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# AN ANALYSIS OF THE INTENTION TO PURCHASE ON THE COLLECTIVE BUYING WEBSITES THROUGH PSYCHOLOGICAL, SOCIOCULTURAL AND SITUATIONAL FACTORS


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## Abstract

*This article proposes to use empirical models, with good adjustment, that can provide an informative measure on the intention to buy consumers considering information about socio-cultural, psychological and situational factors associated with them. It is expected that a measure of probability provided by a model such as that proposed can be useful in strategic marketing decisions where consumers' intention to buy.To achieve the objective, initially interviewed 384 Internet users in places with large circulation of people the city of João Pessoa, Paraíba, Brazil. Then the data obtained from interviews, were used to estimate those models. These models were based on assumptions of theories of the cognitive approach of consumer behavior, especially the Theory of Reasoned Action. The instrument used for data collection was a questionnaire containing market research questions related to psychological factors, sociocultural and situational consumer. The analysis considered only regression models of the class of generalized additive models.The most successful model presented nine variables and a single non-parametric term, obtained from smoothing splines. This model had a pseudo-*$R^2$*of 0,89 and allowed to reach a percentage of correct trials of the observations of the sample equal to 94%.*



**Keywords**: *Purchases intention, Regression model, Generalized Aditive Models, Consumer Behavior.*

## 1. Cognitive Approachand Theory of Reasoned Action

In the cognitive approach of consumer behavior is considered that consumption is determined by a complex decision making process that involves information sociocultural, individual (psychological) and environmental (situational).

The Theory of Reasoned Action (TAR) is a known theory of cognitive approach of consumer behavior.This theory is still widely used today as a basis for models that seek to describe consumer behavior.

The TAR was proposed by Ajzen and Fishibein (1975) to describe the behavior of a generic form.According to this theory, behavioral intention is a direct antecedent of decision behavior. Considering the TAR applied to the purchase behavior, this means that if an individual intends to make a buying behavior then it is expected that this occurred.

The behavioral intention to TAR is determined by attitudes and subjective norms concerning the behavior. The subjective norms consist of the perceived social pressure to perform a behavior and attitudes are evaluations of individual behavior.

The subjective norms are influenced mainly by sociocultural factors, because they depend on how the social environment presents itself. Attitudes are influenced primarily by psychological and situational factors, they depend on individual characteristics. That means it is possible to identify psychological, social and situational explaining indirectly purchase intent of consumers.

## 2. Determinants factors of purchase decision

The identification of the consumer profile allows the development of strategies to effectively satisfy customers, creating value for them, and generating good results for the venture.This profile is traced through features that can be grouped into three levels:

- *Psychological Factors:* at this level the consumer is studied as an individual decision maker based on their psychological characteristics.Psychological factors are known perception, motivation, learning, memory, attitudes and personality traits and lifestyle.(SOLOMON, 2008; PINHEIRO, 2006).

- *Sociocultural Factors:* The sociocultural factors are determined by the influence of social environment on an individual. Social groups and culture are sociocultural factors that may affect the purchase decision process. Individuals belong to several groups and admire. These groups (influence on various purchasing decisions. Demographic variables such as age are important determinants of social groups. Social classes represent a specific type of social groups determined by demographic variables such as income and education (SOLOMON, 2008).

- *Situational factors:* The situational factors involve those who are circumstantial and momentary. Three main types of situations are important in determining the consumer buying process. These types of situations involving communication, the purchase and use of goods or services (ENGEL, BLACKWELL & MINIARD, 2000).

