gakenheimer, 1999) and recent reports indicate that this is worsening. The increasing vehicle sales is a consequence of both the economic growth and the social pressure of owning a car as an essential asset (Gakenheimer, 1999). Between 1995 and 2000 citizens of Bogotá faced several changes in their urban mobility. For instance, Montezuma (2005) described some of the achievements that were met by investing on road infrastructure, especially the implementation of paths reserved exclusively for bicycles, the revitalization of parks and sidewalks, and the implementation of the "Transmilenio" bus rapid transit system. Despite such achievements, the city of Bogotá is still facing problems in their urban mobility, specially when it comes to transforming its decentralized bus transit services into its integrated transit systems (Kash & Hidalgo, 2014). In order to achieve such a transformation, transportation planners must integrate the concerns of the community in the planning process which deals with identifying incompatibilities between users' self-identified needs and project goals. This is a complex task that is not tackled here. Instead, our aim in this paper is to show how consumer researchers in general and consumer psychologists in particular might contribute in this direction by analyzing urban mobility as a consumer behavioral choice under restriction (Botti et al., 2008).

URBAN MOBILITY AS A RELEVANT TOPIC FOR CONSUMER RESEARCH

According to Swait and Adamowicz (2001) most models of choice in economics and consumer research assume that people assess all alternatives in an almost perfect information-processing sense. These assumptions, however, are quite restrictive. In fact, the omission of more realistic assumptions relates to 1) the difficulty of including most of the real-world complexities in formal models and 2) the fact that the data used in economics and consumer research studies tend to be somewhat different from the data structures used in the literature. For instance, the complexity of the choice environment, understood as the number of transportation means required for commuting in a city remains neglected in transportation mode choice models (Aarts et al., 1997; Bamberg, Ajzen, & Schmidt, 2003).

One solution to the problem of modeling consumer's complex choices in urban mobility might be based on perspectives outside the realm of social sciences that are susceptible of being integrated in our approaches. This solution demands a re-orientation in doing consumer research, which has been criticized as one with narrow scope, lenses and epistemology (Pham, 2013). We propose an interdisciplinary approach that exploits the knowledge of more basic sciences like physics (Gonzalez et al., 2008), computer sciences (Giannotti et al., 2011) or geographical information sciences (Chen et al., 2017) to re-orient our endeavors. Let us illustrate. From the physical point of view, it is well-known that urban mobility can be described by the so-called "dispersal curves" (e.g. Gaussian distribution, Exponential distribution) which quantify the relative frequency of travel distances of individuals as a function of geographical distance (Brockmann, Hufnagel, & Geisel, 2006). A related metric, known as travel time uncertainty, is the most important or the second-most important factor for commuters' travel decision-making (Chen et al., 2017) which has been deemed as a type of choice under restriction (Botti et al., 2008).

The formal description of how humans move in a city can then be done in terms of diffusion equations on large spatiotemporal scales (e.g., at the scale of a whole city). In a similar vein, approaches of computer sciences regard human mobility as a complex pattern emerging from the detailed trajectories of tens of thousands private cars with on-board GPS receivers, tracked during weeks of ordinary mobile activity (Giannotti et al., 2011). The inclusion of some of these ideas are already available in psychological research dealing with decisions of drivers and motorcyclists while commuting on the road (Correa, 2016). However, approaches of this sort are very rare, perhaps because their methods have more to do with artificial intelligence rather than traditional methodologies employed in consumer research. In any case, the idea of adopting an interdisciplinary approach for studying urban mobility as a relevant topic for consumer research invites our disposition to rethink the variables we use to model consumers' choices as well as the tools and methods we employ for data analysis.

