# PREDICTING THE RESILIENCE OF THE TOURISM INDUSTRY AFTER THE COVID-19 HEALTH EPIDEMIC

**ROUAINE ZAKARIA[1] , *TAITAI ZINEB [2]***

[1] Ph.D. in economics and management, Laboratory of Economics, Management, and Development of Organizations, Faculty of Economics and Management, Ibn Tofail University, Morocco
[2] Ph.D. in economics and management, Laboratory of management, finance, and accounting, Faculty of Economics and Management, Ibn Tofail University, Morocco

E-mail : [1] rouainezakaria@gmail.com, [2] taitaizineb@gmail.com,

**ABSTRACT**

The tourism industry is a major branch of the service sector that contributes to national wealth creation. It is one of the main drivers of employment and foreign exchange drainage in the economies. However, some tragic events affect and slow down its development. The epidemiological context of the coronavirus has deeply affected the sector, implying a total halt to all tourist activities at national and international levels. In this sense, Dauphiné and Provitolo (2007) [16] state that "it is then possible to adopt another strategy based on the concept of resilience. This strategy aims, not to oppose the hazard, but to reduce its impacts as much as possible. From this reflection, we have attempted in this essay to clarify and analyze the determinants of resilience summarised in the characteristics linked to the environment, the strategies implemented, the personal traits of the manager, and the characteristics specific to tourism organizations contributing to helping these Moroccan economic units, specifically in the Rabat-Salé-Kénitra region, to overcome the setbacks caused by the covid-19 health crisis.

***Keywords:*** *Resilience determinants, tourism sector, the coronavirus epidemic, binary logistic regression, Generalized Linear Models.*

## 1. INTRODUCTION

Despite all the pessimistic scenarios predicting a severe recession for the first quarter of 2022, the assessment of the Moroccan economic fabric has shown that the situation is looking rather good and is part of a confirmed dynamic recovery (HCP, 2021)) [32]. Certainly, the Moroccan economy was marked in 2020 by an acute recession throughout its history (-7% according to the HCP and the IMF). Also, all indications revealed that the crisis had a singular effect on the activity of companies, particularly, those operating in the tourism sector. Notwithstanding that many of them had to slow down their activity or even, to a lesser degree, except that a significant number of them were able to master and overcome the repercussions of the health crisis of covid-19, and adapt to the restrictive measures and diligently seize the opportunities offered in this unfortunate context.

The last study carried out by Inforisk (a subsidiary of the FinAccess Group: specialist in commercial intelligence on Moroccan companies) on the situation of Moroccan SMEs, confirmed this finding and reported that the cessations of companies declared in 2020 have recorded only 6,612 economic units with a decline of 21.6% compared to the year 2019. Certainly, from an academic point of view, this situation seems paradoxical and the reported figures remain biased, mainly, by the almost continuous cessation of activity of the courts and commercial courts from March to September 2020. Nevertheless, from an experimental point of view, the indicators relating to the financing of the Moroccan economy in the first half of 2021 show globally encouraging developments in the national economy (deceleration in the growth of bank credits at the end of March 2021 to +3.3% after +5.3% one year earlier, continued improvement in the indicators of the Casablanca Stock Exchange at the end of April 2021, a notable increase in exports at the end of March 2021 of 12.7%, etc.) (DEPF, 2021) [17].

Reassuring figures that reveal encouraging signals, allowing us to hope for an increase in economic recovery in 2021 and testifying to the ability of

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Moroccan companies, and mainly tourism companies, to overcome the effects of the pandemic and show resilience and flexibility in the face of the magnitude of the shock suffered. In this furrow, the determinants of resilience can judge the survival of the tourist units or their failure. These determinants of resilience cannot be attributed exclusively to the impact of the health and economic crisis on their tourism activities, but rather, can be linked to other elements of the context in which they operate, such as the intrinsic characteristics of the entrepreneurs, or to the technical, financial and relational means available to them.

Several studies have addressed the determinants of business resilience and success specifically during and after the covid-19 health crisis. The study by S. Jabraoui and A. Boulahoual (2016) [37] testifies that the preparatory elements, the environment, the financial means, and the accompanying actions are the factors that impact the most, the success and the resilience of Moroccan companies. However, the results remain mixed, as entrepreneurial success is a complex phenomenon with a polysemic and non-univocal conception (Zotlan J. Acs and László Szerb, 2010) [62]. To this end, given the pandemic context, and the importance of the research topic, we deemed it useful to explore and analyze the determinants of resilience and success during the COVID-19 pandemic in overcoming and managing the health crisis among tourism companies in Morocco. This exploration will focus on four main dimensions: The leader, the organization, the strategies, and the environment.

However, our problem will be articulated around the main question that we will try to answer throughout our essay by trying to analyze from a performance perspective, the endogenous and exogenous determinants that explain the resilience of tourism enterprises in the region of Rabat-Salé-Kenitra during a health crisis?

