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PREDICTION OF THE ACT OF TERMINATION OF CAR INSURANCE CONTRACTS AT THE END OF THEIR TERM

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ABSTRACT

The success of organizations depends not only on retaining customers but also on preventing their defection. However, there is little research on the termination of the company's and its customers' relationship. In other words, a better understanding of the factors involved in the termination process will make it easier to prevent and avoid termination while trying to recover lost customers and attract new prospects. Through this paper, we have attempted to detect, through a literature review, the "determinants of termination" that hurt the relationship between companies and their customer portfolio, and to quantify the impact of each determinant on termination behavior using an extension of generalized linear models, namely the binary logistic regression method.

Keywords: *Car Insurance, Termination Behavior, Generalized Linear Models, Binary Logistic Regression*

1. INTRODUCTION

The termination of a contract is a notion frequently evoked in different fields of action and is guided by the major concerns of managers to preserve the survival of the units they manage. The termination of a contract is by definition, an act in which the contract loses its entity and reaches a point where it no longer conceives of rights. It is extinguished when all the obligations provided during its life have been completely fulfilled by the parties involved. Choosing to work on the termination of non-life insurance contracts, specifically automobile insurance contracts, we can see that this common practice consists of terminating a contractual commitment entered into within a predetermined period at its expiration, assuming that within that period the situation would not be likely to change for the better. However, it is possible that during the life of the contract, a reason may arise that triggers the termination of the contract. This explanation of the decision to terminate indicates that this concept cannot be understood only by the insured, but also by the decision of the insurers. Apart from that, the insured will not voluntarily deprive himself of terminating his insurance contract with his insurer if the latter has good reasons for terminating his contract before the expiry date.

Due to the need for growth, development, and innovation in the motor insurance industry, which requires knowledge and adaptation to customers' needs, monitoring the latter is decisive. Insurance companies whose work is based on actuarial calculations and probabilistic analyses of insurance operations, which are essential for the projection of results, have proved over time to be caught between the search for loyalty, exposure to multiple risks, and, most importantly, massive changes in customer behavior. Except for a better knowledge of the products offered, and the quick processing of insurance requests and claims, today's customers are much more vigilant and expect a lot from their policyholders and it is recognized today that the analysis of their behavior is a key issue in the decision-making process, being one of the main

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challenges faced by insurance companies to promise their sustainability in the long run.

Several works have been developed around the issue of policyholder satisfaction, such as Matthias Ruefenacht's (2018) [6] study that focused on the role of satisfaction and retention for insurers as key drivers of insurance company stability. Alternatively, Ranganathan Venkatesan and Jayanth Jacob (2019) [4] asked whether loyalty and satisfaction promote customer retention in the life insurance industry. It has been shown that a satisfied customer not only maintains a good, stable, and ongoing business relationship but also tends to recommend the entity to others. In addition, they have shown through the structural equation model that providing a high-quality service influences the satisfaction of existing customers. The article by Montserrat Guillen et al, (2008) [13] "The need to monitor customer loyalty and business risk in the European insurance sector" also helps to explain the importance of rigorously monitoring customer loyalty to avoid policy terminations. However, under certain specific conditions, it has been shown that although a customer may be satisfied with the service provided by the target company, he or she may be equally satisfied with other offers. Thus, instead of considering satisfaction as an antecedent of customer loyalty, it should be considered as a variable that induces a certain commitment behavior and that at any time the customer would be led to terminate the contract if a fierce event during the relationship occurs.

Although research on retention and retention strategies has helped to better understand the relationship between the insurer and its insured, except that work on the breakdown of contractual relationships has begun to create its field of research. The findings of Manuel Leiria et al, (2020) [1] "Non-life insurance cancellation: a systematic and quantitative review of the literature" suggest the extent to which some important factors may explain changes in customer behavior in non-life insurance. By facilitating the understanding of the act of insurance contract cancellation, it allows insurance companies to develop, with a significant level of return, measures that seek to retain customers, while yielding better profits for the insurance companies. Other studies, such as those of Christophe Dutang (2012) [10], also examine the effect of links and interactions between the insured, the insurer, and the market. He finds that the insurance premium variable can be a decisive factor for the insured to renew or not renew his car insurance contract with his current insurance company. Alternatively, Leo Guelman (2014) [9] follows the same perspective as the latter. The latter highlights that the higher the insurance premium, the more likely the attention is to leave the institution, and in contrast, if the insurance premium decreases. Thus, we can see the sensitivity of policyholders about changes in insurance rates on the decision to renew or not the contract at its expiration. Montserrat Guillén Estany et al., (2003) [32] has been interested in the issue of explaining customer failures, however, they propose the use of logistic regression models to predict and understand why customers leave an insurance company. In addition, there are many publications related to the study of the contractual breach and customer abandonment in different fields, including works that have studied the breach of the employment contract at the initiative of the employer, the breach of contractual relations between companies, the breach of contract with its supplier and others.

Taking into account the aspects mentioned above, we specify at this level that this research proposes to study the prediction of the act of canceling car insurance contracts initiated mainly by policyholders and the analysis of the impact of the determinants of cancellation on their behavior at maturity. In other words, we will attempt to analyze the impact of a set of factors that stimulate the act of terminating automobile insurance contracts at maturity, taken from the literature. The relevance of the subject is expressed by raising, through the discovery of these determinants, alternatives to reduce the rate of cancellation of automobile insurance contracts by the insured and to stimulate insurers' growth.

However, several works have addressed binary logistic regression models in the prediction of policyholders' churn in different insurance industries, of which we will mention the most recent ones. The essay by Mauricio Henao M., Diego Restrepo T., and Henry Laniado published in (2020) [2]"Customer churn prediction in insurance industries: A multiproduct approach", implements logistic models to predict the departure of policyholders in different insurance lines in a general way and without any segmentation. Thus, the paper by M. À. de la Llave, F. A. Lòpez and A. Angulo published in (2020) [3] entitled: "The impact of geographical factors on churn prediction: an application to an insurance company in Madrid's urban area", highlights the prediction of the churn rate influenced by geographical determinants in the urban area of Madrid using binary logistic regression. Also, the work of Manohar Giri (2018) [5] presented in India, under the title: "A behavior study of life insurance purchase decision" uses the logistic model to predict the surrender behavior of life insurance contracts initiated by policyholders. In addition, the paper by Zhengmin Duan, Yonglian Chang, Qi Wang, Tianyao Chen, and Qing Zhao published in (2018) [6], entitled: "A logistic regression based auto-insurance tariff making model designed for the insurance rate reform" in China, tries to introduce a logistic regression based auto-insurance tariff making model and design an insurance rate reform.

Through these different works, we note that the prediction of the act of termination of the policyholders confers to the use of generalized linear models, and more specifically the binary logistic regression. This choice can be explained by the duality of the policyholders' decision at maturity, either to renew or to terminate their insurance contracts as mentioned above. Binary logistic regression is one of the simplest and fastest machine learning algorithms to implement, offering high simulation efficiency. Also, training a model with this algorithm does not require a lot of computing power. However, it produces well-calibrated probabilities and classification results. This is an advantage over models that only produce the final classification results.

As mentioned above, this article will only present a specific study of the prediction of the act of termination of car insurance contracts initiated by the insured at their due date in the region of Rabat, Salé, and Kenitra. This study will not engage the act of termination of car insurance contracts initiated by the insurers, nor the insurance policies suspended before their end.

2. METHOD: GENERALIZED LINEAR MODEL

Being a set of statistical models used to analyze the relationship of a variable to one or more others, the Generalized Linear Models (GLM), usually known by their English initials, operate as adequate tools to estimate the parameters of the model used in the most impartial way possible. These models are understood as a development of the general linear model, where the dependent variable or variable to be explained is linearly related to the independent variables via a precise link function. They cover statistical models such as linear regression for normally distributed responses, logistic models for binary or dichotomous data, log-linear models for headcount data, complementary log-log models for interval-censored survival data, etc. However, they have been used to address the shortcomings of linear models. In other words, the latter is limited to describing the relationship between a variable to be explained and explanatory variables, to test the significance and compare the intensity of the impact of each independent variable on the variability of the dependent variable. However, the linear model is required to respect certain assumptions that are not verified in other circumstances, and therefore these models are no longer suitable for the analysis envisaged. These assumptions are of the order of four:

Hypothesis 1: Generally, in linear models, the link between the expectation of the dependent variable and the independent variables is a linear relationship. This linearity constraint is therefore not always verified. However, there are certain circumstances for which this relationship is non-linear, such as the example of the sigmoid function, also known as the *S* curve. This function has for asymptotes the lines of equation y=0 and y=1 under the formality of a dichotomous dependent random variable y_i which takes values in the interval [0,1] from where we can note $y_i \sim B(1,\pi)$.

Hypothesis 2: In linear models, the data are assumed to be normally distributed. An absolutely continuous probability law depending exclusively on its expectation (μ), its standard deviation (σ) and y_i a dependent random variable, noting that $y_i \sim N(\mu, \sigma^2)$. It is also called Gaussian law, Gauss law, or Laplace law - Gauss refers to the names of the two mathematicians Laplace (1749-1827) and Gauss (1777-1855). This distribution is particularly important in the measure of calculating the errors and realizing the statistical tests using the table of this law. However, it has a special place thanks to the central limit theorem, which allows us to establish the convergence of the sum of a sequence of random variables to the normal law. Intuitively, this statement affirms that any sum of independent random variables tends to be a Gaussian random variable in certain cases. Thanks to this central limit theorem, the linear model is robust to deviations from normality, but in certain scenarios, for example, if the observations are from a discrete distribution, or if the deviations from the mean present a strong dissymmetry, the assumption of normality is no longer tenable. At this point, we must look for another method to model the data implemented outside the linear model.

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Hypothesis 3: In linear models, the random variables from independent events are assumed to be uncorrelated. In other words, the covariance of two independent random variables is zero, although the converse is not always true. On the other hand, some studies look at the interrelationships between these variables by estimating their interrelational impact and testing their significance. This hypothesis is not verified in cases where the conditions of the experiment lead to correlations between individuals sharing the same experience, for example, or even in conditions where the survey is carried out on the same individual in different periods.

Hypothesis 4: Linear models refer to a constant variance of the random variables, except that there are some cases where the variance changes as a function of the mean, as marked by the distribution of random variables following a Poisson distribution, for example, noting $y_i \sim P(\mu)$.

