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CAUSAL ANALYSIS IN MARKETING: A CUSTOMER SATISFACTION PROBLEM

Abstract:

In recent years, shopping streets are declining in aid of shopping centers. Consequently, to maximize loyalty and competitiveness in an increasingly competitive market it is essential to understand the distinctions characterizing the customers who choose shopping centers from those who opt for shopping centers. To analyse this differentiation, I use the log-linear causal models but, since these have not a complete causal theory, I use a new causal analysis to remedy this problem (Gheno, 2016). Starting from a complex model, I come to a simpler model to understand the different behaviors of the two types of customers. The data analysis shows that shopping centers customers are more driven by the emotions than the more rational and concrete ones who choose shopping centers.

Keywords:

causal analysis, customer satisfaction, log-linear models, shopping centers, shopping street

JEL Classification: C40, M31, C00

INTRODUCTION

In the last decades there has been a slow decline in shopping streets in aid of shopping malls (Teller, 2008; Rajagopal, 2010). There are some benefits in choosing shopping malls for a certain target of consumers. Customers, who use cars to reach stores, find shopping malls more attractive for many large, free car parks and more sliding routes; for those who do not use cars, instead, shopping streets in city centers can be more attractive (Teller, 2008). Pooling and number of stores are a strong point of shopping malls especially appreciated by American and Australian buyers, while Europeans consider walking along city streets a pleasant part of shopping (Reimers and Clulow, 2004). Other strong points of shopping malls are greater presence of hypermarkets due to their particular architectural structure and the choice of businesses for a given target, excluding the opening of particular stores which could have a negative impact on the image of the agglomeration of certain activities (Teller, 2008). The atmosphere plays a mixed role in the choice, since music and decorations in shopping malls positively influence the consumer who, however, may also be fascinated by the unique atmosphere of historical cities (Teller, 2008). The presence of many shops in shopping malls also allows that the purchaser has several proposals so that he can choose the one which is the most convenient (Reimers and Clulow, 2004; Kunc et al., 2012).

Choosing to go shopping in shopping streets instead of shopping malls leads me to assume that there is a disparity in the type of clientele. To analyze this diversity, I study the factors which determine the loyalty and the future behavior of consumers toward stores depending on whether they are in a shopping mall or in a historic street. For the analysis of the various characteristics which differentiate customers, I use the concepts of customer satisfaction theory, which was born in the 1990s to measure how the provided products and services meet or exceed the expectations of the customer. It is used by companies to maximize customer satisfaction, to gain loyalty and to increase customers in a world where competitive pressure is constantly increasing. Therefore, customer satisfaction becomes for competitors a necessity in order to gain a competitive advantage, increasing, for example, fidelity, loyalty and word of mouth. The influence of consumer emotions on satisfaction and loyalty (Oliver, 1993; Phillips and Baumgartner, 2002) plays an important role in the formation of judgments. Consumer emotions can naturally be positive or negative (Phillips and Baumgartner, 2002), as evidenced by some social psychology studies which explain their relative independence. Many researchers have wondered if, for example, happiness and unhappiness were not the extreme measurements of the same variable. This is a field of interest and of research both in psychology and in marketing. In the mid-1980s, the psychological study proposed by Diener et al. (1985) demonstrated the relative independence of positive emotions from negative ones, mainly due to the size of their intensity. In the following years Derbaix et al. (1991) emphasized the existence of both emotions in some consumer conditions, and later marketing studies (Oliver, 1993; Phillips and Baumgartner, 2002) showed that both affect customer satisfaction. Consequently, positive emotions, having a positive impact on satisfaction, bring the customer to repurchase the product or service, while negative ones, lowering satisfaction, induce the customer to choose other shops or consumer goods. Homer (2006) finds that, when the brand is known, positive and negative emotions influence differently the attitude of buyer: the first indirectly, i.e. through other variables, the latter directly. In the analysis of customer satisfaction, due to this different influence, the two emotions are considered to be independent, although after the study made by Diener et al. (1985), other psychological analyses were for their relative independence or for the bipolarity. Barozzi et al. (1999) solved this dualism saying that this choice depends on sex and the type of culture. Their studies about the behavior of women in Western countries, in fact, denote bipolarity, the ones on the Oriental women present a dialectical relationship, and those both on Western men and on Eastern ones produce independence.

Just as culture and sex can influence the type of relationships between emotions, so too the satisfaction, the loyalty and the word of mouth of shopping mall's customers differ from those of city streets. To compare them I study the customers of a chain of jewelers, which have stores in both places, using the log-linear causal models (Vermunt, 1996; Bergsma et al., 2009). Because this methodology is devoid of a comprehensive causal analysis, to analyze the existing causal relationships among the various variables of interest, I use the new causal theory proposed by Gheno (2016), created specifically to fill this gap. Therefore, this paper consists of a first paragraph where I explain the employed data and the used statistical tools, of a second paragraph where I compare the differences and the equality between the two types of customers analyzing how the quality of the products sold in stores can influence the future behavior of customers, of a third paragraph where I study how the interaction with sellers influences the satisfaction of consumers and of a fourth paragraph where I summarize the essential results.

