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Inner city versus urban periphery retailing: store relocation and shopping trip behaviours. Indications from Saint-Etienne

Sonagnon Hounwanou[1], Antonio Comi[2], Jesus Gonzalez – Feliu[1], Natacha Gondran[1]

[1] *Mines Saint-Etienne, Univ Lyon, Univ Jean Moulin, Univ Lumière, Univ Jean Monnet, ENTPE, INSA Lyon, ENS Lyon, CNRS, UMR 5600 EVS, Institut Henri Fayol, F - 42023 Saint-Etienne France*

[2] *University of Rome Tor Vergata, Department of Enterprise Engineering, Via del Politecnico, 00133 Rome, Italy*

Abstract

Many recent studies stress the importance of freight facility location for urban freight movement. Although, tools and reflections are still lacking to shed light on shopkeepers' location choices. Several reasons, e.g. the implementation of long-term city logistics measures or the threat of commercial rent increasing can lead retail-store keepers to move their business from city centre to surroundings. Therefore, it becomes critical for them as for urban policy makers to have tools for simulating or assessing the effects of such a choice on the business, and on the local economy, land-use and environment. This paper assumes that the shopkeepers' choices are mainly influenced by whether their customers accept or reject this move. It aims to forecast the choice of customers to remain or not client of a retail store after its relocation in the urban periphery, by predicting the most significant factors, which are likely to influence their decision. Starting from some surveys carried-out before the movement of an actual city centre store in Saint-Etienne, the paper suggests a conditional inference tree rather than other tree-structured models for this analysis. Over the peculiarities of the store and the city, the model estimated and tested in this paper underpins many findings available in the general literature about shopping trips. The results seem to be indicating that not only customers' residence, but also their shopping trip behaviours and wanderings are to be taken into account in a retail-store location decision.

Keywords: retailing, city center, urban periphery, store relocation, shopping trip, conditional inference tree

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1. Introduction

The utility of city center location of urban retail for urban revitalisation policies is well established. Nevertheless, in spite of the virtues recognized to such a commercial location, city-center retail stores can face several problems.

Several studies have already described the impacts of urban freight transport associated to the city center store restocking (Russo and Comi, 2016; 2017). In France, for example, pollutant emissions, noise and congestion caused by the circulation of trucks in town were indeed at the origin of the national program on Goods Transport ("*Marchandise en Ville*"), started in the nineties about the issue of goods' transport research (Dufour, 2000; Ripert, 2000; Routhier and Gonzalez-Feliu, 2013; Gonzalez-Feliu, 2018).

The issue of logistic sprawl is well documented inter alia by Dablanc and Rakotonarivo (2010), Dablanc and Andriankaja (2011) and Rakotonarivo-Andriankaja (2014). Logistic sprawl implies to move the traffic of delivery trucks away from city centers. It leads to the reduction of the city center inhabitants'exposure to pollutant emissions. This is undoubtedly a great advantage, but there also are many drawbacks, which deserve attention and warrant the analysis carried out in this paper.

First, a whole set of studies aimed thus at optimizing freight delivery to restock city center retail-stores from logistic platform in the urban peripheries close to the main highways (Gonzalez-Feliu, 2018). Nevertheless, the last consumers being located everywhere and not only in the inner city, has the situation remain complicated despite these freight flowed optimizations. Two possible reasons can be identified to explain this. The first is about the centrifugal residential mobility several European mid-sized cities are experiencing. Second, car-use reduction policies are being widespread in inner cities. This may prevent or hinder the city center' stores access to customers living the peri-urban areas, especially if the public transport connection is not enough efficient. Considering besides the rise of the costs in the city centers commercial real estate (Gasnier and Lestrade, 2014), some storekeepers can decide to move their store from city center and settle down in the periphery. Such movement may cause several disruptions in the city-center retailing, which becomes less competitive and less efficient in honoring its social and economic duties to the community. This is harmful to the city center blending and may lead to car traffic increase, if city center inhabitants decide to remain the moved store's clients as shown by Nuzzolo et al. (2014). To address more efficiently this issue, it seems thus critical to forecast the typology of customers that will potentially remain visiting a retail store after its relocation in the outskirts the city.

Second, both public decision-makers need to better anticipate and plan necessary actions for getting a sustainable freight mobility, which we assume, includes shopping trips. Therefore, predicting the profiles of the customers expected at the moved stores and their transport behaviours may help to plan relevant changes in transport system.

