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CASE STUDY

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Credit Scoring Model Weighted by Investment and Financing Decisions: Case Study in a Building Supply Store

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Abstract: Current literature provides various models for credit risk analysis, called credit scoring models (CSMs). However, these models are not suited to the majority of Micro and Small Enterprises (MSEs). This is compounded by a lack of technical knowledge of microentrepreneurs linked to the high costs and complexity of the CSMs. These issues are significant as 99% of Brazilian companies are MSEs. Therefore, this paper aims to propose a CSM for an MSE that commercializes construction materials in São Paulo, Brazil. This research is quantitative and characterized as a case study whose CSM is based on the Naive Bayes algorithm implemented in Microsoft Office Excel 2016. This model calculates the probability of default and adherence by weighting the results based on the Modern Finance Theory with the Cost of Denying and the Cost of Granting. The application of the model demonstrates that the successes in approvals (70%) and disapprovals (66%) of Credit Sales were significant with a result of R$ 32.20 thousand and an increase in net profit by 124.2%. We have evidenced that the proposed CSM is able to weigh the risk in investment and financing decisions for the Credit Sales of an MSE. This paper provides a low-cost CSM, adapted to reality and easy to handle and implement in MSEs. This research is a reference to the development of CSMs focused on the credit concessions conducted by MSEs.

Keywords: credit scoring, optimization methods, credit scoring models, micro and small companies

1. Introduction

Credit granting analysis developed with the delivery of Credit granting analysis developed with the delivery of a good or present value under a commitment to receive a certain amount of money, updated with interest, at a future date [1, 2]. A crucial tool for assessing credit and default risks is credit scoring (CS). This tool refers to formulas that aim to quantify the risk of default by converting relevant data into numerical measures oriented to credit decisions [2, 3]. CS is an estimate based on the probability model of a borrower presenting a behavior considered to be undesirable in the future [4, 5]. The literature discusses different classical (statistical methods) and more sophisticated (computational intelligence) approaches to credit risk analysis, and these approaches are called credit scoring models (CSMs). Logistic Regression (LR), Neural Networks, and Naive Bayes (NB) are increasingly used in CSMs [6]. In CSMs, each data instance is described by several features that represent the level of credit risk [1, 7]. Improving credit management for financial institutions is most CSMs' focus [6]. Such models analyze extensive databases with many variables to obtain greater agility and accuracy in predicting default [2, 4, 6, 7]. Thus, it is large companies with diversified capital structures, low-cost sources of finance, and investments in technology that use CSMs. Micro and Small Enterprises (MSEs) operate in a competitive market that rivals global giants [8, 9]; however, most MSEs have financial limitations regarding making investments and lack the resources and/or access to capital that large companies have [8–10]. Furthermore, MSEs are hindered by the financial limitations for training, the technical incapacity of entrepreneurs, the lack of experts, and the complexity of the CSMs [8–13]. Evidently, much of the literature focuses on large companies while some occasional individual case studies address MSEs [6, 8–13].

Practically, CSMs are still far out of the reach from the majority of MSEs [6]. Therefore, there are two important key issues regarding CSMs: (i) there is a demand for CSMs that are better suited to MSEs and (ii) CSMs are expensive and/or complex for MSEs. As 99% of companies in Brazil are MSEs, these issues are significant. In this context, this paper aims to propose a CSM for a Brazilian MSE that operates in the building materials trade, located in the interior of São Paulo, Brazil. This case study's probabilities of default and delinquency will be obtained by a CSM based on the NB algorithm implemented in Microsoft Office Excel 2016. We emphasize that this paper does not discuss, improve, or conduct a performance analysis related to the application of different statistical and computational techniques applied to CSMs. We chose the NB algorithm because, according to Kamimura et al. [6] and Wu et al. [14], it is a simple, efficient, and popular statistical classifier used in data mining techniques and in the construction of CSMs. This learning method is widely applied in many areas

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and in supervised classification problems with satisfactory accuracy and high computational efficiency [15, 16]. The mechanics of NB is quite simple and can be understood and executed faster than compared to methods with more sophisticated predictive capabilities [15, 16]. Therefore, this paper proposes a low-cost, easy-to-use CSM that is suitable for the reality of Brazil. The focus is on formulating a CSM that enables microentrepreneurs to make more assertive and profitable decisions in Credit Sales made by MSEs. The basic premise is to mitigate the credit risk by weighing it against the profitability of the business through the application of Modern Finance Theory with the Cost of Denying (CD) and Cost of Granting (CG). This is a more modern approach that deals with the economic feasibility of Credit Sales carried out by MSEs. We integrate the assessment of the probability of default and the financial prospects of MSEs. Furthermore, a series of relevant theoretical gaps and practical issues are also considered to adapt the CSM to the needs of MSEs. Therefore, this research transcends the traditional models to integrate Modern Finance Theory into the CSMs.

This paper is structured as follows: Section 2 presents the literature review; Section 3 demonstrates data, method, and model formulation; Section 4 details the experiments and analysis of results; Section 5 presents the discussion and limitations. The paper ends with the study's conclusions, suggestions for application, and future directions regarding CSMs.