EMPIRICAL STUDY: RESEARCH METHOD AND STATISTICAL TOOLS

This dataset is obtained by a questionnaire completed through a personal interview and the perception of the consumers is measured considering their attitude to the product and the service, their positive and negative emotions, their satisfaction and their future behavior. The measurement of quality, emotions and future behavior is carried out through a 7-point scale ranging from 1 to 7, where 1 indicates complete disagreement and 7 absolute agreement to the presented proposition. 841 customers of a well-known jewelry chain with stores located both in shopping malls and in historic centers were interviewed. In previous years, its sales staff followed a training course structured by classroom moments and by practical exercises to create homogeneous behaviors with its customers. Management also started renovating stores to make them similar. The difference in the results of the questionnaires is due to the heterogeneous typology of customers which is different for the buyers of shopping streets if it is compared with that of the consumers of shopping malls. Of the interviewed customers, 396 are consumers of a store in the historical center and 445 of a shopping mall, intentionally belonging to the same geographical area which thus becomes irrelevant in the responses.

The propositions of the questionnaire from which I derive the variable quality of the products are "The store offers fashionable products", "The store offers a wide range of products" and "The store offers high quality products"; The sensations, from which the variable positive emotions is derived, are interest, happiness and relaxation, while those, from which the variable negative emotions arises, are anger, stress and boredom. The variable future behavior is measured by the propositions "I'll be back in the future", "I'll recommend this store to friends" and "I'll say good things about this store to others". To study these data I transform the categorical variables with 7 ordered categories into binary variables with 2 ordered categories. The dichotomous variable is equal to 0 when the categorical variable, from which I derive the binary variable, has lower values than its average and 1 if these values are greater.

To analyze the relationship among the variables I use the log-linear causal model (Vermunt, 1996; Bergsma et al., 2009; Gheno, 2016), which allows a categorical data analysis very similar to that made by SEM for continuous variables (Bollen, 1989; Kline, 2005). Both methods can, indeed, be divided into a measurement part and a structural one. In the measurement part the unobserved variables, called also latent, are derived from the observed variables, or indicators. In the structural part, the causal relationships among the latent variables are analyzed. In the measurement part of this analysis, for example, the latent variable positive emotions is derived from the indicators interest, happiness and relaxation. In the structural part, for example, the causal relationships among the latent variables quality of products, positive and negative emotions and future behavior are studied. Therefore, the SEM method and the log-liner causal method have the advantage of obtaining latent variables, i.e. not directly observable, and their causal relationships simultaneously. The log-linear causal models decompose the joint probabilities in conditional probabilities. If I consider, for example, 9 indicators $X_1, X_2, X_3, Z_1, Z_2, Z_3, Y_1, Y_2, Y_3$ from which I derive the latent variables X, Z and Y, the joint probability of the 12 variables becomes

$$\begin{aligned} &P(X,Z,Y,X_1,X_2,X_3,Z_1,Z_2,Z_3,Y_1,Y_2,Y_3) \\ &= P(X_1|X)P(X_2|X)P(X_3|X)P(Z_1|Z)P(Z_2|Z)P(Z_3|Z)P(Y_1|Y)P(Y_2|Y)P(Y_3|Y)P(X,Z,Y) \end{aligned} \quad (1)$$

The formula (1) is that used in the measurement part. In the structural part the relationship between the latent variables X, Z and Y and their joint probability $P(X,Z,Y)$ is studied. If I assume that the latent variable X influences causally Y and Z, and which the latter affects Y, their joint probability becomes

$$P(X,Z,Y) = P(Y|X,Z)P(Z|X)P(X) \quad (2)$$

The formula (2) represents a classical mediation model where Z is the mediator through which X indirectly affects Y, since in the probability $P(Y|X,Z)$ the variable Y is conditioned both by X and by Z, and X affects Y both directly and indirectly through Z. If I assume that the variable X only affects indirectly Y, the conditional probability of Y becomes $P(Y|Z)$. The causal log-linear model parameterizes the probabilities considering the effects of the various categories of the variables, for example the joint probability of the latent variables X, Z and Y becomes

$$P(X=x,Z=z,Y=y)=\eta\mu^{X=x}\mu^{Z=z}\mu^{Y=y}\mu^{X=x,Y=y}\mu^{X=x,Z=z}\mu^{Z=z,Y=y}\mu^{X=x,Z=z,Y=y} \qquad (3)$$