## 3. Generalized additive models

The generalized additive models are regression models whose relationship between the dependent variable and the independent variables can be expressed in scales defined by different functions (called binding functions) and whose effects on the latter can be expressed by means of constant parameters or non-parametric functions. In this type of model, the parameters and non-parametric functions are estimated considering the characteristics of a probability distribution that satisfactorily describes the relationship between the mean value and the variance of the dependent variable. This probability distribution must belong to the exponential family of distributions.

$$\mu = E\left(y / x_1,\ldots,x_{k+p}\right) \tag{1}$$

$$\mu = g^{-1}\left(x_1\beta_1 + \ldots + x_k\beta_k + f_1\left(x_{k+1}\right) + \ldots + f_p\left(x_{k+p}\right)\right) \tag{2}$$

$$y \sim f\left(y;\phi,\theta\right) \tag{3}$$

$$f\left(y;\phi,\theta\right) = \exp\left(\frac{y\theta - b(\theta)}{a(\phi)} + c(y,\phi)\right) \tag{4}$$

In equation (3), $\phi$ and $\theta$ generically defined parameters that are specified by means of equations of the parameters of each chosen distribution of the exponential family of distributions, shown in equation (4). The functions $a(\ )$, $b(\ )$ and $c(\ )$ also depend on the probability distribution that is chosen to describe the relationship between the mean and the variance of the dependent variable of the model. The specification of $\phi$, $\theta$, $a(\ )$, $b(\ )$ and $c(\ )$ by means of equations associated with probability distribution are used in the procedure of estimation of fixed parameters and non-parametric functions.The estimation method used can be the least squares method iteratively re-weighted with penalty (IRLS-P).

In equation (1), it is defined that the model describes the expected behavior of the dependent variable given the values of the independent variables. In equation (2) the function $g^{-1}(\ )$ is a inverse function of $g(\ )$, which is called link function, defines the scale of the effects of the independent variable on the dependent variable. This function can be any monotonic function. In this scale, the effects of the variables are defined by the fixed parameters $\beta_j$ or by non-parametric functions $f_r(\ )$, where j=1,..., k and r=1,..., p. The use of non-parametric functions allows to admit that the effects of the independent variables on the dependent variable are not constants in the scale of the binding function. A non-parametric function consists of an estimate of a mean function without reference to a previously established functional form (only defines a function space) and obtained by smoothing methods. Smoothing methods are based on functions of the dependent variable and independent variables whose value has the same domain as an independent variable.

There are many methods of smoothing, being one of the most used method by functions base splines (YAO, 2012). The method of smoothing splines applied to a variable consists of a linear combination of the application of the same type of function (called the base function) at different intervals of that variable. A much used type of splines base function is the cube-based function. A cubic spline function is a continuous interval polynomial function, where each part is a degree 3 polynomial in a given interval.Since this function has the first and second continuous derivatives, the cubic splines curve has no peaks and no abrupt curvature changes at the nodes.

Thus, the cubic splines base function can be expressed as in equation (5):

$$h(x) = \sum_{m=1}^{M} \alpha_m q_m(x) \qquad (5)$$

, where the function $q_m(x)$ represents a cubic polynomial of the variable x and $\alpha_m$ are parameters associated with this polynomial in the interval m.

MAG can be seen as an MLG and claims that this makes it possible to construct a likelihood function for that type of model (HASTIE & TIBSHIRANI, 1986). Since this is a MAG likelihood function, it is possible to use it to determine a related deviance statistic. By means of this statistic, some methods similar to those used to test the significance of coefficients of the MLG are used (WOOD, 2006). In addition, it is also possible to calculate the pseudo-$R^2$ value (FARAWAY, 2006). The pseudo-$R^2$ measures are important measures to evaluate the goodness of fit of a regression model, and are very used when using models of the Generalized Linear Models class.

The possibility of obtaining a likelihood function and calculating the deviance statistic for generalized additive models allows inference methods similar to those used in generalized linear models to be used for these. Two of these methods are the likelihood ratio test and the Wald test.

A regression model with a qualitative dependent variable, such as a logistic regression model, can be used as a classifier, since it provides measures of probability of the result of an event being classified in a given group. This probability can be used, with the definition of a cut-off point (probability value that defines the classification), to classify the result of the event in a certain group.Thus, like any classifier, the number of correct classifications of this type of model (i.e., model fit) can be evaluated by means of a ROC curve. Some measures related to the ROC curve are used to infer about the number of correct classifications of a given classifier. Two measures that are widely used are the Area below the ROC curve (AUC) and the accuracy of the classifier.

