Practical Validation in a Neutrosophic Environment of the NEBS Methodology for the Optimization of SME Financing through Machine Learning

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Abstract

Micro and small enterprises (MSEs) have generated great opportunities for the growth of countries in the Latin American region. Unfortunately, as a result of the global crisis caused by the Sar-Cov-2, MSEs were severely affected. The main objective of this investigation is to validate in a practical way in a neutrosophic environment the use of a predictive Machine Learning technique that demonstrates the probability of the return on investment that a candidate investor will obtain with respect to a given business plan. With them it is expected that the investor can make the decision to finance a MSE, with the positive decision will close gaps in the growth of micro and small enterprises in Peru. The research is descriptive and predictive, with a research design of post-test only and control group. Neutrosophic TOPSIS was used as a technique. NEBS turns out to be efficient for the applicability of Machine Learning by obtaining statistical evidence to accept the hypotheses proposed for the finance sector in micro and small en-terprises in Peru. The results showed that the use of Machine Learning is validated, and its implementation increases the amount of financing obtained, decreases the evaluation time of requirements, reduces the number of complaints, and increases the number of formal sources used. Machine Learning research should be continued due to the complexity of this technology, which is constantly evolving.…

Keywords: Machine learning; Financing; SMEs; Neutrosophic TOPSIS

1. Introduction

The financing to micro and small companies (MSEs) using Machine Learning with predictive techniques to reduce financial risks avoids making bad decisions about future investment returns, the occurrence of events with negative financial consequences. It provides investors with intelligent tools for making decisions at the moment to invest quickly, wisely and based on financial data. Investing in shares, real estate and knowledge are the most common ways to generate profits, however, there are other innovative ways to generate higher income in shorter terms and with less risk regarding financial losses[1].

For this reason, the role played by Machine Learning[2] in the prediction of investment financial data based on experience and knowledge is highlighted to assess risks and find opportunities in the market through fundamental and technical analyzes that measure the financial state of micro and small companies, to give investors a broad and accurate perspective for a correct decision making when investing. In that line, believes that innovation and disruption have become an important factor to develop the competitiveness of countries and companies,

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It is described that the critical factors that coexist in small companies do not allow them to adopt information and communication technologies.to take advantage of potential growth opportunities, such as the use of Machine Learning. Although, artificial intelligence has been supporting business development to make it a sustainable and viable company over time, and there is support in terms of science, technology and innovation from government entities such as CONCYTEC, which provides support not only to citizens but also to business sectors that wish to apply for a so-called project, micro, small and medium-sized companies are essential in the social development of nations, with 60% of the economically active population[3].

In the Latin American Region, strategies are being generated to obtain a financing structure model, as well as in Bolivia, which indicates an alternative for financing through the Bolivian stock market. In addition, in Ireland the descriptive findings of micro and small enterprises provide a comprehensive overview of financing issues and the paper presents data on intangible assets and human capital insights not often found in other databases, which, combined with regression analysis, provides original and novel information on the capital structure of high-tech MSEs and the importance of company characteristics[4, 5].

Data science is an emerging field with a significant research focus on improving the techniques available for analyzing data [6]. From this instance, artificial intelligence comes and then automatic learning, better known as Machine Learning. Shown the different edges and backgrounds, automatic learning turns out to be a means that supports growth, since, with potential investors who want to bet on micro and small companies, they will not only be supporting their growth as entrepreneurs but also all the families that are behind all the attempted business plans that have not come to light. Machine learning in finance through the use of neural networks, machine learning, deep learning, among other similar terms, discussed how the application of machine learning algorithms allows explaining and forecasting financial market trends, as well as the current joint evolution of Quantitative and behavioral finance represent some significant and exciting developments in the finance domain.

Machine Learning has a wide variety of techniques, such as: supervised, unsupervised and semi-supervised learning, reinforcement learning, reverse reinforcement learning, learning by imitation, which are described below. Unsupervised learning is a method or technique to help the machine learn patterns. The model algorithm will automatically understand and start learning from the data without guidance. The model will use the unlabeled data to identify new patterns and information due to the design of its algorithm. reinforcement learning it is a method or technique of automatic learning, it is capable of working without large amounts of training data, with only a series of indications to learn through trial and error[7].

