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Optimizing Credit Risk Management in SMEs Through Machine Learning Models in Mexico City

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Abstract

The purpose of this study is to significantly reduce the lack of liquidity of small and medium-sized enterprises in Mexico City, by reducing credit risk management through a model based on Machine Learning to establish credit policies based on their characteristics, behavioral patterns, and payment capacity of customers without compromising the financial situation of the business. For the development of the research, an exhaustive review of the state of the art of credit risk management of companies and banking institutions worldwide was carried out, identifying the best practices of credit risk management, as well as successful cases and cases that were not so successful or failed in their application. Subsequently, a compilation of machine learning models was carried out to analyze the variables that are considered, mathematical calculations, company classification, and linear or multivariate regressions, and to apply them to SMEs in Mexico City. Finally, some tests were carried out with a sample of clients of a specialized collection agency to determine the accuracy of the proposed machine learning model and to quantify financially the savings obtained in implementing the proposal.

Keywords
Credit Risk, Financial Distress, Financial Crisis, Credit Expansion and Machine Learning.

Introduction
According to Proaño (2022), the devastation caused by the COVID-19 pandemic is profound in financial and economic terms for most people and businesses, not counting the 6.3 million human lives lost because of the pandemic. In addition, it will harm financial systems and credit risks, resulting in business closures, damage to key sectors, job losses, massive business failures, reduced demand for goods and services, and a significant increase in poverty. These types of events brought about changes in how institutions analyze credit risk. The risk of lack of liquidity is one of the most important problems that companies must solve, as mentioned by Torres and Ochoa (2022), as they must calculate how much money they must keep in cash to pay all their obligations on time. Relating efficient liquidity management, as a preventive alternative in cases of financial crisis, is a way to give continuity to the company's operations. There

are very specific cases where risks arise when companies fail to meet obligations, although some companies have rules and standards for the classification of loan portfolios, many of these rules and standards are applied incorrectly, resulting in risks that can impact the profits they can make.

Cárdenas et al. (2021) identify that companies that risk their capital to acquire a new client, and that is why they do not carry out prior studies if they are creditworthy, most of them do not have a financial culture that allows them to maintain an adequate payment capacity and thus minimize the risk of non-payment to avoid an increase in indicators such as non-performing loans, delinquency, insolvency, and non-productive assets. Furthermore, Carta et al. (2020) mention that lenders, such as banking institutions offering credit cards, use credit scores to assess the potential risk involved in lending money to consumers and thus mitigate losses due to default. In financial technology, a business-to-business (B2B) approach should be able to operate proactively, without the need to know the behavior of unreliable users.

The latest report on trends in payment practices by the international credit underwriting agency Atradius (2023), highlights that organizations are actively developing and implementing strategies and measures to address the challenges posed by credit risk with their customers. By applying stricter credit policies, they have managed to reduce the average invoice term from 52 days to 36 days, reducing the payment term to suppliers. However, the reinforcement of credit policies represents a challenge in the search for new customers. There is currently a growing interest by institutions in using advanced techniques supported by Artificial Intelligence (AI) and Machine Learning (ML) technologies to improve credit risk management practices, partly due to evidence that traditional techniques are incomplete. Aziz and Dowling (2018) mention that the use of AI to model credit risk is not a new, but growing, phenomenon. It is recorded that, in 1994, Altman and colleagues conducted the first comparative analysis between traditional statistical methods of predicting distress and bankruptcy and an alternative neural network algorithm and concluded that a combined approach of the two improved accuracy significantly.

Razavian et al. (2021) stress that, in the credit market, assessing a customer's default risk over time is essential to enable strategic and timely risk management, because the exposure of the firm's interests to risk and losses from defaults is directly related to the timing of default. Models with the ability to predict not only whether borrowers will default, but also when they are likely to default, have been applied to credit scoring. Gao and Xiao (2021) conducted an in-depth analysis of credit application data analysis of banking applications in China, reviewing the behavioral patterns of credit reports using Big Data, and identifying consumption practices within theoretical, financial, and economic circles. This allowed the market to be classified into the following categories: personal loans, non-performing loans, and these groups allowed financial institutions to establish new variables to their risk model, such as the blacklist and the grey list, to establish new controls in the online financial industry, a default rate and detect illegal usury, to combat possible fraud.