To answer this question, we will begin with an exploratory documentary study that will be supported by a qualitative study through the administration of interview guides with a sample of fifty managers and owners of tourism units in the Rabat-Salé-Kenitra region. This qualitative study will aim to detect and select the exogenous and endogenous determinants of resilience that have a significant impact on tourism units. This selection will mobilize the AFCM method allowing dimension reduction for the statistical exploration of complex qualitative data. Next, our study will move towards a quantitative study to quantify the impact of each resilience explanatory variable on the performance of tourism businesses to overcome the health crisis. This quantitative approach will focus on the use of generalized linear models, specifically, the logistic regression method.

The importance of this study would be to approach the different explanatory factors of the resilience of tourism companies in the context of health and economic crisis to highlight the most significant elements. To do this, we plan to structure our research work around three axes: The first axis will present the theoretical framework of the study, the second will expose the empirical study and the last will be devoted to the discussion of the results.

As mentioned above, this article will only present a specific study of the prediction of the act of resilience of companies operating in the tourism industry in the region of Rabat, Salé, and Kénitra.

## 2. LITERATURE REVIEW, CONCEPTUAL FRAMEWORK, AND THEORETICAL FRAMEWORK OF THE NOTION OF RESILIENCE

The critical economic situation caused by the Covid-19 pandemic has impacted the entire economic fabric at national and international levels. This delicate health situation has directly affected the different economic sectors, specifically the tourism industry. In this vein, Emma Calgaro, et al (2014) [22] state that crises can negatively affect hotel occupancy rates, travel patterns, and tourism revenues. However, Jie Wang, et al. (2010) [38], explain that the tourism industry continuously suffers from the inability to manage crises, disasters, and chance events and their high dependence on security and safety in tourism countries. In the same context, Deborah Blackman et al (2015) [18] explain that ineffective strategies, over-reliance on external funding, government subsidies, and poor planning directly affect the resilience of the industry to tragic and unforeseen events.

Nevertheless, Khalil Rahi (2019) [51] notes that the resilience of organizations is manifested in their ability to overcome chance events, such as crises, external threats, and bankruptcies. In the same framework, Alexandra Bec et al. explain that the act of resilience of an organization in the face of a crisis is not defined by its invulnerability but by its ability to manage the consequences and outcomes of the crisis. However, Pascale Marcotte et al (2018) [49] summarized that there is a highly significant impact between natural disasters, terrorism, epidemics, and other types of crises and the tourism industry. This finding will lead to a range of reflections on the resilience of organizations and specifically tourism businesses. These works have focused on the macro-economic side such as the writings of Marie Delaplace et al. (2018) [43] dealing with the resilience of a destination, and its relationship with tourism, the works of Sylvain Zeghni et al (2020) [54] evoking the issue of the pandemic and its impact on economies, and the works of Perrain Jean-Pierre et al, invoking the smart destination strategy, reflecting a key factor in the mutations of vulnerable tourism destinations.

Similarly, in work of a micro-economic nature, Diana Kutzner's (2019) [19] reflection on environmental change, specifically climate change and the resilience of tourism organizations, the essay by Tarik Dogru et al. (2019) [56] explains the act of resilience of tourism enterprises in an environment characterized by economic turbulence and climate change. Also, Ghedamsi. M. A (2018) [29] explains the resilience of tourism businesses impacted by the rise of terrorism and political disruptions around the world. She adds that these types of crises significantly impact demand in the tourism sector. In this article, we focus on understanding the concept of resilience and its implication for different fields of research, particularly in the tourism sector.

Although several research studies have attempted to develop a model of resilience, they do not offer any unanimous conclusion. Thus, the determinants of resilience particularly in times of recession or health crises, remain an intriguing and under-explored field (Staniewski M. W and Awruk K. 2018) [52]. The academic literature offers a multitude of definitions and approaches to business resilience. It is often associated with business performance, survival, or success.

### 2.1 Resilience as a survival issue

Karl E. W. states that organizational resilience is defined as "the ability of an organization to maintain a system of organized actions in the face of an unusual situation to preserve the organization's survival" (Karl E. W. 2003) [40]. According to Karl E. W, resilience involves three mechanisms namely:

- An absorption capacity that allows the company and the organization to face crises without collapsing;
- A capacity for renewal that allows it to reinvent itself to adapt to a new situation and build new futures;
- A capacity for appropriation that allows it to strengthen itself by learning from the crises it experiences;

### 2.2 Resilience as a performance

Also, Louis Hébert (2009) [27], explains the notion of resilience as an entrepreneurial skill that manifests itself in several ways. It is first and foremost financial and concerns the company's debt, solvency, and the quality of its relations with the various stakeholders. Resilience is also operational, affecting the efficiency of operations and the supply chain. Finally, it is a marketing issue, manifested by the strength of the distribution network and the solvency of customers: Resilience under the aspect of performance (African Development Bank (ADB) International Labor Organization (ILO) 2021) [1]. In other words, resilience aims to ensure the short-term survival of companies without compromising their long-term future, by trying to absorb as much as possible the shocks coming from the context.