The Generalized Linear Model (GLM), is a more flexible device compared to the linear model, agreeing to cross the four assumptions mentioned above, in a process of treatment of the observations, to realize a relevant estimation of the parameters of the model and to test the hypotheses conceived in a motive of exploring the quality of the latter. These models were introduced and defined by Nelder John Ashworth, and Robert Wedderburn (1972) [54] stating that they "allow us to model responses that are not normally distributed, using methods closely analogous to linear methods for normal data. However, Anderson Duncan, Sholom Feldblum, Claudine Modlin, Doris Schirmacher, Ernesto Schirmacher, and Neeza Thandi (2004) [23], present in detail, the concepts of the density function, the exponential distribution function, the form of the moment generating function, and the specific types of the family of exponential distribution functions such as Gamma, Poisson, Bernoulli, Dirichlet, Exponential, Normal, Chi-square, Beta, and so on}. We explain throughout this article, the generalized linear models, and a brief application of one of its extensions namely, the binary logistic regression.

A generalized linear model is an extension of the classical general linear model, so linear models are a suitable starting point for the introduction of generalized linear models. The linear regression model is characterized by four essential elements such as the column vector of dimension (*n)* of the dependent random variables (*Y*), a systematic component defined as a matrix of size ($n \times p$), and rank (p), called the design matrix $X = X_1, X_2, \dots, X_p$, grouping together the column vectors of the explanatory variables, also known as the control variables endogenous, or independent, where (x_i) is the row vector of these explanatory variables associated with the observation (i) such that, $i = 1, 2, \dots n$, (β) the column vector of dimension p of the unknown parameters of the model, i.e. the unknown regression coefficients associated with the column vector of the matrix (X), and finally, the vector dimension n of the errors (ε). The data are assumed to be drawn from observations of a statistical sample of size $n \in \Re^{(p+1)}$(where $n > p+1$). However, linear models seem to be based on a set of assumptions such as (i) ε_i are error terms, of a variable E, unobserved, independent, and identically distributed, noting that $E(\varepsilon_i)=0$, (ii) the $V(\varepsilon_i)=\sigma^2$. I, about the character of homoscedasticity, referring to a constant stochastic error variance of the regression, i.e., identical dispersion for each i, (iii) the normality of the distribution of the error random variable ε noting: $\varepsilon_i \sim N_n(0, \sigma^2 I_n)$ We can also consider that ε_i is an observation of the random variable E, also distributed according to a normal distribution, noting that $\varepsilon_i \sim N(0, \sigma^2$, (iv) the n real random variables ε_i are considered independent, i.e. ε_i is independent of ε_j for $i \neq j$, (v) y_i is an observation of Y of normal distribution, such that, $Y \sim N_n(\beta X, \sigma^2 I_n)$.

The linear regression model is defined by an equation of the form:

$$Y = \beta X + \varepsilon \quad \text{with} \quad \varepsilon \sim N_n(0, \sigma^2 I_n)$$

Where,

- $\mathbf{Y} \in \Re^{(n)}$
- $\mathbf{X} \in M_{(n,p)}$ known, deterministic, with rank p
- $\boldsymbol{\beta} \in \Re^{(p)}$, unknown
- $\sigma^2 \in \Re^{(*+)}$, unknown

In statistics, generalized linear models is an extraordinarily flexible generalization of ordinary linear regression, which takes into account dependent variables, called responses, that have distribution patterns other than the normal distribution. GLM generalizes linear regression by allowing the linear model to be related to these response variables by a (g) link function. This mechanism was founded by John Nelder and Robert Wedderburn (1972) [54], who were able to

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formulate generalized linear models to unify various other statistical models, including linear regression, logistic regression, Poisson regression, etc. However, the model's linear predictor or deterministic component is a quantity with the skill and ability to incorporate information about the independent variables into the model. It is linked to the expected value of the data thanks to the linking function (g). This linear predictor noted η is expressed in the form of linear combinations of the unknown parameters β and the matrix of column vectors of the explanatory variables X (see the works of Denuit M. and Charpentier A. (2005) [20], J-J. Droesbeke, Lejeune M., and Saporta G. (2005) [18]. η can thus be expressed as:

$$\eta = \beta X$$

The normality of the response variable Y, such that, $Y \sim N_n$ (β X, $\sigma^2 I_n$), for any observation i, allows us to write, $E(Y) = \beta X$, and to note $E(Y) = \mu$ for simplification reasons. Thanks to the link function (g), it is possible to establish a non-linear relationship between the expectation of the response variable E(Y) and the explanatory variable(s) and to apprehend observations and responses of diversified natures, such as the example of binary data of failures/successes, frequencies of successes of the treatments, lifetimes, etc., by noting that:

$$g\,(E(Y)) = g(\mu) = \eta = \beta X$$

As mentioned in the work of Esbjörn Ohlsson, and Björn Johansson (2010) [12], we can also write that:

$$E(Y) = \mu = g^{-1}(\eta)$$

The linkage function (g) states the relationship between the linear predictor η and the mean of the distribution function μ. There are many commonly used link functions, and their choice is based on several considerations. There is always a well-defined canonical link function that is derived from the exponential response density function (Y). However, in some cases, it makes sense to try to match the domain of the link function to the range of the mean of the distribution function. A linkage function transforms the probabilities of a category response variable into a continuous unbounded scale. Once the transformation is complete, the relationship between the η predictors and the response can be modeled using linear regression. For example, a dichotomous response variable may have two unique values. Converting these values to probabilities causes the response variable to vary between 0 and 1. When an appropriate linkage function is chosen to be applied to the probabilities, the resulting numbers are between $-\infty$ and $+\infty$. However, any probability law of the random component Y has associated with it a specific function of the expectation called the canonical parameter. For the normal distribution, it is the expectation itself. For the Poisson distribution, the canonical parameter is the logarithm of the expectation. For the binomial distribution, the canonical parameter is the logit of the probability of success. In the family of generalized linear models, the functions using these canonical parameters are called canonical link functions. In most cases, generalized linear models are built using these link functions. Below is a table of several commonly used exponential family distributions, the data for which they are commonly used, and the canonical link functions and their means.

Table 1: Laws of the exponential family and their canonical links

Y distribution	Canonical links	Means
Normal distribution $N(\mu, \sigma^2)$	Identity: $\eta = \mu$	$\mu = \beta X$
Bernoulli distribution $B(\mu)$	Logit: $\eta = \ln(\mu/(1-\mu))$	$\mu = 1/(1 + \exp^{-(\beta X)})$
Poisson distribution $P(\mu)$	Log: $\eta = \ln(\mu)$	$\mu = \exp^{(\beta X)}$
Gamma distribution $G(\mu, v)$	Inverse: $\eta = 1/(\mu)$	$\mu = (\beta X)^{-1}$
Gaussian Inverse distribution $I.G\ (\mu, \lambda)$	Inverse carré : $\eta = 1/(\mu^2)$	$\mu = (\beta X)^{-2}$

Source: Author

2.1. Probability law of the response variable *Y*

The inadequacy of the so-called classical general linear model, of the laws that it associates with the response variables, leads us to use generalized linear models (GLM), which allow us to connect other laws than the normal law, such as Bernoulli’s law, the binomial law, Poisson’s law, Gamma law, etc. These laws are part of the exponential family,

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offering a common framework for estimation and modeling. These laws are part of the exponential family, offering a common framework for estimation and modeling. This natural exponential family has laws that are written in exponential form, which allows us to unify the presentation of results. Let f_Y be the probability density of the response variable Y. We can admit that f_Y belongs to the natural exponential family if it is written in the form:

$$f(Y/\theta,\varphi,\omega) = \exp\left(\frac{Y\theta-\mathrm{b}(\theta)}{a(\phi)}\,\omega + \mathrm{c}(Y,\varphi,\omega)\right),\ Y \in S$$

With :

- a(.), b(.), c(.): Functions specified according to the type of the exponential family considered.
- θ: Natural parameter, also called canonical parameter or mean parameter.
- φ: Parameter of dispersion. This parameter may not exist for some laws of the exponential family, in particular when the law of Y depends only on one parameter (in these cases $\varphi = 1$). Otherwise, it is a nuisance parameter that must be estimated. As its name indicates, this parameter is related to the variance of the law. It is also a very important parameter in that it controls the variance and therefore the risk. In some cases, a weighting is necessary to grant relative importance to the different observations and the parameter φ is replaced by φ/ω, where ω designates a weight known as a priori.
- S: Subset of R or N
- ω: The weights of the observations.

Moreover, if f_Y , belongs to the natural exponential family, we can deduce the following properties:

- $E[Y] = \mu = \mathrm{b}'(\theta) = \partial \mathrm{b}(\theta)/\partial(\theta)$
- $V[Y] = \mathrm{a}(\varphi) \times \mathrm{b}''(\theta) = \mathrm{a}(\varphi) \times \partial^2 \mathrm{b}(\theta)/\partial(\theta)^2$
- $g(\mu) = \mathrm{g}(\mathrm{b}'(\theta)) = \beta X$

With : $\mathrm{b}'(\theta) = g^{-1}(\beta X)$ et $\theta = \eta = \beta X$

For a probability law to belong to the natural exponential family, it is sufficient to write it as an exponential function and determine its terms. We try below to propose some examples of commonly used probability laws, and explain all their components (See the works of Michel Denuit, and Arthur Charpentier (2005) [19], P. de Jong, and Gillian Z. Heller (2008), and Frees E. (2010)) [12]:

-The Gaussian distribution, with mean μ and variance σ^2. $Y \sim N(\mu, \sigma^2)$ belongs to the exponential family, with $\theta = \mu$, $\varphi = \sigma^2$, $\mathrm{a}(\varphi) = \varphi$, $\mathrm{b}(\theta) = \theta^2/2$, and $\mathrm{c}(Y,\varphi,\omega) = -1/2\ (y^2/\sigma^2 + \ln(2\pi\sigma^2))$, where $Y \in$ R.

-The Bernoulli distribution, with mean π, and variance π(1-π). Y ~ B(π) is catalogued among the exponential family, with $\theta = \ln\{\pi/(1-\pi)\}$, $\varphi = 1$, $\mathrm{a}(\varphi) = 1$, $\mathrm{b}(\theta) = \ln(1+\exp(\theta))$, and $\mathrm{c}(Y,\varphi,\omega) = 0$ where $Y \in$ N .