1.1 Objectives

To design a model supported by Machine Learning to establish credit policies based on the characteristics, behavioral patterns, and payment capacity of customers, allowing to significantly reduce the lack of liquidity of small and medium-sized enterprises in Mexico City. To achieve the objective, the following phases are defined:

- Analysis of Machine Learning Models.
- Identify significant variables to be considered by the Model.
- Training of the Model.
- Implementation of the Model to a pilot sample of clients.

2. Literature Review

In an article published by Koulouridi et al. (2020), the Coronavirus pandemic is a humanitarian crisis that continues to impact lives and livelihoods around the world today. Forcing regional and national economies to shut down for weeks and months at a time, causing great hardship - in some cases existential hardship - for many populations. Much epidemiological work remains to be done, as the pandemic may have dangerously active or evolved. Changes in creditworthiness across sectors and sub-sectors, 2. Increased difficulty in differentiating between borrowers in the same sector, 3. Significant changes in relevant data on distressed conditions, i.e. scarce, outdated, or not integrated into the decision-making equation, 4. Physical collections are necessary to know the clients and their economic capacities to reach new agreements, 5. A strong surge of new credit risks due to new digital financial platforms, complicating the recovery of funds.

Companies need liquidity to continue their operations and one of the main paradoxes that exist in organizations is that they have an excellent sales volume, but highly inefficient credit risk management (Gómez 2007), which causes severe problems with cash flow management. There are currently an infinite number of user-friendly automated systems that facilitate operational processes and focus on credit risk management administration, and a recurring problem is that business units do not invest in systems, technology or in increasing the staff assigned to the risk area, leaving this critical department to one side, underestimating the importance it deserves (Mora 2020). The management of non-performing loans is a problem faced by all companies worldwide. More than 50% of sales between companies around the world involve credit and Atradius (2021) estimates that 47% exceed agreed terms. In Mexico alone, this represents more than 500 billion dollars.

Credit risk management based on Bülbül et al (2019) has evolved enormously in the last decades. This is due to major advances in information and communication science and technology, allowing for significant improvements in credit risk monitoring and financial innovations implemented by firms, and access to risk sharing has been facilitated. Financial regulation imposes a certain basic level of risk management on banks. Based on this basic level, banking institutions can choose whether to collect additional information on credit risk and whether to share it. The determinants of these decisions are largely unexplored.

The debate established by Djebali and Zaghdoudi (2020) on the relationship between risks and bank stability is inconclusive because the findings are divergent. These findings can be divided into three types; 1. it supports the negative impact of these two risks on bank stability. 2. On the other hand, it shows the positive effect of both risks on the stability of banks. 3. Current literature demonstrates the negligible impact of liquidity and credit risks on banks' stability. In other words, the results have the merit of adopting different empirical approaches, but on the other hand, they assume a linear correlation between the various risks and corporate stability. The formulation of the linearity assumption leads to erroneous results that may mislead decision-makers because the sign of risks on bank stability does not change; it can be either negative or positive.

Dang et al (2020) state that, first, the relationship between credit growth and risks may follow "herding behavior". Rajan (1994), i.e. it is argued that firms tend to compete with their counterparts in lending in the expectation that they will not be inferior. This competition makes it easier for them to pursue a more liberal lending policy by extending borrowing limits and relaxing credit terms, which explains the higher riskiness of organizations in expanding their lending activities. Firms have the information necessary for management and decision-making but tend to interpret it in a biased way, reinforcing their existing beliefs about the market and customers. Borio et al. (2001) argue that these awareness and behavioral issues will lead to erroneous decisions and cause risks in the process of credit expansion in banks.

Ekinci and Poiraz (2019) identify that the risk arising from a business partner's failure to meet its contractual obligations on time or at any time thereafter can significantly jeopardize the firm's business. On the other hand, a customer with a high credit risk has a high risk of bankruptcy which endangers the operational continuity of the company. A high level of non-performing loans on the company's balance sheet reduces its profitability and directly affects its performance. Therefore, effective credit risk management has become a vital factor for the economic survival and growth of organizations. According to Amato et al. (2022), we currently live in the era of Big Data and data science, the advancement of sophisticated analytical techniques, and the financial and business sector can implement innovative technologies in their systems to obtain crucial information about their customers' behavior and closely monitor their activities. This has seen the emergence and rise of two significant applications, namely customer segmentation systems and early warning systems.