### 2.3. Resilience as success

However, Josée St-Pierre and Louise Cadieux consider resilience under the aspect of business performance as the ability to achieve all the objectives that entrepreneurs have set for themselves, both economic (financial health of the business, increase in revenues) and non-economic (personal well-being, territorial legitimacy, etc.) (St-Pierre and Cadieux, 2009) [39]. Resilience is also a synonym for survival, which is considered to be an element that triggers the process leading the organization and its leader to their success (Witt P. 2004 [61], Tamassy C. 2006 [57]; Lasch F. et al., 2005 [34]; Jean C. Teurlai 2004 [58]). In his aspect of success Cooper A. (1992) [12] announces that "to succeed is to not fail, even if the company remains small and unprofitable. Thus, the concept of success is reduced to that of survival".

In general, a heterogeneity of approaches has focused on the concept of resilience as it relates to the survival, success, and performance of organizations. These include approaches that focus on the leader of the organization, approaches that focus on the strategy and processes implemented, approaches that focus on the characteristics of the organization, and approaches that focus on the business environment.

### 2.4 Analysis of the theoretical and empirical foundations of the research object "Resilience"

The notion of resilience has several endogenous and exogenous antecedents. In other words, the ability of a company to overcome shocks and crises comes down specifically to characteristics related to the company, the managers, or even its environment, citing:
- Approaches to the relationship between organizational leader characteristics and firm resilience.
- Approaches and studies focused on the organization and the resilience of the firm
- Strategy-focused approaches and studies of firm resilience
- Environmental and business resilience approaches and studies

#### 2.4.1 Approaches to the relationship between the characteristics of the organization's leader and the resilience of the firm

The characteristics of the leader can have a direct impact on the resilience of companies during crises or shocks. The personality trait approach focuses on the leader and explains to what extent his or her behaviors, reactions and decisions can overcome economic or health crises, as was the case for companies during the Covid-19 pandemic.

Cooper A. (2002) [12] explains that the failure or the success of the company can be explained by the antecedents of the leader. That is, the strengths and weaknesses of the company can be the result of the personality traits of its leader. In addition, the experience effect of the leader is an important factor in the success of organizations. Cooper A. aligns himself with other authors who defend that entrepreneurial or managerial experience could constitute an inescapable condition of the success of the company. In the same vein, the theory of human capital intervenes, which response to the factors of survival or success of an organization and thus of its resilience in case of crisis.

Van Praag C. M. (2003) [59] indicated that there are links between elements relating to human capital, namely the age of the manager, his experience, his level of education, and the survival and resilience of the company. It also includes other determinants related to motivation, to more psychological elements such as religion or family environment to demonstrate to what extent these factors are capable of influencing his behavior and decisions in the phase of shocks, to overcome them. However, several studies have begun to explore the positive relationship between the profile and characteristics of the leader and the resilience of companies (Bouchikhi H., (1993) [9]; Bhidé A., (1994) [5]; Bouchikhi H. and Kimberly J., (1994) [10]; Jabraoui and Boulahoual, (2016)) [35]. These characteristics can be broken down into four dimensions: personality traits, motivation, entrepreneurial skills, and human capital.

**Human capital theory**

Veronique S. (2003) [53], defines human capital as "human capital is the set of skills, qualifications and other abilities that a person has for productive purposes. It can be innate or acquired during school, university, or professional experience, through the transmission of knowledge and qualifications, the initial human capital takes forms such as intelligence, physical strength, or knowledge transmitted by the family, it responds more to genetic or family factors than economic and is supposed to be little changeable over time. From this definition, it is notable that there is a significant influence of the notion of human capital on entrepreneurship research, economics research, and survival or resilience as our research focus.

**The theory based on the importance of the leader's motivation**

Frank L. and Frederic L. R. (2005) [26] explain that the leader's motivation and engagement are secrets to the success and resilience of companies in case of crisis. This means that the resilience, success, survival, and performance of companies are closely linked to the degree of motivation of managers.

#### 2.4.2 Approaches and studies focused on the organization and resilience of the company

Francesca L., Enrico S., And Marco V. (2001) [42] point out that there is a direct link between the characteristics of the firm and its ability to survive or succeed in any market. They emphasize that the size, age, and growth rate of the firm have a strong impact on its resilience. Also, Rosselier D. et al.

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(2015) [50] indicated the presence of significant effects of the age of the organization on its survival and resilience. On the other hand, Frank S. Coleman (2004) [13], notifies that new firms have a high failure rate due to the asymmetric information of the market and its environment. Referring to this literature review, it appears that the characteristics of a firm can have an important impact on its resilience of firms.