## 4. Methods

The study was based on a market research survey aimed to collect information about their characteristics, preferences and opinions, which may be related to the use of the service under study. The sample consists of 383 Internet users in the city of João Pessoa-Paraíba, Brazil, aged between 18 and 59 years, with income above R$ 620,00 (which was the minimum wage in the year in which the interviews were conducted). The interviews were held in the second half of 2012, in places in the city where there was a great flow of people, such as supermarkets, shopping mall and places with concentration of access to local public transport.

Variables that could be considered in the research were listed from the periodic consultations that dealt with the variables determining the purchase intent of consumers Websites (DEHUA, YAOBIN & DEYI, 2008; VERHAGEN & DOLEN, 2009; CHEN,

HSU & LIN, 2010; LU & HSIAO, 2010; BELANCHE, CASALO & GUINALÍU, 2012; LIN, 2007; HAUSMANN & SIEKPE, 2009).

We selected 25 variables, two discrete metric variables, 15 ordinal categorical variables, three and five categorical dichotomous categorical variables. Using all variables as they appear in the questionnaire, the best model obtained has four variables and presented poorly adjusted (pseudo-$R^2$) equal to 0,25.

To achieve the goal of the research it was necessary to obtain a model with good fit to the data, so that it could be used to make inferences. So it was necessary to use some devices to get a better fit. Some of these devices were: group categories by transforming nominal or ordinal variables into dichotomous variables (this grouping of categories was done, for example, for the variables $z_1$, $x_{10}$, $z_4$, $z_3$ and $x_8$); define a given value for some continuous or discrete variables so that it divides the set of values of this variable into two categories (two intervals), making them dichotomous (this procedure was done for the variables $x_4$, $x_6$ and $x_2$); combine two dichotomous variables by grouping their categories so as to obtain a third dichotomous variable (this artifice was used to obtain $x_4{:}x_6$, $x_2{:}x_4$ e $x_1{:}x_8$); use as a single continuous variable the product or the ratio of two quantitative variables (this procedure was used to obtain the ratio $x_3/x_9$).

Table 1 - Variables research

| | |
|---|---|
| Purchase Intention (Y – Dependent Variable) | |
| Certainly plan to buy in collective buying websites | 11,2% |
| Maybe I will buy in collective buying websites | 12,8% |
| Probably go not buy into collective buying websites | 42,1% |
| Certainly not intend to buy in collective buying websites | 33,9% |
| Gender ($x_1$) | |
| Male | 47,4% |
| Famale | 52,6% |
| Age ($x_2$) | 30 anos (±10 anos) |
| Years ofscholarity ($x_3$) | 13 anos (±3 anos) |
| Household income ($x_4$) | R$ 2539,00 (±R$ 2172,00) |
| Household average incomeper family member ($x_5$) | R$1079,00 (±R$ 940,00) |
| Number of family members (x6) | 2(±2) |
| Attitude as a site feature ($z_j$) | |
| I think the characteristic of a collective buying website very important | **(1)** |
| I think the characteristic of a collective buying website important | **(2)** |
| I think the characteristic of a collective buying website unimportant | **(3)** |
| I believe that the characteristic of a collective buying website is not important | **(4)** |
| Often you visit a website collective buying ($x_8$) | |

| | |
|---|---|
| Never visit a website collective buying | 14,6% |
| Visit a website collective buying few times a year | 43,0% |
| Visit a website collective buying every month1 | 5,4% |
| Visit a website collective buying every week | 17,0% |
| Visit a website collective buying every day | 10,0% |
| Average timeusing the internet daily, according to respondent ($x_9$) | 187 min. (±156 min.) |
| Habit of purchase online stores ($x_{10}$) | |
| Never buyonline stores | 30,5% |
| Buy some in online stores | 51,5% |
| Buy enough in online stores | 18,0% |
| Means by which met the group buying service ($w_k$) | |
| Yes, I have been informed of offers by the communication situation | **(Yes)** |
| No, I was never informed of offers by the communication situation | **(No)** |

In table 1, $z_j$ indicates attitude relative to feature j of site; $w_k$ indicates whether the individual has access to offers from the collective purchase sites through the advertising channel j, p% indicates the proportion of individuals who scored a particular response on a research instrument item.