-The Poisson distribution, with mean λ, and variance λ. Y ~ P(λ), is part of the exponential family, with $\theta = \ln(\lambda)$, $\varphi = 1$, $\mathrm{a}(\varphi) = 1$, $\mathrm{b}(\theta) = \exp(\theta) = \lambda$, et $\mathrm{c}(Y,\varphi,\omega) = -\ln(\lambda!)$ with $Y \in$ N .

-The Gamma distribution, with mean μ and variance v^{-1}. Y ~ G(μ, v), also joins the exponential family, with $\theta = -1/\mu$, $\varphi = v^{-1}$, $\mathrm{a}(\varphi) = \varphi$, $\mathrm{b}(\theta) = -\ln(-\theta)$, and $\mathrm{c}(Y,\varphi,\omega) = ((1/\varphi)-1)\ln(Y) - \ln(\Gamma(1/\varphi))$ where $Y \in R^+$.

Table 2: Components of the exponential family of usual probability laws

Y distribution	θ(μ)	φ	a(φ)	b(θ)	c (Y,φ,ω)
Normal distribution $N(\mu, \sigma^2)$	μ	σ^2	φ	$\theta^2/2$	$-½ (y^2/\sigma^2 + \ln(2\pi\sigma^2))$
Bernoulli distribution $B(\mu)$	ln{μ/(1-μ)}	1	1	ln (1+ exp(θ))	0
Poisson distribution $P(\mu)$	ln(μ)	1	1	exp (θ)	− ln (Y !)
Gamma distribution $G(\mu, v)$	−1/μ	1/v	φ	−ln(−θ)	((1/ φ) − 1) ln (Y) - ln(Γ(1/ φ))
Gaussian Inverse distribution $I.G(\mu, \lambda)$	$-1/2\mu^2$	σ^2	φ	$-(-2\theta)^{1/2}$	$-1/2 (\ln(2\pi\varphi Y^3) + 1/\varphi Y)$

Source: Author

Table 3: Expectation and variance of usual probability laws

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Y distribution	μ = E(Y) =b'(θ)	V(Y) = a(φ)b"(θ)
Normal distribution ***N(μ, σ²)***	θ	σ^2
Bernoulli distribution ***B(μ)***	exp(θ)/((1+exp(θ)	$\mu(1-\mu)$
Poisson distribution ***P(μ)***	exp(θ)	μ
Gamma distribution ***G(μ, ν)***	−1/θ	μ^2/ν
Gaussian Inverse distribution ***I.G (μ, λ)***	μ	μ^3/λ

Source: Author

The two tables above summarize respectively, the different components of the exponential family for usual probability laws, as well as their expectation and variance, assuming that the weight ω = 1.

2.2. Parameters estimation

At this stage, it is a question of estimating the column vector $\beta = (\beta_0, \beta_1, \cdots, \beta_p)$ noted $(\widehat{\beta_0}, \widehat{\beta_1}, \cdots, \widehat{\beta_p})$ of dimension p of the unknown parameters of the model, i.e. the unknown regression coefficients associated with the column vectors of the matrix (X) representing a set of explanatory variables, by maximizing the natural log-likelihood of the generalized linear model. This estimation applies to all laws with a distribution belonging to the exponential family of the form:

$$f(Y/\theta, \varphi, \omega) = \exp\left(\frac{Y\theta - b(\theta)}{a(\phi)}\omega + c(Y, \varphi, \omega)\right), \; Y \in S$$

The main idea of the maximum likelihood method is to look for the parameters' value that maximizes the probability of having observed what we observed. Moreover, the standard approach to finding the maximum of any function of several variables consists in canceling its gradient (first derivative) and checking that it's hessian (second derivative) is negative. However, to obtain the maximum likelihood estimator (L), we solve the following system of p unknowns β:

$$\frac{\partial \ln L(\beta)}{\partial \beta_1} = 0$$

$$\vdots$$

$$\frac{\partial \ln L(\beta)}{\partial \beta_p} = 0$$

Let n be independent variables Y_i, with $i = 1\cdots, n$ of law belonging to the exponential family, X the design matrix, where are arranged the observations of p column vectors representing the explanatory variables, β the column vector of p parameters of the model, η the linear predictor with n components noted $\eta = \beta X$, g the link function, is supposed to be monotonic and differentiable such that, $\eta = g(\mu)$, as well as the canonical link function, is expressed by $g(\mu) = \theta$. For n observations assumed to be independent, and taking into account the link between θ and β, the likelihood (L) and the natural logarithm of the likelihood (ℓ) are written as follows:

$$L(Y, \theta, \phi, \omega) = \prod_{i=1}^{n} f(Y_i, \theta_i, \phi, \omega)$$

$$\ell(Y, \theta, \phi, \omega) = \ln(L(Y, \theta, \phi, \omega))$$

$$= \ln\left(\prod_{i=1}^{n} f(Y_i, \theta_i, \phi, \omega)\right)$$

$$= \sum_{i=1}^{n} \ln(f(Y_i, \theta_i, \phi, \omega))$$

$$= \sum_{i=1}^{n} \ell_i(Y_i, \theta_i, \phi, \omega)$$

With:

$$\ell_i = \frac{Y_i\,\theta_i - b(\theta_i)}{a_i(\phi)}\,\omega + c(Y_i, \phi, \omega), \text{ and } \theta_i = \beta_j . x_i^T$$

Indeed, we try this method to reach the maximum likelihood. The logarithm function is strictly increasing, and the likelihood and the natural logarithm of the likelihood reach their maximum at the same point. Moreover, the search for the maximum likelihood generally requires the calculation of the first derivative of the likelihood, and this is much simpler than the natural log-likelihood, in the case of multiple independent observations, since the logarithm of the product of the likelihoods is written as the sum of the logarithms of the likelihoods, and it is easier to derive a sum of terms than a product. However, the derivative of the natural log-likelihood can be realized by solving the following equality:

$$\frac{\partial \ell_i}{\partial \beta_j} = \frac{\partial \ell_i}{\partial \theta_i} \times \frac{\partial \theta_i}{\partial \mu_i} \times \frac{\partial \mu_i}{\partial \eta_i} \times \frac{\partial \eta_i}{\partial \beta_j}$$

From the above equality, we try to give the meaning of each term of the latter as follows:

- $\frac{\partial \ell_i}{\partial \theta_i} = \frac{Y_i - b\prime(\theta_i)}{a_i(\phi)} = \frac{Y_i - (\mu_i)}{a_i(\phi)}$
- $\frac{\partial \mu_i}{\partial \theta_i} = b''(\theta_i) = \frac{V(Y_i)}{a_i(\phi)}$
- $\frac{\partial \eta_i}{\partial \beta_j} = \frac{\partial(\beta X_i)}{\partial \beta_j} = X_{ij}$

And $\frac{\partial \mu_i}{\partial \eta_i}$ depends on the link function $\eta_i = g(\mu_i)$ with $\eta_i = \beta_j \cdot X_{ij}$

The partial differential equations are therefore written in the following form:

$$\frac{\partial \ell_i}{\partial \beta_j} = \frac{Y_i - (\mu_i)}{a_i(\phi)} \times \frac{a_i(\phi)}{V(Y_i)} \times \frac{\partial \mu_i}{\partial \eta_i} \times X_{ij}$$

$$\frac{\partial \ell(Y,\theta(\beta),\phi)}{\partial \beta_j} = \sum_{i=1}^{n} \left(\frac{Y_i - (\mu_i) \times X_{ij}}{V(Y_i)} \times \frac{\partial \mu_i}{\partial \eta_i}\right) = 0, \forall j = 1, \cdots p$$

In the case where the link function used coincides with the canonical link function ($\eta_i = \theta_i$), these equations are simplified as follows:

$$\frac{\partial \ell_i}{\partial \beta_j} = \frac{\partial \ell_i}{\partial \theta_i} \times \frac{\partial \theta_i}{\partial \mu_i} \times \frac{\partial \mu_i}{\partial \eta_i} \times \frac{\partial \eta_i}{\partial \beta_j} = \frac{\partial \ell_i}{\partial \theta_i} \times \frac{\partial \theta_i}{\partial \eta_i} \times \frac{\partial \eta_i}{\partial \beta_j} = \frac{\partial \ell_i}{\partial \theta_i} \times \frac{\partial \eta_i}{\partial \beta_j}$$

Thus, the partial differential equations can take the following form:

$$\frac{\partial \ell(Y,\theta(\beta),\phi)}{\partial \beta_j} = \sum_{i=1}^{n} \left(\frac{Y_i - (\mu_i)}{a_i(\phi)} \times X_{ij}\right) = 0, \forall j = 1, \cdots p$$

However, μ_i is unknown, so it is impossible to obtain an analytical expression of the maximum likelihood estimator of β by canceling the first derivative (gradient): these equations are called transcendental. In other words, they are non-linear β equations whose solution requires iterative optimization methods, such as the Newton-Raphson algorithm referring to the Hessian matrix and the Fisher-scoring algorithm referring to the information matrix, whose approach can be summarized as follows:

a. Choose a starting point β^0
b. Put down $\beta^{k+1} = \beta^k + A_k \times \nabla L(\beta^k)$
c. Shutdown condition : $\beta^{k+1} \approx \beta^k$

Or : $\nabla L(\beta^{k+1}) \approx \nabla L(\beta^k)$

With:

$A_k = -[\nabla^2 L(\beta^k)]^{-1}$ For Newton-Raphson algorithm

$A_k = -(E[\nabla^2 L(\beta^k)])^{-1}$ For the iterative Reweighted Least Squares

2.3. Properties of the maximum likelihood estimator and confidence interval

In general, it is insufficient for a statistician to stop in the estimation phase of the value of the regression parameters. However, given that the value of the regression estimator depends closely on the sample on which the modeling is done, it is more legitimate to look at the confidence interval in which it lies, by setting a confidence level beforehand. Thus, the smaller the interval, the more robust the estimate. Let us note $\widehat{\beta_n}$ the maximum likelihood estimator (MLE). This estimator verifies certain properties, under certain classical assumptions of the regularity of the probability density, such as:

- $\widehat{\beta_n}$: Converges in probability to β, which implies that $\widehat{\beta_n}$ is asymptotically unbiased.
- $\widehat{\beta_n}$: Converges to a normal distribution.