In highly dense Latin American cities such as Bogotá, Caracas or Mexico the use of several transportation means is the standard practice given the costs of commuting with only one transportation mode. As obvious as it is, the analysis of this fact has been ignored in consumer research. How people combine different transportation means for commuting from home to work and back? What other variables might serve as predictors of this behavior? These questions can be answered with spatial analyses and decision trees. Given the prominent role of distances in urban mobility the application of spatial analysis is well-suited. Spatial analysis deals with the "relationship between geographic reality and how that reality is captured in a digital database in the form of a data matrix containing both attribute data and data on locations" (Haining, 2003, p. xv). Here the use of geographic coordinates to identify the exact locations of specific points within cities is a key ingredient in the analysis. The use of these coordinates can be integrated into the decision tree analysis. According to Rokach and Maimon (2014) a decision tree can be understood as a classifier or regression model. When they are used for classification purposes, it is more appropriately referred to as a classification tree and when they are employed for regression tasks, it is known as regression tree. The key difference between the former and the later relates to the nature of the target or dependent variable (i.e., classification trees are applied for nominal or categorical variables, while regression trees are applied for continuous variables). Trees work as a recursive partition of the instance space (the dependent variable). Its nodes form a rooted tree with a "root" node that has no incoming edges. Other nodes have exactly one incoming edge. The "internal nodes" are those with outgoing edges. All other nodes are called "leaves", "terminal" or "decision" nodes. Each internal node splits the instance space into two or more sub-spaces according to a certain discrete function of independent variables. The simplest case is the one in which each test considers a single categorical attribute, such that the instance space is partitioned according to the attributes value. In the case of numeric attributes, the condition refers to a range of values. The researcher can also specify in advanced the minimum number of observations in a node as well as the decrease in the overall lack of fit that has to be met before attempting a new split for the tree. As an exploratory technique, decision trees are quite useful in indicating the most important predictors/classifiers for our target variables.

MATERIALS AND METHOD

A field survey was conducted to explore commute practices by inhabitants of Bogotá city and its surroundings. Subjects were asked to report the health program affiliation they belonged to, as well as their places of residence and work and its corresponding commute duration. Subjects were also asked to report their weekly frequency of using different transportation means in Bogotá including Uber services, public taxies, busses, private cars, Transmilenio, bicycles, motorcyles and/or walking. A total of 2,135 subjects participated in this study. The geographical coordinates for every reported place of residence and work were looked by using the geobatch geocode tool available at https://www.mapdevelopers.com/batch_geocode_tool.php. Unemployed participants as well as those who did not respond their home and work places were discarded from the spatial analysis which was conducted in R (R Core Team, 2016) with the aid of the ggmap package (Kahle & Wickham, 2013). The decision tree analysis for predicting travel times from other socio-economic variables collected in the survey was also conducted in the R environment with the aid of the rpart package (Therneau, Atkinson, & Ripley, 2015). The resulting sample after discarding missing values consisted of 2,130 subjects. The analysis that is present in this paper can be absolutely reproduced with an easy-to-use R script that we also developed for those interested in replicating the results. This script is available under request.

RESULTS

The regression decision tree (Figure 1A) revealed the health program affiliation type as the first criteria to predict commuters' travel time. Consumers can be split into those with a "contributive" health affiliation and those without it (subsidized or without health affiliation). People in this latter category are also split into those who have the main economic responsibility and those who do not. In contrast, people affiliated to a contributive health program can be split according to their workplace longitude location (inside Bogotá or not); sex and home latitude location (Bogotá or Northern Surroundings).

Figure 1B depicts the geographic distribution of commuters. By analyzing commuting practices, we noticed that the majority of citizens use at least five different transportation modes per travel (bubble size indicates the amount of different transportation means needed to travel in Bogotá city). Particularly, people living in southern localities such as Soacha, Tunjuelito and San Cristóbal (at the bottom of the map) tend to use at least four different transportation modes for each travel between home and work. Commuting time between home and work proved to be highly skewed ranging from virtually zero minutes (i.e., people who worked at their homes) to three hours (i.e., people living out of Bogotá). In general and regardless their health program affiliation, women's travel time is 13.38 minutes longer than men's one ($F = 58.32$; $p < 0.001$). Commuters' travel time proved to be mildly associated with their educational attainment, with longer times for people with higher levels of formal education ($r = 0.17$; $p \leq 0.01$). Commuters with the main economic responsibility for their families travel almost 14 minutes slower compared with those without this charge ($F = 61.26$; $p < 0.001$), but the association between socio-economic status and commuters' travel time proved to be almost zero and non-significant ($r = 0.04$; $p = 0.101$).

CONCLUDING REMARKS

The aim of this paper was to illustrate how consumer researchers in general and consumer psychologists in particular might contribute in urban planning tasks as interdisciplinary data analysts. Such a contribution has already been foreseen by previous consumer researchers involved in the "Transformative Consumer Research" movement (Anderson et al., 2013). The key idea of this paper was to advocate the benefits of exploiting the potential of data analytical tools that are not typically taught in courses of consumer research methods, but are more typical in other sciences like physics, geographic information sciences or computer sciences.