This paper is the first part of a set of research-works, which seize the opportunity of the move of an actual retail store from Saint-Etienne city-center to dig the issue, by developing a general methodology for investigating such a choice. The question addressed is whether the customers accept or reject this store relocation, and this paper aims to identify the main levers influencing their decision. Machine learning technics, which allow managing a large quantity of data, are used to identify the main predictors (Kuhn and Johnson, 2013) and then to select a first set of attributes useful for developing further behavioral models. For this purpose, conditional inference trees are preferred to other well-known decision trees and described in the methodology. After the data collection process, the available literature and the descriptive overview of the data frame obtained help to highlight the prediction of the tree-structured model developed and tested.

2. Data collection and description

This research is based on a specific case of an urban store selling culture and appliance goods and belonging to a well-known group in France. The store located in the city center of Saint-Etienne, decided to move and settle down in an existing shopping center in the urban periphery. This section presents first the data collection process and then provides a descriptive overview of the data obtained.

2. 1. Data collection

Knowing the future location of the store and the date of relocation, a face-to-face customer-based survey has been set up. The data-collection project planned was a double customer enquiry survey, one before and the second after the store move. The “before” survey presented in this section, carried-out in November 2016, was dedicated to collecting the statements about what type of client would remain the store’s customer or not. For two weeks, this face-to-face survey allowed to obtain 1022 filled in questionnaires among which 985 were usable. The clients surveyed were at the end of their visit to the store and on the brink of leaving. Except the details, the surveyors could get without asking, like those related to the date, the time-windows or the gender, the interview was made of twenty questions and lasted for almost five minutes. The data obtained were about the sociodemographic characteristics of the customers, their current trip-chains or wandering and their daily trips characteristics, their opinion about the store ‘relocation and their preference statements about remaining the store customer after the move.

The store having a tool dedicated to entrance counting, it was easy to compare the surveyed sample to the real entrance from Monday to Saturday during the surveying period (Figure 1). One of the main defaults of the data obtained is about the sample rate of the Tuesday, slightly too low, compared to the other days of the week. Moreover, some data collected seemed biased or incomplete, such as the time windows or the article purchased, and they were not finally involved in the analysis.