Indeed, it is possible to write:

$$\sqrt{n}(\widehat{\beta_n} - \beta) \sim \mathcal{N}(0, \mathbb{I}_n^{-1}(\beta))$$

- $\widehat{\beta_n}$: Estimator of the maximum log-likelihood of $\beta = (\beta_0, \beta_1, \cdots, \beta_p)$
- $\mathbb{I}_n^{-1}(\beta)$: $-(E[\partial \ell^2(Y,(\beta),\phi)/\partial^2 \beta])$ is the Fisher information matrix evaluated in β and ϕ on a sample of size n.

Let $\widehat{\beta_n}$ be the estimator of the parameter β such that $\widehat{\beta_n}$ verifies a central limit theorem, i.e., when n tends to infinity, the random variable of centered reduced Gaussian distribution z tends to the value below:

$$\frac{\widehat{\beta_n} - \beta}{\sqrt{V(\widehat{\beta_n})}} \sim z$$

As a way of determining the confidence interval at risk α for $\widehat{\beta_n}$: from the bounds ($z_{1-\alpha/2}$) and ($-z_{1-\alpha/2}$) such that:

$$P\left(-z_{1-\alpha/2} < \frac{\widehat{\beta_n} - \beta}{\sqrt{V(\widehat{\beta_n})}} < z_{1-\alpha/2}\right) = 1 - \alpha$$

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If n is large enough, we can suppose that $\frac{\widehat{\beta_n}-\beta}{\sqrt{V(\widehat{\beta_n})}}$ follows approximately a Gaussian distribution and F the distribution function of the centered reduced Gaussian distribution, so we can write that:

$$P\left(-z_{1-\alpha/2} < \frac{\widehat{\beta_n}-\beta}{\sqrt{V(\widehat{\beta_n})}} < z_{1-\alpha/2}\right)$$
$$= F(z_{1-\alpha/2}) - F(-z_{1-\alpha/2})$$
$$= 2\,F(z_{1-\alpha/2}) - 1$$

With:

$$F(-z_{1-\alpha/2}) = 1 - F(z_{1-\alpha/2})$$

We can then deduce that:

$$2\,F(z_{1-\alpha/2}) - 1 = 1 - \alpha$$
$$z_{1-\alpha/2} = F^{-1}(1-\alpha/2)$$

So, the bounds of the confidence interval for $\widehat{\beta_n}$ are written as follows:

$$B^- = \widehat{\beta_n} - F^{-1}((1-\alpha/2) \times \sqrt{V(\widehat{\beta_n})}$$
$$B^+ = \widehat{\beta_n} + F^{-1}((1-\alpha/2) \times \sqrt{V(\widehat{\beta_n})}$$

However, an asymptotic confidence interval at the level of 100 ×(1−α) % of the regression coefficients β can be designed as follows:

$$I.C_{\beta_n} = \left[\widehat{\beta_n} \pm (z_{1-\alpha/2}) \times \sqrt{V(\widehat{\beta_n})}\right]$$

With :

- $z_{1-\alpha/2}$ is the quantile at (1 − α/2) of the standard normal distribution, N (0, 1)
- $V(\widehat{\beta_n})$ is the diagonal term of the inverse of the Fisher information matrix.

2.4. Binary logistic regression

We consider a population P subdivided into two groups of individuals G_1 and G_2 identifiable by an assortment of quantitative or qualitative explanatory variables $X_1, X_2, \dots X_p$ and let Y be a dichotomous qualitative variable to be predicted (explained variable), worth (1) if the individual belongs to the group G_1, and (0) if he/she comes from the group G_2. In this context, we wish to explain the binary variable Y from the variables $X_1, X_2, \dots X_p$.

2.4.1. Logit transformation

We have a sample of n independent observations of y_i, with i = 1, 2, ..., n. y_i denotes a dependent random variable presented as a column vector such that, $y_i = (y_1, y_2, \dots y_n)$ expressing the value of a qualitative variable known as a dichotomous outcome response, which means that the outcome variable y_i can take on two values 0 or 1, evoking respectively the absence or the presence of the studied characteristic. We also consider a set of p explanatory variables denoted by the design matrix (X) = $(X_1, X_2, \dots X_p)$ grouping the column vectors of the independent variables, of size ($n \times p$) and rank (p), where (x_i) is the row vector of these explanatory variables associated with the observation (i) such that, i = 1, 2, …, n, and the column vector (β) of dimension p of the unknown parameters of the model, i.e. the unknown regression coefficients associated with the column vectors of the matrix (X). We consider that y_i (response variable) is a realization of a random variable y_i which can take the values 1 in the case of the termination of the car insurance contract or 0 in the case of the renewal of the car insurance contract with probabilities (π) and (1−π), respectively.

The distribution of the response variable y_i is called Bernoulli distribution with parameter (π). And we can write y_i ~ B(1, π). Let the conditional probability that the outcome is absent be expressed by P(y_i = 0|X) = 1 − π and present, denoted P(y_i = 1|X) = π, where X is the matrix of explanatory variables with p column vectors. The modeling of response variables that have only two possible outcomes, which are the "presence" and "absence" of the event under study, is usually done by logistic regression (Agresti, 1996) [52], which belongs to the large class of generalized linear models introduced by John Nelder and Robert Wedderburn (1972) [74]. The Logit of the logistic regression model is given by the equation:

$$\mathrm{Logit}(\pi) = \ln\left(\frac{\pi}{1-\pi}\right) = \sum_{k=0}^{p} \beta_k\, x_{ik}, \text{ with } i = 1, .., n \quad (1)$$

By the Logit transformation, we obtain from equation (1) and equation (2):

$$\left(\frac{\pi}{1-\pi}\right) = \exp\left(\sum_{k=0}^{p} \beta_k\, x_{ik}\right) \quad (2)$$

We evaluate equation (2) to obtain π et 1 − π as:

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$$\pi = \exp\left(\sum_{k=}^{p} \beta_k x_{ik},\right) - \pi \exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right) \quad (3)$$

$$\pi + \pi \exp\left(\sum_{k=0}^{p} \beta_k x_{ik},\right) = \exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right) \quad (4)$$

$$\pi \left(1 + \exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)\right) = \exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right) \quad (5)$$

$$\pi = \left(\frac{\exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}{1+\exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}\right) \quad (6)$$

$$\pi = \left(\frac{1}{1+\exp\left(-\sum_{k=0}^{p} \beta_k x_{ik}\right)}\right) \quad (7)$$

In the same way, we obtain $(1 - \pi)$:

$$1 - \pi = 1 - \left(\frac{1}{1+\exp\left(-\sum_{k=0}^{p} \beta_k x_{ik}\right)}\right)$$

$$1 - \pi = \left(\frac{1}{1+\exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}\right)$$

$$1 - \pi = \frac{\exp\left(-\sum_{k=0}^{p} \beta_k x_{ik}\right)}{1+\exp\left(-\sum_{k=0}^{p} \beta_k x_{ik}\right)} \quad (8)$$

2.4.2 Estimation of the β parameters of the nonlinear equations of the Bernoulli distribution using the maximum likelihood estimator (MLE).

If y_i takes strictly two values 0 or 1, the expression for π given in equation (7) provides the conditional probability that y_i is equal to 1 given X, and will be reported as $P(y_i = 0|X)$. And the quantity 1-π gives the conditional probability that y_i is equal to 0 given X, and this will be reported as $P(y_i = 0|X)$. Thus, for y_i =1, the contribution to the likelihood function is π, but when y_i =0, the contribution to this function is $1 - \pi$. This contribution to the likelihood function will be expressed as follows:

$$\pi^{y_i} (1-\pi)^{1-y_i}$$

At this stage, we will estimate the P+1 unknown parameters β, using the maximum likelihood estimator (MLE) as follows:

$$L\,(y_1, y_2, \dots y_n,\ \pi) = \prod_{i=1}^{n} \pi^{y_i}\ (1-\pi)^{1-y_i}$$

Maximum likelihood is one of the most widely used estimation procedures for determining the values of the unknown β parameters that maximize the probability of obtaining an observed data set. In other words, the maximum likelihood function explains the probability of the observed data based on unknown regression parameters β. This method was developed by the British statistician Ronald Aylmer Fisher between (1912 - 1922) as it was assigned in John Aldrich's book "*R. A. Fisher and the making of maximum likelihood 1912-1922* " published in (1997). This method aims to find estimates of the p explanatory variables to maximize the probability of observation of the response variable *Y*.

$$L\,(y_1, y_2, \dots y_n,\ \pi) = \prod_{i=1}^{n} \pi^{y_i}\ (1-\pi)^{1-y_i}$$

$$= \prod_{i=1}^{n} \left(\frac{\pi}{1-\pi}\right)^{y_i} (1-\pi)$$

Substituting equation (2) for the first term and equation (8) for the second term, we obtain:

$$L\,(y_1, y_2, \dots y_n,\ \beta_1, \beta_2, \dots \beta_p,\ ) = \prod_{i=1}^{n} \left(\exp\left(\sum_{k=0}^{p} \beta_k x_{ik},\right)\right)^{y_i} \left(1 - \frac{\exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}{1+\exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}\right)$$

So,

$$L\,(y_1, y_2, \dots y_n,\ \beta_1, \beta_2, \dots \beta_p) = \prod_{i=1}^{n} \left(\exp\left(y_i \sum_{k=0}^{p} \beta_k x_{ik},\right)\right) \left(1 + \exp\left(\sum_{k=0}^{p} \beta_k x_{ik},\right)\right)^{-1}$$

For simplicity, we incorporate the Neperian logarithm into the above equation. Since the logarithm is a monotonic function, any maximum in the likelihood function will also be a maximum in the log-likelihood function and vice versa. Thus, considering the natural logarithm of this equation, we obtain the log-likelihood function ℓ expressed as follows:

$$\ln\left(L\,(y_1, y_2, \dots y_n,\ \beta_1, \beta_2, \dots \beta_p)\right) = \ln\left(\prod_{i=1}^{n} \left(\exp\left(y_i \sum_{k=0}^{p} \beta_k x_{ik}\right)\right) \left(1 + \exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)\right)^{-1}\right)$$

$$\ell\,(y_1, y_2, \dots y_n,\ \beta_1, \beta_2, \dots \beta_p) = \sum_{i=1}^{n} y_i \left(\sum_{k=0}^{p} \beta_k x_{ik}\right) - \ln\left(1 + \exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)\right)$$

Deriving the last natural logarithm equation of the likelihood function above, we should write:

$$\frac{\partial \ell(\beta)}{\partial \beta_k} = \sum_{i=1}^{n} y_i\ x_{ik} - \frac{1}{1+\exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)} \times \frac{\partial}{\partial \beta_k}\left(1 + \exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)\right) \quad (9)$$

