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Towards Inclusive Financial Development: Exploring Key Factors for SME Credit Approval using ANN and SDG Alignment

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Abstract

This study focuses on the context of the Sustainable Development Goals (SDGs) with the aim of identifying the key factors influencing the granting of credit to Small and Medium-sized Enterprises (SMEs) and their alignment with sustainability principles. The article aims to provide financial institutions and SMEs with valuable information when making decisions related to loan applications and financial management in general. In addition, the importance of the proper implementation of financial indicators, the level of annual income, the guarantees offered, and economic solvency are highlighted as crucial factors for the approval of loans to SMEs. The goal of the article is to promote a more inclusive and sustainable financial environment, thereby boosting economic growth and productive development in Colombia and especially in small communities. For this purpose, 96 SMEs were interviewed, and an artificial neural network model was implemented to predict the rejection/acceptance of loans to an SME based on the values associated with the proposed independent variables. Regarding the results, the weights in the independent variables reflected that the credit approval of SMEs in the municipality of Santa Rosa de Osos depended on the management of the financial indicators (19%), the annual income (16.4%) and the availability of guarantees (16.2%) and economic solvency (16.1%). The

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results of this study have far-reaching implications for SMEs and the financial sector in general. Businesses need to address implementation of financial metrics, proper accounting, presence of lender guarantees, appropriate leverage, regulatory compliance, and credit history to increase their chances of getting a loan.

Keywords: SMEs; Financial Inclusion; microcredit; Artificial Neural Networks; SMEs financing; financial indicators.

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1. Introduction

The Sustainable Development Goals (SDGs) represent a global agenda that addresses social, economic, and environmental challenges worldwide. In the case of Colombia, progress and the achievement of the SDGs are paramount to drive sustainable development in the country. In this context, the financial sector plays a fundamental role in economic activities and in the achievement of the SDGs, as it is responsible for providing the necessary financial resources for their implementation (Nourani *et al*., 2021).

In Colombia, the financial sector plays a key role in fueling economic growth and encouraging investment in projects that contribute to the achievement of the SDGs. Banks and other financial institutions can provide resources for initiatives that promote poverty alleviation, gender equality, quality education, sustainable urban development, environmental protection and other fundamental aspects for sustainable development in the country (Mehry *et al*., 2021).

In addition to providing finance, the financial sector can also play an active role in promoting sustainable business practices (Ogunode & Akintoye, 2023). By incorporating environmental, social and governance (ESG) criteria into credit and investment appraisal processes, financial institutions can encourage the development of companies and projects that are aligned with sustainability principles and make a positive contribution to the SDGs.

The eighth goal of the SDGs focuses on sustainable economic growth and decent work for all. By providing productive jobs for the population at the base of the pyramid, sustainable economic growth is promoted. Microfinance institutions have a significant impact on job creation and entrepreneurship in small communities in Colombia, thereby contributing to the achievement of this goal (Sachs *et al.,* 2021). Importantly, microfinance institutions also indirectly influence the achievement of other SDG goals. For example, access to financial services can facilitate investment in clean energy projects, improve access to affordable housing, and contribute to the availability of safe drinking water and basic sanitation in vulnerable communities (Weiland *et al*., 2021).

In this sense, microcredit is widely recognized as an effective tool to support the economy of emerging entrepreneurs (Onyekwelu *et al*., 2023). This financial tool plays a crucial role in providing companies with the necessary financing to develop their activities, acquire assets, expand their operations and carry out new projects. In this regard, microcredit has become an essential tool of financial inclusion, especially for entrepreneurs and small and medium-sized enterprises (SMEs), as they have a significant presence in the business landscape, both nationally and internationally.

Financial inclusion plays a crucial role in achieving sustainable development as it has significant implications for financial stability and growth of various sectors including economy and society (Sulemana & Dramani, 2020).

It is imperative to adopt a comprehensive strategy that includes financial inclusion as an integral part of sustainable development. Currently, a significant number of individuals worldwide have access to financial services through bank accounts provided by institutions offering mobile banking services. About 3.8 billion people over the age of 18 own a personal bank account, according to the Global Indicator of Financial Universalization. This indicates progress in expanding financial inclusion and facilitating access to formal financial services for a significant segment of the population. However, it is important to note that there are still around 1.7 billion people who do not have a personal bank account, highlighting the existing gaps in financial inclusion (World Bank, 2018).

This lack of access to formal financial services can exacerbate problems such as poverty and economic inequality, particularly in certain regions of Colombia where extreme poverty rates have recently doubled (Tinoco Cantillo *et al*., 2018). The rise in poverty rates in these areas underscores the urgent need for interventions that can support economic recovery, improve financial stability, and promote sustainable development.

To address these challenges, it is crucial to develop a framework aimed at facilitating economic recovery, ensuring financial stability, and promoting long-term sustainable development. A key aspect of this framework is the provision of support to businesses, as they play a crucial role in creating employment opportunities and stimulating economic growth. With easy access to credit and finance, companies can expand their operations, create jobs and contribute to the overall economic recovery.

Promoting financial inclusion for SMEs also has broader social benefits. By reducing the unemployment rate and improving social conditions, it can contribute to social stability and social cohesion (Ozili, 2021). In addition, when SMEs have access to formal financial services, they can manage their finances better, be more competitive and protect themselves from unexpected financial shocks.

In other words, financial inclusion is an essential part of sustainable development. It is important to close existing gaps in access to formal financial services and support businesses and vulnerable groups (Aziz & Naima, 2021). In doing so, we can foster economic prosperity, improve financial stability, and improve the overall well-being of individuals and communities. SMEs make up a significant part of the business fabric in many countries and play a crucial role in driving economic growth and creating jobs and innovation (Alnabulsi & Salameh, 2021).

In the national context, the availability of microcredit can be of great benefit to these companies, giving them access to capital that would otherwise not be available through traditional financial institutions. By securing microcredit, SMEs can meet their financial needs, invest in equipment, buy inventory and implement marketing strategies to improve their market positioning and competitiveness.