Semi-supervised learning is a machine learning method, this algorithm is trained on a combination of labeled and unlabeled data. The basic procedure involved is that first, the programmer will group similar data together using an unsupervised learning algorithm, and then use the existing labeled data to label the rest of the unlabeled data, supervised learning consists of the deduction of information from training data. This data is categorized into two sections: training data and test data. The objective is the generation of models to predict results based on historical examples of said variables. It is also the relationship between big data, data science, machine learning, deep learning and artificial intelligence[8]

The objective of this article is to validate the predictive technique of Machine Learning in a neutrosophic environment[9, 10] that allows demonstrating the probability of the return on investment that a candidate investor will obtain with respect to a certain business plan previously registered in the mobile application by a MSE. For this, the neutrosophic TOPSIS method and the new NEBS collaborative metamodel, also developed in this research, were applied. In this way, it is expected that an investor can make the decision to finance a MSE with a positive decision, which will allow closing gaps in the growth of micro and small companies in Peru.

2. Preliminaries

The NEBS methodology presents a life cycle for projects based on Machine Learning and for the development of mobile applications with prediction techniques. It is based on the proposals of successful methodologies such as CRISP-DM, MOBILE-D and SCRUM. The NEBS methodology is divided into six phases and its use will allow people who wish to invest in a ***MSE*** project plan to adopt new and better knowledge for decision-making, with the aim of benefiting both the investor regarding its financial area as the ***MSE*** putting into practice its project plan.

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The phases of the NEBS Collaborative Metamodel are:

Phase 1: Knowing the business. In this first phase, the business criteria are established in order to understand in detail the objectives and requirements of the project that will be developed aimed at improving the business. In this phase, 4 activities will be carried out and the document called "Project Plan" is to be delivered.
Phase 2: Data treatment. In this phase, the collection and verification of the quality of the data is carried out initially; Great care must be taken in this phase, because the data must be selected, the database will be formatted and aligned to the business objective.
Phase 3: Perfecting Machine Learning. In this phase, the Machine technique or techniques that add value to the business objective are selected and therefore, data cleaning must be aligned with the objective described in Phase 1 NEBS. Once completed, we will proceed to build, integrate, and establish the format that corresponds to the data. For this phase, the Learning deliverable that will be used to meet the business objective, the selection of the Machine Learning technique will depend on the evaluation that is carried out, and the ML technique that is counted with more precision, will be the one that should be use for business. For this phase the deliverable will be the completed prediction algorithm.
Phase 4: Mobile development. In this phase, the mobile application will be developed, the input that will be used will be the complete prediction algorithm; To do this, the scope must be defined and then the project will be established, proceeding to its configuration for the iterations by configuration, by planning day, by workday and by release day. For this phase, the deliverable will be the developed mobile application.
Phase 5: Review and retrospective. In this phase, the deliverable of Phase 4 will be reviewed, for this, the sprint must be validated with its respective retrospective; if the development is satisfactory, they will be socialized.
Phase 6: Socialization. This is the final phase, at this stage the roles such as ***MSE*** and as a prospective investor of a business plan will begin, as part of the socialization the consultation will be carried out in the mobile application, which must show the results for the decision of respective decisions.
Next, the stages corresponding to the applied research method (NEBS methodology) for the development of a Machine Learning Solution aimed at optimizing financing in ***MSEs*** in Peru are presented.
Operationalization of Variables:Regarding this scientific article, the starting point was to find the variables for its respective development. The independent variable used is Machine Learning. Likewise, the dependent variable used is Financing in micro and small companies in Peru. The indicators of the dependent variable were identified, which is presented in Table 2 below.

Table 1: Operationalization of Variables – Dependent Variable Indicators

Indicator	Index	Unit of measurement	Observation unit
Amount of financing obtained per week	[0 - 5]	Amount of financing obtained/week	Manual registration.
Requirements assessment time per week	[1 - 158]	Hours/week	Reports
Number of complaints per week	[1-2000]	Number of complaints/week	Reports
Number of formal sources used per week	[0 - 6]	Number of formal sources/week	Manual report

Research design: This paper will make use of a Posttest Design only and a control group, where the manipulation of the independent variable reaches only two levels: presence and absence.

RGe	X	O1
RGc	--	o2

Where:
R = Random selection of the elements of the Group.
Ge = Experimental group: Study group to which the stimulus will be applied.
Gc = Control group: Control group to which the stimulus will not be applied.
O1 = Post-test data for VD indicators: Measurements in the experimental group.
O2 = Post-test data for VD indicators: Measurements in the control group.
X = Machine Learning: Stimulus or experimental condition.
- - = Lack of stimulus or experimental condition.

For the experimental Group (Ge), its elements have been chosen randomly (R), formed by the Financing process in ***MSEs***, to which the Machine Learning (X) stimulus was applied, then the results are recorded for each one of the indicators of the dependent variable (O1). A second group (Gc), with elements also chosen randomly, made up of the Financing process in ***MSEs***, is not given any stimulus, serving only as a control group; Simultaneously, the results for each of the indicators of the dependent variable (O2) are recorded.