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$$\frac{\partial \ell(\beta)}{\partial \beta_k} = \sum_{i=1}^{n} y_i\, x_{ik} - \frac{1}{1+\exp(\sum_{k=0}^{p} \beta_k x_{ik})} \times \exp\left(\sum_{k=0}^{p} \beta_k\, x_{ik}\right) \times \frac{\partial}{\partial \beta_k} \sum_{k=0}^{p} \beta_k\, x_{ik} \quad (10)$$

$$\frac{\partial \ell(\beta)}{\partial \beta_k} = \sum_{i=1}^{n} y_i\, x_{ik} - \frac{x_{ik}}{1+\exp(\sum_{k=0}^{p} \beta_k x_{ik})} \times \exp\left(\sum_{k=0}^{p} \beta_k\, x_{ik}\right) \quad (11)$$

Knowing that:

$$\frac{\partial}{\partial \beta_k} \sum_{k=0}^{p} \beta_k\, x_{ik} = x_{ik}$$

So,

$$\frac{\partial \ell(\beta)}{\partial \beta_k} = \ell'_{\beta_k} = \sum_{i=1}^{n} y_i\, x_{ik} - \pi . x_{ik} \quad (12)$$

Therefore, the estimation of the parameters $\hat{\beta} = (\widehat{\beta_0}, \widehat{\beta_1}, \cdots, \widehat{\beta_p})$that maximize the log-likelihood function l can be determined by canceling each of the *P +1* equations of ℓ' (gradient of ℓ) as mentioned in equation (12), and verify that its Hessian matrix (second derivative) is negative definite, i.e. that each element of the diagonal of this matrix is less than zero (Gene H. Golub and Charles F. Van Loan 1996) [52]. The Hessian matrix consists of the second derivative of equation (12). The general form of the second partial derivative matrix (Hessian matrix) can be written as follows:

$$\frac{\partial^2 \ell(\beta)}{\partial \beta_k \partial \beta_{k'}} = \frac{\partial}{\partial \beta_{k'}} \sum_{i=1}^{n} y_i\, x_{ik} - \pi . x_{ik} \quad (13)$$

$$\frac{\partial^2 \ell(\beta)}{\partial \beta_k \partial \beta_{k'}} = \frac{\partial}{\partial \beta_{k'}} (-\ \pi . x_{ik}) \quad (14)$$

$$\frac{\partial^2 \ell(\beta)}{\partial \beta_k \partial \beta_{k'}} = -\ x_{ik} \frac{\partial}{\partial \beta_{k'}} \left(\frac{\exp(\sum_{k=0}^{p} \beta_k x_{ik})}{1+\exp(\sum_{k=0}^{p} \beta_k x_{ik})}\right)$$

$$\ell''_{\beta_k \beta'_k} = -\ x_{ik}\, \pi(1-\pi)\, x_{ik} \quad (15)$$

To solve the $(P+1)$ nonlinear β equations (12), we use the Newton-Raphson iterative optimization method, referring to the Hessian matrix. Using this method, the estimation of the β parameters starts with the first step of choosing a starting point β^0 or β^{old}. The second step consists in mentioning the way the method works by posing: $\beta^{k+1} = \beta^k + A_k \times \nabla L(\beta^k)$, and finally stop when the condition $\beta^{k+1} \approx \beta^k$ or $\nabla L\beta^{k+1}) \approx \nabla L(\beta^k)$ is realized. The result of this algorithm in matrix notation is:

$$\beta^{new} = \beta^{old} + [-\ \ell''(\beta^{old})]^{-1} \times \ell'(\beta^{old})$$

By putting $\hat{\beta} = (\widehat{\beta_0}, \widehat{\beta_1}, \cdots, \widehat{\beta_p})^t$ we have:

$$V(\hat{\beta}) = \left(-\frac{\partial^2}{\partial \beta^2} \ln L(\beta, Y)\right)^{-1} \|_{\beta=\hat{\beta}} = (X^t W X)^{-1}$$

To simplify this equation above, we substitute the value of $\ell'(\beta)$, and $\ell''(\beta)$ with another matrix form in the following way:

$$\beta^{new} = \beta^{old} + (X^t W X)^{-1} \times X^t (Y - \mu) \quad (16)$$

$$\beta^{new} = (X^t W X)^{-1} \times X^t W (X\beta^{old} + W^{-1}(Y-\mu))$$

$$\beta^{new} = (X^t W X)^{-1} X^t W Z \quad (17)$$

Where $Z = (X\beta^{old} + W^{-1}(Y-\mu))$

Where, $Z = (X\beta^{old} + W^{-1}(Y-\mu))$ is a vector, and W is the vector of weights of the values of the diagonal of the inputs $\widehat{\pi_i}(1-\widehat{\pi_i})$. We can also write:

$$\beta^{new} = \beta^{old} + (X^t W X)^{-1} \times X^t (Y - \mu) \quad (18)$$

With:

$$X = \begin{pmatrix} 1 & x_{1,1} & \cdots & x_{1,p} \\ 1 & x_{2,1} & \cdots & x_{2,p} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{n,1} & \cdots & x_{n,p} \end{pmatrix}$$

$$\hat{V} = \begin{pmatrix} \widehat{\pi_1}(1-\widehat{\pi_1}) & 0 & \cdots & 0 \\ 0 & \widehat{\pi_2}(1-\widehat{\pi_2}) & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & \widehat{\pi_n}(1-\widehat{\pi_n}) \end{pmatrix}$$

And:

$$W = \mathrm{Diag}\ \widehat{\pi_1}(1-\widehat{\pi_1}), \cdots, \widehat{\pi_n}(1-\widehat{\pi_n}),$$

2.5 Direct and indirect determinants of termination

In Morocco, the motor insurance market is extremely competitive. In the context of continuously increasing claims rates and decreasing profitability, several questions are currently being asked by insurance companies. Should we expect an increase in motor vehicle insurance premiums? How would policyholders react to this increase? Will this positive change in premium precipitate a decision to cancel the insurance contract? Are there other incentives to cancel? Do they have the same

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impact on the decision to cancel? etc. There are several determinants of termination, which can be divided into two types. The first type refers to direct drivers of the decision to cancel, such as unfair premium increases, service quality failures, low insurer commitment, angry incidents, etc. The second type refers to the direct drivers of the decision to cancel, such as unfair premium increases, service quality failures, low insurer commitment, etc. On the other hand, the second type refers to the indirect moderating determinants that slow down this decision, such as the involvement of the insured, the cost of changing the current insurer, the alternatives in the insurance market, etc. A brief review of the literature on the direct and indirect determinants of switching from the current provider allows us to present below an assortment of works in this sense.

Direct determinants:

Regarding direct determinants, the works of Hess R. L., Ganesan S. and Klein N. M. (2003) [29] and Bell S. J., Auh. S., and Smalley K. (2005) [17] make it clear that sustained quality strengthens the interrelationship between the customer and their service provider, while poor quality precipitates change. In the same vein, Bansal H. S., Taylor S. F., and James Y. S. (2005) [22] add that poor quality of service, or a degraded change in the level of the latter, triggers a change of aptitude in consumers towards their supplier and probably in their behavior. Hence the following hypothesis:

- **H1:** Customers' poor perception of service quality is positively correlated with their intention to dissolve the relationship with the provider.

However, Homburg C., Hoyer W. D., and Koschate N. (2005) [21] describe that an unfair price generally generates a consumer's tendency to switch to his or her usual supplier. Also, Athanassolpoulos A. D. (2000) [49], Bansal H. S., Taylor S. F., and James Y. S. (2005) [22] join the same path and suggest that among the reasons why consumers may change their supplier is the excessive or unfair price. In this regard, we put forward the following two hypotheses:

- **H2:** Unfair price increase is positively correlated to dissolving the relationship with the provider by the customer.

- **H3:** The price increase is a good argument and will reinforce the intention to keep the relationship with the provider by the client, and vice versa.

However, Fullerton G. (2003) [30] proclaims that the notion of commitment is part of a multidimensional model, namely, the calculated, normative and affective dimensions. The calculated dimension refers to the adoption of behavior based on thoughtful, economic, and rational actions. While the normative dimension refers to the obligation of sincerity and loyalty. While affective commitment pretends a close identification of the prospect and assiduity in the realization of the objectives and expectations of the latter. In this vein, Wathne K., Biong H. and Heide J. B. (2001)) [39], defend the idea that a high commitment rate and an extended relationship decrease the probability of provider change and increase the added value created between the stakeholders. In this regard, we put forward the following hypothesis:

- **H4:** Consumers' perception of low provider commitment positively affects their intention to dissolve the relationship with the provider.

Also, anger is assumed to be a direct determinant impacting consumers' decisions and intentions to change the usual provider, as pointed out by Roos I. in his book "Methods of investigating critical incidents" published in (2002) [34]. At this stage, we can extract the following hypotheses:

- **H5:** The severity of the problem has a direct positive impact on anger.

- **H6:** The persistence of the problem has a direct positive impact on anger.

- **H7:** The degree of responsibility of the supplier has a direct and positive impact on anger.

- **H8:** Customer anger has a direct positive impact on relationship termination

Indirect determinants:

Regarding indirect determinants, Juhl H. J., Poulsen C. S. (2000) [43], Olsen S. O. (2001) [36], Bell R. and Marshall D. W. (2003) [28], and Verbeke W. and Vackier I. (2004) [25] have identified involvement as a factor that can have a significant impact on prospects' decision-making process. In other words, the notion of involvement is a predictive and explanatory variable of the behavior of customers about a product or service offered by their provider. B. M. Chérif (2001) [35] explains the state of involvement as being "the intensity, direction, and nature of the consumer's interest in an object". In this context, Warrington P. and Shim S. (2000) [41] state that highly involved consumers react more strongly to changes in provider behavior. From the above, we can extract the following hypotheses:

- **H9:** The more highly involved the consumer, the stronger the positive effect of perceived low service quality on the intention to change provider.

- **H10:** The more involved the consumer is, the stronger the positive effect of a perception of low commitment on the intention to switch.

- **H11:** The more involved the consumer, the stronger the positive effect of a perceived unfair price on the intention to switch.

- **H12:** The higher the consumer involvement, the stronger the positive effect of an angry incident on the intention to switch.