2. Literature Review

From the 2000s, new types of approaches emerged to better deal with CS. Baesens et al. [17] apply Decision Tables and Neurorule, Trepan, and Nefclass (ANN). Sinha and Zhao [18] compare the performance of LR, ANN, k-NN, and Support Vector Machine (SVM), Data Mining, Decision Table, and Decision Tree (DT). Antonakis and Sfakianakis [15] have analyzed the efficiency of Bayes' Theorem comparing it with NB, LR, ANN, k-NN, Classification Trees, and Linear Discriminant. Finlay [19] generates ensembles of linear scoring models using Genetic Algorithm (GA). Šušteršič et al. [20] have implemented ANN for consumer analysis, variable selection GA, and principal component analysis (PCA). Ince and Aktan [21] have analyzed CSMs that applied traditional approaches and artificial intelligence such as DA, LR, ANN, and Classification and Regression Trees.

In 2010, there was an exponential increase in CS research. Finlay [22] has modeled continuous financial measures (default, revenue, and profit contribution). Liu and Song [16] have used Simulated Annealing in conjunction with GA for the selection of NB attributes. Vukovic et al. [23] have exposed a system of four CBR models that use GA. Bravo et al. [24] have applied LR and Knowledge Discovery in Databases. Kruppa et al. [25] have used Random Forests (RF) and k-NN together with LR. Řezáč [26] proposes a new ESIS2 that estimates the information value and evaluates the discriminative power of CSMs. Verbraken et al. [27] find a trade-off between expected and default losses by adapting the Expected Maximum Profit (EMP) measure. Kozeny [28] fills a gap in the use of GA. Lessmann et al. [4] have compared 41 classifiers, updating Baesens et al. [17], and made comparisons with Ensembles, Hybrid Systems, and Single Model Approaches. Serrano-Cinca and Gutiérrez-Nieto [29] have proposed a system for profit scoring oriented to Person to Person (P2P) lending based on MR and using the Internal Rate of Return (IRR). Maldonado et al. [30] have relied on profit to select models and attributes based on linear SVM. Krichene [31] has deployed NB in predicting defaults in a bank in Tunisia. Bastani et al. [32] have focused on allocating funds from the loan market to P2P whose credit and profit scores are integrated based on Learning Algorithms. Sariannidis et al. [33] have compared the prediction accuracy of LR, NB, DT, k-NN, RF, Support Vector Clustering (SVC), and Linear Support Vector Clustering (LSVC) methods. Kozodoi et al. [34] have used EMP and number of attributes as two fitness functions to address both cost-effectiveness and interpretability. Çiğşar and Ünal [35] have used Data Mining to prevent default risk and NB, J48 Algorithm, Multilayered Perceptron, Six Classification Algorithms, and Regression through WEKA 3.9 Data Mining. Trivedi [36] has presented a prediction model and a CSM using NB, RF, DT, and SVM.

Nalić and Martinovic [37] have proposed a CSM deploying Generalized Linear Classification and SVM. Li and Chen [38] have performed a comparative evaluation for RF, AdaBoost, XGBoost, and LightGBM stacked together with ANN, LR, DT, and SVM. Ashofteh and Bravo [39] have relied on the initial Kruskal-Wallis non-parametric statistical analysis to formulate a CSM based on Machine Learning (ML) and utilized RF, ANN, SVM, and LR with a Ridge penalty for the learning and evaluation of the CSM. Carta et al. [40] have proposed a stochastic ensemble criterion that uses a real-world dataset to apply RF, DT, Adaptive Boosting, Multilayer Perceptron, and Gradient Boosting (GB). Dastile and Celik [41] have used DL that converts tabular datasets into images to enable the application of 2D CNNs in a CSM. Djeundje et al. [42] have evaluated the use of psychometric variables and/or email usage characteristics to predict the probability of default by applying LR, DL, PCA, XGBoost, Ridge Regression (RR), and Least Absolute Shrinkage and Selection Operator (LASSO). Kang et al. [43] have proposed a CSM for the Rejection Inference (RI) problem by analyzing RF, DT, XGBoost, LightGBM, and Modified Synthetic Minority Oversampling Technique (Borderline-SMOTE); therefore, the researchers used a Borderline-SMOTE and Label Spreading for RI. Kozodoi et al. [44] have addressed the retail credit market by revisiting profit-oriented statistical fairness criteria with ML applications using real data through EMP and LR, RF, ANN, and XGBoost classifiers with codes made available on GitHub. Laborda and Ryoo [45] have proposed LR, RA, SVM, and k-NN. Li et al. [46] have used Multi-Layer Structured Gradient Boosted DTs with Light Gradient Boosting Machines (ML-LightGBM). Roa et al. [47] have applied an EMP measure and Stochastic Gradient Boosting (SGB) while using tree-based SHapley Additive exPlanation (SHAP) (TreeSHAP) for the interpretation of SGB. Roy and Shaw [48] have integrated the Analytic Hierarchy Process (AHP) and the Technique of Order Preferences by Similarity to an Ideal Solution (TOPSIS) for the so-called AHP-TOPSIS. Roy and Shaw [49] have developed a multi-criteria model formulated through a hybrid method that combines TOPSIS and Best-Worst Method (BWM). Furthermore, Xia et al. [50] have combined application data with the data frequency and delays of Multi-Level Macroeconomic Variables (MVs). Xia et al. [50] have proposed a Bayesian selection and delay optimization method to deal with MVs. Roy and Shaw [51] have formulated a multi-criteria Sustainability Credit Scoring System (SCSS) that considers environmental and social aspects, as well as financial and managerial issues, combining BWM and TOPSIS. For a theoretical background on these types of modeling, see Louzada et al. [2], Kamimura et al. [6] and Andriosopoulos et al. [7]. These studies demonstrated that estimating only the probability of default is no longer the main objective of all CMSs. Recent research has focused on loan yields and profit scoring as a focus for CMS. This change presents a new perspective on maximizing the financial results of loans in analyses that include CS. There is also a significant demand for studies aimed at MSEs for installment sales and commercial credit through improvements or new CSMs [6].