The hypotheses of influence of each of these variables on purchase intention in collective buying websites were tested by means of regression models the class of generalized additive models. This class of models allows nonparametric functions are used in the regression model to identify nonlinear relationships between an independent variable and a continuous dependent variable whatsoever. These variables are indicated in table 1.

Table 2 specifies the means by which the individual can learn about the collective purchasing service ($w_k$), the characteristics of the websites of that sector whose respondents' attitudes were evaluated ($z_j$).

Table 2 **-** Features websites, communication situations and products / services addressed in research

| **Features of the website collective buying treated in research** | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| Easy to get help on the website ($z_1$) | 4,7% | 20,3% | 54,9% | 19,8% |
| Variety of payment methods ($z_9$) | 2,3% | 10,7% | 25,5% | 61,5% |
| **Communication situations considered in the research** | | **Yes** | | **No** |
| Direct communication with other individuals ($w_1$) | | 48,7% | | 51,3% |

## 5. Results

After analyzing the adjustment of several semi-parametric regression models (models with parametric and non-parametric terms) and parametric models, the model that presented the best fit was a generalized semiparametric additive model with logit link function (so the model can be considered a logistic regression model in the class of generalized additive models) and assuming that the dependent variable has a binomial distribution.To fit a logistic regression model for dichotomous responses (binary dependent variable), the categories of the responses of the item that addresses the purchase intention of the respondents were grouped. It was considered that the respondent had a clear intention to use the service only when he stated that "he would certainly use a collective purchasing website". It was conceded that even when a respondent stated that he "would probably use the collective purchasing service, "there was uncertainty in his intention to use it, so that this intention was not obvious. The variables present in the model as well as its categories and es are shown in table 3.

Table 3 - Model variables

| |
|---|
| **<u>Purchase Intention (Y - Dependent variable)</u>** |
| Certainly plan to buy in collective buying websites |
| Maybe I will buy in collective buying websites |
| |
| **<u>Demographic variables and the interaction between them</u>** |
| Household average incomeper family member ($x_5$) |
| R$ |
| |
| Income and Number of family members ($x_4$:$x_6$) |
| Have household income greater than $ 2.000,00 and be the only members in the family |
| My household income is less than $ 2.000,00and/orthere is more than one members in the family |
| |
| Age and Income ($x_2$:$x_4$) |
| Have household income greater than $ 2.000,00 and have over 35 years |
| My household income is less than $ 2.000,00 and / or do not have more than 35 years |
| |
| **<u>Interaction between demographic and lifestyle variables</u>** |
| Gender and Often you visit a website collective buying ($x_1$:$x_8$) |
| I am male and I visit weekly collective buying sites |
| I'm not male and / or do not visit sites of collective buying weekly |
| |
| Ratio between scholarity and time internet browsing daily ($x_3$/$x_9$) |
| Years/hours |

| | |
|---|---|
| **Lifestyle variable** | |
| Experience in accessing websites from collective purchases ($x_8$) | |
| Never visit a website collective buying | |
| Visit a website collective buying | |
| | |
| Habit of purchase online stores ($x_{10}$) | |
| No, Never buy in online stores | |
| Yes, buy in online stores | |
| | |
| **Attitude as a website feature** | |
| Attitude as the ease of obtaining help on website ($z_1$) | |
| I think the characteristic of a collective buying website very important or important | |
| I think the characteristic of a collective buying website unimportant or not important | |
| | |
| Attitude as a variety of payment methods ($z_9$) | |
| I think the characteristic of a collective buying website very important or important | |
| I think the characteristic of a collective buying website unimportant or not important | |
| | |
| **Communication situations considered in the research** | |
| Knowledge of offers websites for collective purchasing by direct communication with others ($w_1$) | |
| Yes, I have been informed of offers by the communication situation | |
| No, I was never informed of offers by the communication situation | |

Equation (6) shows the adjusted model using the iteratively penalized (IRLWS) least squares algorithm.