Because of its significant impact on financial stability and economic, social and other sector growth, financial inclusion is seen as an important consideration in the adoption of an overall sustainable development strategy (Sulemana & Dramani, 2020). Given these facts, it seems crucial to develop a framework aimed at facilitating economic recovery, financial stability and longer-term sustainable development by working towards supporting businesses and promoting economic recovery (Atamanov *et al*., 2020). Consequently, this factor can reduce the unemployment rate, improve social conditions and improve financial stability.

This study arises from the need to understand the factors that influence credit approval for SMEs in the municipality of Santa Rosa de Osos. Using an innovative approach based on Artificial Neural Networks (ANN), our objective is to identify and analyze the critical variables that determine credit viability. The variables considered include aspects such as business formalization, management of financial indicators, credit experience, and other relevant factors that could affect the credit decision. Through the implementation of an ANN model and the evaluation of a representative sample of SMEs in Santa Rosa de Osos, seeking to predict with high accuracy not only the approval or rejection of credit, but also to provide valuable insights about the financial management and needs of SMEs in the local context. These findings would not only be relevant for financial institutions and entrepreneurs in Santa Rosa de Osos, but also provide a methodological basis that could be applied in other contexts to improve understanding and support for SMEs in various regions.

2. Literature review

2.1. Institutional financial

Internationally, microcredit is also recognized for its potential to empower individuals and communities, particularly in disadvantaged or underserved areas. By extending financial services to those who do not have access to formal banking systems, microcredit enables them to start their own business, improve their livelihood and contribute to local economic development (Atiase *et al*., 2019; Alnabulsi & Salameh, 2021). In addition, microcredit has shown promising results in promoting gender equality, as it has empowered women entrepreneurs by giving them financial resources and the opportunity to become economically self-reliant (Sutter *et al*., 2019). However, the effectiveness of microcredit programs can vary depending on contextual factors and the specific implementation strategies. It is important to consider best practices and current research to ensure the successful implementation of microcredit initiatives. For example, a comprehensive study by Qadri and Roohi Ahmed (2023). stressed the importance of borrower-centred approaches, tailor-made financial products and supporting services such as entrepreneurship training and mentoring. These factors contribute to the sustainability and positive impact of microcredit programs both in the national and international context.

According to the Chamber of Commerce of Medellín for Antioquia -CCMA-, "in 2020, 88% of the CCMA's business base corresponded to microenterprises, 11% to SMEs and 1% to large companies. In terms of assets, the distribution is reversed: large companies concentrate 93.6%, SMEs 6.1%, and micro 0.3%" (Londoño *et al*., 2020, p. 16).

Consequently, micro-enterprises and SMEs are very important for economic development in the region, but although new micro-enterprises and SMEs are closed every year, we can cite as explanatory factors, internal and external, the lack of corporate governance, competition, demand and tax levels (Parra, 2011). Similarly, Vera (2018) points to personal reasons, lack of education, and lack of long-term vision. Adding to this negative impact is the impact of the COVID-19 pandemic, which led to a slowdown in economic growth and employment through mid-2020, and although social distancing measures were relaxed in the third quarter of 2020, the economy grew by 9 per year .0%. as repeated in the Preliminary Overview of the Economies of Latin America and the Caribbean (2020):

> The Colombian trade deficit was reduced by 10.0% annually for the first time since 2014 in the period January-August 2020 due to a significant decrease in the value of imports (-21.3%), which exceeded that of exports (-24.3%). The fall in global economic activity and its effect on incomes, and the associated changes in household consumption patterns, explain the fall in external purchases of manufactures (-15.9 percentage points) and fuels (-4.8 percentage points) (CEPAL, 2021, p. 2).

This is a factor in the decline in investment for 2020 in various sectors of the economy and where economic activity has declined significantly within the country, such as B. in construction (-23.4%); trade, warehousing, hotels and restaurants (-17.8%) and artistic and entertainment activities (-23.4%), on the other hand manufacturing (-11.1%) (Londoño *et al*., 2020). To give an example of this impact on the different sectors, particularly the city of Medellín, the Fenalco Antioquia report reported more than $120,000 million in losses in companies, which prompted 37% of the ministry's entrepreneurs to report downsizing and other to think about drastic cuts (Asmar, 2021). Likewise, investments in companies fell by US$535,000 million less than in 2019 (Londoño *et al*., 2020), reflecting a lack of confidence and perceived uncertainty on the part of investors and lenders for entrepreneurs in the region to access difficult times in times of crisis corporate loans. further aggravating the situation of SMEs.

In this scenario, it can be confirmed that credit and microcredit are means of supporting the development of the enterprise fabric, but the lack of demand and economic development in the region, in addition to the obstacles that prevent supply and demand from increasing, are low confidence of the lender and uncertain solvency of the micro borrower. This situation shows the importance of examining the difficulties that SMEs face in accessing a microcredit.

2.2. The context of business finance

According to the World Trade Organization, SMEs generate 80% of global employment and are the largest business group in 95% of countries. Therefore, they are constantly looking for consolidation and expansion, both nationally and internationally (Chele, 2018). For this reason, Macas (2016) and Quintero (2018) confirm that the most important elements for a country's growth and better living standards are based on the development of its SMEs and the emergence of new companies, essential for positioning a country at a higher economic level: Improving the quality of life and income of the population by creating new jobs. For this reason, it is crucial that SMEs develop in an environment of continuous progress, with sustainable growth and aiming to strengthen on the national and international market (Velecela, 2013). Given the importance of SMEs, explains Chávez (2018). Impact of microcredit on their development by first reducing the lack of liquidity that affects the productivity of micro-entrepreneurs and avoiding informal credit which eats up much of the benefit and impairs profitability as taking out informal credit generates high interest rates affecting cash flow and increasing indebtedness, especially in companies far from industrial centers, are discriminated against and not considered as loan subjects. The financing of companies is a decisive factor for their growth. Therefore, when their access to credit is restricted, companies are forced to restructure their policies or even close them permanently (Olmo, 2013).