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The two groups are randomly constituted and are statistically representative. Both in the absence and in the presence of the proposed stimulus. In this way, internal and external validity is achieved in the research.

Universe and Sample: The universe is made up of all the Financing processes in micro and small companies worldwide. Because the number of the aforementioned processes cannot be known or determined, the size of the universe N = Undetermined. The sample is the Financing process in **MSEs** in Peru, where n = 30. Sampling Type: Random.

Data Collection Procedures: In this paper, the data collection procedure was carried out by direct and spontaneous or unstructured observation, likewise, databases and cloud storage were consulted.

Statement of Hypotheses: In this article the following hypotheses were raised:

H1: If Machine Learning is used through the new NEBS methodology, then the amount of financing obtained increases.

H2: If Machine Learning is used through the new NEBS methodology, then the requirements evaluation time decreases.

H3: If Machine Learning is used through the new NEBS methodology, then it reduces the number of complaints.

H4: If Machine Learning is used through the new NEBS methodology, then the number of formal sources used increases.

For the contrasting of the hypotheses, the following solution has been proposed:

$\mu1$= Population mean (H1, H4) in the Gc Posttest.

$\mu2$= Population mean (H1, H4) in the Posttest Ge.

Where: Ho:$\mu1 \geq \mu2$

Ha: $\mu1 < \mu2$

Besides:

$\mu1$= Population mean (H2, H3) in the Gc Posttest.

$\mu2$= Population mean (H2, H3) in the Ge Posttest.

Where: Ho: $\mu1 \leq \mu2$

Ha: $\mu1 > \mu2$

Finally, the hypotheses were confirmed using the Student's T test and the specialized software Minitab. Data normality tests, descriptive statistical analysis and inferential statistical analysis and hypothesis testing were performed.

After carrying out an exhaustive and systematic review of the models, a new model was developed whose flowchart is shown in Figure 1.

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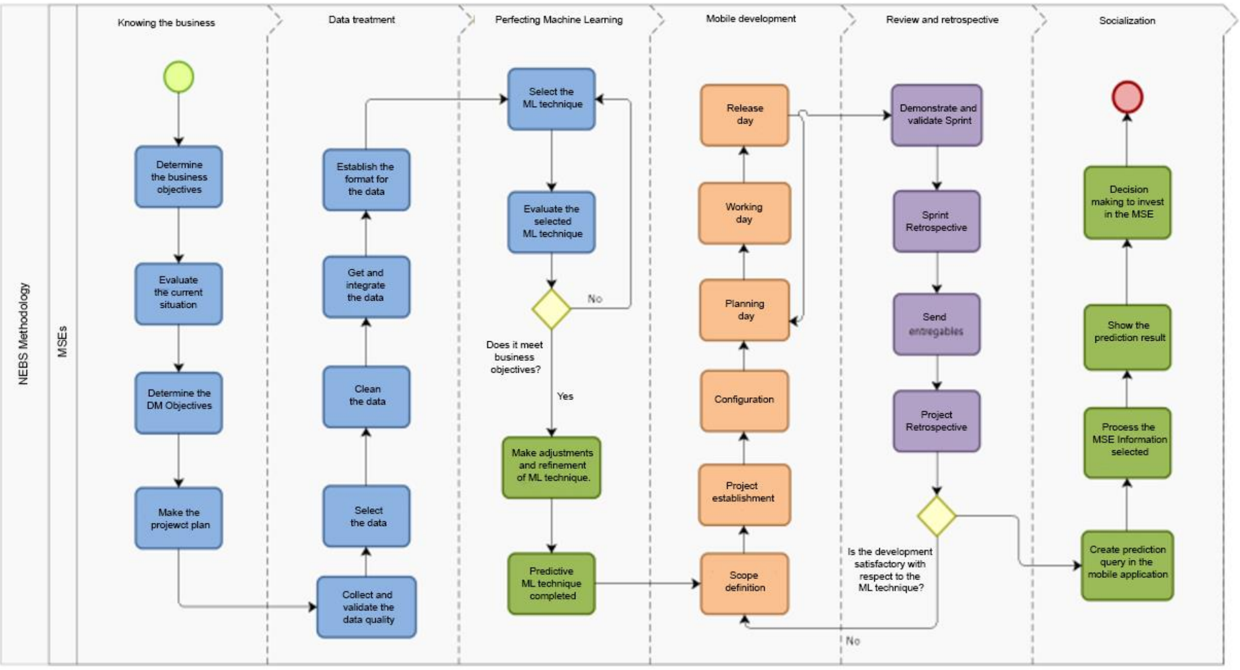
Methodology legend:



CRISP-DM
MOBILE-D
scrum
CONTRIBUTIONS

Figure 1: NEBS methodology

3. Methods

For the practical validation of the model, the technique of Order of Preference by Similarity to the Ideal Solution, TOPSIS, was used. This technique is a very common and useful method for solving decision-making problems in certain and uncertain environments. In this method k-represents the decision makers, m the alternatives, and n the criteria, where k evaluates the importance of m-alternatives under n-criteria and presents a ranking of n-criteria in relation to the statement converted into neutrosophic values[11-13]. Decision makers often use a set of weights where W = (most important, important, medium, unimportant, very unimportant) and the importance weights are based on the unique neutrosophic values for the defined terms [14, 15].The technique can be exhaustively consulted at [16]. Table 1 shows the linguistic terms defined for this technique.

Table 2: Neutrosophic values of the linguistic terms. Source:[17]

Linguistic term	SVNSs
Very Low Influence/ (VLI)	(0.9;0.1;0.1)
No Influence/(NI)	(0.75;0.25;0.20)
Medium Influence/(MI)	(0.50;0.5;0.50)
Influence/(I)	(0.35;0.75;0.80)
Very High Influence/(VHI)	(0.10;0.90;0.90)

On the other hand, the TOPSIS method for SVNS consists in adopting that A = $\{\rho_1, \rho_2, \dots, \rho_m\}$ is a set of alternatives, and G = $\{\beta_1, \beta_2, \dots, \beta_n\}$ is a set of criteria.

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On the other hand, the TOPSIS method for SVNS used consists of the following: Assuming that A={ρ1,ρ2,…,ρm } is a set of alternatives and G={β1,β2,…,βn } is a set of criteria, the following steps will be carried out:

Step 1: Determine the relative importance of the experts: The experts evaluate according to the linguistic scale shown in Table 1, and the calculations are made with their associated SVNN. Le$A_t = (a_t, b_t, c_t)$ be the SVNS corresponding to the t-th decision maker $(t = 1, 2, \dots, k)$. The following formula is used to calculate:

$$\delta_t = \frac{a_t + b_t\left(\frac{a_t}{a_t+c_t}\right)}{\sum_{t=1}^{k} a_t + b_t\left(\frac{a_t}{a_t+c_t}\right)} \quad where: \delta_t \geq 0 \; and \sum_{t=1}^{k} \delta_t = 1 \tag{7}$$

Step 2: Construction of the aggregate single value neutrosophic decision matrix: This matrix is defined by $D = \sum_{t=1}^{k} \lambda_t D^t$, where $d_{ij} = (u_{ij}, r_{ij}, v_{ij})$and is used to aggregate all the individual evaluations. It is calculated as the aggregation of evaluations given by each expert, using the weights of each one with the help of equation 7. In this way, a matrix D = $(d_{ij})_{ij}$ is obtained, where each d_{ij} is a SVNN $(i = 1,2,..,m;\ j = 1,2,\dots,n)$..

Step 3: Determination of the Weight of the Criteria: Assume that the weight of each criterion is given by $W = (w_1, w_2, \dots, w_n)$, where w_j denotes the relative importance of the criterion $\lambda_t w_j^t = (a_j^t, b_j^t, c_j^t)$. Si is the evaluation of the criterion λ_t by the t-th expert. Equation 7 is then used to aggregate the w_j^t with the weights λ_t [18].

Step 4: Construction of the weighted average of single values neutrosophic decision matrix regarding the criteria.

$$D^* = D * W, where\ d_{ij} = (a_{ij}, b_{ij}, c_{ij}) \tag{8}$$

Step 5: Calculation of the positive and negative SVNN ideal solutions: The criteria are classified as cost-type or benefit-type. Let G_1 be the set of benefit-type criteria and G_2 the cost-type criteria. The ideal alternatives will be defined as follows [19]:

The positive ideal solution that corresponds to G_1.

$$\rho^+ = a_{\rho+w}(\beta_j), b_{\rho+w}(\beta_j), ac_{\rho+w}(\beta_j) \tag{9}$$

The negative ideal solution that corresponds to G_2.

$$\rho^- = (a_{\rho-w}(\beta_j), b_{\rho-w}(\beta_j), ac_{\rho-w}(\beta_j)) \tag{10}$$

