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Credit Risk Assessment in Microfinance Institutions Through Scoring: Moroccan Case

Loubna Assairh, ***(Phd Student)***
Laboratory of Economic Sciences and Public Policies
Faculty of Economics and Management.
Ibn Tofail University, Kenitra, Morocco

Mohammed Kaicer, ***(Phd, Professor)***
Laboratory Analysis, Geometry and Applications
Faculty of sciences of Kenitra
Ibn Tofail University, Kenitra, Morocco

Mounir Jerry, *(Phd, Professor)*
Laboratory of Economic Sciences and Public Policies
Faculty of Economics and Management
Ibn Tofail University, Kenitra, Morocco

Correspondence address:	Faculty of Economics and Management Ibn Tofail University, Morocco (Kenitra) B.P 242- Kenitra assairh.loubna@gmail.com
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Abstract:

Microfinance institutions are organizations that provide financial services to people who are poor or excluded from the financial system. However, they often face many difficulties, such as non-repayment of loans by borrowers. In developing countries like Morocco, this situation has led to the failure of several microcredit institutions, before granting such loans, MFIs face difficulties in assessing the riskiness of potential borrowers. In this context, efficient instruments are needed to assess credit risk.
The credit scoring model is a mathematical model used to estimate the probability of default, i.e., the likelihood that customers will trigger a credit event (i.e., bankruptcy, bond default, payment default, and cross-default events), the effectiveness of scoring depends not so much on the technical tools used as on the systematic training of users, credit officers and branch managers will only be convinced that scoring can help them make decisions if they understand how it works and can observe it in concrete tests. This paper describes how credit scoring works, what microcredit institutions can expect from it and how they can use it, as well as the data required.
An empirical study was conducted on 1021 borrowers of a Moroccan microfinance institution, in order to show the predictive capacity of credit scoring models and to identify the explanatory variables of the probability of default of loans granted by MFIs, using a logistic regression model. The results obtained show that the main variables in this regard are Gender, Age, Schooling, Type of Customer, Persons in Charge, Loan amount. The results presented advance the results of previous research and may be useful to MFI managers, regulatory institutions, financial analysts, and academic researchers.

Keywords: Microcredit, Scoring, Credit risk, Microfinance, logistic regression

JEL Classification: G2, G3, C58
Paper type: Empirical research

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1. Introduction:

The mission of microfinance institutions is to provide financial services to people who are poor or excluded from the financial system, the microfinance sector plays an increasingly important role in financial inclusion, sustainable economic development, job creation and poverty alleviation (Sierra & Rodríguez-Conde, 2021).

As with all financial institutions, the greatest risk in microfinance is that a borrower will not repay the loan. Credit risk is a particular concern for MFIs because most microcredit is unsecured. (That is, they are not subject to any formal, conventional or bank guarantee) (Kofarmata & Danlami, 2019).

However, they often face many difficulties, such as non-repayment of loans by borrowers.

In developing countries such as Morocco, this situation can lead to the failure of several microcredit institutions. However, before granting these loans, MFIs face difficulties in assessing the riskiness of potential borrowers (Bauchet & Morduch, 2013).

The credit scoring model is a mathematical model used to estimate the probability of default, i.e., the likelihood that customers will trigger a credit event (i.e., bankruptcy, bond default, payment default, and cross-default events), this technique compares quantitative and qualitative data about the borrower, loan, and lender with similar past cases. Sharing the same characteristics with past cases that had repayment problems is a sign that the current loan will also have repayment problems (Kaicer & Aboulaich, 2014).

However, country statements have increased the interest and timeliness of analyzing the factors believed to influence MFI loan defaults, indicating that the study of credit ratings supports decision makers in the provision of microcredit, thereby improving performance and sustainability.