#### 2.4.3 Approaches and studies focused on corporate strategy and resilience

R. Ettenson and A. Crouch (2000) [24] explained that a strategy focused on innovation, and modernization of products and services offered by any company guarantees survival in its market. They add that innovation can be a way to overcome crises and bad surprises.

Looking back at the Covid-19 health crisis, despite the difficulties experienced, several companies were called upon within weeks or even days of the outbreak of the pandemic to imagine entirely new strategies and operating modes, from telecommuting to home delivery to strengthening online sales. These methods have proven to be effective and have become normality and a reliable operating rule that guarantees continued success (Frimousse S. and Peretti J. M., 2020) [25].

#### 2.4.4 Approaches and studies focused on the environment and the resilience of the company

Fotopoulos, G. and Louri, H. (2000) [27] state that there is a significant impact of the environment of the company on its ability to survive and its resilience. They add that operating in an urban area is largely different from operating in a rural area. In other words, location is seen as an important antecedent or determinant of the firm's future survival and resilience.

However, several other studies have argued for the link between environmental context and resilience. According to Morgan G., (2006) [45], the context and the entrepreneurial environment is a factor that influences the survival of companies or, on the contrary, their disappearance. The Covid-19 crisis, for example, has been for many companies a gas pedal of transformation and change that has structured a new normality and a new way of operating.

### 2.5 Elementary hypothesis

Our problem focuses on the analysis of endogenous and exogenous determinants that explain the resilience and performance of tourism enterprises in the Rabat-Salé-Kenitra region, in times of health and economic crisis. In other words, we will proceed to quantify the impact of each explanatory determinant of resilience on the capacity of tourism organizations to overcome crises, specifically the Covid-19 pandemic. To answer this question and achieve the objective of this paper, we will look at generalized linear models, specifically the logit model. For these purposes, we formulate four main hypotheses:

***Hypothesis 1*:**
Characteristics related to the leader contribute positively to the resilience of tourism enterprises in the Rabat-Salé-Kenitra region.

***Hypothesis 2*:**
Process and strategy characteristics contribute positively to the resilience of tourism enterprises in the Rabat-Salé-Kenitra region.

***Hypothesis 3*:**
Organizational characteristics contribute positively to the resilience of tourism enterprises in the Rabat-Salé-Kenitra region.

***Hypothesis 4*:**
Environmental characteristics contribute positively to the resilience of tourism enterprises in the Rabat-Salé-Kenitra region.

## 3. METHODOLOGY

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.

*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) [47] 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) [1], 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,

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where $(x_i)$ is the row vector of these explanatory variables associated with the observation $(i)$ such that, $i$ = 1, 2, …n, $(\beta)$ 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) $\varepsilon_i$ 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 $\varepsilon_i$ 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 $\varepsilon_i$ are considered independent, i.e. $\varepsilon_i$ is independent of $\varepsilon_j$ 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) [47], who were able to 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 $\eta$ is expressed in the form of linear combinations of the unknown parameters $\beta$ 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]. $\eta$ can thus be expressed as:

$$\eta = \beta X$$

The normality of the response variable Y, such that, $Y \sim N_n\ (\beta X, \sigma^2 I_n)$, 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), 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

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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*

### 3.1 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, 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:

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

With :

- a(.), b(.), c(.): Functions specified according to the type of the exponential family considered.
- $\theta$: Natural parameter, also called canonical parameter or mean parameter.
- $\varphi$: 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 $\varphi$ is replaced by $\varphi/\omega$, where $\omega$ designates a weight known as a priori.
- S: Subset of R or N
- $\omega$: The weights of the observations.

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

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

With : $b'(\theta) = g^{-1}(\beta X)$ 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), P. de Jong, and Gillian Z. Heller (2008), and Frees E. (2010)):

**-The Gaussian distribution**, with mean $\mu$ and variance $\sigma^2$. $Y \sim N(\mu, \sigma^2)$ belongs to the exponential family, with $\theta = \mu$, $\varphi = \sigma^2$, $a(\varphi) = \varphi$, $b(\theta) = \theta^2/2$, and 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 $\theta = \ln\{\pi/(1-\pi)\}$, $\varphi = 1$, $a(\varphi) = 1$, $b(\theta) = \ln(1+\exp(\theta))$, and 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 $\theta = \ln(\lambda)$, $\varphi = 1$, $a(\varphi) = 1$, $b(\theta) = \exp(\theta) = \lambda$, et c $(Y,\varphi,\omega) = -\ln(\lambda!)$ with $Y \in$ N .

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

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

| Y distribution | θ(μ ) | $\varphi$ | a($\varphi$) | b(θ) | c (Y,$\varphi$,ω) |
|---|---|---|---|---|---|
| **Normal distribution $N(\mu, \sigma^2)$** | μ | $\sigma^2$ | $\varphi$ | $\theta^2/2$ | $-\frac{1}{2}(y^2/\sigma^2 + \ln(2\pi\sigma^2))$ |
| **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 | $\varphi$ | −ln(−θ) | ((1/ $\varphi$) − 1) ln (Y) - ln(Γ(1/ $\varphi$)) |
| **Gaussian Inverse distribution $I.G(\mu, \lambda)$** | $-1/2\mu^2$ | $\sigma^2$ | $\varphi$ | $-(-2\theta)^{1/2}$ | $-1/2\ (\ln(2\pi\varphi Y^3) + 1/\varphi Y)$ |

*Source: Author*

*Table 3: Expectation and variance of usual probability laws*

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

*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.