Also, Wathne K., Biong H., and Heide J. B. (2001) [39] explain that switching costs are a real barrier to consumers switching from their provider to another alternative. Burnham A., Frels J. K., and Majahan V. (2003) [26] add that a perception of switching costs at the time of switching implies that customers maintain their relationship with their usual provider. Except, a perspective of low switching costs, and dissatisfaction of the prospects with the failure of the offered quality of service, high prices, or the weak commitment of the organization, implies a strong tendency of switching. Some work by authors such as Burnham A., Frels J. K. and Majahan V. (2003) [26], Jones M., Mothersbaugh D., Beatty S., (2000) [42], as well as Sharma N. and Patterson P. G. (2000) [44], have shown that the cost of switching providers is a moderating variable, negatively affecting the correlation between the degree of satisfaction and the willingness to retain the relationship. That is, a high switching cost can reduce the intention to switch, despite the dissatisfaction of the client and vice versa. In this context, we propose the following hypotheses:

- **H13:** The higher the switching costs, the weaker the positive effect of perceived poor service quality on switching intention.
- **H14:** The higher the switching costs, the smaller the positive effect of a perception of low commitment on the intention to switch.

- **H15:** The higher the switching costs, the lower the positive effect of a perception of unfair price on the intention to switch.

- **H16:** The higher the switching costs, the lower the positive effect of an anger incident on the intention to switch.

Caprapo A., Broniarczyk S., and Srivastava R. K. (2003) [27] explain that true knowledge of the competition, and the best alternatives offered by a market, is a sufficient preliminary to orient the intentions of consumers either towards a decision to repurchase or a substitution option of the usual provider. Sharma N. and Patterson P. G. (2000) [44], on the other hand, have already touched on the same subject in previous works, confirming the presence of a positive correlation between the knowledge of favorable alternatives as a moderating variable and the intention experienced by the customer to change or keep his daily supplier. On the other hand, the writings of Caprapo A., Broniarczyk S., and Srivastava R. K. (2003) [27] as well as the essays by Bansal H. S., Taylor S. F., and James Y. S. (2005) [22], report that there is a direct effect between awareness of other alternatives and attractive opportunities within an industry and the prospect's intention to switch or remain in the relationship. Jones M., Mothersbaugh D., and Beatty S., (2000) [42], come back once again to confirm the set of reflections presented by the other authors, advising that cognition of the prerogatives presented by the alternatives or other suppliers in the same market, will only consolidate the intention of the clients to stop their relationships, at the moment when they feel dissatisfaction and discontent with the quality of service, the perceived commitment, the imposed prices, and the tantrums. From this perspective, we attempt to formulate the following hypotheses:

- **H17:** The higher the attractiveness of the alternative, the stronger the positive effect of perceived low service quality on the intention to switch.

- **H18:** The higher the attractiveness of the alternative, the stronger the positive effect of a perception of low firm commitment on the intention to switch.

- **H19:** The higher the attractiveness of the alternative, the stronger the positive effect of a

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perceived unfair price on the intention to switch.

- **H20:** The higher the alternative attractiveness, the stronger the positive effect of an angry episode on the intention to switch.

The objective of this study is not essential to question the body of evidence in the literature on the factors affecting the intention of prospects to dissolve their relationships with their service providers, but to predict the act of termination of policyholders and to assess the impact of a set of selected termination determinants precipitating the change of the usual insurer at the expiration of their contracts. This study will trace its scope in the Moroccan car insurance sector. We will use this modeling software (IBM SPSS Statistics version 23)

Keaveney S. M. and Parthasarathy M. (2001) [26], give large importance to this problem and notify that the intention of the customers to change their insurance provider, worries the globality of the insurers, since they recover the costs of the insureds only after several years of subscription of contracts with them, whereas in case of cancellation the company can support considerable losses. In the same vein, we can cite some works of authors, operating on the same aspect, such as the work of Walter A. and Ritter T. (2000) [40], "Value-creation in customer-supplier relationships: the role of adaptation, trust, and commitment" analyzing the behavior of customers of insurance companies in its entirety, as well as the work of Caprapo A., Broniarczyk S. and Srivastava R. K. (2003) [27], "Factors influencing the likelihood of customer defection: the role of consumer knowledge", studying more specifically the attitude of policyholders in a medical insurance market. they add in the same essay that the insured is in permanent search of adequate information to stabilize on a single choice of an insurance company since he is supposed to renew his contract with his provider periodically. Given the limited number of works that flow in the same direction of our study, we have chosen to initiate this work to present an added value to the non-life insurance sector, especially the automobile branch.

3. RESULTS AND DISCUSSION

The present study focuses on the use of an online questionnaire for data collection. The construction of the questionnaire used in this research is inspired by the literature of several works and books authors. This survey mainly covers two question areas. The first one is about the insured's information, vehicle, and car insurance. The second component includes questions about the determinants of termination of the relationship between the insured and their auto insurance provider. However, customer information is private and would not be disclosed.

We carefully use sampling to control for the representativeness of the sample (simple random sample). The sample is composed of 1100 policyholders, taking into account the size of the survey population. After deducting the questionnaire from the original 1100, we obtain a total of 1000 valid questionnaires. The first introductory part of the questionnaire is dedicated to the personal information of the respondent (insured) and his relationship with his insurer. This section of the survey is dedicated to the gender of the insured, age range, city of residence, socio-professional category, insurance companies contracted by the insured, car insurance contract types, and frequency of car insurance. The second part is reserved for responses to multiple-choice questions related to the explanatory determinants of the dependent variable using a Likert scale. Finally, the survey is completed with a dichotomous response question concretizing the scenario of actual termination or renewal of car insurance contracts at the end of the contract.

We consider a sample n split into two groups of insureds G_1 and G_2 identifiable by a set of in-dependent variables X_1, X_2, X_7. More precisely, X_1 represents: Positive and unfair price changes, X_2: The perception of service quality, X_3: The provider's commitment to the customer, X_4: Anger incident, X_5: Consumer involvement, X_6: Switching costs, and X_7: Alternative attractiveness. Let Y be the dichotomous qualitative variable to be predicted (response variable) expressing: The decision to cancel the car insurance contract at the end of the term. Y has the value (1) if the insured belongs to the group G_1 and (0) if he comes from the group G_2. Noting also that G_1 is dedicated to policyholders choosing to terminate their car insurance contracts at the end of the contract, and G_2. is dedicated to those who decide to renew their contracts at the end of the contract. Hence, we can write:

- **Y = 1**: Cancellation of the automobile insurance contract at maturity.
- **Y = 0**: Renewal of auto insurance policy at

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maturity.

However, the explanatory variables introduced in the "Logit" model to predict the "decision to terminate" (dependent variable) are in the order of seven dimensions.

- X_1: The unfair increase in premiums
- X_2: Failure of the quality of services offered
- X_3: Failure of the provider's commitment to the client
- X_4: Incidents of anger
- X_5: Consumer involvement
- X_6: The cost of changing the provider
- X_7: Alternative attractiveness

In this study, we have tried to identify the variables that predict the act of termination and to measure the impact of each of them on the decision of policyholders to renew or terminate their contracts with their usual insurer. However, the predictor variables introduced into the model to explain the act of switching are qualitative.

Table 4: Reliability test

Cronbach's Alpha	Cronbach's Alpha based on standardized elements	Number of elements
0.822	0,821	7

Source: Author

According to the reliability test, we notice that the value of the coefficient $\widehat{\alpha}$ = 0.822 exceeds the conventional minimum threshold of α = 0.70 (Nunnally J. C. 1978), (Darren and Mallery 2008) revealing that we obtain, for this assortment composed of seven elements, a satisfactory internal consistency.

Table 5 : Interelements correlation matrix

	X_1	X_2	X_3	X_4	X_5	X_6	X_7
X_1	1	0,28	0,17	0,40	0,34	0,50	0,39
X_2	0,28	1	0,39	0,40	0,37	0,33	0,28
X_3	0,171	0,39	1	0,36	0,41	0,29	0,24
X_4	0,40	0,40	0,36	1	0,55	0,56	0,45
X_5	0,34	0,37	0,41	0,55	1	0,50	0,43
X_6	-0,50	-0,33	-0,2	-0,5	-0,50	1	-0,6
X_7	0,39	0,28	0,24	0,45	0,439	0,61	1

Source: Author

The matrix of inter-element correlations is a matrix of statistical correlation coefficients calculated based on several variables taken two by two. It allows for quick detect the existing links between the introduced variables by foreseeing several studies and statistical explanations beforehand. However, the correlation matrix is symmetrical, and its diagonal is made up of 1's since the correlation of a variable with itself is perfect. The correlation matrix based on our study's answers shows that all the variables used are sufficiently correlated, with a correlation coefficient varying between r = 0.171 and r = 0.617 noting that: 0.171 ≤ r ≤ 0.617, confirming moreover the result of Cronbach's Alpha reliability coefficient.

Table 6: Table of variables in the equation

	β	**E. S**	**Wald**	**ddl**	**Sig**	**Exp(β)**	**Confidence interval for Exp (β)(95%)** *Inferior*	*superior*
X_1	1,615	0,46	11,98	1	0,001	5,030	2,015	12,552
X_2	1,871	0,617	9,21	1	0,002	6,490	1,941	21,753
X_3	1,558	0,57	7,34	1	0,007	4,751	1,542	14,642
X_4	3,117	0,30	105,90	1	0,000	22,589	12,475	40,903
X_5	1,094	0,37	8,36	1	0,004	2,986	1,423	6,265
X_6	-1,885	0,31	36,95	1	0,000	0,151	0,110	0,425
X_7	0,871	0,32	7,35	1	0,007	2,388	1,273	4,482
Constant	-8,295	0,95	74,91	1	0,000	0,000	-	-

Source: Author

This table provides the regression coefficients $\hat{\beta}$, the Wald statistic for testing statistical significance, the odds ratio $\exp(\hat{\beta})$ for each predictor variable, and finally the confidence interval for each odds ratio (OR). Looking at the results first, we see a highly significant effect of all the predictor variables on the response variable "decision to

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cancel car insurance contracts at the end of their term". However, the p (Premium) = 0.001 ≤0.05, p (Quality) = 0.002 ≤0.05, p (Commitment) = 0.007 ≤0.05, p (Anger) = 0. 000 ≤0.05, p (Involvement) = 0.004 ≤0.05, p (Costs) = 0.000 ≤0.05, and p (Alternatives) = 0.007 ≤0.05. However, it is easy to interpret the meanings of p, but the question at this point is how to interpret the regression coefficients $\hat{\beta}$. What is this coefficient, and how can it be interpreted? Nevertheless, the regression coefficient $\hat{\beta}$ can only explain the direction of fluctuation between the explanatory variable and the response variable. That is to say, a positive sign of the coefficient $\hat{\beta}$ refers to a change in the same direction between the predictor variable and the dependent variable, whereas a negative sign refers to a change in two opposite directions of the two variables. Apart from the coefficient, $\hat{\beta}$ is not interpretable. However, the exponential of $\hat{\beta}$ "(exp($\hat{\beta}$))" has a meaning that is easily interpreted by statisticians. The "exp($\hat{\beta}$)" also called odds-ratio (OR), odds ratio, or close relative risk, designates a statistical measure, disclosing the degree of dependence and effect of an explanatory factor on the response variable.