In particular, we showed the usefulness of obtaining and analyzing the geographic coordinates of consumers' homes and workplaces to classify them for eventual purposes of transformative consumer research (Anderson et al., 2013). Our results showed that people who work and pay for their own health program travel slower than those who do not completely pay their health program. As consumer researchers, the recognition of this mobility difference might be used for policy-making purposes, like planning suitable schedules for workers. Despite the fact that our focus was on mobility patterns of Bogotá, this approach is naturally extensible to other cities and countries. It is clear that our work, as consumer researchers, might be benefited from the use of these tools that urge us to collect data (i.e., geographic coordinates) not commonly known in our field. Perhaps a good leap to jump into this interdisciplinary approach might be facilitated with the use of data mining techniques already available in the Renvironment. The R script that we developed as a supplementary material for this paper might be handy for both interested researchers and students.

A final observation relates to the possibilities of using classifications of mobility patterns for advancing our knowledge of consumer choices under transportation restrictions (Botti et al., 2008). This is indeed a promising topic where consumer researchers might meet with colleagues of other fields to collaborate in interdisciplinary research projects committed to identify complex relationships between transportation and consumption.

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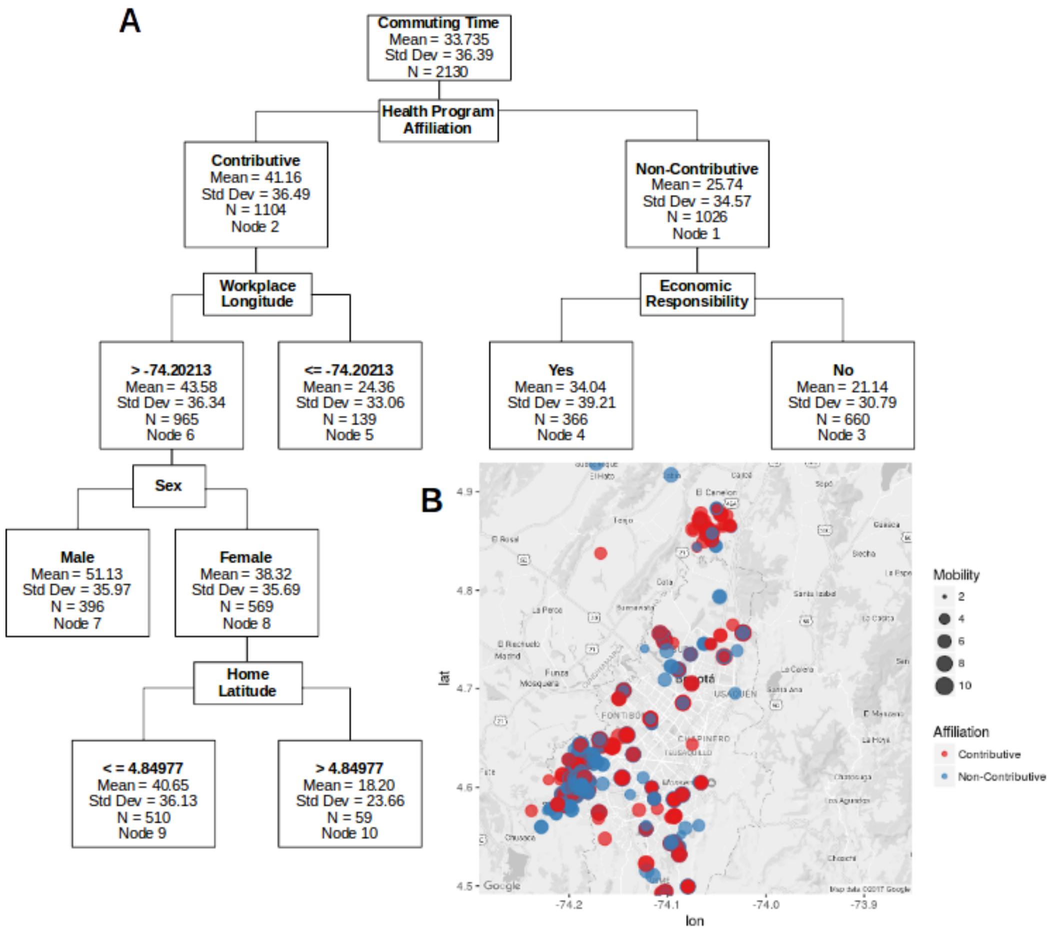

Figure 1. (A) Regression decision tree and (B) geographical distribution of Commuters

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