Most research (Tsai & Hung, 2014) suggests that scoring combined with credit bureaus have the potential to significantly improve the performance of formal lending in high-income countries. With good risk knowledge, lenders can approve poor but risky borrowers and reject non-poor but risky borrowers. In this way, lenders can save time that would have been wasted in searching for the right course of action. With this motivation, this paper aims to generate new knowledge and improve our understanding of MFI loan default.

The main objective of the study is to identify the credit risk factors of Moroccan MFIs, we carry out an empirical study of 1021 on 1021 borrowers of a Moroccan microfinance institution, in order to determine the significant explanatory variables of the probability of default, by the scoring model using logistic regression. The approach adopted in this paper is innovative because the methodology used has received little attention in previous studies on loan default in Moroccan MFIs. Therefore, we expect to obtain more accurate and robust results. We expect these results to be useful to MFI managers, financial analysts, and academic researchers.

This paper proceeds as follows. Section 2 presents an overview of the literature on credit risk in microfinance and the basic relative concepts of credit scoring. Section 3 explores the data and describes the methodology used. Section 4 summarizes the results. Finally, section 5 contains the discussion of the results and the conclusion.

2. Literature review:

2.1. Credit risk in Microfinance institutions

Microcredit is a real success both because of its "real involvement and efficiency in the fight against poverty" and because of its developmental vision. It is adjusted to fit in with the participation in the economic take-off. By requiring guarantees in order to grant loans, banks exclude a good number of people deemed not to have the necessary funds to repay a loan, since "not everyone can obtain a bank loan" . However, microcredit is above all a credit like any other because it embodies and "retains all the characteristics of credit as it is developed in banking organizations". Based on a contract between lender and borrower to guarantee repayment, microcredit is prescribed as a small, repayable short-term loan used to finance a sustainable and profitable economic activity. It is intended to support the start-up of income-generating projects and activities of individuals who do not have access to conventional banking services. Its objective is to promote social development, and thus it participates in the fight for the eradication of poverty thanks to its innovative form of aid which is no longer identified with pure and simple assistance.

Credit risk is inherent in any money lending transaction. The business model of credit institutions, including microfinance institutions, is not only about setting up channels that facilitate financial intermediation - finding those who want to save and those who need financing - and maturity transformation - converting short-term investments into medium- and long-term credits and vice versa. (Agarwal, Ambrose, Chomsisengphet, & Liu, 2016).

Microfinance institutions bear these risks more intensely than conventional financial institutions, because micro-borrowers, often living in poverty, lack solid guarantees and have a low capacity to absorb personal and professional shocks (Pantoja, 2002).

Credit risk management is essential to optimize the performance of microfinance institutions. It has been found that in order to minimize loan losses and improve financial performance, it is essential that financial institutions have an effective credit risk management system.

An efficient system is one that guarantees repayment of loans by borrowers is essential to address the problems of information asymmetry and to reduce the level of loan losses, thus the long-term success of microfinance organizations.

2.2. Credit scoring

Credit scoring is a tool that allows banks to assess the risk represented by the loan applicant. In other words, it allows the credit institution to guarantee the creditworthiness of the loan applicant. A credit institution will always seek to limit the risk of non-repayment of the loans it grants. Thus, credit scoring allows the bank to limit these risks based on a number of criteria. The criteria put forward concern the reliability and solvency of the borrower.

Credit scoring is not a new method. Its re-emergence is about sixty years old. In considering Fisher's discriminant linear function dating from 1936, (Capon, 1982) was the first to identify that statistical techniques can be used to discriminate between non-defaulting and defaulting borrowers. Since then, this technique has begun to expand and its application has been extended to real estate credit, the credit card sector, credit for car purchases, marketing, etc.

Several statistical models have linked arrears to the characteristics of the lender, the borrower, and the borrower (Kwong, Ip, & Chan, 2002). In general, these models have not been very useful as scorecards (they were not popular for this purpose) for three reasons. First, these models use small sample sizes which makes them very robust. Second, some models use features that most predators don't collect or are expensive to collect . Finally, and most importantly, these models lack predictive power (Vaish, 2013).