3. Data, Method, and Model Formulation

3.1. Data

The case study company operates in the retail trade of construction materials and is in the interior of the state of São Paulo, Brazil. It was established in 2019 with a capital of R$ 300 thousand, of which R$ 90 thousand (30%) came from the partners and R$ 210 thousand (70%) came from bank loans. The loan term was 36 months with a 60-day grace period for payment of the first installment and a nominal interest rate of 2.7% p.m. In June 2020, and under the same conditions, a new loan of R$ 100 thousand was taken. The monthly installments, including interest and amortization of the outstanding balance, resulted in a payment of more than 126 thousand reais in 2021. Table 1 shows the simplified income statement (with values expressed in thousands of reais) adapted to the inclusion of the Provision for Credit Losses (PCL). Note that the evolution of gross revenue led to the realization of a positive net result in 2021 (R$ 89.49 thousand); furthermore, the growth in financial expenses with PCL consumes 33.1% of the gross profit.

The approval of Credit Sales is based on two criteria: (i) the judgmental and empirical analyses (experience and feeling) of the entrepreneur and (ii) consultations on the basis of credit protection companies. These companies are Serasa, the Central Credit Protection Service (SCPC) of the Commercial Association of São Paulo, and the Register of Issuers of Bottomless Checks (CCF). For financial control, the company uses Microsoft Office Excel 2016. Sales and inventory controls are conducted by a licensed software in which there are 1,963 registered customers and over-the-counter sales and withdrawals by the customer are accounted for under code "00001 – consumer".

A customer is only registered in the case of sales (i) of greater volume and (ii) that require deliveries, and (iii) are made with the contracting of credit. However, only the fields "Name", "CIC/CNLE", "Address", "Neighborhood", and "City" are completed, ignoring "Income", "Work", and "Billing". Therefore, the variables analyzed were "Customer Code", "Purchase Amount", and "CIC/CNLE". The forms of payment are Cash (cash species), Check (cash or post-dated), and Credit Card. In the Check option (checks issued by third parties can be accepted), the entrepreneur finances the sale and assumes the credit risk, classified as Store Credit. Table 2 shows that Credit Sales had a significant share in revenues (in thousands of reais) for the years 2019 (9.77%), 2021 (11.40%), and 2022 (15.39%).

Table 2 shows that the Store Credit closed at more than 852 thousand reais in September 2021, after experiencing an increase higher than the total sales (57.54%). Between 2019 (6), 2020 (147), and 2021 (183), the company made 330 sales in the Credit Union, resulting in a growth of 2,950%. The numbers of customers who used the Store Credit are (i) up to 2 thousand (195), (ii) up to 5 thousand (62), (iii) up to 10 thousand (38), (iv) up to 20 thousand (26), and (v) greater than 20 thousand (9). These data show that 59% of clients made purchases of up to R$ 2 thousand while only 3% made purchases above R$ 20 thousand. Figure 1 illustrates the graph referring to the amounts (in thousands of reais) not received in the Credit Register and the impacts on the MSE's annual revenues.

Note that the accumulated default is R$ 479.2 thousand (5.3%), that is, 2019 (17.68%), 2021 (14.70%), and 2022 (44.17%). In relation to total turnover, default increased from 6.8% (2021) to 322.4% (2019). The number of customers in default, compared to Credit Sales, is 44.2%, with the share of unpaid amounts growing by 149.8% since 2019. However, Credit Sales, if compared to turnover, represented 15.39% of sales, corresponding to BRL 852.75 thousand, of which 44% is from defaulting customers (BRL 327.12 thousand). The problem, however, is that the partners do not have sufficient knowledge to apply any credit risk analysis techniques or CSMs. Added to this are the economic and financial aspects that require investment decisions in a context of intense competition and high mortality rates as is the reality in Brazil.

Table 1
Statement of income for the year

Income statement	2019	2020	2021
Gross Revenue	271.86	3,234.83	5,541.90
(−) Deductions and Allowances	−22.50	−90.00	−90.00
(=) Net Revenue	249.36	3,144.83	5,451.90
(−) Cost of Goods Sold	−209.13	−2,488.33	−4,313.79
(=) Gross Profit	40.24	656.50	1,138.11
(−) Selling Expenses	−5.44	−64.70	−110.84
(−) Administrative Expenses	−94.80	−410.40	−434.40
(−) Financial Expenses	−9.48	−150.57	−126.74
(−) PCL	−4.38	−98.18	−376.64
(=) Net Result	−73.87	−67.35	89.49

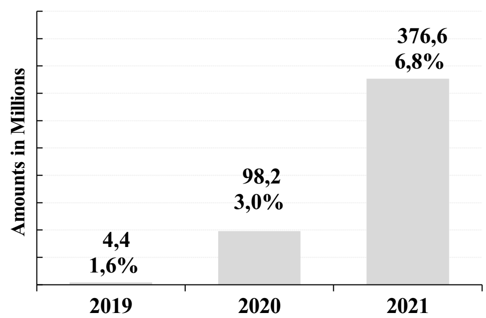
Note: PCL – Provision for Credit Losses (Thousands of R$).