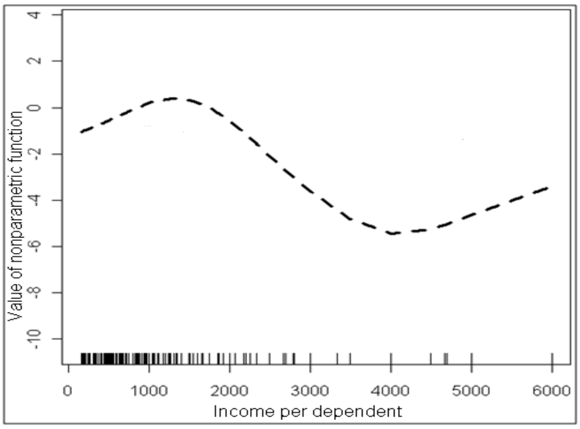
$$chance = \frac{P(Y=1)}{1-P(Y=1)} = e^{f(x5)}.(4{,}22)^{w1}.(3{,}68)^{z1}.(16{,}78)^{x10}.(6{,}02)^{z9}.(7{,}01)^{x8}.(0{,}13)^{x4:x6}.$$
$$.(0{,}11)^{x1:x8}.(0{,}25)^{x2:x4}.(0{,}01)^{x3/x9} \quad (6)$$

Most of the effects of the variables on the chance of an individual intending to use the service were admitted as constants. The model presents two quantitative variables, one of which is income per family member ($x_5$) and a ratio between the number of years of schooling and the average daily access time to the internet ($x_3/x_9$). The latter represents a degree of belonging to a group defined by both schooling and the use of the Internet.

The model has eight variables that are qualitative and define groups of individuals more likely to have a clear intention to use the service. Some of these variables are defined by combinations of different characteristics and reflect interaction effects. In the model there are three variables that are used to consider interaction effects.

Most of the effects were admitted as constants in the model, which was plausible since the parameters were significant. These effects reflect how much it increases or decreases the chance that an individual intends to use the collective purchasing service when the variable assumes a certain value. Thus, if an individual, for example, met the collective purchasing service through direct communication with other users ($w_1 = 1$), then he / she has 4,22 times more chance of to want to use the service than those who did not know the service In this way ($w_1 = 0$).

Figure 1 – Curve of the effect of income per dependent




The only quantitative variable of the model that has a constant effect on chance is the ratio between schooling and time of access to the Internet.As this effect has a value between 0 and 1 (0,99), it indicates that the chance of using the service is reduced with increasing schooling ($x_3$) and decreasing the average time of internet access ($x_9$). Note also that, in equation (6), the effect of household income on the probability that an individual intends to use the service was not admitted as constant. The effect is described by means of a function that has been adjusted by the smoothing method splines (figure 3). The measure described in figure 1 represents the exponent of the odds ratio of the variable income per family member. Thus, any increment indicated in the graph represents an increase in the odds ratio of that variable.

Through simple mathematical manipulation it is possible to express the same model by explaining the value of the probability measure, instead of the measure of chance. This way of expressing the model makes it easier to understand the use of this to classify individuals or groups of individuals with similar characteristics according to the intention to use the collective purchase service (purchase intention).

The test used the term nonparametric tests the significance of the variation in estimated curve. If you can not reject the hypothesis that variation is equal to zero, then we can say that there is no relationship between the response variable and the covariate in question.In the case of ships GAM this variation is significant. Table 4 also shows the coefficients of the terms of the parametric model. From these coefficients estimated the value of the *odds ratio*.

Table 4 - Coefficients, odds ratio and p-value of the Wald test. Significance:*0,05; **0,01