### 3.2 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 $\beta$:

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

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, $\beta$ 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 $\theta$ and $\beta$, the likelihood ($L$) and the natural logarithm of the likelihood ($\ell$) are written as follows:

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

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

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

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

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

With:

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

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:

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

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, $\mu_i$ is unknown, so it is impossible to obtain an analytical expression of the maximum likelihood estimator of $\beta$ by canceling the first derivative (gradient): these equations are called transcendental. In other words, they are non-linear $\beta$ 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 $\beta^0$
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

### 3.3 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 $\beta$, 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 $\beta$ and $\phi$ on a sample of size $n$.

Let $\widehat{\beta_n}$ be the estimator of the parameter $\beta$ 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:

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

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

### 3.4 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 $X_1, X_2, \ldots X_p$ 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 $X_1, X_2, \ldots X_p$.

### 3.5 Binary logistic regression, an extension of generalized linear models

The essays of Hosmer D. W., and Lemeshow S. (2000) [34] as well as the work of King G., and Zeng L. (2001) [28], underline that logistic regression is understood as a relevant statistical choice, for situations in which the occurrence of a binary outcome must be predicted. In addition, Burns R. B., Burns R., Burns, R. P. (2008) [11], and Muijs D., (2010) [44] have offered clarifications of the steps necessary to perform such an analysis using a variety of statistical packages, such as SPSS, R, etc. While the explanation of the phases of performing such analysis in different particular contexts has also been mentioned on many websites, as highlighted in the works of Greenhouse J. B., Bromber, J. A., and Fromm D. A. (1995) [30] as well as the writings of Wuensch D. (2009) [60].

#### 3.5.1 Logit transformation

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 $X_1, X_2, \ldots X_p$ 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 $X_1, X_2, \ldots X_p$.

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, $y_i = (y_1, y_2, \ldots y_n)$ 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) = $(X_1, X_2, \ldots X_p)$ 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 ($\beta$) 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 in this paper that $y_i$ (response variable) is a realization of a random variable $y_i$ that can take the values 1 in the case that corresponds to the probability of tourism companies succeeding in overcoming the health crisis or 0 in the case of the probability of failing to overcome this crisis with probabilities of (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 $P(y_i = 0|X) = 1 - \pi$ and present, denoted $P(y_i = 1|X) = \pi$, 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) [2], which belongs to the large class of generalized linear models introduced by John Nelder and Robert Wedderburn (1972) [36]. The Logit of the logistic regression model is given by the equation:

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

By the Logit transformation, we obtain from equation (1) the 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 $1 - \pi$ as:

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

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

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

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

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

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

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

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

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

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### 3.5.2 Estimation of the $\beta$ 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 $\pi$ 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 $\beta$, 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 $\beta$ 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 $\beta$. 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 $\ell$ expressed as follows:

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

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

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

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

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

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

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 $\ell$' (gradient of $\ell$) 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). 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 $\beta$ equations (12), we use the Newton-Raphson iterative optimization method, referring to the Hessian matrix. Using this method, the estimation of the $\beta$ parameters starts with the first step of choosing a starting point $\beta^{0}$ or $\beta^{old}$. 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:

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

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 $\widehat{\pi_\iota}(1 - \widehat{\pi_\iota})$. We can also write:

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

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:

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

### 3.5.3 Odds and Odds-ratios

The odds ratio (OR) is a statistical procedure used to evaluate the association between two qualitative random variables. This procedure is often used in logistic regression to measure a relative effect. Knowing that we are in a case of a dichotomous response variable $y_i$ (binary logistic regression), the probability of having Y=1 knowing that X= x is noted $\pi_i$. We determine the chance (odds) of having (Y =1|X = x) rather than having (Y = 0|X = x) by the ratio $\{\pi\}/\{1-\pi\}$. The odds ratio can be expressed as follows:

$$OR = \frac{\pi(x+1)/[1-\pi(x+1)]}{\pi(x)/[1-\pi(x)]}$$

## 4. RESULTS AND DISCUSSION

This study focuses on the use of an online questionnaire for data collection. The construction of the questionnaire used in this research is based on the literature of several authors of works. This survey mainly covers two areas of questions. The first one is about the information in the tourism company's identification sheet. The second area includes questions about the impact of resilience determinants on the ability of these tourism units to overcome the covid-19 health crisis. However, the business 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 consists of 112 tourism units, taking into account the size of the survey population. After reviewing the collected questionnaires, we obtain a total of 100 valid questionnaires. The first introductory part of the questionnaire is devoted to the personal information of the company, such as the range of the realized turnover, number of years of experience, the capacity of the tourist unit, type of tourists accommodated, quality certificate obtained, number of deployed staff, etc. The second part is reserved for answers to multiple-choice questions on the explanatory determinants of resilience using a Likert scale. Finally, the survey is completed with a dichotomous response question concretizing the resilience or failure scenario of these tourism companies interviewed after the covid-19 epidemic