A literature search is needed to confirm that credit scoring can actually predict risk, and most importantly convince loan officers and credit managers that credit scoring works well.

(Schreiner & Woller, 2003) defines scoring as the use of knowledge of repayment outcomes and characteristics of loans repaid in the past to predict the outcomes of future loans. According to this author, scoring quantifies risk as a probability. It consists of a statistical evaluation that uses information about borrowers' repayment performance and the characteristics of loans repaid in the past to anticipate the likelihood of success for future loans.

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Credit scoring increases the robustness of the assessment process by providing an objective assessment of the expected risk for different risk classes of borrowers. It also makes it possible to detect highly problematic loans (Mester, 1997; Zuccaro, 2010).

Credit risk assessment is a complex process that involves a careful and conservative analysis of the borrower's information in order to estimate the probability that the loan will be repaid regularly. The likelihood of regular repayment depends on objective factors relating to the borrower's operating environment, the borrower's attitude towards the commitment, and the institution's ability to assess these two aspects through the information at its disposal.

Reliability criteria make it possible to determine the nature, behavior and respect of the applicant's commitments. Consequently, inserting a maximum of criteria such as age, marital status, type of housing, housing situation, profession and number of children of the applicant in the database will enable the bank to have a global overview of the applicant's situation and his ability to meet his responsibilities. However, while the creditworthiness criteria provide some information about the applicant's personality, they do not determine his or her standard of living or ability to repay (Serrano-Cinca, Gutiérrez-Nieto, & Reyes, 2016).

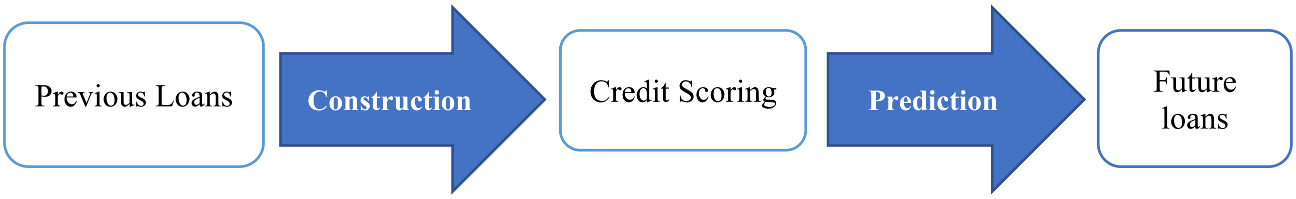
Thus, the candidate's solvency criteria must also be taken into consideration. To do so, his income, profession, seniority and professional category will also be inserted in the tool to know if the candidate has the necessary resources to repay the credit.

Because of the way it works, credit scoring is an advantageous tool for the credit organization because it allows it to limit the risks. On the other hand, it handicaps the candidate, who may be refused a loan application on the basis of his standard data, which may not reflect the candidate's real situation.

Credit Scoring uses quantitative and qualitative measures of performance and characteristics of previous loans to predict future loan performance with similar characteristics. Credit Scoring does not approve or reject a loan application, but can rather predict the probability of occurrence of poor performance (Juridiques et al., 2020).

The figure1 below illustrated the credit scoring technique:

Fig.1: *credit scoring technique*



Source: *(Liu, 2001)*

Credit scoring, according to (Hand & Henley, 1997), is a statistical procedure used to classify credit applicants, including those who are already customers of the lender, into "good" and "bad" risk types. In the early 1970s, credit scoring applications were built using statistical techniques (particularly discriminant analysis). Subsequently, the methods used to have evolved towards mathematical, econometric and artificial intelligence techniques. In all cases, the construction of any credit scoring application is done by giving information about the customer contained in the credit applications, from internal and even external sources of information.

Here is a summary of the main works on credit scoring in the banking sector, grouped according to the statistical methodology applied.