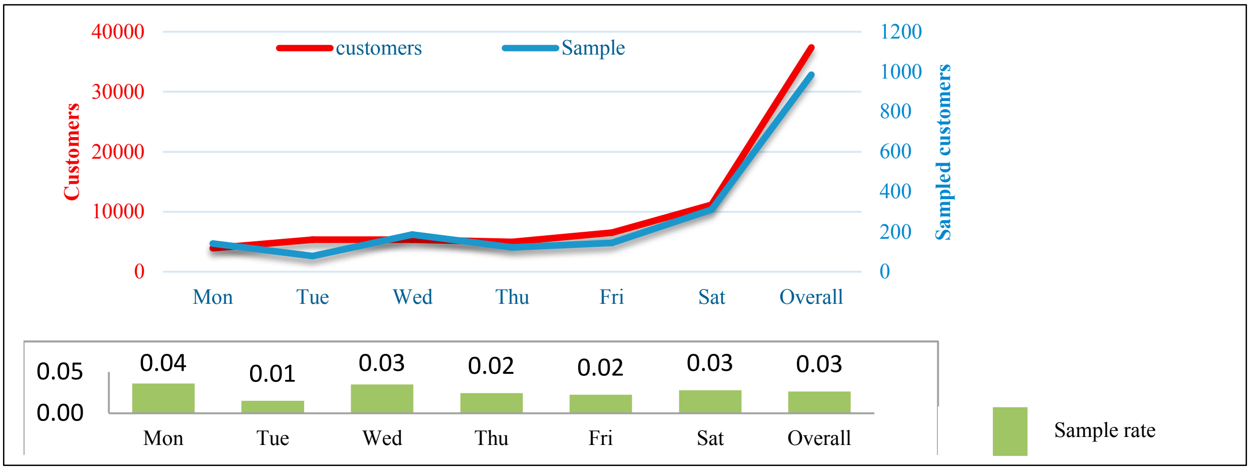

Figure 1: Sampling details

2. 2. Descriptive overview of the data frame

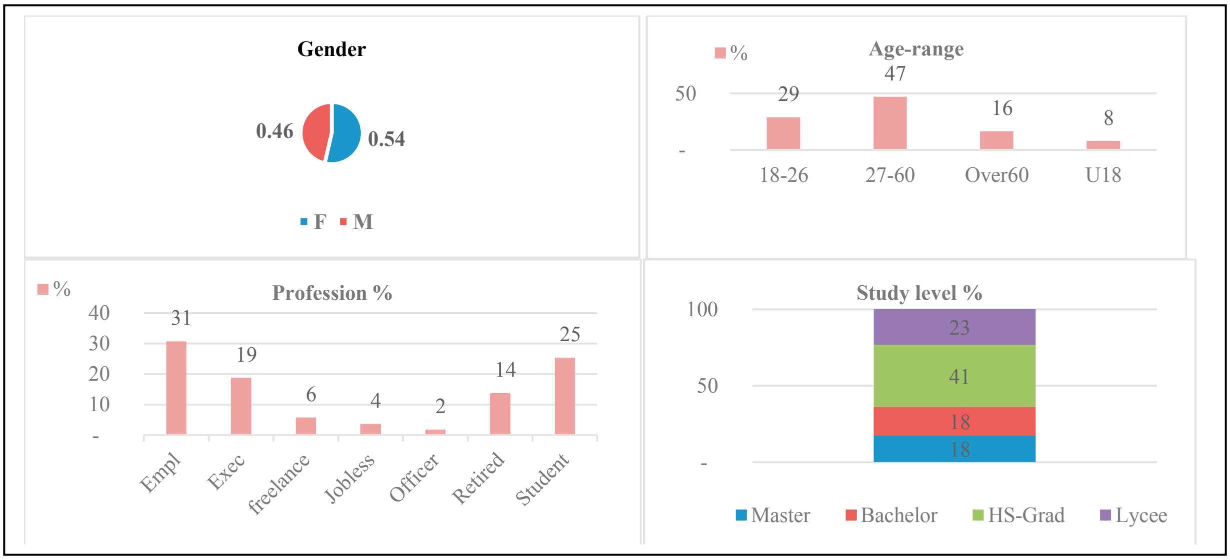

Figure2: The surveyed customers: socio-demography

According to the survey, there are slightly more women than men among the customers of the store. Most of them are employees, executives and students; unemployed, retired, freelance-workers and officers being put together, twenty-five percent of overall. The dominant age-range is the one of active persons (27 to 60), and customers under eighteen are less than ten percent (Figure2).

Customers living very close are frequent in the store, and those who live far use to come rather by quarter (Figure 3 –a), as do most of private-employees (“*Empl”)* and executives (“*Exec*”) on Figure3-b. The variable *Trip-chain* makes the link between the residence and the origin of the trip. Therefore, it provides insights on people living more than two kilometers far from the store and coming on foot: they are probably coming from another store or from work. *Figure 4- b* is thus showing that people coming from work (“*Resid-W- S”)* come rather on foot or tramway than by car. The use of the public transports increases with the distance until 5 km, and decreases beyond, and car-use increases with the distance covered obviously unlike coming on foot (Figure 4-a). The variable “Actual purchase” helps separate actual purchasers from the others. The trip characteristics can vary depending on this variable. Although overall customers come more often to purchase (60%), those living very close to the store in the city center mostly visit the store just for a walk, unlike customers living 10 km or farther(Figure 5-c). Moreover, actual purchasers come rather by car (Figure 5-a) and at most once per month (Figure5-b).

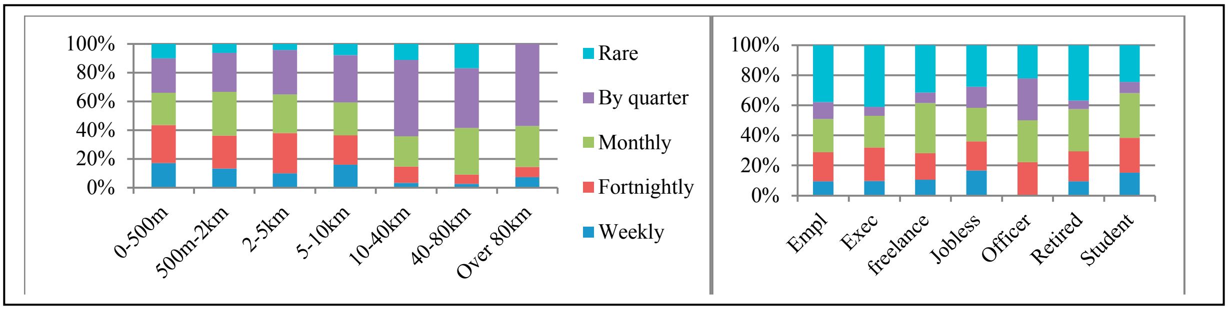

Figure3: (a) Frequency in the store according to residence’ distance (b) Frequency in the store according to profession