Table 2
History of the share of store credit in sales

Type of sale	2019	2020	2021
Store Credit	24.80	359.88	852.75
Credit Card	31.65	338.78	472.66
Debit Card	52.39	390.81	327.12
Cash (At Sight)	145.01	2,066.55	3,888.50
Grand Total Sales	253.85	3,156.00	5,541.03

Note: Thousands of R$.

Figure 1
Impact of defaults on annual billings



3.2. Method

This case study is quantitative in nature and explores documentary analysis to propose a CSM for an MSE [52, 53]. The research considers the database of the MSE and formulates a CSM, based on the NB algorithm, to calculate the probability of default and adherence. The construction and interface of the CSM are elaborated (data inputs/outputs and the analysis of the results) using Microsoft Office Excel 2016. The data analysis included: (i) Financial Diagnosis, (ii) Customer Registrations, and (iii) Credit Sales Process. Therefore, the foundation for the CSM's construction comprises the credit risk and cost of capital analysis models, whose Credit Sales' economic viability is based on Modern Finance Theory. The CSM is constructed in three steps; the first is called the Credit Risk Model Flow, illustrated in Figure 2.

In this step, the probability of default and delinquency are calculated through the NB algorithm. Based on the data and history, financial modeling is then performed to calculate the variables to obtain and analyze the Cost of Capital and the Weighted Average Cost of Capital (WACC), as shown in Figure 3.

Finally, the adaptation of the CD and CG is formulated to calculate the score of the operations configured in the CSM. The entire flow of the adapted CG and CDC is illustrated in Figures 4 and 5.

From the credit risk, we can obtain the cost of capital analysis model that enables the attainment of the Net Present Value (NPV) and the IRR for calculating the WACC. The calculation of the NPV together with the results of the risk modeling makes it possible to calculate the scoring of the operation through the $CG_{(\text{Adapted})}$ and the $CD_{(\text{Adapted})}$. Figures 4 and 5 reinforce the combination of risk and capital assessment models in the formulation of the CG and CD.

Figure 2
Flow of the credit risk model

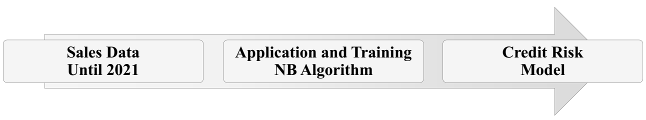


Figure 3
Flow of the cost of capital analysis model

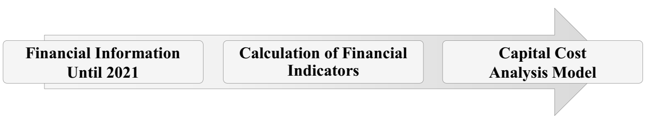


Figure 4
Costing flow of the grant

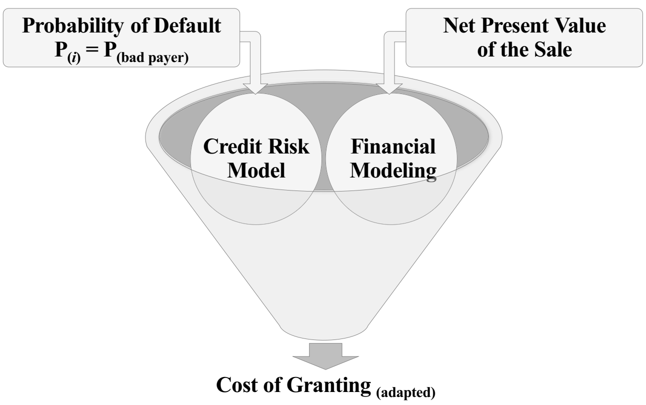
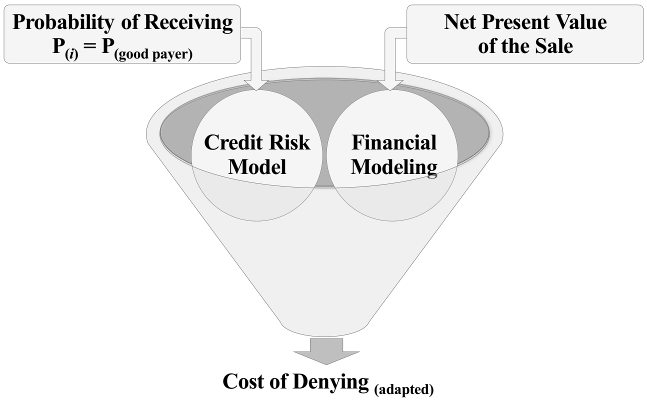


Figure 5
Flow of elaboration of the cost of denying



3.2.1. Model formulation

This section details the steps of the modeling that create the credit risk and financial analyses necessary to formulate the proposed CSM for MSEs. In the credit risk modeling, customers with overdue amounts until December 2020 were classified as "bad payers" and the rest were classified as "good payers". Therefore, the frequency of each attribute obtained from the customers' registration data and selected checks is calculated for the following distribution of sales by value range in 2020: (i) up to 2 thousand (99), (ii) up to 5 thousand (23), (iii) up to 10 thousand (17); (iv) up to 20 thousand (5), and (v) greater than 20 thousand (3). The distribution of sales in the "Value Range" field was then divided according to the 99 occurrences in the range of up to R$ 2 thousand and the three above R$ 20 thousand. Thus, 67.4% of the Store Credit has values of up to R$ 2 thousand, and only 2.0% thereof have values above R$ 20 thousand. The frequency of clients classified as "good payers" and "bad payers" is presented in Table 3.