In our study, the response variable "the act of success in overcoming the health crisis" is binary with two modalities that can be coded as 1 if they succeed and 0 if they fail to overcome the health crisis. Let Y be the event "act of success in overcoming the health crisis" representing our variable to be explained, so we have two probabilities:

- $\pi\,(Y = 1)$: Corresponds to the probability of success in overcoming the health crisis.
- $\pi\,(Y = 0)$: Corresponds to the probability of the act of failure to overcome the health crisis.

The resilience variables selected to explain the act of success in overcoming the health crisis are summarized as follows:

- $X_1$ : Characteristics related to the managers
- $X_2$ : Characteristics of the companies
- $X_3$ : The strategies decided by the company
- $X_4$ : The company's environment

The main idea of this study is to model the probabilities of success conditioned by an assortment of explanatory determinants $X_1$, $X_2$, $X_3$, et $X_4$.

$$\pi\,(x) = P\,(Y = 1|X = x) \text{ et } 1-\pi\,(x) = P\,(Y = 0|X = x)$$

Our model is formulated as follows:

$$g\,(\pi\,(x)) = \beta.\,X$$

The function g represents the link function that one is supposed to define, $\beta$ the vector of regression coefficients referring to the strength of the explanatory variables on the response variable, and $X$ the vector of explanatory variables. Determining the link function confers focus on the values that $(x)$ can accept (0 or 1) and that $(\beta.\,X)$ can take any value from the set R. In this context, binary logistic regression consists of modeling the transformation "$logit$" of $(x)$ by a linear function of our $(p)$ explicit variables. In this study, we attempted to identify predictors of the act of resilience and measure the impact of each on the ability of tourism businesses to overcome the negative fallout of the covid-19 health crisis. However, the predictor variables introduced into the logit model to explain the act of resilience are qualitative.

*Table 4: Reliability test*

| Cronbach's Alpha | Cronbach's Alpha based on standardized elements | Number of elements |
|---|---|---|
| 0.856 | 0,855 | 4 |

*Source: Author*

According to the reliability test, we notice that the value of the coefficient $\widehat{\alpha} = 0.856$ exceeds the conventional minimum threshold of $\alpha = 0.70$ (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*

| | $X_1$ | $X_2$ | $X_3$ | $X_4$ |
|---|---|---|---|---|
| $X_1$ | 1 | 0,281 | 0,171 | 0,403 |
| $X_2$ | 0,281 | 1 | 0,395 | 0,401 |
| $X_3$ | 0,171 | 0,395 | 1 | 0,617 |
| $X_4$ | 0,403 | 0,401 | 0,617 | 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: $0.171 \leq r \leq 0.617$, confirming moreover the result of Cronbach's Alpha reliability coefficient.

*Table 6: Chi-square test*

| | $X_1$ | $X_2$ | $X_3$ | $X_4$ |
|---|---|---|---|---|
| ***Chi-square value of pearson*** | 59.512 ddl = 1 | 45.376 ddl = 1 | 61.876 ddl = 1 | 75.376 ddl = 1 |
| ***Asymptotic significance (bilateral)*** | 0.000 <0.05 | 0.000 <0.05 | 0.000 <0.05 | 0.000 <0.05 |

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*Source: Author*

The Chi-square test shows the relationship between the explanatory variables $X_1$: The characteristics related to the managers, $X_2$: The characteristics of the firms, $X_3$: The strategies decided by the company, and $X_4$: The environment of the company, and the response variable "the act of success of tourism companies to overcome the health crisis" is highly significant, and an asymptotic significance (two-sided) of $p = 0,000 < 0.05$. These results refer to rejecting the null hypothesis $H_0$:. In other words, the explanatory variables selected in this study have a significant relationship with the response variable, that is, a significant influence on the ability of tourism units to overcome the health and economic crisis produced by the covid-19 epidemic.

*Table 7: Cramer test*

| | | Value | Approximate significance |
|---|---|---|---|
| Cramer's V | $X_1$ | *0,416* | *0,000* |
| | $X_2$ | *0,581* | *0,000* |
| | $X_3$ | *0,526* | *0,000* |
| | $X_4$ | *0,488* | *0,000* |

*Source: Author*

The value of Cramer's V varies in the interval [0,1]. In our case, we notice that the four explanatory variables $X_1$: the characteristics related to the managers, $X_2$: the characteristics of the firms, $X_3$: the strategies decided by the firm, and $X_4$: the environment of the company, has a strong relationship with the response variable, "the act of success of tourism companies to overcome the health crisis" (Louis M. Rea and Richard A. Parker (1992)). According to the work of Louis M. Rea and Richard A. Parker, if Cramer's V value is between 0.4 and 0.6, the association between the dependent variable and the independent variables is relatively strong. As shown in the Cramer's V test table, the set of values is bounded between the values 0.4 and 0.6.