Where:

$$a_{\rho+w}(\beta_j) = \begin{cases} max_i a_{\rho iw}(\beta_j), si\ j\epsilon G_1 \\ min_i a_{\rho iw}(\beta_j), si\ j\epsilon G_2, \end{cases} \qquad a_{\rho-w}(\beta_j) = \begin{cases} min_i a_{\rho iw}(\beta_j), si\ j\epsilon G_1 \\ max_i a_{\rho iw}(\beta_j), si\ j\epsilon G_2, \end{cases}$$

$$b_{\rho+w}(\beta_j) = \begin{cases} max_i b_{\rho iw}(\beta_j), si\ j\epsilon G_1 \\ min_i b_{\rho iw}(\beta_j), si\ j\epsilon G_2, \end{cases} \qquad b_{\rho-w}(\beta_j) = \begin{cases} min_i b_{\rho iw}(\beta_j), si\ j\epsilon G_1 \\ max_i b_{\rho iw}(\beta_j), si\ j\epsilon G_2, \end{cases}$$

$$c_{\rho+w}(\beta_j) = \begin{cases} max_i c_{\rho iw}(\beta_j), si\ j\epsilon G_1 \\ min_i c_{\rho iw}(\beta_j), si\ j\epsilon G_2, \end{cases} \qquad c_{\rho-w}(\beta_j) = \begin{cases} min_i c_{\rho iw}(\beta_j), si\ j\epsilon G_1 \\ max_i c_{\rho iw}(\beta_j), si\ j\epsilon G_2, \end{cases}$$

Step 6: Calculation of the distances to the positive and negative SVNN ideal solutions: With the equations 9 and 10 the following equations are calculated:

$$d_i^+ = \left(\frac{1}{3}\sum_{j=1}^{n}\left\{(a_{ij} - a_j^+)^2 + (b_{ij} - b_j^+)^2 + (c_{ij} - c_j^+)^2\right\}\right)^{\frac{1}{2}} \tag{11}$$

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$$d_i^- = \left(\frac{1}{3}\sum_{j=1}^{n}\left\{\left(a_{ij}-a_j^-\right)^2+\left(b_{ij}-b_j^-\right)^2+\left(c_{ij}-c_j^-\right)^2\right\}\right)^{\frac{1}{2}} \tag{12}$$

Step 7: Calculation of the Coefficient of Proximity (CP): The CP of each alternative is calculated to the positive and negative ideal solutions [20].

$$\tilde{\rho}_j = \frac{s^-}{s^+ + s^-} \tag{13}$$

Where: $.0 \leq \tilde{\rho}_j \leq 1$

Step 8: Determining the order of the alternatives: Alternatives are ranked according to what was achieved by $\tilde{\rho}_j$. The alternatives are ordered from greatest to least, with the condition that $\tilde{\rho}_j \rightarrow 1$ is the optimal solution [21], based on the results of machine learning methodologies evaluated.

4. Case study

For the case study on the use of Machine Learning for financing in the ***MSEs*** of Peru through the NEBS methodology, 6 phases were designed: Knowing the Business, Data Processing, Perfecting Machine Learning, Mobile Development, Review and retrospective and finally Socialization. Likewise, the collaborative metamodel identifies and establishes the stages and activities necessary to develop a Machine Learning solution in a mobile application to use ***MSEs*** and investor prospects.

Knowing the Business: In this phase, the project plan is analyzed, which allows to know the business in more depth to have clarity of the goals, objectives and requirements that must be met for the correct development of the project, with the purpose of identifying, determining, evaluating and approve business objectives with a strategic edge.

Data treatment: In this phase, the data is shown for its respective treatment, the source of the data provider for the training of the Machine Learning model to be implemented is selected. In the transformation phase, the selection, purification, and cleaning of data is carried out, in accordance with the business objectives and Machine Learning needs. Likewise, the calculation of new variables necessary for the training of the Machine Learning model is carried out. Finally, in the loading stage, all the data is formatted, according to the types of data they present, and the master tables of the generated model are recorded.

Perfecting Machine Learning: The selected ML technique for its respective training and completeness is shown; Once the data processing process has been executed, the dependent and independent variables are standardized, their transformation, division, scaling, optimization, generation, in order to proceed with the adjustment of the ML technique through training; Finally, the results are displayed.

Mobile Development: From this stage, users will be able to access the functionalities developed by the project through a mobile application, whose main integrations are obtaining information from regulatory entities of micro and small companies in Peru, as well as from central risk and the financial entities that are the banks. The project will be divided into the following functionality containers. The first mobile container called "InvestApp" has all the functionalities developed for the application. The second REST API container called "Invests API" serves for the integration and orchestration of functionalities, as well as to support the requirements of the mobile application. Finally,

Review and Retrospective: A demonstration is carried out for the group of interested parties, where the functionalities developed by the project team are shown. In this phase, the different opinions are received for the acceptance or improvement of the development, with the purpose of fulfilling the requirements and exceeding the expectations.

Socialization: The mobile application is socialized with the target audience, showing its benefits.