Therefore, the matrix for calculating the Probability (P) of a client being a "bad payer" or "good payer" is formulated according to Equation (2).

$$P = \frac{n(\mathrm{A})}{n(\Omega)} \tag{2}$$

where $n(\mathrm{A})$ is the number of cases that matter for event A, and $n(\Omega)$ is the total number of cases for "bad payer" and "good payer". Table 4 details the matrix for calculating P.

Therefore, the conditional probability calculated by NB is given using Equation (3).

$$P(A/B) = \frac{P(A) \ \times \ P(B/A)}{P(B)} \tag{3}$$

Thus, for the construction of the NB, let $a_1, \ldots, a_n$ be attributes of the database and c a class to be predicted, then the optimal prediction is a class of value c such that $P(a_1, \ \ldots, a_n/c)$, according to Equation (4).

Table 3
Client classification of the company

Client cadastral attributes		Bad payer	Good payer	Total payers
Clients	Attributes	63	84	147
Type of Person	IC	40	74	114
	LE	23	10	33
Bad Credit	Yes	25	7	32
	No	38	77	115
Bad Check Databases	Yes	20	11	31
	No	43	73	116
Value Range (Thousand Reais R$)	Up to 2K	38	61	99
	Up to 5K	12	11	23
	Up to 10K	7	10	17
	Up to 20K	4	1	5
	Greater than 20K	2	1	3

Note: IC – Individual Consumer; LE – Legal Entity.

Table 4
Probability calculation matrix

Cadastral attributes of clients		Bad payer (%) payer		Good payer (%) payer	
Type	IC	40/114	35,09%	74/114	64.91
	LE	23/33	69,70%	10/33	30.30
Bad Credit	Yes	25/32	78,13%	7/32	21.88
	No	38/115	33,04%	77/115	66.96
Bad Check Databases	Yes	20/31	64,52%	11/31	35.48
	No	43/116	37,07%	73/116	62.93
Value Range (Thousand Reais R$)	Up to 2K	38/99	38,38%	61/99	61.62
	Up to 5K	12/23	52,17%	11/23	47.83
	Up to 10K	7/17	41,18%	10/17	58.82
	Up to 20K	4/5	80,00%	1/5	20.00
	Greater than 20K	2/3	66,67%	1/3	33.33

Note: IC – Individual Consumer; LE – Legal Entity.

$$\frac{P(a_1/c) \times P(a_n/c) \times P(c)}{P(a_1) \times P(a_n)} \tag{4}$$

The prediction of P for each variable, assuming the condition that a client is a "good payer", is given by Equation (5).

$$P_{(\text{good payer})} = \frac{P(\text{type/good}) \times P(\text{restriction/good}) \times P(\text{check/good}) \times P(\text{amount/good})}{P(\text{total clients/good})} \tag{5}$$

The calculation to predict P for each variable, assuming the condition that a client is a "bad payer", is given by Equation (6).

$$P_{(\text{bad payer})} = \frac{P(\text{type/good}) \times P(\text{restriction/good}) \times P(\text{check/good}) \times P(\text{amount/good})}{P(\text{total clients/good})} \tag{6}$$

From Table 4, it is possible to apply the NB and calculate the "good payer" and "bad payer" scores until 2020. The possible combinations are shown in Tables 5 and 6.

Tables 5 and 6 also detail all combinations for Individual (IC) and Corporate (LE) clients and show the P of each combination of being a "good payer" and "bad payer" according to the NB. In the modeling of the cost of capital, elaborated with data from 2020, the concept of Real-levered Beta (βr), given by Equation (7), was used.

$$\beta r = \beta d \times \left[1 + \left(\frac{D}{E}\right) \times (1 - T)\right] \tag{7}$$

where βd is the Unlevered Beta, D is Debt, E is Market Value/Equity, and T is Income Tax Rate. For this modeling, βd corresponds to the Beta of the last year of the stock LJQQ3 of Lojas Quero-Quero (large retailer of construction materials with shares traded on São Paulo Stock Exchange – B3). Table 7 shows the calculation of βr and the Capital Asset Pricing Model (CAPM).

R_m, the return on the market, is based on Lojas Quero-Quero's dividends in 2021, and the R_f is based on the target selic rate. Therefore, Table 8 presents the result of the Weighted Average Cost of Capital (WACC).

In the WACC, the financial cost of the company in granting credit was calculated with third-party capital and equity through the application of CAPM. Therefore, for the construction of the CSM, the NPV was calculated referring to the values of the loans or installments discounted with the WACC interest rate, according to Equation (8).