*Table 8: Table of variables in the equation*

| | $\hat{\beta}$ | E. S | Wald | ddl | Sig | Exp(β) | Confidence interval for Exp (β )(95%) Inferio | superi |
|---|---|---|---|---|---|---|---|---|
| $X_1$ | 1,61 | 0,460 | 11,98 | 1 | 0,001 | 5,030 | 2,015 | 12,552 |
| $X_2$ | 1,87 | 0,617 | 9,21 | 1 | 0,002 | 6,490 | 1,941 | 21,753 |
| $X_3$ | 1,55 | 0,571 | 7,34 | 1 | 0,007 | 4,751 | 1,542 | 14,642 |
| $X_4$ | 1,34 | 0,211 | 6,878 | 1 | 0,000 | 3,834 | 1,331 | 12,871 |
| Consta | - | 0,950 | 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, there is a highly significant effect of all the predictor variables on the response variable "act of success of tourism businesses in overcoming the health crisis". However, the $p\ (X_1) = 0.001 < 0.05$, $p\ (X_2) = 0.003 < 0.05$, $p\ (X_3) = 0.007 < 0.05$, $p\ (X_4) = 0.000 < 0.05$.

However, it is easy to interpret the p-meanings, but the question that arises at this point is how to interpret the regression coefficients $\hat{\beta}$.. What does this coefficient correspond to, 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, 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 also a close relative risk, designates a relationship to the response variable.

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The column exp($\hat{\beta}$) (Odds Ratio) tells us that the different explanatory variables each influence the variable to be predicted distinctly. Consistent with our case, we can claim that managerial characteristics generate five times more chance ($OR(X_1)$ = 5.0 30, $IC^{5\%}$ = [2.015, 12.552]) that tourism companies are likely to overcome the negative impact of the crisis than to fail. Also, firm-specific characteristics make it six times more likely ($OR(X_2)$ = 6.497, $IC^{5\%}$ = [1.941, 21.753]) to escape the economic crisis. In addition, the strategies implemented by the tourism units were four times more likely ($OR(X_3)$ = 4.751, $IC^{5\%}$ = [1.542, 14.642]) to deflect the negative consequences of the health epidemic. Similarly, the characteristics related to the internal and external environment of tourism enterprises offer three times the chance ($OR(X_4)$ = 3.834, $IC^{5\%}$ = [1.331, 12.871]) that they will be able to overcome the covid-19 epidemic.

Finally, we find that resilience determinants such as managerial characteristics, company-specific characteristics, implemented strategies, and characteristics related to the internal and external environment of tourism companies were able to help them overcome the covid-19 health crisis in an average of 5 times more likely than failing.

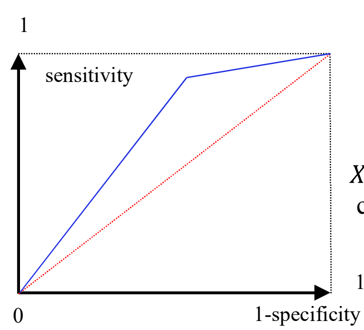
*Table 9: Area under curve*

| ` | AUC | Standard error | Asymptotic Sig. | Asymptotic confidence interval for 95% | |
|---|---|---|---|---|---|
| | | | | Inferior | superior |
| $X_1$ | 0,718 | 0,029 | 0,000 | 0,693 | 0,751 |
| $X_2$ | 0,623 | 0,028 | 0,020 | 0,601 | 0,676 |
| $X_3$ | 0,661 | 0,028 | 0,030 | 0,654 | 0,712 |
| $X_4$ | 0,720 | 0,027 | 0,000 | 0,702 | 0,818 |

*Source: Author*

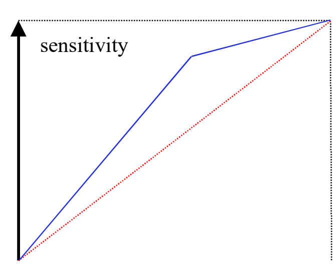
The AUC (area-under-curve) expresses the probability of placing a positive element in front of a negative element. However, this technique proposes an AUC = 0.5 as a baseline situation that our classifier needs to improve. At first glance, all results are highly significant with a $p = 0.000 \leq 0.05$. On the other hand, the table also reports AUCs that exceed the baseline situation (AUC = 0.5), which means that the explanatory variables used in the model all have a significant impact on the response variable.