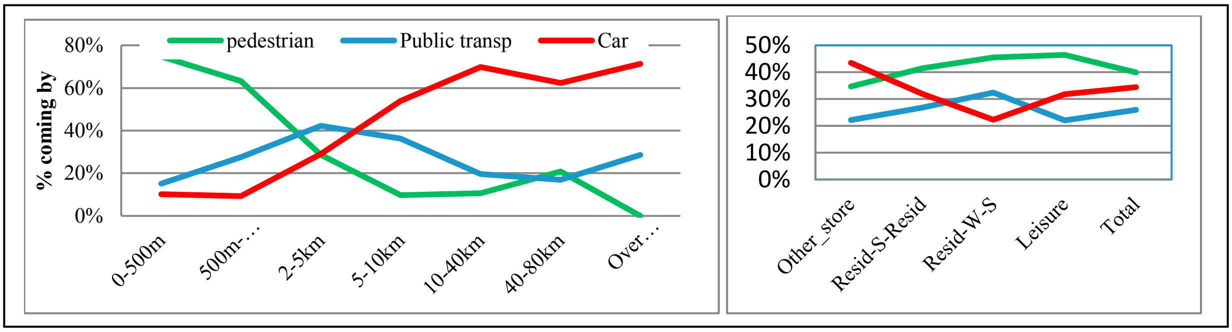

Figure 4 (a) Trip-mode and residence distance to the store (b) Trip-mode and trip-chain

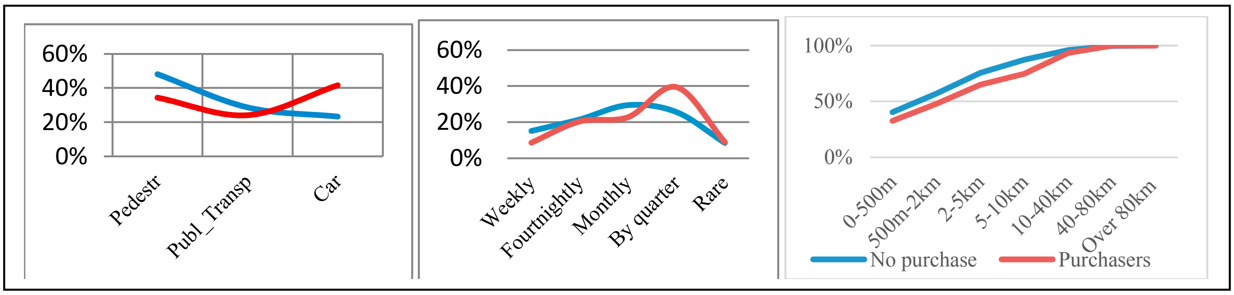

Figure 5 (a) Actual purchase and trip-mode (b) Actual purchasers’ visit frequency (c) Residence distance & actual purchase

The variable “*Intention*” presents the statements of customers about their choice between remaining visiting the store after its movement or not. It has four values, but we changed them into two as explained in Figure 6, assuming that "*visit less*" is an understatement to mean "*no more visit*". This binary variable obtained is the dependent variable in the model developed and tested below. For a better accuracy as well, the variable "*Frequency"* was also changed into a binary one, customers coming fortnightly or more frequently being described with the value *"Frequent",* and the others, which visit monthly, by quarter or less frequently being described with the value "*Rare*" of this variable.

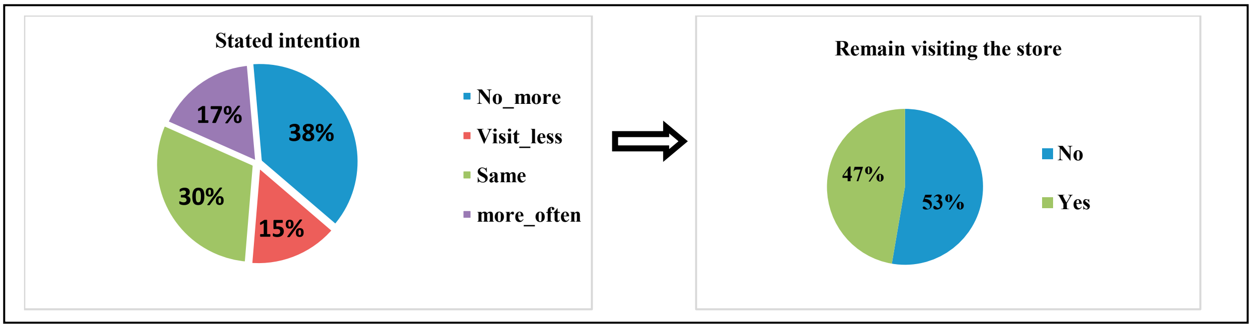

Figure 6: "Intention": from a four values variable to a binary one.