2.2.1. Discriminant analysis

The discriminant analysis is a multivariate technique that allows the simultaneous study of the behavior of a group of independent variables with the aim of classifying a series of cases into previously defined and mutually exclusive groups (Hastie, Tibshirani, & Buja, 1994). The main advantage of this technique lies in the differentiation of the characteristics that define each group, as well as the interactions that exist between them. It is an appropriate model for classifying good and bad payers when repaying a loan. Disadvantages of discriminant analysis include the rigidity of the initial assumptions (linearity, normality, homoscedasticity and independence) and, above all, the impossibility of calculating default probabilities.

(Altman I Edwarrd, 1968) developed the most widely used methodology for assessing firm efficiency. The Commission developed a new tool for predicting corporate insolvency by applying the following principles of explanatory variables in the form of ratios. The Altman Z-score was interpreted through the following variables: net income/turnover, retained earnings/assets, EBIT/assets, market value of equity/book value of debt and turnover/assets. This methodology was then adapted to predict the delinquency of bank customers.

2.2.2. Logit models

Logistic regression models are used to calculate the probability that a client belongs to one of the groups established a priori (non-payer or payer). The classification is based on the behavior of a series of independent variables for each observation or individual. The main advantage of the logistic regression model is that it is not necessary to make any initial assumptions, such as the normality of the distribution of variables, which improves the treatment of qualitative or categorical variables. In addition, this model has the advantage of measuring the probability of non-compliance by keeping the explained variable always in a range between zero and one.

(Clark, The, Analysis, & Mar, 2015) was one of the first authors to publish a credit scoring model using this methodology. This author conducted a comparative study between discriminant analysis and information analysis.

the Logit model in which he found that the Logit model gave a better classification rate than the discriminant analysis.

2.2.3. Linear probability models

Linear probability models use a least squares regression approach, where the dependent variable (dummy variable) takes on the value of one (1) if a customer defaults, or the value of zero (0) if the customer is in compliance. The regression equation is a linear function of the explanatory variables. (Orger, 1970) pioneered this technique by using regression analysis in a model for commercial loans. The same author used this technique to build a credit scoring model for consumer loans, highlighting the high predictive power of the variables on customer behavior, classified essentially into four main groups: liquidity, profitability, leverage and activity.

2.2.4. Linear programming models

This method belongs to the non-parametric credit scoring models. In general, this type of model is more valid when the form of the functional relationship between the variables is unknown. Linear programming models allow for the programming of scoring models or systems without losing sight of the optimization criterion of correctly classified customers. (Shi, Peng, Xu, & Tang, 2002) laid the foundation for the applicability of this technique in the banking industry; since then, other authors have developed this methodology to predict loan default.

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2.2.5. Neural networks

It is a methodology classified as a non-parametric credit scoring technique. Artificial neural networks attempt to mimic the nervous system, allowing them to build systems with some degree of intelligence. The network consists of a series of simple processors, called nodes, which are interconnected with each other. As input nodes, we consider the characteristics or variables of the credit transaction. The output node would be the response variable defined as the probability of non-payment. The purpose of each node is to respond to a given input signal. The credit scoring process using this technique is complicated because the internal learning process operates as a "black box" (hidden layer), where understanding what is going on inside requires specialized knowledge.

(Natasha, Prastyo, & Suhartono, 2019) published a paper comparing this technique to other alternative customer classification techniques. Subsequently, (Natasha et al., 2019) described some of the applications of neural networks.

(Ala'raj, Abbod, & Majdalawieh, 2021) used in credit management decisions and fraud detection. Since then, with the advancement of new technologies, advanced systems have been designed to classify "good" and "bad" potential customers.

2.2.6. Decision trees

The main advantage of this methodology is that it is not subject to statistical assumptions about distributions or functional forms. Although they involve a difficult internal understanding of how they work, they present visual relationships between variables, groups of response variables and risk, which is why this method is widely used in credit assessment. The most common algorithms for building decision trees are ID3, C4.5 and C5. In each of these, the aim is to achieve an optimal separation in the sample, so that the groups of response variables offer different risk profiles.