where x, z and y indicate arbitrary categories of the variables X, Z and Y, and the parameters measure the effects of the categories of the variables. The parameters $\mu^{X=x},\mu^{Z=z},\mu^{Y=y}$are, respectively, the one variable effects of the categories x, z and y of the variables X, Z and Y; the parameters $\mu^{X=x,Y=y},\mu^{X=x,Z=z},\mu^{Z=z,Y=y}$are respectively the two variable effect of the categories x and y of X and Y, of the categories x and z of X and Z and of the categories z and y of Z and Y; the parameter $\mu^{X=x,Z=z,Y=y}$ is the three variable effect of the categories x, z and y (Heinen, 1996). The parameter η is called the overall effect and is a constant which ensures that the sum of probabilities is equal to 1 (Heinen, 1996). The parameters μ can only be positive and their value equal to 1 means a lack of effect, so if they have values between 0 and 1, they have a negative effect, and if they are greater than 1 a positive effect. In this analysis, the variables X, Z and Y are binary and hence the categories become x, z, y = 0,1. The number of parameters is greater than the number of the probabilities (24> 8) and therefore the parameters of the equation (3) cannot be estimated without the addition of constraints. Consequently, I constrain the parameters with the dummy code criterion so that they are identified, then

$$\begin{gathered}\mu^{Y=0}=\mu^{X=0}=\mu^{Z=0}=1\\ \mu^{Z=0,Y=0}=\mu^{X=0,Y=0}=\mu^{Z=0,Y=1}=\mu^{X=0,Y=1}=\mu^{Z=1,Y=0}=\mu^{X=1,Y=0}=1\\ \mu^{X=0,Z=0}=\mu^{X=0,Z=1}=\mu^{X=1,Z=0}=1\\ \mu^{X=0,Z=0,Y=j}=\mu^{X=0,Z=1,Y=j}=\mu^{X=1,Z=0,Y=j}=\mu^{X=1,Z=1,Y=0}=1 \quad j=0,1\end{gathered} \qquad (4)$$

With such constraints, the parameters, which have to be estimated, are reduced to 8 and become estimable. In the structural part I have to consider the decomposition of the joint probability $P(X,Z,Y)$ choosing the causal relations among the variables. If I consider that proposed in the formula (2), i.e. $P(Y|X,Z)P(Z|X)P(X)$, then the equation (3) becomes

$$
\begin{aligned}
P(X=x) &= \frac{\mu_c^{X=x}}{1+\mu_c^{X=1}} = \eta_c^{X}\mu_c^{X=x} \\
P(Z=z|X=x) &= \frac{\mu_c^{Z=z}\mu_c^{X=x,Z=z}}{1+\mu_c^{Z=1}\mu_c^{X=x,Z=1}} = \eta_c^{Z|X=x}\mu_c^{Z=z}\mu_c^{X=x,Z=z} \\
P(Y=y|X=x,Z=z) &= \frac{\mu^{Y=y}\mu^{X=x,Y=y}\mu^{Z=z,Y=y}\mu^{X=x,Z=z,Y=y}}{1+\mu^{Y=1}\mu^{X=x,Y=1}\mu^{Z=z,Y=1}\mu^{X=x,Z=z,Y=1}} \\
&= \eta^{Y|X=x,Z=z}\mu^{X=x,Y=y}\mu^{Z=z,Y=y}\mu^{X=x,Z=z,Y=y}
\end{aligned}
\tag{5}
$$

where η indicates the normalization factor and the subscript c identifies the parameters estimated by the conditional probabilities (Gheno, 2016). The parameters without subscript c are estimated by the joint probability. The parameters of the conditional probability $P(Y=y|X=x,Z=z)$ are the same obtained from the joint probability $P(Y=y,X=x,Z=z)$. The presence or absence of the three variable parameter, i.e. $\mu^{X=x,Z=z,Y=z}$, in causal terms represents the presence or the absence of a multiplicative interaction term, which indicates that the effect of a variable on another variable depends on the value of a third variable and vice versa. The measurement part conceptually reflects the same analysis of the structural part, hence

$$
\begin{aligned}
P(X_i=x_i|X=x) &= \frac{\mu_c^{X_i=x_i}\mu_c^{X=x,X_i=x_i}}{1+\mu_c^{X_i=1}\mu_c^{X=x,X_i=1}} = \eta_c^{X_i|X=x}\mu_c^{X_i=x_i}\mu_c^{X=x,X_i=x_i} \\
P(Z_i=z_i|Z=z) &= \frac{\mu_c^{Z_i=z_i}\mu_c^{Z=z,Z_i=z_i}}{1+\mu_c^{Z_i=1}\mu_c^{Z=z,Z_i=1}} = \eta_c^{Z_i|Z=z}\mu_c^{Z_i=z_i}\mu_c^{Z=z,Z_i=z_i} \\
P(Y_i=y_i|Y=y) &= \frac{\mu_c^{Y_i=y_i}\mu_c^{Y=y,Y_i=y_i}}{1+\mu_c^{Y_i=1}\mu_c^{Y=y,Y_i=1}} = \eta_c^{Y_i|Y=y}\mu_c^{Y_i=y_i}\mu_c^{Y=y,Y_i=y_i}
\end{aligned}
\tag{6}
$$

where X_i, Z_i, Y_i with i = 1,2,3 are the indicators and X, Z, Y are the latent variables.