3. Methodology

This paper is a part of a whole work underway, which aims in developing a general methodology to simulate shopping trips decision towards urban periphery, associating machine-learning technics to probabilistic discrete choice modelling. The forecasting method described in this section is therefore, not the only a way of investigating the issue, but the first stage in a larger reflection.

3.1. Conditional inference tree, a statistical-significance-tests based decision tree

Decision trees, known as Classification and Regression Trees (CART), are a type of machine learning process, commonly used to develop predicting models, explaining quantitative or qualitative dependent variables with statistical tests. Morgan and Sonquist (1963) are probably the precursors, but this method was really developed by Breiman, Friedman, Olshen and Stone in 1984 (Morgan et al., 1963; Breiman et al., 1984; Rakotomalala, 2005; Hothorn and al., 2015). The use of decision trees today is very varied. Regression trees are used for a continuous dependent variable while classification trees help to explain discrete dependent variable. Whatever the dependent variable is discrete or continuous, decision trees are also used for discriminant analysis (Rakotomalala, 2015). Various algorithms can be used to build decision trees. Among the most known we can quote "*CART*" (Breiman and al, 1984) and "*C4.5*" (Quinlan, 1993).
Hothorn, Hornik and Zeileis developed in 2006 the *"ctree"* algorithm to build "conditional inference trees" by a recursive method of unbiased partitioning (Hothorn et al, 2006). The method was originally implemented in the package "Party" entirely in "*C*" programming language. Then, they improved this algorithm which is now almost entirely in R free software (Hothorn et al, 2015). This algorithm of conditional inference trees is appropriate for univariate or multivariate continuous regression, ordinal regression, discrete regression and for classification.

Other algorithms, such as "*C4.5*" or "CART", use information measures like the *Index of Gini* or *the Shanon entropy* to perform the recursive splits on the dependent variable. They can therefore introduce a bias in the analysis, because the explanatory variables who have the maximum of probability to be chosen are those offering many splitting possibilities or having a lot of missing values. They maximize the information measure, whereas "*ctree"* algorithm uses a multiple statistical significance tests, also known as randomisation tests, to perform the recursive splits. These tests are based on statistical theories, such as the one of Strasser and Weber (1999) known as *the theory of permutation test* or the older one of Ronald Fisher (Fisher, 1934; Hothorn et al, 2006). Therefore, "*ctree"* uses a statistical test that defines a significance level $\boldsymbol{\alpha}$ so that a result is statistically significant when the "***p-value***" is less than $\boldsymbol{\alpha}$:

$$\boldsymbol{p - value < \alpha}$$

***p-value** being the probability to obtain a result equal to, or more extreme than what was observed; **α** being the probability to reject the null hypothesis*.

To sum up, what makes "*ctree"* different from the other available decision tree algorithms is the splitting method based on statistical theories.

"*Ctree"* can be used in both explanatory and predictive perspective. Moreover, the parameter α "*can be interpreted in two different ways: as a pre-specified nominal level of the underlying association tests or as a simple hyper parameter determining the tree size*" (Hothorn et al., 2006, p7). In the first sense, α controls the probability of falsely rejecting H0 (the null hypothesis) in each node. Otherwise (in the second way), α can be seen as a hyper parameter that is subject to optimisation with respect to some risk estimate, e.g., computed via cross-validation or additional test samples (Hothorn et al., 2006, p7).

Another peculiarity of this method is that, in contrast to algorithms incorporating pruning based on resampling, the models suggested with "*ctree*" can be fitted deterministically, provided that the exact conditional distribution is not approximated by Monte-Carlo methods. Thus, for this method, "*predictive performance is as good as the performance of optimally pruned trees*" (Hothorn et al, 2006 p3). Actually, the authors conducted a benchmark (empirical comparison) and compared this algorithm to the more famous ones, like QUEST, RPART and GUIDE. The results are interesting:

"*Conditional inference trees as suggested in this paper select variables in an unbiased way and the partitions induced by this recursive partitioning algorithm are not affected by overfitting. Even in a very simple simulation model, the partitions obtained from conditional inference trees are, on average, closer to the true data partition compared to partitions obtained from an exhaustive search procedure with pruning*" (Hothorn et al, 2006 pp 17-18).