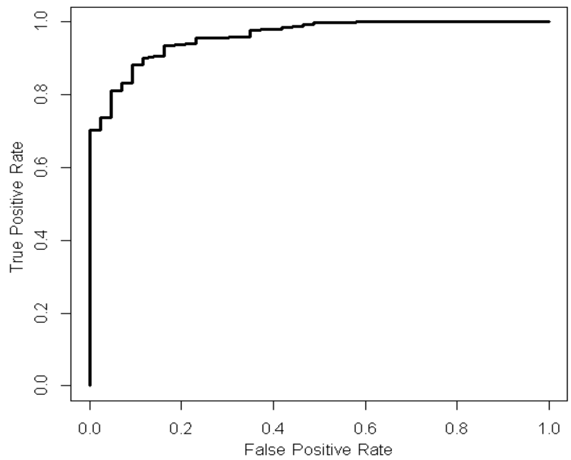
| Variables | Coefficients | Odds | p-value |
|---|---|---|---|
| Household average incomeper family member($x_5$) | - | - | 0,00116** |
| Met the collective shopping service through direct communication with others ($w_1$) | 1,442 | 4,223 | 0,01281* |
| Attitude as the ease of obtaining help on website ($z_1$) | 1,304 | 3,684 | 0,01564* |
| Attitude as a variety of payment methods ($z_9$) | 1,796 | 6,025 | 0,00953** |
| Habit of purchase online stores ($x_{10}$) | 2,82 | 16,776 | 0,00002** |
| Experience in accessing websites from collective purchases ($x_8$) | 1,947 | 6,958 | 0,00059** |
| Income and number of family members($x_4$:$x_6$) | -2,043 | 0,13 | 0,00258** |
| Age and income ($x_2$:$x_4$) | -1,365 | 0,255 | 0,02257** |
| Gender and often you visit a website collective buying ($x_1$:$x_8$) | -2,2 | 0,111 | 0,00793** |
| Ratio between scholarity and time internet browsing daily ($x_3/x_9$) | -4,456 | 0,012 | 0,00205** |

The model shows that purchase intention is determined by a complex process that involves not main effects (assigned to a single variable) of psychological, sociocultural and situational factors. The effects of interactions between these factors are important for this explanation.

The model fit the data can be analyzed defining a probability value, called the cutting point, from which the purchase of the event is defined as expected to occur and thus is classified.

The number of judgments made by the model in these four categories determines the most appropriate cut-off point and as a model with binary response variable is well fitted to the data.

Figura 2 - Curva ROC para MLG com variável resposta binária




By means of the ROC curve (figure 2), it is verified that the value of the probability measure equal to 0,5609 provides the best rate of correctness in the classifications made based on the model. Considering this cutoff, measures of the goodness of fit of the model were calculated.

Table 5 - Measures of goodness of fit and p-value Chi-square test. Significance:*0,05; **0,01

| | |
|---|---|
| Pseudo-$R^2$ | 0,89 |
| Acuracy | 0,94 |
| AUC | 0,95 |
| p-value | 0,0001** |

Table 5 presents the p-value of the Chi-square test. This test is used to test the hypothesis that all coefficients are zero. The rejection of this hypothesis means that there is at least one of the independent variables is related to purchasing intention.

Through this framework shows that the estimated model gives a percentage of success, considering the judgments made for the observations of the sample, approximately equal to 94% (model accuracy equal to 94%).

Another measure of the quality of fit is the *pseudo-$R^2$*. This measure varies between 0 and 1. Values close to 1 indicate that the model provides best fit to the data. The proposed model showed the *pseudo-$R^2$* equal to 0,89.

A third measure that is used to check the quality of fitting a regression model with binary response variable is the area under the ROC curve (AUC).This area also has values ranging between 0 and 1. Values close to 1 indicate a good model fit to the data. For both positive and negative judgment, the value of AUC was found to be around 0,95 (note in Table 3).

## 6. Conclusions

Research has shown it is possible to explain the purchase intent of collective buying websites via factors proposed in the cognitive approach of consumer behavior. The model obtained showed that in fact the intention of using the service is a result of a process of interaction between those factors.

The possibility of obtaining a model with a good fit to the data, shown by indicators such as the *pseudo-$R^2$*, accuracy and AUC, may make it possible to use the model to make predictions and to guide decisions in order to better serve individuals who have more likely to use the service.Given some characteristics represented by the factors in the model, one obtains a measure of the chance of individuals with this profile using the service.

The study also proved possible to obtain a good model to explain the intention of purchasing from individuals through variables that are included in the three levels of factors treated.The variables used in previous studies are presented in general these three levels, although somewhat mentioned.The main objective of the organization of these three levels variables in the study was to show that this can be a good way to get a good explanation of the intention of purchasing a product or service. This may be important to guide future research in the search for these variables.

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