The use of the causal log-linear models can have problems because of the lack of a causal theory which allows to calculate the intensity of the effects of a variable on another variable. Gheno (2016) proposed formulas to calculate direct, indirect and total effects, solving this problem. In the structural model given by the formula (2) ($P(X,Z,Y) = P(Y|X,Z)P(Z|X)P(X)$), the effect of a variation of the variable X on the variable Y can occur both directly and through its influence on Z, which in turn affects Y (indirect effect). The causal direct effects, $Or^{LDE}_{x^0,x^1}(Z)$ and $Or^{NDE}_{x^0,x^1}(Z)$, that indirect $Or^{IE}_{x^0,x^1}$ and that total $Or^{TE}_{x^0,x^1}$ of the variable X on the variable Y are so calculated

$$
Or^{TE}_{x^0,x^1} = \frac{P(Y=1|X=x^1)}{1-P(Y=1|X=x^1)}\frac{1-P(Y=1|X=x^0)}{P(Y=1|X=x^0)} = \underbrace{Or^{LDE}_{x^0,x^1}(Z)\,Cell^{effect}_{x^0,x^1}(Z)}_{Or^{NDE}_{x^0,x^1}}\frac{1}{Or^{IE}_{x^1,x^0}}
\tag{7}
$$

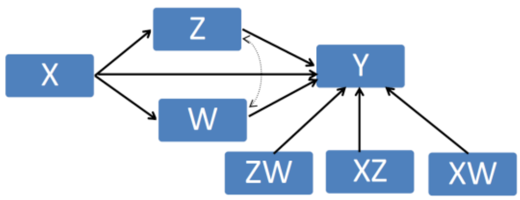
$$Or^{LDE}_{x^0,x^1}(Z) = \frac{P(Y=1|X=x^1,Z=z)}{1-P(Y=1|X=x^1,Z=z)}\frac{1-P(Y=1|X=x^0,Z=z)}{P(Y=1|X=x^0,Z=z)} \quad (8)$$

$$Cell^{effect}_{x^0,x^1}(Z) = \left[\frac{\sum_Z P(Y=1|X=x^1,Z=z)P(Z=z|X=x^0)}{1-\sum_Z P(Y=1|X=x^1,Z=z)P(Z=z|X=x^0)}\frac{1-P(Y=1|X=x^0)}{P(Y=1|X=x^0)}\right]$$
$$\left[\frac{P(Y=1|X=x^1,Z=z)}{1-P(Y=1|X=x^1,Z=z)}\frac{1-P(Y=1|X=x^0,Z=z)}{P(Y=1|X=x^0,Z=z)}\right]^{-1} \quad (9)$$

$$Or^{IE}_{x^0,x^1} = \left[\frac{\sum_Z P(Y=1|X=x^0,Z=z)P(Z=z|X=x^1)}{1-\sum_Z P(Y=1|X=x^0,Z=z)P(Z=z|X=x^1)}\right]\left[\frac{1-P(Y=1|X=x^0)}{P(Y=1|X=x^0)}\right] \quad (10)$$

where the subscript (x^0, x^1) indicates that the causal effect measures the effect of the variation of X from x^0 to x^1. The distinction between the natural direct effect $Or^{NDE}_{x^0,x^1}(Z)$

Figure 1: A parallel multiple mediators model with interactions



Source: Own path diagram

and the direct controlled effect $Or^{LDE}_{x^0,x^1}(Z)$ was originally proposed by Pearl (2009, 2012) and then gotten again by Gheno (2016). The difference between the two effects depends on how the variable Z is evaluated, which in the natural one is obtained from the initial value of X, i.e. x_0, while in the controlled one (or suggested in literature) is set at choice. Gheno (2016) found that the natural direct effect is obtained by the cell effect multiplied by the direct controlled effect. The cell effect can be interpreted as an interaction effect and, in general, it does not depend on the relationship between the variables X and Z, i.e. on the parameter $\mu_c^{X=1,Z=1}$, but only by their joint presence in influencing the response variable Y (Gheno, 2016). These causal effects can only assume positive values and therefore a value between 0 and 1 assumes a negative effect, a value greater than 1 a positive effect and a value equal to 1 the absence of effect.

To study the difference between the customers choosing shopping malls and those who prefer shopping streets, I analyze a more complex model than the one described above, but simplified by eliminating non-significant parameters, thus removing, for example, the parameter $\mu^{X=x,Z=z}$ if $\log(\mu^{X=x,Z=z}) = 0$. To test the significance of the parameters I use Wald test. The initial model considers 4 latent variables X, Z, W, Y linked causally as in Figure 1, where the arrows represent the direct causal effects, the double arrow the covariance and ZW, XZ and XW the multiple interaction terms. To calculate the causal effects in an equivalent model Gheno (2016) proposed the following formulas

$$\widetilde{Or}^{TE}_{x^0,x^1} = \frac{\tilde{P}(Y=1|X=x^1)}{1-\tilde{P}(Y=1|X=x^1)} \frac{1-\tilde{P}(Y=1|X=x^0)}{\tilde{P}(Y=1|X=x^0)} \tag{11}$$