3.2. Model development and testing process

Many estimation and validation process are available in the literature for decision trees in general. One of the most commonly used is the crossed validation, which the one we chose. The process consists of dividing the total number of observation in the database into three parts A, B, and C. Three models will be estimated respectively with two tiers, and validated with the third tier.

In this study, after specifying the dependent variable and the predictors, we set-up *chi-square* tests between all the variables held for the analysis in order to know more about their correlation. Analyses were conducted keeping in mind that decision tree analysis can hide a variable highly correlated to another one.

The split of the data frame into three sub-samples supposed to face the traditional problem of decision trees instability with random sampling. The solution we applied for this problem was to fix the first element of each the sub-sample. Three regular sequences will thus be generated, starting respectively from 1, 2 and 3, the step being three. The data frame has 985 observations, what leads to obtaining three sub-samples of 328, 328, and 329 observations. Three different models were thus developed and tested with these combinations:

- 656 observations for 1st estimation, and 329 for validation,
- 657 observations for 2nd estimation, and 328 for validation
- 657 observations for 3rd estimation, and 328 for validation

After validation tests, the relevant model will be the one with the best results. The validation test considered is the one of "*Out of bag error"* which gives the number of wrong prediction of the developed model on the validation data frame.

The model is developed with the algorithm *"ctree"* and tested with the algorithm "*predict*" both implemented on the last version of R statistical free software: R version 3.4.3 (Kite-Eating Tree) available on https://cran.r-project.org/src/base/R-3/

4. Results and discussion

4.1. Dependent variable, predictors and correlation

Figure 7 shows that some variables are highly correlated. In particular, three variables are concerned with the statements about their eventual trips toward the store after the movement: "*Intention"* is already detailed above

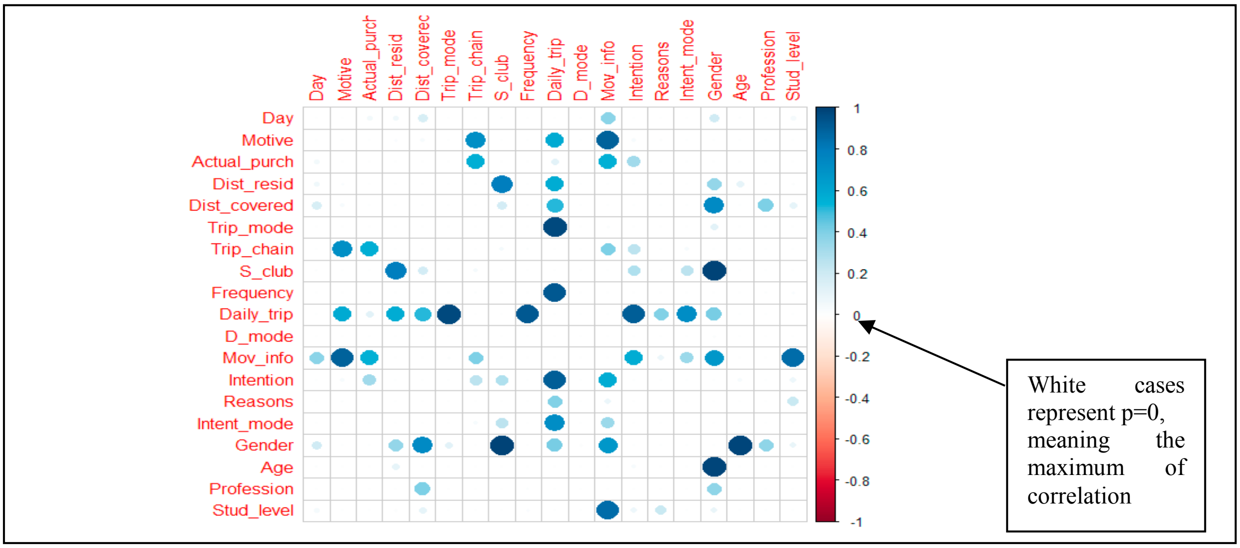

Figure7: Correlation between the variables with a two-by-two chi-square test.