5. Results

For the validation of the proposed NEBS methodology, the neutrosophic TOPSIS technique was used, through the application of the 8 steps that comprise it. For this, 10 experts with demonstrated knowledge of data analysis and construction and development of analytical models were selected. These were also selected for having previous experiences validating machine learning models for financial institutions. The criteria considered in the research development are the following: effectiveness, feasibility, complexity, and profitability. Other data analysis and machine learning methodologies such as SCRUM, CRISP-DM and Mobile-D were considered as alternatives, which have in common the fact that they are proven methodologies for data analysis and machine learning.

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As a first step, the weight of the decision-making groups was determined. Then, the five heaviest were selected. The results are shown in Table 3:

Table 3: Determination of the weight of the main components.

	Group 1	Group 2	Group 3	Group 4	Group 5
Importance vector λ_t	(0.9;0.1;0.1)	(0.9;0.2;0.1)	(0.9;0.1;0.3)	(0.9;0.4;0.3)	(0.75;0.25;0.2)
Numerical importance	0.190401259	0.207710464	0.187516391	0.230789405	0.183582481

Next, it was necessary to take into account the consideration of these groups, who were asked to fill out a questionnaire to evaluate alternatives against criteria according to the neutrosophic linguistic scale determined in section 2 (see Table 1), which gave way to the elaboration of the unique value criteria matrix. The results shown below in Table 4 are the result of the mode of the respondents' classifications.

Table 4: SVNS aggregate decision weighted matrix.

Alternatives	Criterion 1	Criterion 2	Criterion 3	Criterion 4
NEBS	(0.69149;0.85283;0.84875)	(0.66556;0.42762;0.41631)	(0.50509;0.7944;0.7608)	(0;0.67632;0.59826)
Scrum	(0.66897;0.33103;0.30027)	(0.4306;0.5694;0.53603)	(0.61515;0.39143;0.36349)	(0;0.2;0.2054)
CRISP-DM	(0.13688;0.88636;0.89449)	(0.16683;0.87155;0.88509)	(0.15455;0.88173;0.89483)	(0;0.2777;0)
Mobile-D	(0.20749;0.8445;0.86605)	(0.24899;0.76511;0.76212)	(0.37789;0.79764;0.60327)	(0;0.3001;0)

Once the matrix is determined, weighted aggregate decision of SVNS, we proceeded to find the results corresponding to the values of the proximity coefficient that served as the basis for determining the ranking of machine learning methodologies for the optimization of the financing of SMEs, and finally the ideal values and distances positive and negative. The results corresponding to the values of the proximity coefficient are shown in table 5 in such a way that the NEBS methodology is validated as the alternative to apply for the optimization of the financing of SMEs, taking into account their characteristics in terms of effectiveness, feasibility, complexity and profitability.

Table 5: Ranking of components according to Proximity Coefficient (CP).

Alternatives	d+	d-	PC	Order
NEBS	0.4356423	0.67375	0.60732	1
Scrum	0.6206401	0.90453	0.59307	2
CRISP-DM	0.8830175	0.4575	0.34129	4
Mobile-D	0.7143758	0.51422	0.41854	3

Experimental Results: The measurements were made in two groups called Control Group and Experimental Group, taking advantage of techniques and instruments, 30 values were obtained for each of the indicators established in this investigation. The results are specified below in Table 6.

Table 6: Post-test results of the Gc and Post-test of the Ge for the indicators

I1. Amount of financing	I2. Evaluation time requirements	I3. Number of complaints	I4. Number of formal sources used

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	(Financing/ Week)		(Hour)		(Complaints/week)		(Sources/ week)	
No.	Gc post-test	Ge posttest	Gc post-test	Ge posttest	Gc post-test	Ge posttest	Gc post-test	Ge posttest
1	4	6	41	6	1358	157	2	15
2	3	10	60	18	711	301	4	29
3	3	5	155	9	452	98	0	21
4	5	4	152	7	502	75	3	18
5	2	7	88	4	608	121	5	30
6	2	6	110	1	1255	59	1	27
7	4	7	65	5	643	83	1	17
8	2	6	59	9	542	124	1	10
9	2	8	109	5	1462	168	6	31
10	5	12	157	2	701	101	4	17
11	1	2	40	1	935	327	2	16
12	1	2	16	6	681	268	2	24
13	3	6	59	8	752	299	5	35
14	5	8	108	14	654	302	1	30
15	4	1	154	8	782	158	2	19
16	3	7	82	7	1245	421	4	23
17	1	6	107	5	864	247	0	20
18	3	5	131	9	1257	347	0	31
19	2	7	41	4	824	129	3	14
20	1	10	35	2	974	241	5	15
21	2	5	18	5	912	164	0	18
22	1	4	64	12	875	210	6	20
23	1	9	111	9	1655	52	2	26
24	0	6	61	15	1185	435	4	33
25	5	8	88	16	842	421	2	35
26	3	6	135	2	1587	324	3	27
27	0	8	85	15	875	256	3	24
28	2	11	41	6	540	68	5	19
29	4	8	60	18	1001	76	1	16
30	3	9	155	9	1058	191	0	3. 4