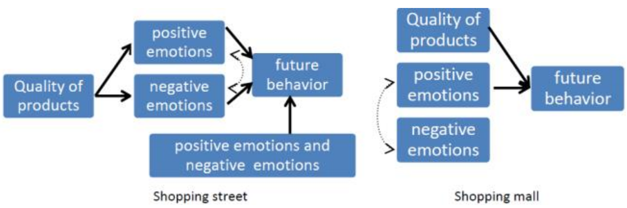
$$\widetilde{Or}^{TE}_{x^0,x^1} = \underbrace{Or^{LDE}_{x^0,x^1}(Z,W)\widetilde{Cell}^{effect}_{x^0,x^1}(Z,W)}_{\widetilde{Or}^{NDE}_{x^0,x^1}} \frac{1}{\widetilde{Or}^{IE}_{x^1,x^0}} \tag{12}$$

$$\widetilde{Or}^{IE}_{x^0,x^1} = \left[\frac{\sum_{Z,W} P(Y=1|X=x^0,Z=z,W=w)\tilde{P}(Z=z,W=w|X=x^1)}{1-\sum_{Z,W} P(Y=1|X=x^0,Z=z,W=w)\tilde{P}(Z=z,W=w|X=x^1)}\right] \tag{13}$$

$$\left[\frac{1-\tilde{P}(Y=1|X=x^0)}{\tilde{P}(Y=1|X=x^0)}\right]$$

$$\mathrm{Or}^{\mathrm{LDE}}_{\mathrm{x}^0,\mathrm{x}^1}(\mathrm{Z},\mathrm{W}) = \frac{\mathrm{P}(\mathrm{Y}=1|\mathrm{X}=\mathrm{x}^1,\mathrm{Z}=\mathrm{z},\mathrm{W}=\mathrm{w})}{1-\mathrm{P}(\mathrm{Y}=1|\mathrm{X}=\mathrm{x}^1,\mathrm{Z}=\mathrm{z},\mathrm{W}=\mathrm{w})} \frac{1-\mathrm{P}(\mathrm{Y}=1|\mathrm{X}=\mathrm{x}^0,\mathrm{Z}=\mathrm{z},\mathrm{W}=\mathrm{w})}{\mathrm{P}(\mathrm{Y}=1|\mathrm{X}=\mathrm{x}^0,\mathrm{Z}=\mathrm{z},\mathrm{W}=\mathrm{w})} \tag{14}$$

Figure 2: Customer comparison (quality of products on future behavior)



Source: Own path diagram

$$\widetilde{Cell}^{effect}_{x^0,x^1}(Z,W) =$$
$$\left[\frac{\sum_{Z,W} P(Y=1|X=x^1,Z=z,W=w)\tilde{P}(Z=z,W=w|X=x^0)}{1-\sum_{Z,W} P(Y=1|X=x^1,Z=z,W=w)\tilde{P}(Z=z,W=w|X=x^0)}\frac{1-\tilde{P}(Y=1|X=x^0)}{\tilde{P}(Y=1|X=x^0)}\right] \quad (15)$$
$$\left[\frac{P(Y=1|X=x^1,Z=z,W=w)}{1-P(Y=1|X=x^1,Z=z,W=w)}\frac{1-P(Y=1|X=x^0,Z=z,W=w)}{P(Y=1|X=x^0,Z=z,W=w)}\right]^{-1}$$

where the modified conditional probability $\tilde{P}(Z=z,W=w|X=x)$ is calculated without considering the parameter $\mu_c^{W=w,Z=z}$, which measures the correlation between the mediators Z and W. This particular probability is so defined

$$\tilde{P}(Z=z,W=w|X=x) = \tilde{\eta}_c^{Z,W|X=x}\mu_c^{Z=z}\mu_c^{W=w}\mu_c^{X=x,Z=z}\mu_c^{X=x,W=w} \quad (16)$$

The parameters μ_c of formula (16) are estimated using the probability $P(Z=z,W=w|X=x)$ in which the parameter $\mu_c^{W=w,Z=z}$ is considered. As the parameter $\eta_c^{Z,W|X=x}$ ensures that the sum of the conditional probabilities $P(Z=z,W=w|X=x)$ is equal to 1, so the parameter $\tilde{\eta}_c^{Z,W|X=x}$ ensures that the sum of the modified conditional probabilities $\tilde{P}(Z=z,W=w|X=x)$ is equal to 1.