The column exp($\hat{\beta}$) (Odds Ratio) tells us that the different explanatory variables each influence the variable to be predicted distinctly. In our case, we can claim that an unfair increase in car insurance premiums can generate a fivefold increase in the chance (OR(X_1) = 5.0 30, IC5% = [2.015, 12.552]) that the insured is likely to cancel his or her insurance contract and leave his or her current insurer. In the same vein, a failure and weakness in the quality of the services provided by the company also makes it six times more likely (OR(X_2) = 6.497, IC5% = [1.941, 21.753]) that he will choose to terminate his commitment with his usual insurer at the end of the term. Also, a low commitment to him is four times more likely (OR(X_3) = 4.751, CI5% = [1.542, 14.642]) to leave him. Similarly, incidents of anger have a greater impact on policyholders abandoning their insurance providers with twenty-two times greater chance (OR(X_4) = 22.589, CI5% = [12,475, 40,903]) that they will dissolve their insurance contracts.

In addition, a high level of involvement of the policyholders in the products offered by their insurer and the good knowledge of the alternatives offered by the Moroccan car insurance market, introduce a stimulating effect on the cancellation history, i.e. increase the effect of the direct factors (mentioned above) on the cancellation decision. It can be seen that there is a significantly positive relationship between involvement and the four direct determinants such as unfair premium increases r = 0.344, failure of the quality of services offered r = 0.371, insurer's commitment r = 0.410, and anger incidents r = 0.559. Conversely, the second indirect factor, "the cost of changing the insurer" has a negatively significant impact on the direct termination history, from which we can report that the correlation coefficient linking "the cost of changing" and the direct termination variables such as "unfair premium increases", "failure of the quality of services offered", "insurer commitment", and "anger incidents" are respectively r (premium)= −0.500, r (Quality) = −0.337, r (Commitment) = −0.291, r (Anger) = −0.564. However, the independent variable "alternative attractiveness" is positively correlated with the direct factors of the dissolution of the contractual relationship, hence the correlation coefficients are r = 0.397 for "unfair premium increases", r = 0.281 for "failure of the quality of the services offered", r = 0.241 for "insurer's commitment", and r = 0.452 when it comes to anger incidents.

Nevertheless, the two indirect variables "implication" and "alternative" generate twice the chance (OR: Implication = 2.986, IC$^{5\%}$ = [1.423, 6.256] and OR: Alternatives = 2.388, IC$^{5\%}$ = [1.273, 4.482]) that the prospect will cancel his insurance contract. On the other hand, the costs incurred at the time of switching are seen as negligible or derisory and do not lead to significant risks of cancellation (OR: Cost) = 0.151, IC$^{5\%}$= [0.110, 0.425]). All in all, the unfair and positive variations in insurance premiums, the failure in the quality of the services provided, the low commitment of the companies to their policyholders, and the incidents of anger, therefore, represent explanatory factors for cancellation at the end of the contract. In addition, the degree of involvement of policyholders in insurance products and their knowledge of alternatives and competition are precipitating and catalyzing factors in the switching process. On the other hand, the cost of changing the insurance company is only a weak moderator of the decision to terminate.

Table 7: Area under curve

Asymptotic confidence	superior	0,674	0,600	0,612	0,818	0,698	0,610	0,740

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`	AUC	Standard error	Asymptotic Sig.	Inferior
X_1	0,618	0,029	0,000	0,562
X_2	0,564	0,028	0,020	0,492
X_3	0,557	0,028	0,030	0,502
X_4	0,766	0,027	0,000	0,714
X_5	0,641	0,029	0,000	0,585
X_6	0,522	0,026	0,000	0,482
X_7	0,685	0,028	0,000	0,630

Source: Author

The area under the curve expresses the probability of placing a positive element in front of a negative one. However, this technique proposes an AUC = 0.5 as a reference situation which our classifier must do better. At first sight, all results are highly significant with a $p = 0.000 \leq 0.05$. Moreover, the table also reports AUCs that exceed the reference threshold (AUC = 0.5), i.e. the explanatory variables used in the model all significantly impact the response variable. In the same sense, we can predict that the insured has a 61.8% ($IC^{5\%}$ = [0.562, 0.674]) chance of canceling his or her automobile insurance contract than of renewing it if he or she is exposed to an unfair increase in insurance premiums. Similarly, a failure in the quality of insurance services is likely to result in 56.4%. ($IC^{5\%}$ = [0.492, 0.600]) chance of termination compared to the renewal decision. In addition, the commitment to the insured, the incidents of anger, the involvement of the insured with the insurance products, the costs of changing the usual insurer, and the knowledge of alternatives can generate 55.7%, 76.6%, 64.1%, 52.2%, and 68.5% of the chance of termination against the act of renewal respectively.

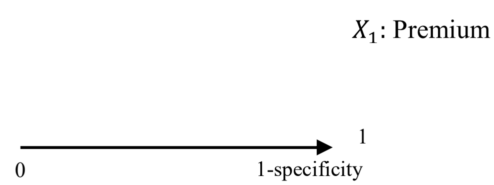


Figure 1: Area under the curve for Premium

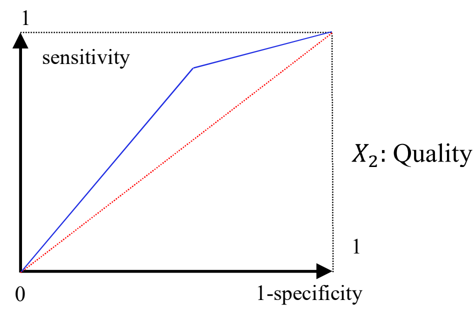


Figure 2: Area under the curve for Quality

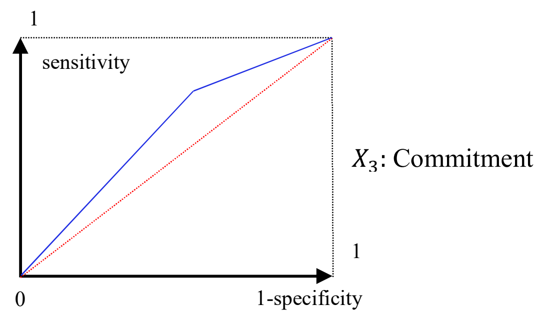


Figure 3: Area under the curve for Commitment

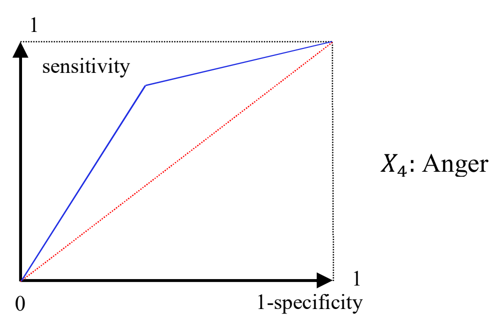
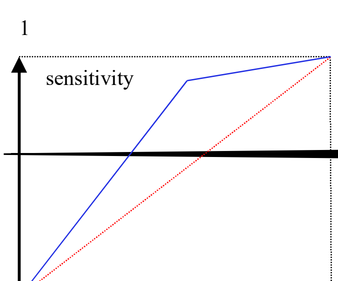
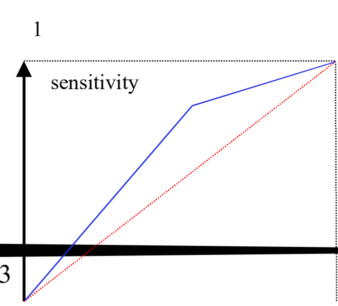


Figure 4: Area under curve for Anger





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X_5: Involvement

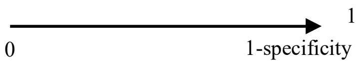
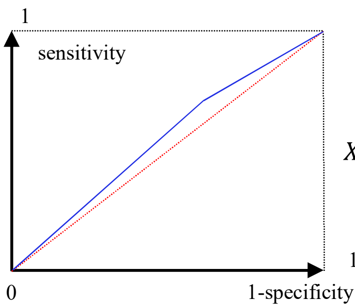
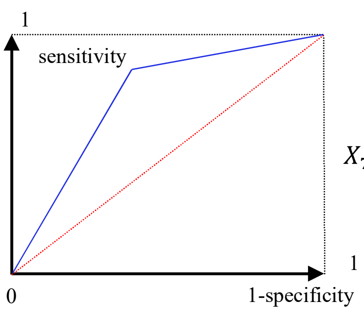


Figure 5: Area under the curve for involvement



X_6: Cost

Figure 6: Area under the curve for Cost



X_7: Alternatives

Figure 7: Area under the curve for alternatives

The termination probability cannot take the form of a straight line, because this one is included between the values 0 and 1. However, it can take the form of a sigmoid function, also called *S*, representing the logistic law's distribution function. Nevertheless, it is a mathematical function that can accept any real value of R and make it correspond to a value between 0 and 1 to obtain a function in the form of the letter S. The logistic function has two asymptotes such that, Y= 1 and Y= 0, so is defined by:

$$Y = \pi = \left(\frac{\exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}{1+\exp\left(\sum_{k=0}^{p} \beta_k x_{ik}\right)}\right)$$

Thus:

- Y = 1: Termination of the automobile insurance contract at the end of the term.
- Y = 0: Renewal of the automobile insurance contract at the end of the term.