Based on Mahalakshmi et al (2022) highlight that AI plays a key role in credit decisions. Because it offers better assessment and greater accuracy of various factors, leading to well-informed and data-backed decisions. Additionally, machine learning-supported models provide more sophisticated and complex rules-based credit scoring as opposed to conventional scoring systems. A benefit of the application of artificial intelligence in the financial sector is the ability to analyze large volumes of information providing unbiased decisions. Various loan issuing applications and digital banks use machine learning algorithms to examine in detail the possible personalized alternatives and eligibility of loans. Artificial intelligence models cannot be underestimated in risk assessment and risk management. Algorithms can identify and assess different risk cases by determining timely alerts of future threats and/or fraud. With the increase in the offer of online financial platforms, the potential risks of fraud in transactions that are conducted online are increasing. The models can detect fraud based on location, time, amount, and customer purchase patterns.

Subsequently, Bussman et al. (2021) identify that credit risk can be quantified through machine learning models, which can extract non-linear relationships between financial information contained in financial statements. In addition to establishing a standard data science lifecycle, models are chosen to optimize predictive accuracy. In regulated business sectors, models must be carefully chosen by balancing accuracy with explainability (Murdoch et al. 2019). The construction of a data imputation method based on Zhao et al.(2022) for accurate prediction of missing data, in this case, the level of risk is very beneficial. Generally, building an effective imputation model is very difficult due to the high rate of missing data and the complex pattern of arbitrary missing data.

According to Arora et al. (2021), artificial neural networks are one of the most widely used techniques to investigate the root cause of risk associated with credit customers. It is a technique that uses interconnected neurons to solve a problem by simulating the way the human brain works. Zhao et al. (2021) indicate that complex network theory is often used to analyze default risk. Network-based modeling states that the connectivity of interacting nodes is a systemic approach to determining the propagation of risk, and a model of financial contagion can be constructed using Watts' cascade dynamics theory based on complex networks (Deng and Chen 2014). Taking the European continent's financial market for sovereign credit default swaps as an example, it is a complex network system. That is, the source of risk propagation must be identified and how risk is distributed can be analyzed using complex network theory (Chen et al.2020b). By integrating the idea of complex networks, a robust model of financial market risk propagation can be built from the perspective of organizations. The spread of infectious diseases is like the contagion of internal crises in firms. Therefore, the SEIRS model is suitable for studying the mechanism of risk diffusion among member firms of a corporate group (Mi et al. 2007).

3. Methods

The methodology used for the development of this research was carried out in 3 phases, which are detailed below:

3.1 Analysis of existing credit management software on the market.
3.2 Identification of significant variables for the mathematical calculations of the proposed model.
3.3 Execution of pilot tests with clients of the specialized collection agency.

4. Data Collection

The case study was conducted in a collection agency in Mexico that offers debt collection services to more than 30 national and international companies.

A needs and root cause analysis with customers has identified that credit policies have too much slack for the payment of the invoice that is issued at the end of each month. In addition, customers set such policies to retain the customer or to make the prospect become a customer.

A search for specialized credit risk management software identified the main providers:

Figure 1. Magic Quadrant for Invoice-to-Cash Applications

The strongest manufacturer in the industry is HighRadius, in addition to being the leader in Gartnert's magic table (2024), in which vision, technology, and customer service stand out, and its success is because of the fiscal context of its country of origin (United States).

Table 1. Credit Risk Management Software Comparison Chart

Manufacturer	Analysis	Cost	Outreach
a. HighRadius	A leader in the collection automation industry, although the shortcoming is that it is only offered in the United States. A consultant is required for the implementation of the system.	A sales assistant is required because tailor-made solutions are offered.	Establishment of manual credit policies, including an information board for the monitoring of loans granted.
b. BlackLine	A distinguishing feature is that knowledge is available by industry. A consultant is required for the implementation of the system.	From $105 per month.	It offers collection and credit risk management services, including real-time dashboards.
c. Invoiced	Easy implementation through APIs, the whole system is integrated online, and no infrastructure adaptations are required.	From $39 to $499, if any additional implementation is required, a quotation is possible.	Reconciliation of payments, receipts, and accounts payable.
d. Sidetrade	A consultant is required for the implementation of the system.	A sales assistant is required because tailor-made solutions are offered.	It focuses specifically on credit risk management.

Source: a. (HighRadius,2024), b. (BlackLine, 2024), c. (Invoiced, 2024), d. (SideTrade, 2024)

That allows the extraction of information in an automatic way, allowing users who make use of the software to control it remotely. The software allows users to monitor invoices issued, overdue invoices, accounts receivable, accounts payable, by having the information concentrated in one place it is possible to have all the necessary data for the proper management of credit risk.