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Normality Tests: Using the Minitab software, the Normality Test is performed for each of the indicators, which allows you to compare the Empirical Cumulative Distribution Function (ECDF)of the data with the expected distribution if the data were normal. Tests were performed for four indicators, which are described below:

- Indicator 1 Amount of financing obtained: The Normality Test for the indicator Quantity of financing obtained per week yielded a result that indicates that, for Gc and Ge, the values of p (0.088 and 0.372) are greater than α (0.05), therefore, the values of the indicator have a normal behavior.
- Indicator 2 Requirements evaluation time: Evidence of the Normality Test for the indicator Requirements evaluation time per week. The result indicates that, for Gc and Ge, the values of p (0.235 and 0.109) are greater than α (0.05), therefore, the values of the indicator have a normal behavior.
- Indicator 3 Number of complaints: La Normality Test for the Number of complaints per week indicator indicates that, for Gc and Ge, the values of p (0.132 and 0.105) are greater than α (0.05), therefore, the values of the indicator have a behavior Normal.
- Indicator 4 Number of formal sources used: La Normality Test for the indicator Number of formal sources used per week indicates that, for Gc and Ge, the p values (0.071 and 0.124) are greater than α (0.05), therefore, the indicator values have normal behavior.

5.1 Discussion of Results with Descriptive Statistics

Tables 7 and 8 show the results after a descriptive analysis of the data, which has made it possible to clearly determine a set of patterns.

Table 7: Descriptive Statistics Results

Sample	no	Half	StDev	AD	p-value
I1: Gc post-test	30	2,533	1,525	1,635	1,088
I1: Ge posttest		6,633	2,566	0.385	0.372
I2: Gc posttest	30	86.8	42.66	0.466	0.235
I2: Ge posttest		7.8	4,752	0.599	0.109
i3: Gc posttest	30	924.4	324.0	0.564	0.132
i3: Ge posttest		207.4	116.5	0.606	0.105
i4: Gc posttest	30	2,567	1,888	0.673	0.071
i4: Ge posttest		23.13	7,109	0.574	0.124

According to the results of the Anderson Darling normality test, the p-value is > α (0.05); therefore, the normal behavior of the data was confirmed for analysis. It was observed that, with a confidence level of 95%, the mean and the standard deviation revealed normal results in the indicator data:

Table 8: Summary of results for the indicators

Sample	n	95% confidence intervals for the mean	Kurtosis	Asymmetry	Q3
I1: Ge posttest	30	5.6751 - 7.5915 financing	0.162575	-0.164979	8.0000
I2: Ge posttest	30	6.0257 - 9.5743 hours	-0631747	0.517598	11.2500
I3: Ge posttest	30	163.93 - 250.94 complaints	-0.900821	0.450082	301.25
I4: Ge posttest	30	20,479 - 25,788 sources	-1.13558	-0.164979	30,000

In summary, for each indicator in the Table it shows that around 95% of the values are within 2 standard deviations of the mean, Kurtosis indicates that there are values with very low peaks, Skewness indicates that most of the values are low, the 3rd Quartile (Q3) indicates that 75% of the values are less than or equal to this value.

For indicator I1: The results of show that the model used allows ***MSEs*** that use digital finance to be 7.5% more likely to be able to apply for new investment projects than those that do not, managing to obtain financing. Another result of the investigation about access to credit for the development of ***MSEs*** in the La Plata region and surroundings, expressed that 62 small and medium-sized companies obtained loans, however expressed that, in the region, ***MSEs*** have the particularity of not having easy access to bank financing.

Also, in their research, they have as a result that digital finance can effectively improve the value of strategic start-ups, which leads to obtaining credit financing to improve value and continue to grow. In the results ***MSEs*** obtain financing through the use of delayed payment through collaboration with the retailer and the financial provider, it is an access to financing seen from another perspective, but valid. It should be noted that the challenge of