THE INFLUENCE OF QUALITY OF PRODUCTS ON FUTURE BEHAVIOR

In the study of customer satisfaction it is very important how the quality of products can affect future behavior, meant as loyalty and word of mouth. To analyze this relationship, I consider the structural model of Figure 1, in which the variable X represents quality, the variable Z positive emotions, the variable W negative emotions, and the variable Y future behavior. Since these four variables are not directly observable, I introduce three indicators for each of them. The indicators of the variable quality of the products (X) are respectively X_1= "The store offers fashionable products", X_2 = "The store offers a wide range of products" and X_3 = "The store offers high quality products". The indicators of positive emotions (Z) are Z_1= interest, Z_2= happiness and Z_3 = relaxation, while those of negative emotions (W) are W_1= anger, W_2 = stress and W_3 = boredom. Future behavior (Y) is obtained by the indicators Y_1= "I'll be back in the future", Y_2 = "I'll recommend this store to friends" and Y_3= "I'll say good things about this store to others." As already pointed out in the previous section, the estimate of the parameters of the measurement part and those of the structural part are performed simultaneously in the causal log-linear models. The two and three variables parameters are shown in Table 1. The estimated models for both types of customers (Figure 2) are both good, indeed, the p-value of the L-squared statistic is about 1 for both. The parameters of the structural part are all greater than 1 and therefore, existing a positive relationship between the observed variables and the latent ones, the latter continue to have in the category 0 the values below the average and in the category 1 the values above the average. This relationship can be exemplified by observing the conditional probabilities of the latent variable X (Table 2). Subjects in category 0 of the latent variable are most likely to be in the category 0 of the observed variable X_i with i = 1,2,3, such as subjects in category 1 of the latent variable are most likely to be in category 1 of the observed variable X_i with i = 1,2,3. From this association, I conclude that the subjects in category 0 of the latent variable are those who give a lower value to the quality of products. The same analysis can be applied to the other latent variables Z, W and Y. In the structural part, all the estimated parameters are significant at 0.05 level, with the exception of the parameter $\mu^{W=1,Y=1}$ which has to be inserted equally being significant the parameter $\mu^{W=1,Z=1,Y=1}$ (Gheno, 2016) and precisely because of its non-significance it is not interpreted individually. The future behavior of the customers who buy in shopping streets is only indirectly influenced by quality of products through emotions, while that of the customers of shopping malls are directly influenced by quality of products (Figure 2). Therefore, people who buy in shopping streets have the direct controlled effect and the cell effect equal to 1 while the indirect effect equal to 1.6645. Being the indirect effect greater than 1, an increase of quality of products leads to more favorable future behaviors. However, the customers who choose shopping malls have an indirect effect equal to 1, while the direct controlled effect and the cell one equal to 28.8857 and 0.4895 respectively. Therefore, since the direct natural effect is equal to 14.1400, even in this case an increase of quality of products induces more favorable future behaviors. The probability of having a positive behavior conditioned by the highest quality of the products is greater in the subjects who choose shopping malls (0.9060> 0.6260, without covariance, 0.8561>0.6495 with covariance). This analysis shows that people who choose shopping malls are less guided by the emotions, more logical and rational than those who prefer shopping streets. These results are explained by recalling that many customers choose shopping malls for the ability of buying a product with a good price-quality ratio, for easier accessibility and consequently less waste of time. Therefore, I can conclude that they are more concerned with concrete factors. For people who prefer shopping streets, the direct natural effect of negative emotions on future behavior is 0.3850, so an increase of these decreases the positive future behavior. The same effect of positive emotions is 6.7745, and as result an increase of these increases the positive future behavior. These results are in line with the theory of customer satisfaction.

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THE INFLUENCE OF INTERACTION WITH STAFF ON SATISFACTION

The analysis of the previous data shows that shopping malls' customers are more

Table 1: Estimated parameters

Measurement part			Structural part		
parameter	Shopping street	Shopping mall	parameter	Shopping street	Shopping mall
$\mu^{X=1,X_1=1}$	420.5105***	1047.121***	$\mu_c^{Z=1,W=1}$	0.4443**	0.2439**
$\mu^{X=1,X_2=1}$	124.4138***	57.8214***	$\mu_c^{X=1,W=1}$	0.4053***	1.000^a
$\mu^{X=1,X_3=1}$	72.5465***	71.8910***	$\mu_c^{X=1,Z=1}$	2.0224*	1.000^a
$\mu^{Z=1,Z_1=1}$	173.0032**	9.7961***	$\mu^{X=1,Y=1}$	1.000^a	28.8857***
$\mu^{Z=1,Z_2=1}$	5.8930***	25.2193***	$\mu^{W=1,Y=1}$	1.1224	1.000^a
$\mu^{Z=1,Z_3=1}$	9.6149***	9.3963***	$\mu^{Z=1,Y=1}$	31.7549***	12.6276***
$\mu^{W=1,W_1=1}$	75.7388***	7.1189***	$\mu^{W=1,Z=1,Y=1}$	0.1182**	1.000^a
$\mu^{W=1,W_2=1}$	81.3897***	8.0237***			
$\mu^{W=1,W_3=1}$	128.6299***	20.3342**			
$\mu^{Y=1,Y_1=1}$	68.8122***	107.6263***			
$\mu^{Y=1,Y_2=1}$	108.3450***	172.2314***			
$\mu^{Y=1,Y_3=1}$	81.7377***	209.7789***			
L-squared (shopping street)=1244.9703 (p≈1)			L-squared (shopping mall)=1230.6576 (p≈1)		
Signif. Codes: 0"***" 0.001"**" 0.01"*" 0.05"°" 0.1"" 1					
a= constrained parameter					