However, with all the sensitive information that is held, the contracting company must ensure that best practices of data governance are in place to prevent information leakage because information getting into the wrong hands not only poses a risk to the company but also to customers and suppliers. The analysis of manufacturers specialized in credit risk management shows that all of them offer their services outside Mexico and that not all SMEs could afford a service costing USD 499 per month. This means that there is an unsatisfied potential market. For these social organizations to survive, they need to have a credit risk management system so that they can establish credit policies based on the characteristics of their client portfolio. For the definition of the significant variables for the construction of the Machine Learning model, the agency specialized in the recovery of non-performing loans has the following data:

- Turnover
- Credit days
- Average collection period
- Invoicing life cycle
- Industry
- Location
- Number of customers
- Collection processed by debtor
- Financial indicators
- Market size assessment

For the final client to have a tangible product and not just a code in a programming language, the deliverable of this research will be a user interface in the form of a strategic dashboard so that they can visualize and/or monitor in real time where the credit is distributed. Therefore, below are the logic diagrams of how machine learning models operate based on the available information.

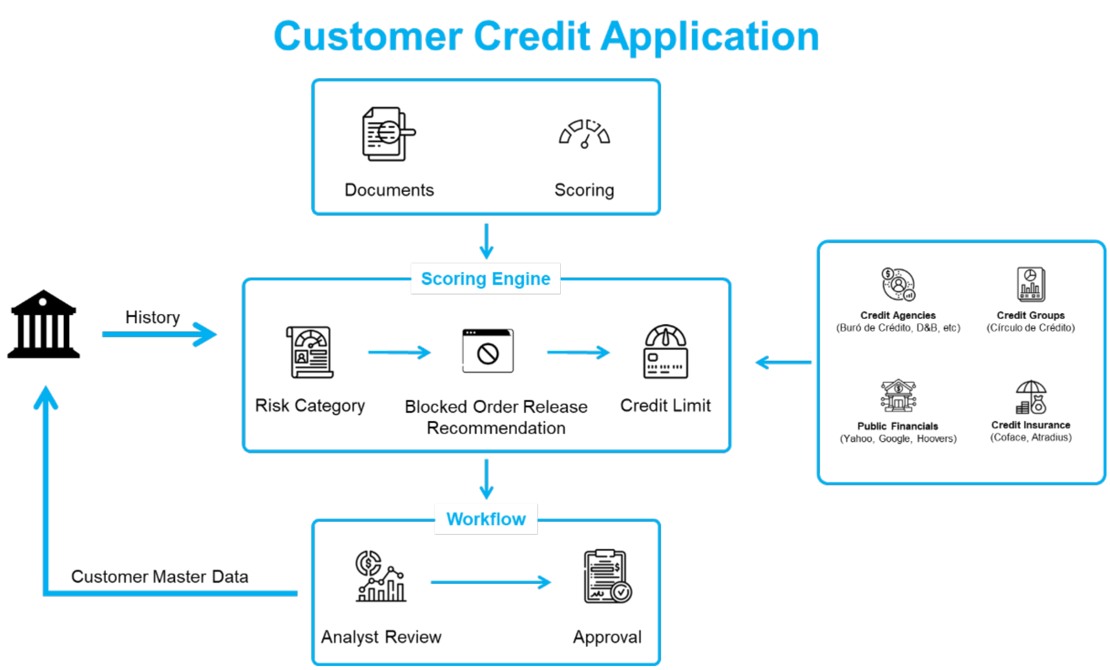

Figure 2. Customer Credit Application

With the historical information stored in the database, the system extracts documents such as invoices, purchase orders, deposit slips, cheques, and receipts, for analysis, and then enters the engine that will perform the mathematical calculations identifying the category to which it belongs, according to its previously deciphered behavior patterns, The engine makes a comparison with public databases, publicly available financial information, banking behavior so that the credit limit can then be defined, for validation it will be sent to a credit analyst who, based on his experience, will be responsible for determining whether the credit limits calculated fit the profile. And this person will be the one who will make the final decision to approve or reject the credit application, as a way of training for piloting with customers.