"*Reasons"* and "*Intent_mode*" are respectively the reasons of the intention stated, and the trip-mode customers are intending to use for eventually visiting the moved store. These three variables are highly correlated, what means that no one of them should be used to explain the others. "*Intention"* being the main dependent variable, it was therefore necessary to remove the remaining two, "*Reasons"* and "*Intent_mode*", from the explanatory variables. They could nevertheless be involved in the analysis for a better comprehension of the developed model's predictions. All the variables involved into the analysis are presented on Table 1 below.

Table 1: Dependent and independent variables

Dependent variable	"Intention"
16 Predictors :	"Day", "Motive", "Actual_purch", "Dist_resid", "Dist_covered", "Trip_Mode", "Trip_chains", "S-club", " Frequency", "Daily_trip", "D_Mode" "Move_info'', ''Gender'', "Age", "Profession", "Study_level"

"*Day*" describes the day of the week of the survey (from Monday to Saturday). "*Motive*" describes whether the customer is visiting the store for *After-sell-support, just for a walk or intending to purchase.* "*Daily_trip*" is the binary variable about whether the surveyed customer moves daily for work or study, and then "*Daily_mode*" describes the trip-mode he eventually uses. "*S-club*" describes the store-club membership, and "*Move_info"* describes whether the customer is just getting informed (during the survey) about the store relocation or not. The other variables are already presented above.

4.2. Which factors are most significant in the decision to remain client? Conditional inference tree model

Table2: Comparing OOB errors to choose the fitting model

	Estimation data frame			Test data frame		
	M1	**M2**	**M3**	**M1**	**M2**	**M3**
OOB for "0" (=No)	29%	31%	35%	38%	32%	31%
OOB for "1" (= yes)	31%	34%	29%	**33%**	35%	34%
Over all OOB	30%	33%	32%	36%	33%	33%

Three different models are estimated as explained, and the point about their predicting errors is in Table2. The comparison of the "Out-of-bag" (OOB) errors on the estimation data frame and the validation tests identify the model M1 (Figure 8) as the fitting model. It has in fact the lower OOB error in predicting the right hypothesis.

This tree-structured model depicted in Figure 8 confirms a priori the conception widely shared in the literature, according to which shopping trips towards peri-urban areas closely depends on the trip-mode, particularly in car-use (Van De Walle, 2005; Wiel, 1999; Wiel 2002; Massot & Orfeuil, 2005). People visiting the city center store by car are the most interested in remaining the store client after its relocation. Their probability can reach 80% if they are male, and a little less for female customers (60%).

Customers coming by public transports or on foot are more reluctant. Their visit to the moved store depends on their frequency and on the distance they use to cover to reach the city center store. The probability is about 20% for customers who visit the store at least twice per month, (described with the value "*Frequent*" of the binary variable "*Frequency*"). Less frequent customers (the value "*Rare*" of the variable) have almost the same probability to continue visiting the moved store if the covered distance is about two kilometers or less. Rare customers covering longer distances mind less the relocation: their probability can reach 55%. Therefore, Trip-mode, Frequency, distance covered and Gender are the most significant factors the model suggests, in remaining client of the store after its move.

Trip-mode generally reveals many other things about the customers. Ravalet (2007), citing Salomon (1980) and Amar who developed the theory of *urban bonding of transports ((*1993, 2004) explains that trip-mode is not only the use or the lack of a mechanical or technical object to move. It also means a personal link to the urban territory, and some constraints imposed by the traveler's socioeconomic status, household, activity sites or access to transport system. Knowing the trip-mode of a customer can then be a first stage in predicting their behavior.

The model seems substantiate many scholars' works in the literature. Indeed, in a literature review in 2006,