Latent variable		Indicator	
Quality of products	X	The store offers fashionable products	X_1
		The store offers a wide range of products	X_2
		The store offers high quality products	X_3
Positive emotion	Z	Interest	Z_1
		Happiness	Z_2
		Relaxation	Z_3
Negative emotion	W	Anger	W_1
		Stress	W_2
		Boredom	W_3
Future behavior	Y	I'll be back in the future	Y_1
		I'll recommend this store to friends	Y_2
		I'll say good things about this store to others	Y_3

Source: Own dataset

Table 2: Conditional probability

	Shopping street		Shopping mall	
$P(X_1 = x_1 \mid X = x)$	P(0 | 0)	0.9662	P(0 | 0)	0.9701
	P(1 | 0)	0.0338	P(1 | 0)	0.0299
	P(0 | 1)	0.0637	P(0 | 1)	0.0300
	P(1 | 1)	0.9363	P(1 | 1)	0.9700
$P(X_2 = x_2 \mid X = x)$	P(0 | 0)	0.9212	P(0 | 0)	0.8865
	P(1 | 0)	0.0788	P(1 | 0)	0.1135
	P(0 | 1)	0.0859	P(0 | 1)	0.1190
	P(1 | 1)	0.9141	P(1 | 1)	0.8810
$P(X_3 = x_3 \mid X = x)$	P(0 | 0)	0.8235	P(0 | 0)	0.8478
	P(1 | 0)	0.1765	P(1 | 0)	0.1522
	P(0 | 1)	0.0604	P(0 | 1)	0.0719
	P(1 | 1)	0.9396	P(1 | 1)	0.9281

Source: Own dataset

driven by rationality. In this further study, I check whether the interaction with salespeople (K) affects satisfaction (H) through emotions (Z and W). Since the variables of interest are not directly observable, I obtain them from the indicators, three for each latent. The indicators of interaction with salespeople (K) are K_1 = "The

Figure 3: Customer comparison (interaction with staff on satisfaction)

Source: Own path diagram

staff is willing to help me right away", K_2 = "I have received high quality service (from the staff)" and K_3 = "The staff is efficient in managing my request" . The indicators of positive emotions (Z) are Z_1= interest, Z_2 = happiness and Z_3= relaxation, while those of negative emotions (W) are W_1= anger, W_2 = stress and W_3= boredom. Satisfaction (H) is obtained from the indicators H_1= "I'm happy with the experience I had in the store", H_2= "I'm happy with the experience I had in the store" and H_3 = "I enjoyed this shop". Starting from a complex structural model like the one in Figure 1, I arrive to a simpler model (Figure 3) eliminating the non-significant parameters at 0.05 level and if there is the same number of parameters I choose the model according to BIC index. The parameters are shown in Table 3. The parameters of the measurement part are all greater than 1 and therefore the latent variables continue to have in the category 0 the values below the average and in category 1 the values above the average. Interaction with salespeople positively influences the satisfaction both of shopping malls and of shopping streets. Interaction with salespeople positively influences both directly and indirectly the satisfaction of the consumers of city centers, indeed the direct controlled effect is 55.0371, the cell effect is 0.3938 and the natural direct effect is 21.6736. The indirect effect is also positive, being greater than 1 and equal to 2.064, so the total effect is positive and equal to 50.7238. A good relationship with salespeople brings greater satisfactions both directly and indirectly through positive emotions. For customers who choose shopping malls, the interaction with salespeople affects satisfaction directly because emotions do not affect. The intensity of the direct effect is 110.1110. This result confirms what was claimed earlier, i.e. that the buyers who prefer shopping malls are driven less by emotions. In this particular analysis, the direct effect is greater than the indirect one, i.e. that mediated by emotions, so the emotions of the shopping streets are less important. The chances of being satisfied over the average, conditioned by a high interaction, for those who choose shopping streets and for those who choose shopping malls are almost the same (0.9357≈0.9320 without correlation, 0.9259≈0.9320 with correlation). A particular result to point out is the positive relationship between interaction with the salespeople and negative emotions observed in shopping malls' customers. This particular positive relation can be clarified by analyzing the conditioned probabilities of Table 4. Generally, given the high value of the interaction (K = 1), the higher conditional probability is associated with $P(Z = 1, W = 0|K = 1)$, i.e. with high positive emotions and low negative emotions, which is also found to be correct in this case (0.5362> 0.2226> 0.1578> 0.0834). A strange anomaly occurs when I consider the conditional probabilities of the emotions given a low value of interactions (K = 0). The highest probability occurs in the situation with low positive emotions and low negative emotions (0.6321> 0.2453> 0.1176> 0.0050). If I consider the modified conditional probabilities, the strange result there is for both of the values of interaction (Table 4). This unusual result can be explained by thinking that the customer who gives low value to interaction with salespeople is driven to have low negative emotions precisely due to the lack of collaboration. Shopping malls, especially hypermarkets, are generally self-service in almost all departments and hence there is little interaction between sales staff and buyers. This autonomy is considered a time saving factor. The expectation of being supplied of goods, perceived as a waste of time, can lead to negative emotions. Shopping malls are often preferred by customers to save time and money and have plenty of choice in autonomy, so a low value of the interaction with salespeople can be considered lack of stress, namely "the staff did not help me but I did not want to be helped", while a high value of interaction, with the same motivation, can be seen unnecessary or also bothersome.