The contribution of (Bensic, Sarlija, & Zekic-Susac, 2005) was decisive for the development of other works using this technique. Among them, (Bastos, 2008) applied decision tree models to rank customers in terms of credit scoring.

3. Data and methodology

3.1. Data

The data used for the realization of this model are data collected from Moroccan microfinance institutions. It is descriptive information on the customers as well as on their history of Microfinance institutions with regard to the various loans they have contracted

The objective of this paper was to develop a credit scoring model for Moroccan microfinance institutions to predict the default probability of new loan applicants. Using binary logistic regression on 1021 borrowers, of which 258 defaulting and 763 non-defaulting.

Moroccan microfinance institutions, the determination of the client profile (distinction between non-defaulting and defaulting clients) is based on a key factor measuring the client's ability to repay the loan, which is the number of days the loan is past due. In this context, a client is considered bad if he or she is more than 30 days late in the loan cycle. On the other hand, a good client is one who is never more than 30 days late in repayment.

3.2. Method

In line with the objective of our study, which is to determine the factors that discriminate between non-defaulting and defaulting borrowers, we opted for binary logistic regression. This type of model uses the maximum likelihood approach to estimate the model parameters.

The purpose of logistic regression also called as the Logit mode is to study the effect of one or more explanatory variables on a variable to be explained measured on a dichotomous or

Boolean scale. The model allows us to obtain a number between 0 and 1, corresponding to the probability of default of the customer.

In this context, we will assume that the dependent variable that interests us represents concerns the creditworthiness or not of a customer.

$$Ln\ (\frac{P}{1-p}) = \beta_0 + \beta_1\ X_{i1}\ + \beta_2\ X_{i2} + \cdots + \beta_p\ X_{ip} + \text{e} \qquad (1)$$

With: $\frac{P}{1-P}$ is an (Exp(B), or "Odds Ratios") which is defined as the ratio of the probability of success and the probability of default

3.1.1. Measurement of variables

The descriptive statistics (Table 1) indicate that men outnumber women (56% versus 44%). Most borrowers have secondary education 27% compared to 17% with tertiary education, 32% with primary education and 8.3% with no education. Also, urban borrowers represent 42% against 58% urban, in terms of activities, most borrowers work in commerce against 38% , Industry 27%, 11% agriculture, 23% other activities, new clients represents 84% against 16% old clients, 28 % of borrowers have a credit of less than 10,000 DH and 11% have a credit of less than 30,000 DH.

In our sample, 40% are responsible for less than 2 persons against 38% who are responsible for 3 dependents, 21% are responsible for more than 4 persons

Table 1: *description of variables*

Variables	Description	Modalities	frequency	Pourcentage
Gender	Borrower's gender	0= women 1=Man	445 576	44% 56%
Age	Borrower's age	0 =18-30 years old 1=30-50 years old 2=<50 years old	278 563 180	27% 55% 18%
Urban/Rural	Place of living (Rural, Urban)	0=Rural 1=Urban	427 594	42% 58%%
Residency	Residential status	0=Tenant 1=Owner	255 766	25% 75%
Activity	The business segment	0= Industry 1= Commerce 2=Agriculture 3=Other activities	276 395 111 239	27% 39% 11% 23%
Schooling	The level of schooling	0=Illiterate 1=Primary 2=Secondary 3=Highschool 4=sup	85 329 278 152 177	8% 32% 27% 15% 17%
Type_customer	Type of customer	0=Old customer 1=New cutomer	161 860	16% 84%

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www.ijafame.org

Loan_Amount	Loan amount.	0=<5000 DH 1=5000 DH -10 000 DH 2=10 000 DH – 20 000 DH 3=20 000 DH – 30 000 DH 4=<30 000 DH	343 289 236 45 108	34% 28% 23% 4% 11%
Pers_charg	Number of persons in charge (1,2,..)	0=0-2 1=2-4 2=<4	412 390 219	40% 38% 21%