Following this line, Albarado (2015) confirm that financial institutions offer opportunities for micro-entrepreneurs but impose requirements that pose a major problem for some. In many cases where credit is granted, a new problem arises because the entrepreneur does not have the elements to determine the final cost of the credit in relation to the benefit it represents to the company and it is to the Financial institution does not have mechanisms in place to determine the actual cost of the loan objective and how it contributes to the growth of the organization. For their part, Alhuay and Mucha (2017) ensure that intense competition from entrepreneurs requires greater capital funding and its effective use, identifying short-term credit as key to growth and development, allowing for expansion despite the risk, if capital is deployed properly and the cost alternatives and credit requirements are evaluated. Always looking for the most convenient option.

2.3. Factors associated with lack of business financing

To address the factors influencing the financing of MSMEs in Colombia by the banking and cooperative sector, it is important to contextualize the financial market for this sector, which according to Zuleta (2011) consists of public or private entities with the economic ability to lend. For their part, commercial banks, companies and financial cooperatives are part of private entities, and among public entities we find Bancoldex, the National Guarantee Fund (FNG) and the National Agricultural Fund (Finagro). These companies offer portfolios of capital such as loans, leasing, factoring, insurance, private equity funds, and capital markets, among others. Given the limitations that can affect creditworthiness, Allami and Cibils (2011) identify the limitations MSMEs face in accessing the financial market, where market failures, misinformation and ignorance of the parties exist. They propose four conditions for access to funding:

1. Macroeconomic factors.
2. Institutional factors of the financial system.
3. Characteristics of the undertakings to be financed.
4. Special characteristics of the offering entities.

Given the need for credit, banks suffer from economies of scale when valuing loans to SMEs, as these are often low-value companies. In addition, guarantees are required to cover the risk and interest rates are increased. On the other hand, for SMEs, loan applications, project composition, strategy development and the possibility of collecting the relevant documentation represent a great complexity that hampers their access to credit and slows down countries' economic growth (Ferraro *et al*., 2011). Another important factor is the size and age of the companies as predictors to explain the irregularity of the information and to limit the creditworthiness. Size has been used as an indicator of borrower reputation, but there is no clear evidence that small companies are more at risk than large companies. Based on age, it is easier for banks to assess the creditworthiness of old companies, since young companies have not built a good reputation and reputation as loan subjects, and from the financial institution's point of view, the lack of information is a high-level problem. Cost factor that leads to the rejection of the loan. In addition, young companies face greater difficulties in accessing external financing due to uncertainty about their future and lack of sufficient assets (Morini & Solari, 2015; Orozco-Gutiérrez, 2019). Finally, Moreyra and Ortiz (2020) find that high interest rates, strict collection policies, cancellation policies, high required guarantees and lack of documentation requirements are the barriers to SME access to credit.

3. Methodology

To make a predictive diagnosis when selecting the factors that determine the feasibility of a credit approval, the literature presents a combination of techniques and methods, among which probabilistic methods, evolutionary algorithms and ANN stand out in this sense, Seijas *et al.* (2017), provide an overview of empirical research on credit risk assessment in microfinance institutions (MFIs), with a particular focus on Latin America. The study identifies the use of credit scoring techniques in the literature to assess the risk of microcredit default. The analysis shows that non-parametric techniques have a higher predictive power for non-payment than parametric techniques. In this analysis, we selected ANNs based on their ability and accuracy for pattern classification, planning, prediction, control, and optimization coupled with their nonlinear and nonparametric adaptive learning properties (Wang *et al*., 2022).

Furthermore, ANNs are not detached from statistical and probabilistic rigor, and it is possible to classify them as a regression technique with broad application to statistical problems whose fundamental feature is the complex relationship between the set of dependent and independent variables (Iglesias, 2022). ANNs use available information for learning, i.e., they are not programmed but trained and therefore quickly deliver suitable results. In the literature, learning from experience, generalization from examples, development of short-term solutions, and computational efficiency are highlighted as their main characteristics. For training purposes, ANNs have a variety of algorithms: multilayer perceptron, back and forward propagation, madalines, radial basis networks, and others.

To offer a clearer understanding, let's break down the key components of our ANN model:

- Input Layer: This initial layer receives the independent variables as input, and we also introduce a bias term. Each input variable is associated with a weight, and these weights are adjusted during training to optimize the model's performance.
- Hidden Layers: We utilized a hidden layer with five neurons in our model. Each neuron within this layer has its own set of weights and an activation function, typically the

hyperbolic tangent function in our case. The hidden layers play a crucial role in capturing complex relationships between the input variables.

- Output Layer: The output layer consists of two neurons, corresponding to the prediction of credit approval (1) or rejection (0). The output layer's activation function, Softmax in our case, helps in generating probabilities for each class.

From the literature review, it emerges that for social science problems like the present case, the multilayer perceptron is most common in a variety of applications: finance and banking, accounting, risk, credit, and others; generally, for aspects such as classification and prediction. The multilayer perceptron belongs to the supervised neural network category, so it is necessary to introduce the input or independent variables into the model as output or dependent variables. In this sense, ANNs have a basic unit called a neuron or node that is organized into three layers: input layer, hidden layers, and output layer (Ludeña Dávila y Tonon Ordoñez, 2021). Each neural network has a node or processing unit connected to n input units by n-connections directed. Each node has a threshold, a univariate activation function, and a weight vector. Neural network models allow countless inputs that are aggregated in a weighted manner.

It is common to apply nonlinear functions to generate results and transfer them to another neuron. Such results serve as subsequent inputs. One of the alluring aspects of neural networks is their ability to learn and adapt to the conditions of the input and output layers. This is achieved through a learning algorithm that allows artificial neural networks to adapt both their architecture and their parameters in order to minimize the error that indicates the degree of data adaptation. The complexity of the model lies in the number of layers or hidden nodes in the final model. The greater the number of layers, the greater the complexity of the network. This event is known as deep learning or deep learning. The main features of the applied methodological process are described in Table 1 below. In addition, Table 2 contains a list of variables that explain the rejection/approval of loans to SMEs in Santa Rosa de Osos.