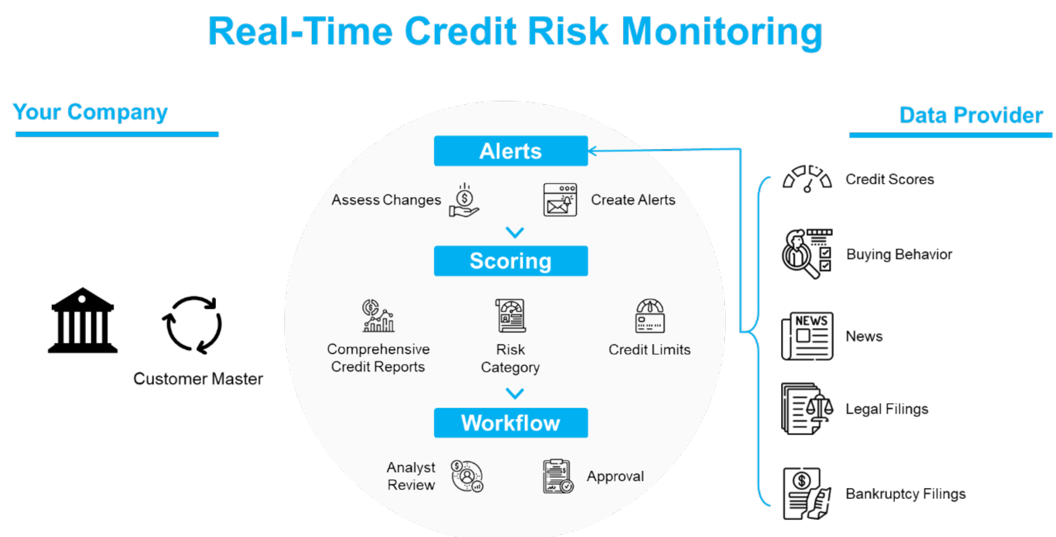

Figure 3. Real-Time Credit Risk Monitoring

The information will then feed into the information dashboard for continuous credit monitoring, i.e. credit risk alerts, rating through analytical reports, risk classification, setting of credit limits, approval or rejection of credit requests through internal consumption data, in other words, data from the company's database. The external input to strengthen the model is how it is rated by other companies, behavior with other clients, analysis of the public legal file, and historical information on whether it has had bankruptcies or events that have significantly impacted the company's finances.

5. Results and Discussion

5.1 Numerical Results

After data is entered into the model, it will result in a numerical value that will rate the customer based on the data in Table 2.

Table 2. Credit Rating Table

Credit Score Card		
Score	**Qualification**	**Description**
1 to 99	Lousy	Company in too early stage to authorize credit.
100 to 550	Low	Needs improvement.
551 to 650	Regular	Intermittent behavior.
651 to 700	Good	Above-average rating.
701 to 850	Excellent	Admirable behavior.

Source: Own elaboration based on results obtained in the model.

With this classification, the analyst will have a detailed analysis to be able to approve or reject the credit application, because the quantitative and qualitative data have already been processed.

5.2 Graphical Results

As mentioned above, the user of the financial platform will visualize key information for decision-making in the form of an executive summary, enabling strategic planning of credit and collection policies. In addition, this application will allow the establishment of a credit risk management system, as well as significantly reducing possible losses or bad debt reserves.