Source: *Authors*

4. Results

Table 2 allows us, on the one hand, to observe the variables that have been induced in the equation and, on the other hand, to examine their significance (Signif. box). When the variables are significant, we proceed to the interpretation of the odds ratios (Exp(B), or "Odds Ratios"). These odds ratios correspond to the number of times a person belongs to a group when the value of the independent variable increases by 1 (i.e. in the case of binary variables when moving from one state to another). An odds ratio greater than 1 indicates an increase in the odds of belonging to the bad borrower group, while a ratio less than 1 indicates a decrease in the odds of belonging to that group.

Table 2 : *Variables de l'équation*

		B	E.S	Wald	ddl	Sig.	Exp(B)
Pas 1[a]	Gender(Men)	-,290	,201	2,076	1	,150	,748
	Age	-,444	,159	7,826	1	,005	,642
	Schooling			49,846	4	,000	
	Schooling (Primary)	-3,668	1,024	12,831	1	,000	,026
	Schooling (Secondary)	1,089	,362	9,041	1	,003	2,971
	Schooling (Highscool)	,757	,360	4,410	1	,036	2,132
	Schooling (Sup)	-,072	,459	,025	1	,875	,930
	Residency (Tenant)	,144	,215	,445	1	,505	1,154
	Urban/Rural (Urban)	,773	,208	13,874	1	,000	2,167
	Activity			118,785	3	,000	
	Activity (Commerce)	,188	,312	,362	1	,547	1,207
	Activity (Agriculture)	1,545	,302	26,163	1	,000	4,687
	Activity (Other activities)	3,316	,374	78,615	1	,000	27,553
	Type_Customer (New customer)	-,615	,247	6,199	1	,013	,541
	Pers_charge	-1,417	,409	11,997	1	,001	,243
	Loan_amount	-,244	,122	3,992	1	,046	,784
	Constante	-2,479	,522	22,525	1	,000	,084

Source: *Authors*

The results show that the Moroccan MFI, according to the regression coefficient Exp(B), out of the nine variables analyzed, six variables had a positive influence on the probability of default, while four had a negative influence. Our results show that five variables (Gender, Age, Schooling, Type_customer, Pers_charge, Loan_amount), were positively associated with the Probability of default, while four others (residency, Urban/Rural, activity) were negatively associated with the Probability of default.

From the above, the score of the model is expressed as:

$$Score = -2{,}479 - 0{,}29 * Gender\ (Men) - 0{,}444 * age - 3{,}66 * Shooling(Primary) + 1{,}089\ Schooling\ (secondary) + 0{,}757\ Schooling(highschool) - 0{,}72\ Schooling(Sup) + 0{,}144 * Residency - 0{,}773 * Rural + 1{,}88 * Activity\ (\ commerce) - 1{,}544 * Activity(agriculture) - 3{,}316 * Activity\ (\ others) - 0{,}615 * Type\_customer - 1{,}47\ Pers\_charge - 2{,}44 * Loan\ amount.$$

Table 3 :*Summary of models*

step	Likelihood log -2	R-two of Cox et Snell	R-two of Nagelkerke
1	664,431	,340	,518

Source: *Authors*

Table 3 is done by examining the model summary. This is the Nagelkerke R^2, which represents the variance explained by the model. The field of study and the underlying theories must be used to judge this variance. In the following example, the R^2 is 0.340, which is considered satisfactory given the exploratory and novel nature of this study. Thus, the model explains 51.8% of the variance of the dependent variable.