Table 3: Estimated parameters

Measurement part			Structural part		
parameter	Shopping street	Shopping mall	parameter	Shopping street	Shopping mall
$\mu^{K=1,K_1=1}$	16.7439***	9.0347***	$\mu_c^{Z=1,W=1}$	0.3484***	0.1103***
$\mu^{K=1,K_2=1}$	2.1689**	2.3749***	$\mu_c^{K=1,W=1}$	1.000^a	7.5836**
$\mu^{K=1,K_3=1}$	72.9449***	396.2335*	$\mu_c^{K=1,Z=1}$	6.3772***	8.7532***
$\mu^{Z=1,Z_1=1}$	50.8642***	8.1536***	$\mu^{K=1,H=1}$	55.0371***	110.1110***
$\mu^{Z=1,Z_2=1}$	8.2392***	29.4499***	$\mu^{W=1,H=1}$	0.2476*	1.000^a
$\mu^{Z=1,Z_3=1}$	11.5497***	8.1838***	$\mu^{Z=1,H=1}$	9.7464**	1.000^a
$\mu^{W=1,W_1=1}$	72.7589***	3.1712**			
$\mu^{W=1,W_2=1}$	84.4111***	5.8584***			
$\mu^{W=1,W_3=1}$	141.1981***	65.2094*			
$\mu^{H=1,H_1=1}$	171.8869***	70.1114***			
$\mu^{H=1,H_2=1}$	2.1312**	3.3941***			
$\mu^{H=1,H_3=1}$	6.2633***	3.9062***			
L-squared (shopping street)=1439.1181 (p≈1)			L-squared (shopping mall)=1728.4508 (p≈1)		
Signif. Codes: 0”***” 0.001”**” 0.01”*” 0.05”°” 0.1”” 1					
a= constrained parameter					

Latent variable		Indicator	
Interaction with salespeople	K	The staff is willing to help me right away	K_1
		I have received high quality service (from staff)	K_2
		The staff is efficient in managing my request	K_3
Positive emotion	Z	Interest	Z_1
		Happiness	Z_2
		Relaxation	Z_3

Negative emotion	W	Anger	W_1
		Stress	W_2
		Boredom	W_3
Satisfaction	H	I'm happy with the experience I had in the store	H_1
		I'm happy with the experience I had in the store	H_2
		I enjoyed this shop	H_3

Source: Own dataset

Table 4: conditional probability for shopping mall

Conditional probability			Modified conditional probability		
$P(Z = z, W = w \vert K = k)$	P(0, 0 | 0)	0.6321	$\tilde{P}(Z = z, W = w \vert K = k)$	P(0, 0 | 0)	0.6074
	P(0, 1 | 0)	0.1176		P(0, 1 | 0)	0.1130
	P(1, 0 | 0)	0.2453		P(1, 0 | 0)	0.2358
	P(1, 1 | 0)	0.0050		P(1, 1 | 0)	0.0439
	P(0, 0 | 1)	0.1578		P(0, 0 | 1)	0.0943
	P(0, 1 | 1)	0.2226		P(0, 1 | 1)	0.1331
	P(1, 0 | 1)	0.5362		P(1, 0 | 1)	0.3205
	P(1, 1 | 1)	0.0834		P(1, 1 | 1)	0.4521

Source: Own dataset

CONCLUSION

Shopping malls and shopping streets, being structurally diverse, offer to customers two types of heterogeneous shopping. Shopping malls provide the convenience and cost-effectiveness of free parking, quick shopping, and propose many stores offering the same type of merchandise, giving them more choices and thus allowing the customer to be more focused on quality-price. The shopping streets are more attractive to the customer who prefers to buy walking in a historical-cultural atmosphere without worrying about the quality-price ratio and who likes relating to sellers individually. These are some of the substantial differences between the two types of customers. To study such differences I analyze the type of the customers of a chain of jewelers which has stores both in historical streets and in shopping malls. I look at their purchasing attitudes with the theory of customer satisfaction, created to optimize customer satisfaction in order to increase it and to increase loyalty. Data analysis confirms that the buyers of shopping streets are more driven by the emotions of those who choose shopping malls. The study of the area and user basin can be useful for designing openings for one or more stores in shopping malls or city centers.

From this analysis I also deduce that shopping mall's customers have a practical and efficient approach to purchase, both in the interaction with salespeople and in the quality of products, while shopping street's customers interpret it with a more emotional mood. From this distinction on the type of clientele, the owner or manager of a store can obtain economic benefits, attracting more customers with the personalization of the exhibition environment in a more eye-catching way for each category of buyers. To increase the number of consumers, city center's shopkeeper must focus mostly on attracting interest and emotion, for example making the showcases more attractive and appealing by placing the goods on the shelves in an original and evocative way with colored and suffused light. On the other hand, the stores of shopping malls must be practical and have an immediate impact, for example by exposing the products to be sold in a visible and easy way, even with impacting and brilliant light games, however, taking care of not subtracting their characterizing practical aspect.

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