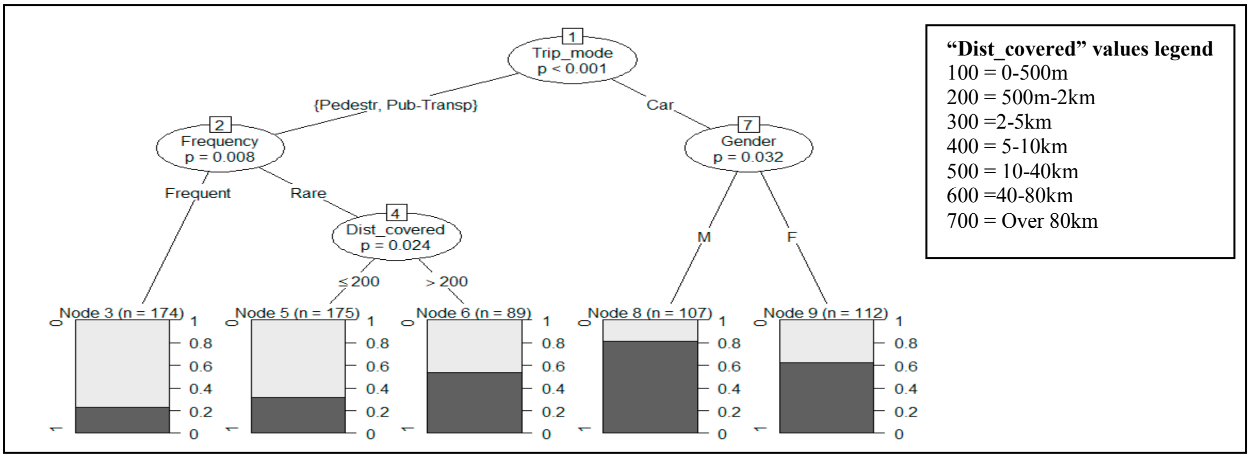

Figure 8: Conditional inference tree of "Intention"

Magalie Pierre asserts, citing among others, Massot & Orfeuil (1991), Bonnel et al., (2003); Guidez et al., (2000); Frenay, (1997); Turrentine & Kurani, (2006); that trip-mode is only the representation of a set of elements, namely the available transport system, the trip characteristics, and the traveler's own household peculiarities. Talking about trip-mode, several factors are critical. First, one might consider whether the traveler has the freedom to choose: driving a car requires a driving-license, and to travel with public transports supposes that both origin and destination of the trip are well connected. Second, time budget, and financial cost of the travel to the traveler, and what the trip-mode used implies for the community or nature (Pierre, 2006). Thus, trip-mode can be hiding other factors as the time windows or the trip-motive, customer's residence, trip-chains or trip-origin. The model estimated actually mentions that trip origin is important. In Saint-Etienne, the local context of the survey, citizens can enjoy good public transport connections two kilometers around the city center-store. However, these connections become derisory beyond, as shown by the local public transport plan (STAS, 2017). Hence, while new location of the store has a good car accessibility, it's connection to public transport is definitely worse. One can thus understand that customers covering two kilometers or less, who used to enjoy a good public transport connection to visit the city center store are not intending to remain the store's client after the relocation.

Trip origin is also a link between customers' residence and their trip-chains. In fact, as shown in the descriptive analysis above, for more than 60% of the surveyed customers, the trip-origin is their residence or their work site. Actually, coming from city-center means to live or to work in the city center, or have another purchase or a leisure activity in the city-center. Thus, the significance of trip-origin revealed by the model also means that not only the residence location is critical. For urban retail customers, trip-chains or wanderings become the dominant mobility behaviour, because the optimization of trips becomes the rule. Hani (2009) already underlined the importance of trip chain and wanderings, linking them to trip-mode and gender, while studying the case of the urban area of Le Havre (Hani, 2009). The prominence of the customer's gender suggested by our model can thus fit among the other factors, with regards to the literature (Hesse, 1999; Hani, 2009).

Conclusion

Lessons learned from this study are many. First, residential location is well known to be critical in store location models, and it remains, of course. Nevertheless, the model estimated in this paper is showing that residential location is a part of a more significant combination made of the trip-origin, the trip chain and the mobility possibilities available to link different parts of the city. To put it another way, the relative distribution of residences, activities and stores is probably something that matters a lot in shopping-trip behaviours. Second, trip-mode is very significant, meaning that local authorities and urban planners can reduce the negative externalities of shopping trips by mastering the links between store location and public transport connections. Third, and this seems the most important, the relevant factors identified in the model highlights findings in the literature, passing over the peculiarities of the store and the city under study. Thus, the analysis can have a great utility for the decision-makers particularly for the storekeepers. Indeed, these reflections can help storekeepers anticipating on the relevance and impacts of their store relocation. Although, it looks more interesting to conduct similar studies, suggesting customers to choose among a trade-off of many locations, in order to select in fine the most fitting. Moreover, these analyses deserve to be strengthened. After the significant factors are selected, they may be involved as predictors into a probabilistic discrete choice model, or in a sensitive analysis either, with Indices of Sobol and Shapley or the Method of Morris to quantify their influence.

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