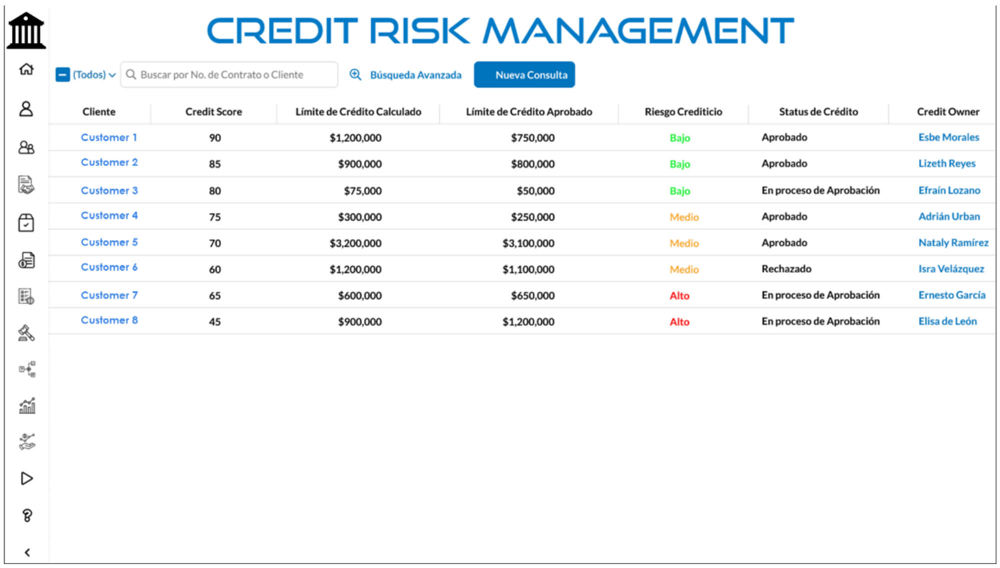

Figure 4. User interface of the credit risk management module

The following is the executive dashboard showing how the information contained in the database is reflected, allowing the user to monitor in real-time the behavior of clients and enter credit applications to establish tailor-made credit policies for clients, based on each client's profile. Three highly relevant graphs are shown, such as the volume of credits granted historically, grouped risk level, credits collected, in addition to recent requests, which are information cards that show the level of risk, industry, age of the company, credit limit requested, credit limit granted, and the border is painted as if it were a traffic light, to establish a visual control, green as low risk, orange as medium risk and red as high risk.

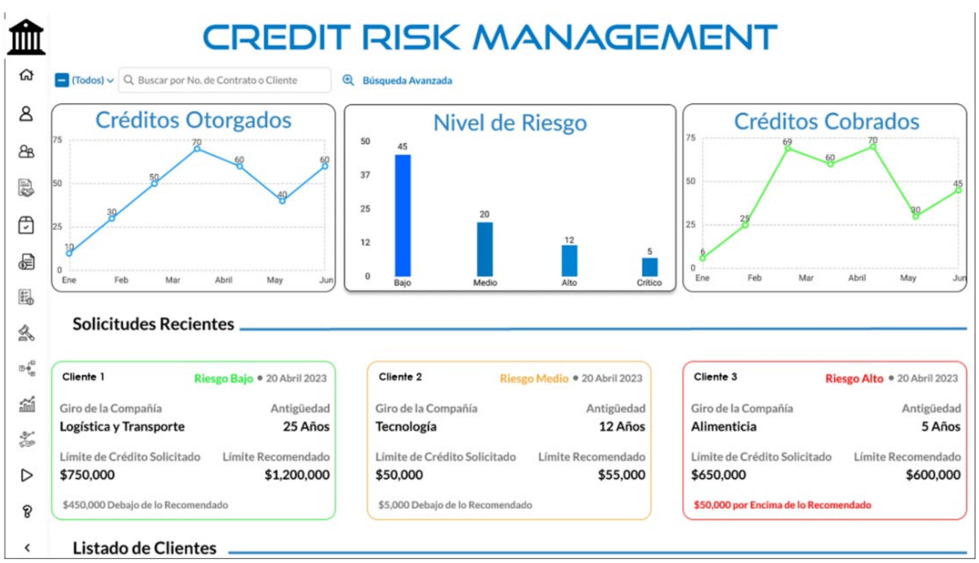

Figure 5. User interface of the credit risk management module

5.3 Proposed Improvements

The next stage of development will consist of continuous training of the models to refine accuracy, and artificial intelligence with NLP (Natural Language Processing) functionality will be developed, in which it will be able to write credit policies so that approval is automated and does not depend on a credit analyst.

5.4 Validation

The pilot test was a success because the response from customers was very positive, they gave us feedback through a survey to know the NPS (Net Promoter Score), and their comments to improve the model consisted of adding new variables to the model to make it more accurate, and the analytical dashboards were highly functional for monitoring and managing credit risk.

6. Conclusion

We currently live in the era of Big Data and Artificial Intelligence, that is, the information era, all transactions, operations, and processes that we carry out every day generate historical information that is very useful for the generation of models that allow us to know, propose and design models for the solution of a specific problem. In this case, one of the challenges faced by SMEs in Mexico City and worldwide is the scarcity of liquidity, which does not allow the growth or continuity of these social organizations. It is worth mentioning that there are providers that offer credit risk software but that are not affordable for emerging companies, in addition to the fact that some require too many requirements, such as adjustments to infrastructure, hours of training, long implementation times, and the purchase of specific software. The proposed solution is affordable for any business that needs it, as well as establishing a risk-based culture to facilitate data-driven decision-making.

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