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continuing to disseminate the use of Machine Learning, as a technological tool that allows supporting the growth of micro and small companies in the first instance in Peru and consecutively extrapolating the use in Latin America.
For indicator I2: he loan adjudication times for 68% correspond to the fast adjudication of the loans, 18% the adjudication was slow, with 10% very fast and only 5% responded that it was very slow.
For indicator I3: There is a very low percentage of reporting the crime of usury, in addition, given the harsh reality in Colombia, it is not reported for fear of direct and personal reprisals, because 16.9% of the Colombians' source of credit continues to be informal. On this regard, show results regarding complaints such as personal data fraud and illegal fintech loans when Fintech P2P loans are made in Indonesia.
here are complaints of money laundering and common fraud in the Malaysian banking sector, as well as several cases and attempts of internal and external fraud in banking institutions. Using cash is preferable to the alternative, which involves worse types of crimes committed in the absence of cash. Therefore, it is important that national security government entities carry out the pertinent actions on complaints regarding illegal loans, as well as raise awareness about the risks of obtaining loans through illegal financing sources to citizens and businessmen of all business sectors and sizes.
For indicator I4: Regarding the results presented above, 87.47% of micro and small businesses acknowledged having used financing sources such as partners, family members or friends, with the lowest percentage financing sources being banks, government entities and other unspecified sources.
Likewise, 79.37% of micro and small companies consider that their main source of financing is the income generated within the company. sing the multivariate probit model, the result is that micro and small companies use the following types of financing sources: 92.9% type 3F (founders, and their family and friends, and employees), 6.9% type Subsidies , 10% type Corporations, 14.7% type Public Banks, 16.2% type Private Banks, and 4.1% type Private Equity (VC and angel investors). On the research[22]It is reported that there are standard internal and external sources of financing, but there are also other sources of financing that SMEs can resort to, such as: credit from suppliers, credit cards from department stores, sale or rental of obsolete or non-obsolete assets. strategic, leasing of manufacturer assets, sponsorship, subsidies, and support from suppliers.
Microfinancing (crowdfunding) is a great source of financing for sustainable entrepreneurs. At the same time, there is a gap regarding the open data of formal financing sources, due to the non-existence of databases that contain information from various financing sources, to which the owners of micro and small companies in Peru and Latin America could access to request financing without having to resort to informal financing sources.

5.2 With Inferential Statistics: Hypothesis Test

Table 9 shows the values of the application of the statistical tests for the contracting of the hypotheses.

Table 9: Hypothesis Testing for Parametric Indicators

Sample	n	Ho	t-value	p-value
I1: Gc post-test I1: Ge posttest	30	$\mu 1 \geq \mu 2$	-7.52	0,000
I2: Gc post-test I2: Ge posttest	30	$\mu 1 \leq \mu 2$	10.08	0,000
I3: Gc post-test I3: Ge posttest	30	$\mu 1 \leq \mu 2$	11.40	0,000
I4: Gc post-test I4: Ge posttest	30	$\mu 1 \geq \mu 2$	-15.32	0,000

The results of the parametric tests of the 4 proposed hypotheses indicate that since all the p values are less than α (0.05), the results provide sufficient evidence to reject the null hypotheses (Ho), and therefore the alternative hypotheses were true. The tests turned out to be statistically significant.
It is necessary to mention that, due to the scarcity of research related to financing in Micro and Small Enterprises, the comparison of the validation of the hypotheses has been limited. Therefore, the findings of this developed research provide information on the financial sector, being specifically for Micro and Small Companies in Peru, which involves improving their indicators regarding obtaining better financing for business growth. Also, it is important to address the challenges related to the elimination of informal financing sources in Peru and Latin America.

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6. Conclusions

The Neutrosophy allowed validating the collaborative metamodel NEBS as a Machine Learning solution to optimize the financing process in micro and small enterprises in Peru. The experimental results obtained allowed concluding that the application of Machine Learning in the different business sectors has had great relevance due to the great contribution generated, which translates into the reduction of time and cost, in addition, it will allow the international community to have an endless number of applications to solve their most immediate and complex problems. It has been proven that the use of this metamodel has also increased the amount of financing obtained by micro and small enterprises in Peru. Likewise, it is notorious that the successful development of Machine Learning reduced the number of complaints filed by the owners of micro and small businesses in Peru. Therefore, it is proven that the use of the Machine Learning solution brought as a benefit the increase in the number of formal sources used, which has allowed micro and small businesses in Peru to continue providing jobs to many employees and the new methodology has allowed the efficient development of the Machine Learning solution. Its considerable contribution to innovation in different areas and services will allow for obtaining scientific results and predicting behaviors in the financial sector. However, this scientific paper has limitations due to the complexity of Machine Learning developments as it is a constantly evolving technology that limits how it can be used effectively. Therefore, future experimental research should consider the most current published articles on Machine Learning in the financial sector, thus allowing to contribute and disseminate the great importance of this field among people and especially among other business sectors in Peru and Latin America, a simple and common way to make decisions quickly, safely, without errors and based on financial data.

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