Table 5
Company clients' scores (Type IC)

Bad credit	Bad check	Sale value in store credit (Thousand R$)	Type IC "Bad Payer"	"Good Payer"
Yes	No	Up to 2	0.3470	0.6530
Yes	Yes	Up to 2	0.6212	0.3788
No	Yes	Up to 2	0.1847	0.8153
No	No	Up to 2	0.0684	0.9316
Yes	No	Up to 5	0.4820	0.5180
Yes	Yes	Up to 5	0.7417	0.2583
No	Yes	Up to 5	0.2841	0.7159
No	No	Up to 5	0.1139	0.8861
Yes	No	Up to 20K	0.7733	0.2267
Yes	Yes	Up to 20K	0.9133	0.0867
No	Yes	Up to 20K	0.5927	0.4073
No	No	Up to 20K	0.3204	0.6796
Yes	No	Greater than 20K	0.6304	0.3696
Yes	Yes	Greater than 20K	0.8404	0.1596
No	Yes	Greater than 20K	0.4211	0.5789
No	No	Greater than 20K	0.1907	0.8093

Note: IC – Individual Consumer.

Table 6
Company clients' scores (Type LE)

Bad credit	Bad check	Sale value in store credit (Thousand R$)	Type LE "Bad Payer"	"Good Payer"
Yes	No	Up to 2	0.6933	0.3067
Yes	Yes	Up to 2	0.8747	0.1253
No	Yes	Up to 2	0.4909	0.5091
No	No	Up to 2	0.2380	0.7620
Yes	No	Up to 5	0.7983	0.2017
Yes	Yes	Up to 5	0.9244	0.0756
No	Yes	Up to 5	0.6280	0.3720
No	No	Up to 5	0.3536	0.6464
Yes	No	Up to 20K	0.9355	0.0645
Yes	Yes	Up to 20K	0.9782	0.0218
No	Yes	Up to 20K	0.8609	0.1391
No	No	Up to 20K	0.6673	0.3327
Yes	No	Greater than 20K	0.8789	0.1211
Yes	Yes	Greater than 20K	0.9573	0.0427
No	Yes	Greater than 20K	0.7558	0.2442
No	No	Greater than 20K	0.5007	0.4993

Note: LE – Legal Entity.

Table 7
Real-levered beta and capital asset pricing model

Real-levered beta (βr)		Capital asset pricing model	
βd	0.68	Rf	0.52%
D/E	4.44	βr	3.02
βr	3.02	R_m	0.70%
		CAPM	1.06%

Table 8
Calculation of the weighted average cost of capital

Weighted average cost of capital WACC	Main value	Percentage (p.m.)	Cost (p.m.)
Market Value of the firm's Equity	R$ 90	1.06%	R$ 0.95
Market Value of the Firm's Debt	R$ 310	2.70%	R$ 8.37
Total	R$ 400	2.33%	R$ 9.32

$$\text{NPV} = -\text{I} + \sum\nolimits_{t=1}^{n} \frac{FC_t}{(1+i)^t} = 0 \tag{8}$$

In view of this, adaptations were made to the probability of being a "good payer" or "bad payer" by applying the NPV weighted by the WACC. Therefore, the calculation of the $CG_{(\text{Adapted})}$ and $CD_{(\text{Adapted})}$ was adapted from CDC and CDN brought by Silva (2016). Thus, with probabilities $P_{(\text{bad})}$ of "bad payer" and $P_{(\text{good})}$ of "good payer", the adapted CDC and CDN are obtained from Equations (9) and (10).

$$CG_{(Adapted)} = P_{(bad)} \times NPV \tag{9}$$

$$CD_{(Adapted)} = P_{(good)} \times NPV \tag{10}$$

Therefore, the final score of the client transaction consists of the difference between the $CD_{(\text{Adapted})}$ and the $CG_{(\text{Adapted})}$, as shown by Equation (11).

$$SCORE = CD_{(Adapted)} - CG_{(Adapted)} \tag{11}$$

Thus, the higher the NPV-weighted score, the higher the chance of payment, as the $CD_{(\text{Adapted})}$ will be higher than the $CG_{(\text{Adapted})}$. Note that using the NPV, calculated on the WACC, makes the CSM sensitive to the probabilities of collection and default, as well as to changes in the structure and the cost of capital.

4. Experiments and Analysis of Results

4.1. Experiments

The experiments used a base of 1,013 sales orders with Store Credit checks for a total of 183 customers between January and September 2021. Table 9 shows the history of bounced checks and the existence of restrictions for both IC and LE clients. Thus, loans were approved for 274 applications from individuals with records of restrictions while the history of Bad Check Databases totaled to 248. Credit Sales were approved for 255 LE clients with a history of bad checks while restrictions totaled 109.