However, we can predict that tourism units are likely to overcome the economic crisis caused by the coronavirus epidemic thanks to the characteristics related to the managers at 71.8% ($IC^{5\%}$ = [0.601 - 0.751]). Also, the characteristics related to the companies can help the tourism companies to overcome this crisis at the rate of 62.3% ($IC^{5\%}$ = [0.693 - 0.676]). On the other hand, the strategies implemented during the pandemic can contribute up to 66.1% ($IC^{5\%}$ = [0.654 - 0.712]). to escape the negative effects of this crisis. However, the characteristics of the internal and external environment of the tourism companies participate at the level of 72% ($IC^{5\%}$ = [0.702 - 0.818]). to help them to deviate from the negative consequences of this economic shock.




$X_1$: managerial characteristics

*Figure 1: Area under the curve for managerial Characteristics*




$X_2$: company-specific characteristics

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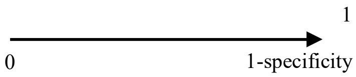


*Figure 2: Area under the curve for company-specific characteristics*

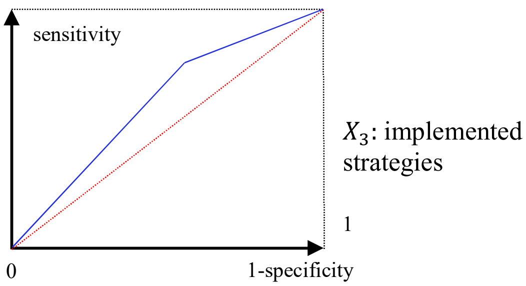


*Figure 3: Area under the curve for implemented strategies*

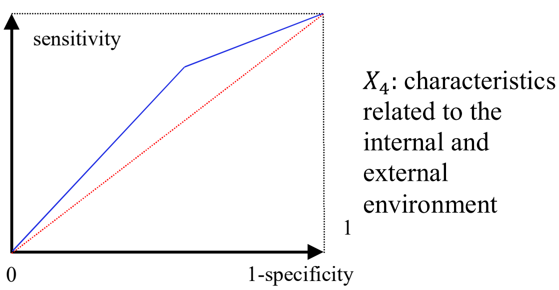


*Figure 4: Area under the curve for characteristics related to the internal and external environment*

## 5. CONCLUSION

The coronavirus epidemic has greatly exacerbated the difficulties of the tourism industry in Morocco due to the restrictions imposed on the activities associated with it such as the cessation of air and sea transport between countries, the closure of hotel companies, stores, and restaurants, the cessation of handicraft activities, etc., causing significant losses in tourism revenues and thus further increasing the State's budget deficit.

The persistence of the health crisis and the deterioration of the economic context has necessitated the updating of the measures and strategies implemented by tourism companies to preserve continuity and employment. In this pandemic context and the importance of the issue of sustainability of tourism units, our essay was content to explore and analyze the determinants of resilience during the pandemic of COVID-19 to overcome and manage the situation of the health crisis in tourism enterprises in Morocco, specifically the region of Rabat-Salé-Kénitra.

This study focused on four main dimensions such as the characteristics related to the leaders, the characteristics of the companies, the strategies decided by the company, and the environment of the company. These dimensions are introduced in a statistical model of prediction "binary logistic regression" with a motive to explain the ability of the Moroccan tourist companies to overcome the health crisis of covid-19.

However, the analysis of the results obtained showed the existence of a highly significant relationship between the explanatory variables of resilience and the response variable "act of success of tourism companies to overcome the health crisis". Furthermore, the quantification of the impact of each explanatory variable on the response variable explained that the characteristics related to the leaders generate five times more chance (OR ($X_1$) = 5.0 30, IC5% = [2.015, 12.552]) that the tourism enterprises are likely to overcome the negative impact of the crisis than to fail. However, firm-specific characteristics also make it six times more likely (OR($X_2$) = 6.497, CI5% = [1.941, 21.753]) to escape the economic crisis. In addition, the strategies implemented by the tourism units were four times more likely (OR($X_3$) = 4.751, CI5% = [1.542, 14.642]) to deflect the negative consequences of the health epidemic. Similarly, the characteristics related to the internal and external environment of the tourism companies offer three times more chance (OR($X_4$) = 3.834, IC5% = [1.331, 12.871]) that these will be able to overcome the epidemic of covid-19. The importance of the study would be to approach the different explanatory factors of the resilience and performance of tourism enterprises in the context of health and economic crisis to highlight the most significant elements and help decision-makers in their decision-making.

The analysis of the determinants of resilience covering factors related to strategy, environment, leadership traits and characteristics specific to tourism organizations offers a range of avenues for future research to further the understanding of the resilience of tourism organizations after the Covid-19 epidemic. The determinants used in this survey can be broken down into several items and analyzed from different aspects. Furthermore, this survey can be general, incorporating all actors and stakeholders in the tourism sector, or it can focus on a single tourism sector. It can also cover different areas or widen the scope.

**Conflict of interest**
The authors have no conflicts of interest

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