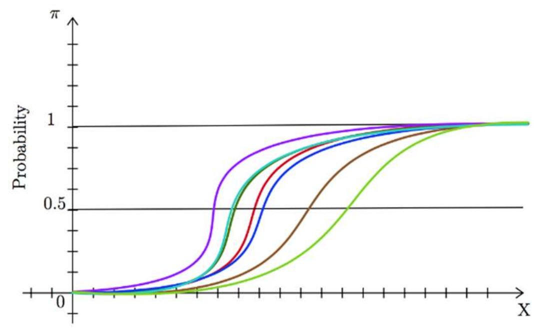


Figure 8: Logistic function

- Unfair premium increases
- Failure to provide quality services
- Failure of the provider's commitment to the customer's
- Anger incidents
- Low consumer involvement
- Low cost of changing provider
- Attractiveness of alternatives

On the other hand, if the value of x tends towards more than infinity ($x \rightarrow +\infty$), the value of Y tends towards 1 ($Y \rightarrow 1$) making explicit a scenario that translates the possibility of termination. On the other hand, if x tends towards minus infinity ($x \rightarrow -\infty$), the value of Y tends towards 0 ($Y \rightarrow 0$) signaling a possible renewal of the contract at maturity. Also, we choose to label the probabilities of the realization higher than the threshold of 0.5 with class 1 and put the probabilities lower than 0.5 with class 0. We can note :

- $\pi > 0.5 \rightarrow$ Class 1
- $\pi \leq 0.5 \rightarrow$ Class 0

We see from the logistic curves that the "anger incident" is a direct termination determinant with a powerful influence on policyholders to decide to terminate their insurance contracts at maturity. However, the sigmoid curve appropriate to this antecedent of termination was the first to change the direction of its variation and exceed the probability $\pi = 0.5$ passing from $\pi = 0$ expressing the renewal of the contract to join the class 1 from where the probability $\pi = 1$ translating the termination of this commitment, noting that the $\hat{\beta}$ (anger) = 3.17 and the OR = 22.589. However, the second curve returns to the direct factor of termination

"perception of service quality failure", registering the crossing of the probability $\pi = 0.5$ just after the curve of the determinant "anger incident", to position itself in class 1. This second rank is concretized by the coefficient $\hat{\beta}$ (Quality) = 1.871 and the OR = 6.497.
Third and fourth place was given to the two direct termination antecedents: "unfair premium increase" and "insurer commitment" respectively. These two termination promoters are respectively characterized by the regression coefficients $\hat{\beta}$ (Premium) = 1.615 and $\hat{\beta}$ (Commitment) = 1.558, as well as the odds ratios OR (Premium) = 5.030, and OR (Commitment) = 4.751. Moreover, both of their curves are ahead of the probability $\pi = 0.5$ just after the one representing "the perception of the failure of the quality of the services".

On the other hand, the indirect determinants of termination, acting favorably or unfavorably on the direct factors, also significantly impact the termination decision. However, the sigmoid curve of the indirect determinant "cost of changing the insurer" comes in the first order to cross the probability $\pi = 0.5$, characterized by a regression coefficient $\hat{\beta}$ (Cost) = 1.885 and an OR = 6.586 Then, in the second and third place are the two indirect factors such as, "involvement of the insured" and "attractiveness of alternatives" marked respectively by the regression coefficients $\hat{\beta}$ (Involvement) = 1. 094 and $\hat{\beta}$ (Alternatives) = 0.871 as well as the odds-ratio OR (Involvement) = 2.986 and OR(Alternatives) = 2.388, respectively crossing the threshold of $\pi = 0.5$ after the curve of the moderating determinant of the act of termination "the incidents of anger".

4. CONCLUSION

As interrelationships are characterized by a certain dynamism, the nature of the existing interconnections between customers and their suppliers represents a driving force influencing the termination process and the strategies to be implemented (Giller C. and Matear S. (2001)) [37] . In the same context, several works have focused on the nature of these correlations and their impact on the process of termination or breakup of a relationship, citing the work of (Halinen A. and Tähtinen J. 2002 [33]), and (Tähtinen J., Matear S. and Gray B. 2000 [45]), explaining that the nature of the relationship manifests itself as a temporal construction and an edifice forged between the two actors customer-supplier, formulating a reason why the links between the latter two can end. For his part, Ganesan S. (1994) [53] points out in his work "Determinants of long-term orientation in buyer-seller relationships" that the conditions in which a customer-supplier relationship develops are likely to play an important role in the maintenance of long-term relationships, while also influencing the duration of these relationships and the subsequent decisions of customers to change supplier decisively, as also explained by Reinartz W. J. and Kumar V. (2003) [31] in their paper "The impact of customer relationship characteristics on profitable lifetime duration". Similarly, Keaveney S. M. (1995) [51] points out in his work "Customer switching behavior in service industries: an exploratory study" that prospect churn can be a result of a negative incident. However, Coulter R. A. and Ligas M. (2000) [50] add in their book "The long good-bye: the dissolution of customer-service provider relationships" that the process of dissolving the relationship can only be initiated through a stimulus and an assortment of incentive factors for the breakup. Also, Giller C. and Matear S. (2001) [37] explain that the beginning of the end of the relationship begins with an interaction between the triggering event and the current state of the relationship. Throughout this article, we have tried to focus on an assortment of determinants directly impacting the policyholder’s decision to terminate his or her relationship with his or her automobile insurer, while measuring the influence of each factor on the act of termination, so that insurance companies have a more or less accurate view of the sensitivity of their policyholders to their policies, strategies and management methods.

The binarity of the termination decision prediction directed us to use generalized linear models, more precisely binary logistic regression. Our exploration was in two lines. The first line of study involved the use of seven explanatory variables of the act of termination. They are compartmentalized into two types: the direct or precipitating determinants and the indirect determinants. However, the direct drivers of termination include unfair premium increases, quality failures, angry incidents, and low commitment from the regular provider. These determinants directly impact the decision to dissolve contracts at maturity. However, indirect factors such as policyholder involvement, the cost of switching providers, and the degree of awareness of alternatives play a dual role. The first is that of a precipitator in the termination process and the second is that of a brake on the termination process. Moreover, the previously selected drivers of termination significantly impact the act of termination of car insurance contracts initiated by the insured upon their expiration. However, it is remarkable that the prospects have a serious sensitivity towards unfair premium increases, failure of the quality of services offered, angry incidents, and low insurer commitment. In addition, the involvement of policyholders, the low cost of switching providers, and the alternatives offered by the insurance market only serve to boost policyholders' sensitivity to the precipitating determinants of switching.

However, we can rank these determinants according to their intensity of impact on the act of termination. First, policyholders are 22 times more likely to terminate than to renew their contracts if they are angry with their usual provider, hence OR(X_4) = 22,589. Second, failure in the quality offered refers to six times more likely to drop their insurer than to stay with it, hence the OR(X_2)) = 6.497. Third, unfair premium increases stimulate churn at a reason more than five times as likely as continuing with it hence the OR(X_1)) = 5.030. And fourth, the deficiency of the insurer's commitment to its insured presents four times the chance that he will leave for another insurance company than to re-commit to him, i.e. OR(X_3)) = 4.751.

In addition, the moderating determinants can motivate the act of termination or slow it down. However, in our case study, a better involvement and a perfect knowledge of the car insurance product by the insured only increases his sensitivity towards the termination decision, hence the OR(X_5)) = 2.986. Also, greater awareness of the alternatives offered by the insurance market stimulates the act of churn, hence the OR(X_7)) = 2.388. Nevertheless, low switching costs encourage policyholders to terminate their contracts at the end of their term, while high switching costs reduce the impact of the precipitating factors for terminating the contractual relationship between the policyholder and their insurer, i.e., OR(X_6)) = 0.151.

In conclusion, the success of organizations depends not only on satisfying prospects with the services offered but also on preventing their defection. However, there is little research on the termination of the relationship between the entity and its customer portfolio. Moreover, by better understanding the customer churn process, it will be easier to prevent and prevent the act of termination while trying to recover those lost and attract new ones. On the other hand, Halinen A. and Tähtinen J. (2002) [33], explain that the customer is a capital entity, offering to any organization a source of income and also of costs, representing an integral component in the creation of the global net value of the company.

Being interrelationships characterized by a certain dynamism, the nature of the existing interconnections between customers and their suppliers represents a driving force influencing the process of termination and the strategy to be implemented (Giller C. and Matear S. (2001)) [37]. In the same context, several works have focused on the nature of these correlations and their impact on the process of churn or relationship termination, citing the work of (Halinen A. and Tähtinen J. 2002) [33], (and (Tähtinen J., Matear S. and Gray B. 2000) [45], explaining that the nature of the relationship manifests itself as a temporal construct and an edifice forged between the two customer-supplier actors, formulating a reason why the connections between these two actors can end.

For his part, Ganesan S. (1994) [53] points out in his book "Determinants of long-term orientation in buyer-seller relationships" that the conditions in which a customer-supplier relationship develops are likely to play an important role in the maintenance of long-term relationships, while also influencing the duration of these relationships and the subsequent decisions of customers to change supplier decisively, as explained by Reinartz W. J. and Kumar V. (2003) [31] in their paper "The impact of customer relationship characteristics on profitable lifetime duration".

Keaveney S. M. (1995) [51] points out in his work "Customer switching behavior in service industries: an exploratory study" that prospect termination can be a result of a negative incident. While Coulter R. A. and Ligas M. (2000) [50] add in their book "The long good-bye: the dissolution of customer-service provider relationships" that the process of dissolving the relationship can only be engaged through a stimulus and an assortment of incentive factors for the breakup. Also, Giller C. and Matear S. (2001) [37] explain that the beginning of the end of the relationship starts with an interaction between the triggering event and the current state of the relationship. They comment on the stage that follows the change by stating that once the switching process starts, the next path can be better described in terms of characteristics, phases, and process types.

The client then has two alternatives, either terminate the relationship with the service provider or continue it. This final decision depends essentially on the nature of the interrelationship and its evolution over time. According to Halinen A. and Tähtinen J. (2002) [33]., termination refers to the end of the switching process or change of provider. At this point, the links begin to weaken, but there may be a temporary intensification of interactions in an attempt to adjust and correct the attributes involved in the decline of the relationship and the decision to change. In this sense, Coulter R. A. and Ligas M. (2000) [50] note that after dissolution, some customers reflect on the possibility of returning to their provider in the future who chose to leave. For that they made the distinction in their works between the relations with the customers which are likely or not to be reactivated using strategies of restoration of the relations.

In this paper, we have tried to predict the act of termination of car insurance contracts at the end of their term and to analyze the impact of a set of termination determinants on the decision of policyholders to terminate their engagements at the end of the contract.

CONFLICT OF INTEREST

The authors have no conflicts of interest

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