Sales by value range, due dates, and total orders per customer were measured from Table 8. For the number of orders by value range, we have the following consolidated data from January to September 2021: (i) up to 2 thousand (320), (ii) up to 5 thousand (231), (iii) up to 10 thousand (189), (iv) up to 20 thousand (180), and (v) greater than 20 thousand (93). Therefore, requests with values of up to five thousand reais

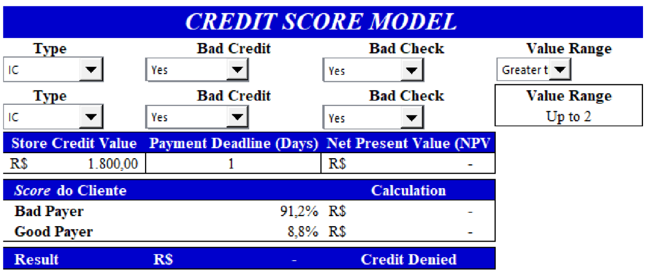
Table 9
Distribution of pending registrations by application

Cadastral attributes of clients	Bad check Yes	Bad check No	Bad credit No	Bad credit Yes	Total General
Individual Consumer	248	349	323	274	597
Up to 2K	67	161	142	86	228
Up to 5K	67	79	89	57	146
Up to 10K	65	43	42	66	108
Up to 20K	49	48	32	65	97
Greater than 20K	–	18	18	–	18
Legal Entity	255	161	307	109	416
Up to 2K	57	35	53	39	92
Up to 5K	48	37	46	39	85
Up to 10K	67	14	63	18	81
Up to 20K	64	19	73	10	83
Greater than 20K	19	56	72	3	75
Grand Total	503	510	630	383	1,013

Table 10
Clients by band and quantity of requests

Total clients	Range of ordering	Quantity of requests
76	1	76
84	2 to 10	329
14	11 to 20	214
2	21 to 30	51
3	31 to 40	107
1	41 to 50	44
2	51 to 60	102
1	90	90
183	1,013	1,013

Figure 6
Model interface



comprise 54.4%. Regarding payment terms, 97.3% of orders have terms of one month: (i) one month (986), (ii) two months (22), and (iii) three months (5). Orders with payment terms of up to two months were 99.5%. The consolidation of clients by range and quantity of orders is presented in Table 10, and Figure 6 illustrates the CSM interface.

Table 10 shows that 107 clients, due to the stages of work, have made several orders that can vary from 1 to 90. In the interface, it is enough to fill in the fields “Type”, “Value and Term”, “Value Range”, “Bad Credit”, and “Bad Check Databases” to obtain the result calculated by the CSM. The hidden spreadsheets allow updated information to be entered so that the conditional probabilities of the customer as a “good payer” or “bad payer” are presented at each run by the CSM.

4.2. Analysis of results

The trials showed that 496 applications presented a positive outcome with the application of the CSM. Among the applications that would be approved, 151 customers were defaulted after the application of the CSM. The percentages of errors and successes regarding customers with approved credit are illustrated by the pie charts in Figure 7. Figure 7(a) shows that, of the total orders with approved credit, 30% (151) defaulted with a loss of R$ 171.25 thousand. In relation to the 514 applications that would be denied, the graph in Figure 7(b) shows that applications with defaulting customers were 341.

Defaults with a negative score resulted in R$ 205.39; therefore, it is possible to obtain savings with losses due to default using the CSM. The demonstration of the results arising from the errors and successes of the CSM was R$ 32.30 (Table 10) and will impact the PCL. Table 11 shows the final values of the income statement adjusted to the CSM experimentations.

The analysis of the adjusted income statement shows that the application of the CSM leads to a decrease in gross revenue by 7.68%. However, there is an improvement in credit risk management since there was an increase in the financial result due to the disapproval of defaulted sales by the CSM. Denied sales totaled R$ 427 thousand and were subtracted from gross revenue. Proportionally to the value of goods sold, we adjusted the value of cost of goods sold. Consequently, the value of PCL was updated with the entry of R$ 171.25 thousand. Table 12 ratifies the positive impacts, in which the better control of credit risk resulted in a net profit of R$ 200.60, corresponding to a percentage increase of 124.2% in net income compared to the income statement without the application of the CSM. It is possible to affirm that the proposed CSM is effective for risk assessment when using a combination of SC and the tools of Modern Finance Theory. In addition, this research extended to improving the MSE’s investment and financing decisions in conjunction with the financial returns generated with the application of the CSM. A broader view on making more assertive and profitable decisions in the process of granting or not

Figure 7
Errors and successes of the model applied to credit requests

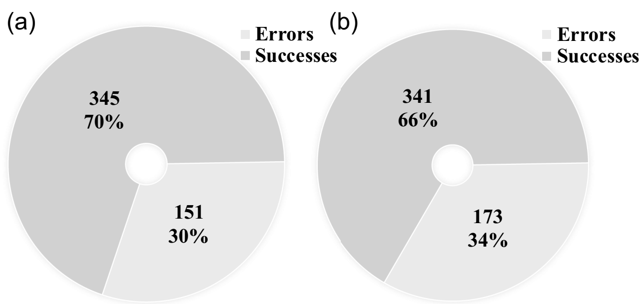


Table 11
Model results

Result of sales	Credit score	Store credit	PCL	Results
Positive (> 0)	Approved Credit	425.46	171.25	254.21
Negative (< 0)	Credit Denied	427.29	205.39	−221.91
Total Result	–	–	–	32.30

Note: PCL – Provision for Credit Losses.