Table 4 : *Area Under the Curve*

Test results variable				**Confidence interval asymptotic à 95 %**	
	Area	**Std**	**Sig. asymptotic**	**Lower bound**	**Upper bound**
Predicted probability	,853	,017	,000	,820	,886

Source: *Authors*

In general, an AUC of 0.5 suggests no discrimination, 0.7 to 0.8 is considered acceptable, 0.8 to 0.9 is considered excellent, and more than 0.9 is considered outstanding.

Indicators in the table 4 show that the model can be validated since the error rate is low and the area under the ROC curve, AUC = 0.853 is excellent (see ref, table Model efficiency according to AUC value).

5. Discussion

The results show that the proposed model has an accuracy in predicting default of 85%, which is high for microfinance institutions to handle non-paying borrowers. The results represent a step forward from previous research findings, providing new knowledge useful to MFI managers, regulatory institutions, financial analysts, and microcredit applicants.

The methodology used in this article is new to microfinance institutions. Also, in the case of MFIs located in Morocco.

The results of this study show that loans taken out by Men are riskier than those taken out by women. Thus, a woman is less likely to be a defaulting borrower. Moreover, our research confirms and incorporates previous findings on the positive impact of borrower gender on portfolio credit risk (Santandreu, Pascual, & Rambaud, 2020) Conversely, our results contrast with (Agier & Szafarz, 2013).

This suggests that the gender effect may depend on the socioeconomic context of the country, which is a new finding. These results confirm the belief of some authors (Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, 2021; Johannsen, 2015).

These findings may help us to understand that the sector of activity and more specifically the commercial activities carried out by the borrowers reduce the risk of being a defaulting

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www.ijafame.org

borrower. These results confirm the belief of some authors (Mußhoff, 2017) that the variability of production income, such as that from agriculture, makes this sector risky.

Our results also show that borrowers with more dependents are more likely to default. This high risk can be attributed to very large family burdens that increase the borrower's debt burden, These burdens are a source of disruption to the borrower's financial situation and therefore increase the borrower's degree of risk.

Home ownership, which is an indicator of the borrower's wealth, is negatively correlated with default, a borrower who owns a home is in a different situation than a borrower who rents. Rent is a monthly expense that adds to the borrower's financial burden and thus increases the probability of default.

Our results also show that the more intellectually educated the borrower, the more likely they are not to default, given that illiterate borrowers are more likely to default, illiteracy limits borrower's ability to use management tools (management specifications, accounting to separate costs and revenues) to improve their business performance.

Our results are consistent with (Johannsen, 2015), these findings provide new insights for the specific case of Morocco. Similarly, our results advance the findings of (Addi & Souissi, 2020; Durango-Gutiérrez et al., 2021).

6. Conclusion

The objective of this research was to develop a credit scoring model to predict the probability of default of new loan applicants. To do this, logistic regression was used with a sample of 1021 borrowers from a Moroccan microfinance institution.

Microfinance institutions are organizations that provide financial services to people who are poor or excluded from the financial system. However, they often face many difficulties, such as non-repayment of loans by borrowers. In developing countries like Morocco, this situation has led to the failure of several microcredit institutions, before granting such loans, MFIs face difficulties in assessing the riskiness of potential borrowers. In this context, efficient instruments are needed to assess credit risk, credit scoring is a tool that allows financial institutions to assess the risk represented by the loan applicant. In other words, it allows the credit institution to guarantee the creditworthiness of the loan applicant.

Through this analysis, the results obtained show that the characteristics related to the borrower and his activity determine the default rate of clients.

The results of this study indicate that scoring not only predicts risk, but also reveals how borrower and loan characteristics affect the risk, to ensure the viability of this sector in Morocco, a number of recommendations were made in the previous section, this research could have yielded more interesting results if we had a larger sample size and more information on variables related to the client's business and performance.

In addition, strengthening the information system is necessary to support the strategic development of the institution, to strengthen the granting process, and to ensure the proper implementation of scoring systems.

In our view, the findings of this study are useful for regulators in identifying which MFIs and types of credit operations may be most exposed to the effects of economic crises.

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