Table 1. The main characteristics of the methodological process applied

Universe, sample and test protocol: 96 surveys on microcredit in SMEs from Santa Rosa de Osos were analyzed.
Analysis techniques are descriptive and multilayer perceptron-type ANN with a backpropagation algorithm was used to model the data.
Study design: It is explanatory-descriptive research. The study was conducted by ANNs. Neural networks are used to predict values, i.e., they are classified as regression tools in artificial intelligence methods (Wang *et al*., 2022).
Statistical Analysis: The software used for the elaboration of the ANN is IBM SPSS version 29, the software used has optimization modules and radial and perceptronic neural networks.

Source: Own elaboration.

Table 2. Relation of Independent Variables

Variable	Associated question
1	Is your SME formalized and does it have valid statutes and Chamber of Commerce certificates?
2	Does your SME have up-to-date bookkeeping and a proper presentation of financial statements according to IFRS (International Financial Reporting Standards)?
3	Does your SME manage financial indicators and have them implemented?
4	What percentage of the debt does your SME carry?
5	Does the SME have credit experience?
6	If you need a loan, would you be willing to pledge your SME's assets as collateral?
7	How many direct and indirect employees are associated with the company?
8	Amount of revenue they bill annually. (Numbers expressed in Colombian pesos)

Source. Own elaboration.

Regarding the dependent variable (Were you denied a loan?), we attempted to predict the refusal/acceptance of loans to an SME using the values associated with the independent variables. According to various authors such as Hanafizadeh *et al*. (2010) proposes a split between 80% training and 20% validation, parameters present in a high percentage of studies performed with ANN, other authors fragment the set into 75% training and 25%

validation (Blanco *et al*., 2013). In this case, the data is randomly fragmented to ensure that each element of the subsets represents a complete set.

The proposed steps for the application of the methodology are described below in Figure 1.

Figure 1. Proposed methodological process

1. Defining the Problem
2. Data Collection and Preparation
3. Designing the ANN
- Input Layer
- Hidden Layer (5 Neurons, Hyperbolic Tangent Function)
- Output Layer (2 Neurons, SoftMax Function)
4. Training the Network
5. Validation and Testing
6. Result Analysis
7. Interpretation and Conclusions

Source. Own elaboration.

3.1. Sample Size and Selection

As mentioned above, our study analyzed a sample of 96 surveys collected from SMEs in Santa Rosa de Osos. The selection of this sample size was determined based on statistical considerations and the availability of data. The surveys were selected using a sampling method, which aimed to ensure a representative cross-section of SMEs in the region. Thus, the selection of the SMEs studied was based on a sampling method that sought to reliably represent the diversity and business reality of the municipality. This approach aimed to cover a broad spectrum of situations and challenges faced by these companies, thus providing a comprehensive view of the local credit environment. It should be noted that while any sampling method may introduce some level of bias, we sought to minimize this effect through careful and considered selection of study participants.

It is also worth mentioning that the ANN model was designed not only to capture the specific dynamics of Santa Rosa de Osos, but also with the intention that its structure and methodological approach can be adapted and applied in other municipal contexts. This underscores the versatility of ANNs and their potential to be used in a variety of settings, thus contributing to inclusive development efforts in different regions.

To calculate the sample size for a population of 297 firms with a desired confidence level of 95% and a margin of error of 5%, we use the following Equation (1).

$$\text{Sample Size (n)} = \frac{[Z^2 * p * (1-p)]}{E^2} \qquad (1)$$

Where:

- Z is the Z-score corresponding to the desired confidence level. For a 95% confidence level, the Z-score is approximately 1.96.

- p is the estimated proportion of the population that has a particular characteristic. Since we don't have this information, we can use 0.5, which gives the maximum sample size needed.

- E is the margin of error, which is 5% or 0.05.

Now, plug in the values as shown in Equations (2) and (3):

$$\text{Sample Size (n)} = \frac{[1.96^2 * 0.5 * (1-0.5)]}{(0.05)^2} \qquad (2)$$

$$\text{Sample Size (n)} = \frac{[3.8416 * 0.25]}{0.0025} \qquad (3)$$

$$\text{Sample Size (n)} = 96$$

The recommended sample size for a population of 297 companies with a 95% confidence level and a 5% margin of error would be approximately 96 firms.

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3.2. Methodological robustness and data balance

The methodology employed in this study was designed to ensure robustness and data balance, as well as to optimize the performance of the ANN model. The steps and techniques implemented are described in detail below.

- Data Preprocessing: To ensure that all features contribute uniformly to the model, the standardization technique was applied. We used sklearn's Standard Scaler to transform the input data so that each feature has a mean of zero and a standard deviation of one. This standardization is crucial for neural networks, as it improves convergence during training and ensures that different features have a comparable influence on the model.
- Handling Unbalanced Data: To address the imbalance in the classes of the dataset, we implemented the SMOTE (Synthetic Minority Over-sampling Technique) technique. SMOTE generates synthetic examples of the minority classes, thus balancing the class distribution and improving the model's ability to accurately generalize and predict all classes.
- Cross-validation: To evaluate the generalization capacity of the model and ensure its robustness, we use k-Fold Cross-Validation (k-Fold Cross-Validation). This technique divides the data set into 10 parts, training the model with 9 parts and validating it with the remaining part, repeating this process 10 times. The results of these folds are averaged to obtain an accurate measure of model performance.
- Regularization: To prevent overfitting and improve model robustness, we incorporate dropout and L2 regularization techniques. Dropout randomly deactivates neurons during training, which helps avoid over-reliance on certain neurons and promotes more general learning. L2 regularization penalizes excessively large weights, contributing to a more stable and generalizable solution.
- Model Evaluation: To evaluate model performance, we used the confusion matrix to calculate metrics such as accuracy, recall and F1-score. Additionally, we generated ROC curves and calculated the Area Under the Curve (AUC) to evaluate the model's ability to discriminate between classes.