Table 12
Adjusted income statement for the year

Income statement	2021
Gross Revenue	5,116.44
(−) Deductions and Rebates	−90.00
(=) Net Revenue	5,026.44
(−) Cost of Goods Sold	−3,982.61
(=) Gross Profit	1,043.83
(−) Selling Expenses	−110.84
(−) Administrative Expenses	−434.40
(−) Financial Expenses	−126.74
(−) PCL Expenses	−171.25
(=) Net Result	200.60

granting credit, including a view of finance and not only of probability of default, was provided by the constructed CSM. Therefore, the improvement of the client classification process by weighing the risk of default and the investment and financing decisions was satisfactorily presented by the CSM. This CSM is low cost, adapted to reality, and easy to handle and implement in Microsoft Office Excel 2016. It is possible for the entrepreneur to perform different simulations simply by feeding the CSM spreadsheets. The simulations for different Credit Sales proposals with post-dated checks allow a better adaptation to the new realities and risk contexts of the company and demonstrate the flexibility of the CSM. We also present gaps in the application of CSMs and important understandings to the entrepreneur regarding the risk of default in Credit Sales and investment and financing decisions based on the Modern Finance Theory. The managerial implications of this research are significant for MSEs in the construction materials sector that wish to use CSMs.

5. Discussion and Limitations

The analysis of the results presented by the proposed CSM proved promising in meeting the CS needs of a single MSE in Brazil. However, it is important to consider the potential application of CSM for a large department store chain and MSEs. The reality is that these types of expansions necessitate discussions about how a CSM can be integrated into a broader framework within an Enterprise Architecture (EA). EA provides a holistic view that assists MSEs (structure, processes, and technology) deal with the business environment (complexity and uncertainties) and the challenges of digital transformation when implementing a CSM. A strategy to expand the use of CSMs is to consider interdependencies within store networks or supply chains in the context of EA [54, 55]. This may require a strong business outcome-oriented focus and the creation of a framework to assess the implications of a CSM on the entire network and MSEs. A significant challenge lies in balancing the need for network standardization with the flexibility required to meet the unique needs of each MSE. Particular attention must be paid to adapting CSMs to rapidly changing digital scenarios in a way that maintains simplicity and accessibility for each individual MSE. Therefore, the limitations of CMs in the face of rapid digital transformation should be considered by both EA and Information Technology (IT). Moreover, broader perspectives on customer risk require the secure and efficient sharing and integration of Credit Score data among MSEs. This can be achieved through cloud-based data and/or social media, which raises concerns regarding ethical, privacy, and security issues [54, 55]. The introduction of different methodologies may also alter the key insights and performance of a CSM. For instance, the employment of advanced machine learning techniques will increase the accuracy of the forecast obtained by a CSM. In this context, two factors may render a CSM less accessible to MSEs: (i) increased CSM complexity and (ii) limited technical knowledge within MSEs. In general terms, the presented CSM offers an important tool for individual MSEs. There are opportunities to apply it within store networks or supply chains of a group with multiple MSEs. However, this CSM needs to be adapted to the agile structures of larger network ecosystems and ensure seamless integration with other systems, including Microsoft Office Excel.

6. Conclusion

This paper proposed a CSMs to a MSEs of building materials trade in São Paulo, Brazil. The proposed CSM was developed in Microsoft Office Excel 2016 and calculates the probability of default and delinquency based on the traditional algorithm known as NB. The weights of the CSM were based on the investment and financing decisions of Modern Finance Theory and employed the CD and CG. These costs were based on the Net Present Value (NPV), Capital Asset Pricing Model (CAPM), Cost of Capital, and the Weighted Average Cost of Capital (WACC). The CSM experiments using data that the MSE uses for Credit Sales approvals showed a positive result of R$ 32.20 thousand and an increase in net profit higher by 124.2%. The accuracy rates for clients with approved (70%) and denied (66%) credits generated satisfactory results for MSEs. These results showed that the CSM can weigh the risk in investment and financing decisions in the granting of Credit Sales. This paper also demonstrated that there are important gaps in the application of CSMs that focus on the profitability of MSEs. Thus, a series of relevant theoretical and practical issues were considered to adapt the CSM to the needs of MSEs. The main contribution of this research is to present a low-cost CSM that can be easily adapted to the reality of MSEs. Fact is that SMEs represent 99% of all companies in Brazil. However, most traditional CSMs proposed by the literature are often inaccessible or unsuitable for SMEs. This is also due to the lack of technical training of microentrepreneurs linked to the high costs and complexity of the CSMs. Therefore, the CSM proposed combines simplicity, accessibility, and effectiveness for MSEs in Brazil. This CSM is also easy to implement and handle in Microsoft Office Excel 2016. Thus, this CSM reduces the distance between the sophisticated financial tools and the practical constraints faced by MSEs. Additionally, this research transcends the traditional approaches to managing the risk-return relationship by integrating a CSM with Modern Financial Theory. Implemented economic feasibility analyses balance risks with Credit Sales and business profitability in the context of MSEs. This assists in the formulation of policies focused on reducing default rates to improve decision-making and financial management in MSEs. Insights aimed at guiding the development of training and capacity-building programs for microentrepreneurs were also presented by combining CS with Modern Financial Theory. Suggestions for future research are as follows: (i) formulate and compare CSMs targeted at different sizes and types of MSEs and (ii) develop an EA framework that incorporates CSMs while addressing the specific needs of MSEs.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data are available from the corresponding author upon reasonable request.

Author Contribution Statement

Elias Shohei Kamimura: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Anderson Rogério Faia Pinto:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Marcelo Seido Nagano:** Conceptualization, Methodology, Investigation, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition.

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