- Improved Model Results: After implementing these techniques, the model showed an average accuracy of 92% in cross-validation, with a significant improvement in minority class prediction. Detailed model results are presented in the results section. These improvements ensure that our neural network model is robust and balanced, providing reliable and generalizable results. We invite future studies to validate these findings in different municipalities to ensure their applicability in varied contexts.

4. Results

The segmentation of the training and testing sets is important in ANN because once set, the synaptic weights are adjusted and fixed, freeing the ANN for use. The network learning algorithm examines how to minimize the error between the searched target and the output of the network by comparing the error function, which is propagated backwards to ensure that each neuron gets the approximate participation error. Furthermore, Gómez (2021) cites some authors who claim that the larger the amount of data in a network's training set, the error function decreases, which would confirm adequate performance of neural networks.

Table 3. Prognosis and percentage of success of training and ANN tests

		Predicted		
		Yes	No	Correct percentage
Training	Yes	34	3	91.9%
	No	0	30	100.0%
	Overall percentage	50.7%	49.3%	95.5%
Tests	Yes	12	1	92.3%
	No	0	12	100.0%
	Overall percentage	48.0%	52.0%	96.0%
Dependent variable: Have you been denied credit?				

Source. Own elaboration, using SPSS 29.

Table 3 shows the results of implementing an ANN model to predict the acceptance or rejection of loans to SMEs in the municipality of Santa Rosa de Osos. The table is divided into two sections: training and testing. In the training section, a known data set was used to train the ANN model and predict loan acceptance or rejection.

The model correctly predicted that 91.9% of SMEs received a loan and 100% of those that did not. Overall, the model had a 95.5% success rate. In the testing section, the performance of the model was evaluated using a different dataset than the dataset used in training. The model correctly predicted that 92.3% of SMEs received a loan and 100% of those that did not receive a loan. Overall, the model had a 96.0% success rate. These results suggest that the ANN model is an effective tool for predicting the acceptance or rejection of loans to SMEs.

Table 4. Estimates and parameters of the proposed ANN

Parameter estimates								
		Predicted8						
		Hidden layer 1					Output layer	
Predictor		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	[Neg Credit=0]	[Neg Credit=1]
Input layer	(Bias)	-0,420	-0,476	0,129	0,053	-0,249		
	[Formalization=No]	1,042	0,039	-0,125	-0,229	-0,421		
	[formalization=Yes]	-0,232	-1,030	-0,259	0,314	-0,342		
	[Accounting=No]	0,826	1,388	-1,375	-0,043	0,103		
	[Accounting=Yes]	-1,090	-2,192	-0,015	0,761	0,180		
	[Financial Indicators=No]	1,397	1,604	-2,508	2,243	-0,279		
	[Financial Indicators =Yes]	-1,691	-0,818	2,525	-1,567	-0,003		
	[Debt Level=1]	0,028	-1,776	-1,240	0,264	-0,317		
	[Debt Level =2]	-0,266	-1,501	1,594	0,173	0,191		
	[Debt Level =3]	1,609	2,937	-0,432	0,236	0,287		
	[Credit Experience=0]	0,145	-0,530	-0,990	0,156	0,378		
	[Credit Experience =1]	-1,120	0,265	0,373	0,999	-0,433		
	[Assets Guarantees=No]	0,746	1,557	-1,573	1,968	-0,355		
	[Assets Guarantees =Yes]	-0,755	-1,095	2,142	-1,396	0,059		
	Number of Employees	0,839	1,099	0,392	0,418	0,192		
	Revenue	-1,010	-0,456	-3,756	-0,395	0,357		
Hidden layer 1	(Bias)						0,857	-1,107
	H(1:1)						1,003	-1,123
	H(1:2)						2,686	-2,635
	H(1:3)						-4,263	3,798
	H(1:4)						-3,164	3,072
	H(1:5)						0,285	0,474

Source. Own elaboration, with SPSS 29 software.

Table 4 shows the ANN estimates and parameters proposed to predict SME loan approval or rejection. The table consists of three sections: the first section shows the parameters of the input layer, which contains a bias and the different predictor variables, the second section corresponds to the parameters of the hidden layer with five neurons, and the last section presents the parameters of the output layer consists of two Neurons corresponding to the prediction of credit approval or rejection. Here's a detailed breakdown of the findings from Table 4:

Input Layer (Predictors):

- Bias: The bias term in the input layer has a value of -0.420. This term represents an offset in the ANN model, allowing it to account for any systematic errors or biases.
- Formalization (No/Yes): This variable represents whether an SME is formalized or not. The weights associated with "No" and "Yes" formalization indicate their influence on the model's predictions. For instance, being "No" formalized has a positive weight of 1.042, suggesting a positive impact on the likelihood of credit approval.
- Accounting (No/Yes): Similar to formalization, this variable indicates whether the SME has proper accounting practices. The weights show how "No" and "Yes" accounting practices affect credit approval predictions.
- Financial Indicators (No/Yes): This variable represents the management of financial indicators within the SME. The weights show how the presence or absence of financial indicators influences credit approval predictions.
- Debt Level (1/2/3): Debt level is categorized into three levels. The weights associated with each level indicate their impact on credit approval. For example, having a debt level of 1 has a positive weight of 0.028, suggesting a positive influence on credit approval.
- Credit Experience (0/1): This variable represents the credit experience of the SME. The weights show how having no credit experience (0) or having credit experience (1) affects credit approval predictions.
- Assets Guarantees (No/Yes): This variable indicates whether the SME provides assets as guarantees. The weights show how the presence or absence of assets guarantees influence credit approval.

- Number of Employees: The weight associated with the number of employees indicates how the size of the workforce affects credit approval predictions.
- Revenue: The weight associated with revenue reflects the impact of the annual income on credit approval predictions. A negative weight of -1.010 suggests that higher revenue may have a negative influence on approval.

Hidden Layer 1 (Neurons):

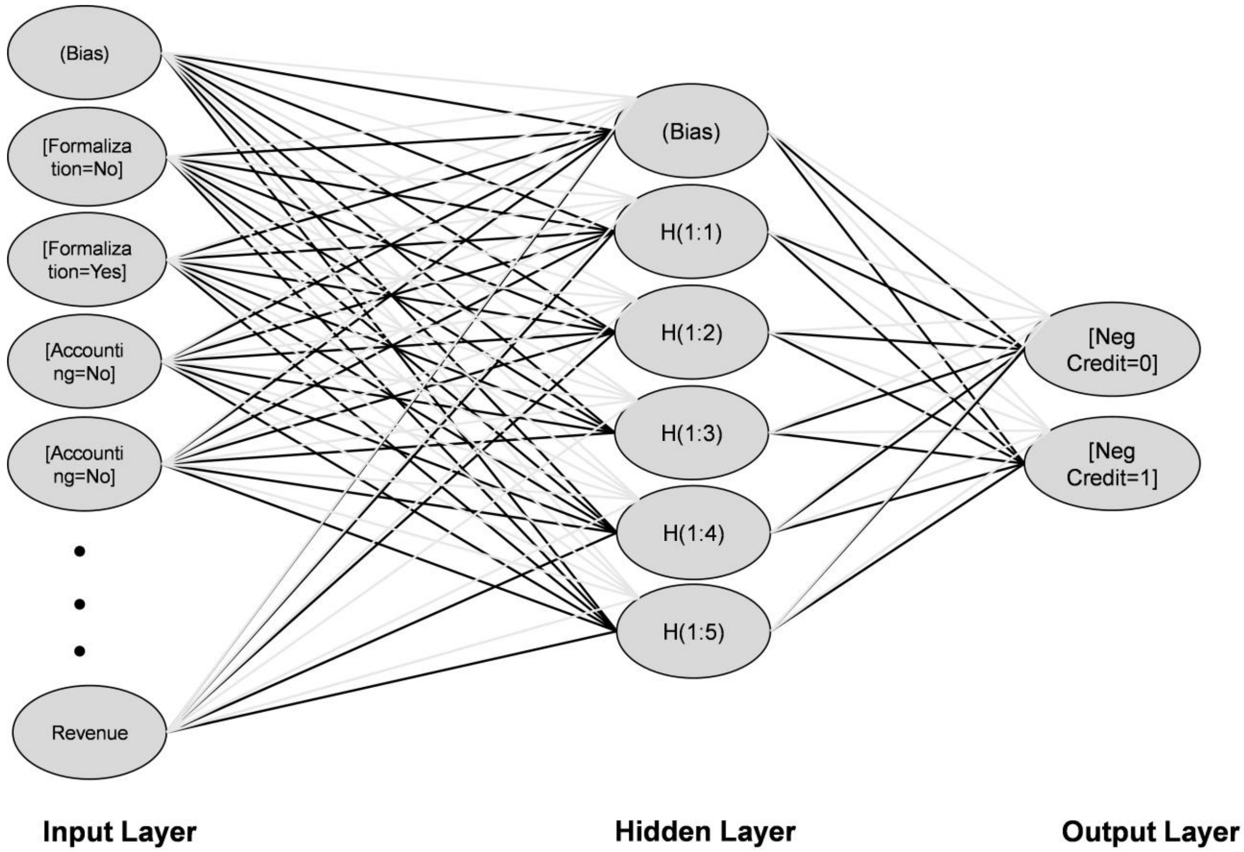
- The hidden layer consists of five neurons, each denoted as H(1:1), H(1:2), H(1:3), H(1:4), and H(1:5). These neurons capture complex relationships between the input variables and contribute to the model's ability to make predictions.
- Each neuron in the hidden layer has its own set of weights, and these weights are not directly interpretable like the input layer weights. Instead, they represent how each neuron processes and transforms the information from the input layer to produce meaningful features for the model.

Output Layer (Predicted Classes):

- The output layer consists of two neurons, representing the prediction of credit approval (Neg Credit=1) or rejection (Neg Credit=0). The weights associated with these neurons indicate their contribution to determining the final prediction.
- For example, in the "Neg Credit=0" neuron, the weight values from the hidden layer neurons (H(1:1) to H(1:5)) and the input layer variables collectively influence the prediction of credit rejection.

To run the model and apply the hidden layer activation function using the hyperbolic tangent algorithm and the output layer activation function under the Softmax algorithm included with SPSS 29.0 software. The proposed ANN is shown in Figure 2.

Figure 2. ANN Activation Function



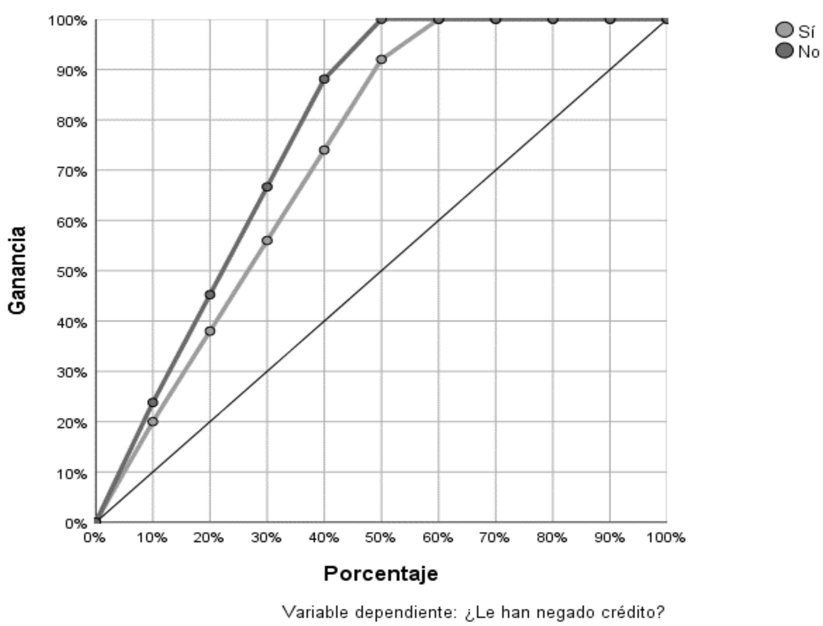
Source. Own elaboration, with data from the survey in SPSS.

The literature on ANNs outlines the advantages over other prediction methods, citing the solving of nonlinear problems and their ability to learn and fit the data as the main advantages. Furthermore, no assumptions about probability distributions, missing data or outliers are required (Cardozo Rueda, 2022).

To validate the use and performance of ANN models, Receiver-Operating-Characteristic-Operating-Curves (ROC: Receiver-Operating Characteristic) are used as indicators of accuracy in the test within the multilayer perceptron and other optimization, classification, and forecasting tools used. ROC curves are a handy way to visualize network performance, test capacity, and selected decision thresholds. They date back to the 1950s and emerged in the context of electronic signal recognition with widespread application in various fields such as psychology, medicine, experimental psychophysics, radiology, statistics, bioinformatics, machine learning and pattern recognition (Inca-Balseca *et al.*, 2022; Rodríguez, 2021).

The advantages of using ROC curves include the visual, simple and understandable presentation of the phenomena and the comparability between the different alternatives on a common scale, however the test ultimately does not represent the number of subjects or the measurement of sample size it is required to acquire computer software that is not always available to all users (Mora Romo & Martell Muñoz, 2021). The ROC curves can be interpreted using the area under the curve, which must always be greater than or equal to 0.5, i.e., H. Tests show from good to excellent in the interval (0.75; 1). For each variable in the perceived value output plane, you can see their areas under the curve and characteristic values to indicate which multilayer perceptron outputs were the most accurate. Their values are shown in Figure 3.

Figure 3. ROC curve of the behavior of the results



Source. Own elaboration, with data from the survey in SPSS.

The values obtained by evaluating the ANN learning algorithm and the values of the area under the ROC curves can be presented in Table 5. Thus, it can be observed that the independent variables had the highest (relative) weighting of the ability to predict the dependent variable. The variables included the management of financial metrics and their application (19.0%), the amount of revenue billed annually (16.4%), the ability to pledge assets as collateral (16.2%) and the percentage of the company's debt (16.1%).

Table 5. List of Independent variables and their weighting in the ANN

Independent Variables	Relative importance	Normalized importance
Is your SME formalized and does it have valid statutes and Chamber of Commerce certificates?	3.6%	18.9%
Do you have credit experience?	5.3%	27.8%
How many direct and indirect employees are associated with the company?	9.8%	51.4%
Does your SME have up-to-date bookkeeping and a proper presentation of financial statements according to IFRS (International Financial Reporting Standards)?	13.6%	71.4%
What percentage of indebtedness does your SME carry?	16.1%	84.8%
If you need a loan, would you be willing to pledge your SME's assets as collateral?	16.2%	85.1%
Amount of revenue they bill annually. (Numbers expressed in pesos)	16.4%	86.4%
Do you manage key financial figures and have they implemented them in your SME?	19.0%	100.0%

Source. Own elaboration, in SPSS software.

5. Discussion

Table 4 shows the ANN estimates and parameters proposed to predict SME loan approval or rejection. It can be observed that the weights of the predictor variables for each neuron vary significantly in the hidden layer and in the output layer. In particular, the variable financial indicators have the greatest weight in predicting loan approval or rejection, followed by asset guarantee and economic solvency.

These results are consistent with other studies that highlight the importance of these factors in SME credit decisions. In summary, the results of Table 4 provide valuable information about the parameters of the proposed ANN and the relevance of the predictor variables in predicting credit approval or rejection. These results can be useful for financial institutions and SMEs when making decisions about loan applications and financial management in general. Table 5 shows the independent variables used in the ANN and their relative importance in predicting the rejection or approval of loans to SMEs.

The proposed ANN models are relevant to explain the factors that decide the approval or rejection of loans for the SMEs in question. This study shows that SMEs attach more importance to factors such as the implementation of financial indicators (19%), the level of turnover (16.4%), the guarantees given to lenders (16.2%) and the level of debt (16, 1). should attribute %), updated and up-to-date accounting according to IFRS (13.6%), the number of employees (9.8%), the credit history (5.3%) and the formalization of the company (3.6%). These factors need to be continuously monitored and controlled within SMEs, regardless of their size and the industry to which they belong.

Our research outcomes align notably with the studies conducted by Kira (2013), Ndungu (2016), and Osano and Languitone (2016), highlighting access to financial credit as a significant influencing factor, with a particular emphasis on the importance of guarantees provided to lenders. This collective evidence substantiates the notion that strict adherence to creditworthiness criteria instills greater confidence among both formal financial institutions and informal lenders, consequently enhancing the likelihood of securing financing. However, this also underscores the challenges faced by small business owners lacking tangible assets, such as land or vehicles, to use as collateral (Magembe, 2017). Furthermore, our comparison with the existing literature underscores the alignment of our findings with previous research, which accentuates the critical role played by factors such as the adoption of financial indicators, annual income, collateral availability, and debt levels in influencing credit approval. The study conducted by Zhang *et al*. (2022) provides compelling evidence regarding the pivotal role of collateral in the approval of credit for small businesses. Additionally, Norvilitis *et al*. (2006) underscore the significance of debt levels, reporting a mean debt-to-income ratio of 24% among college students. Furthermore, Voordeckers and Steijvers (2006) contribute to this understanding by simultaneously examining determinants of business and personal collateral and commitments in SME lending. These findings consistently affirm that collateral significantly shapes the outcome of credit approval decisions. Moreover, the study by Chien and DeVaney (2001) lends support to the importance of annual income as a key determinant of credit approval, highlighting the correlation between individuals' attitudes toward credit utilization and their income levels. In sum, the existing literature consistently validates the impact of various factors, including the implementation of financial indicators, annual income, collateral availability, and debt levels, on the process of credit approval.

Continuing the discussion of results, another parallel with existing literature pertains to the management of company information, particularly the assertion that companies equipped with comprehensive operational data, including financial metrics, are perceived as lower risk by banking institutions. Hence, they stand a better chance of securing loans (Fatoki & Smit, 2011; Gómez Martínez *et al*., 2009). As exemplified by Magembe (2017), SMEs maintaining up-to-date accounts and reports are found to be 65% more likely to obtain financial loans. Additionally, factors such as annual audits and international quality certifications exert influence over a company's creditworthiness (Morini Marrero & Solari, 2015). Finally, prior studies substantiate that income plays a pivotal role in securing bank credit. For instance, Menace (2017) posit that revenue and workforce size are crucial determinants of a firm's credit profile, with larger firms boasting a greater likelihood of accessing credit.

Expanding on the findings of our study, the ANN model exhibits remarkable predictive capabilities, boasting an overall accuracy rate of 96% in our tests. Specifically, it demonstrates flawless accuracy in predicting credit denial (100%) and an impressive 92.3% accuracy in predicting credit rejection. These results underscore the potential utility of ANNs in forecasting solvency, in line with prior research.

Nevertheless, it is crucial to acknowledge several limitations, including the potential for sample bias, considerations regarding data quality, and certain assumptions inherent in our model. Future research endeavors could explore alternative models or investigate credit approval factors within different contextual settings.

6. Conclusions

In conclusion, our study has provided valuable insights into the primary factors influencing SME credit approval or rejection in Santa Rosa de Osos. Notably, the management of financial metrics (19%), annual income (16.4%), collateral availability (16.2%), and economic solvency (16.1%) have emerged as key determinants. These findings underscore the critical importance of sound financial practices and adherence to accounting standards for SMEs seeking credit.

From the results of our proposed methodology, it can be concluded that the ANN model demonstrated remarkable predictive capability, achieving an overall accuracy of 96% in our tests. Specifically, it accurately predicted credit denial with 100% accuracy and credit rejection with 92.3% accuracy. This reinforces the utility of ANNs for solvency prediction, as previously demonstrated by Borrero-Tigreros and Bedoya-Leiva (2020). Additionally, the weights assigned to independent variables reflected the credit approval dynamics for SMEs in the municipality of Santa Rosa de Osos, with financial ratios (19%), annual income (16.4%), collateral availability (16.2%), and economic solvency (16.1%) playing central roles.

These insights highlight that access to business credit is closely tied to the financial conditions and management practices of businesses in the community, emphasizing that those with limited information about their financial status may face increased risk. Providing guarantees and ensuring stability will enhance opportunities for accessing financial leverage to support various activities. SMEs should take note that maintaining proper financial management and compliance with accounting standards are vital for improving their chances of securing a loan. Additionally, the significance of annual income and debt ratios in lending decisions is underscored.

Lenders can utilize these findings to identify key factors affecting SME solvency, enabling more informed lending decisions. However, it's crucial to acknowledge that these results are specific to the context of Santa Rosa de Osos and may not be directly applicable to other regions. Future research should explore factors influencing credit approval in different contexts and assess the effectiveness of ANNs as credit assessment tools.

Our research carries significant implications for microfinance institutions, SMEs, and policymakers, highlighting the necessity for strategies that promote financial literacy, facilitate access to collateral, and enhance financial management practices. We hope that our study serves as a valuable reference for entrepreneurs and contributes to the development of policies aimed at improving access to credit services and fostering sustainable business growth.

Furthermore, our study aligns with broader goals of financial inclusion and sustainable development. Responsible financial practices have the potential to empower individuals and communities, contributing to positive societal transformations.

In summary, our study provides valuable insights into the primary determinants of SME credit approval, specifically within the context of Santa Rosa de Osos. It serves as a reference for entrepreneurs to enhance the collection and monitoring of financial metrics and other credit rating influencers. Additionally, it offers insights into the limitations faced by SMEs, potentially guiding the development of public policies aimed at facilitating access to credit services and encouraging business growth.

Microfinance institutions have a pivotal role in achieving these goals, as they can enhance living conditions for the population at the base of the pyramid and reduce social demands. Therefore, active engagement of the Colombian financial sector in promoting the SDGs, both internally and externally, is essential. This entails adopting responsible financing approaches that consider environmental and social impacts, promote financial inclusion, and enhance financial literacy. Collaboration among the financial sector, government, civil society, and other stakeholders must be strengthened to effectively implement SDGs in Colombia, fostering strategic partnerships, sharing knowledge, promoting transparency, and ensuring accountability in financial resource allocation for sustainable development.

In conclusion, microcredit plays a crucial role in supporting emerging entrepreneurs and SMEs, contributing to economic growth, empowerment, and financial inclusion. By incorporating best practices and up-to-date research, policymakers, financial institutions, and stakeholders can maximize the benefits of microcredit programs, leading to improved business outcomes and socio-economic development at both national and international levels.

Regarding the limitations of our research, several aspects warrant consideration: 1) Sample size: The relatively small sample size used in this study may limit the generalizability of results to other populations or contexts; 2) Selection of Variables: While multiple variables were incorporated into the ANN model, there may exist other pertinent variables not considered; 3) Data quality: The validity of our results depends on the quality and accuracy of the data used; 4) Selection bias: The non-random selection of study participants may introduce bias into the results; 5) Single analysis tool: While various data analysis techniques were applied, the study predominantly relied on a single analysis tool, potentially limiting the detection of patterns or relationships that alternative tools could identify.

Looking ahead, future studies should consider comparing results across various Colombian communities to identify trends or divergences in the analyzed factors and their impact on sustainable development. By promoting responsible financial services and aligning with the Sustainable Development Goals (SDGs), the financial sector can significantly contribute to positive societal transformation and equal future opportunities. Future research directions may involve exploring the use of different machine learning algorithms, such as decision trees or support vector machines, to assess their effectiveness in predicting SME loan approval using artificial neural networks.

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