

Digital Object Identifier: 10.24054/rcta.v1i43.2801

Tool for estimating the reliability of prospective clients in the financial sector through the use of sentiment analysis and fuzzy logic techniques

Herramienta de estimación de la confiabilidad de clientes potenciales del sector financiero mediante el uso de técnicas de análisis de sentimientos y lógica difusa

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Received: November 8, 2023. Accepted: January 10, 2024. Published: March 01, 2024.

How to Cite: C. D. Moreno Peña, A. Vega Yanes, and G. E. Chanchi Golondrino, "Tool for estimating the reliability of prospective clients in the financial sector through the use of sentiment analysis and fuzzy logic techniques", RCTA, vol. 1, no. 43, pp. 24–34, Mar. 2024. Recovered from <u>https://ojs.unipamplona.edu.co/index.php/rcta/article/view/2801</u>

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Abstract: Colombia faces challenges in access to education for low-income people, generating limited job opportunities and high levels of poverty. This situation contributes to the increase of defaulters in the financial sector, complicating the identification of client trustworthiness. This paper proposes a tool to estimate the trustworthiness of financial clients in Cartagena, Colombia, through sentiment analysis and fuzzy logic, using Pratt's iterative research pattern. The tool collects data from the lender on the perceived trustworthiness of the borrower and applies sentiment analysis to the borrower through a survey, the results are fuzzified to determine perception levels, and 36 inference rules are used to obtain the borrower's trustworthiness. A case study demonstrated that the tool provides an adequate assessment of financial customer trustworthiness, matching the inputs and opinion of an expert lender.

Keywords: Sentiment analysis, reliability, fuzzy-logic, perception, financial sector.

Resumen: Colombia enfrenta desafíos en el acceso a la educación para personas de bajos recursos, generando limitadas oportunidades laborales y elevados niveles de pobreza. Esta situación contribuye al aumento de morosos en el sector financiero, complicando la identificación de la confiabilidad de los clientes. Este artículo propone una herramienta para estimar la confiabilidad de clientes financieros en Cartagena, Colombia, mediante análisis de sentimientos y lógica difusa, utilizando el patrón iterativo de investigación de Pratt. La herramienta recopila datos del prestamista sobre la percepción de confianza hacia el prestatario y aplica análisis de sentimientos al prestatario a través de una encuesta, los resultados son fuzzificados para determinar los niveles de percepción y se utilizan 36 reglas de inferencia para obtener la confiabilidad del prestatario. Un caso de estudio demostró que la herramienta proporciona una evaluación adecuada de la confiabilidad del cliente



financiero, coincidiendo con las entradas y la opinión de un prestamista experto.

Palabras clave: Análisis de sentimientos, Confiabilidad, Lógica difusa, Percepción, Sector financiero.

1. INTRODUCTION

Colombia is globally recognized as the happiest country in the world, according to various surveys, attributable to the playful and carefree behavior of its residents [1]. This element of playfulness and nonchalance, coupled with the country's low social performance and educational quality [2], where individuals with fewer resources face barriers to education from an early age [3]–[5], results in them being unable to pursue decently paying jobs as adults, consequently forcing them into poverty [6]-[8]. This situation, guided by the so-called "indigenous shrewdness" [9], contributes to Colombia becoming one of the countries with the highest rates of defaulters in Latin America, based on data from the Latin American Federation of Banks (Felaban) [10], [11]. In 2018, Colombia held the highest number of registered defaulters in banks in Latin America [12] and according to the National Comptroller General's Office, there are 1.1 million defaulters in Colombia with a collective debt exceeding 117 trillion Colombian pesos [13]. If there exists such a substantial number of individuals in Colombia failing to meet their financial obligations to both banking institutions and the government, both of which have the authority to pursue legal actions against defaulters [14], [15], it is evident that the number of defaulters is even higher in the case of informal loans.

Due to the high volume of delinquent debtors in the country, decision-making in the financial sector and among informal lenders has become a challenge [16], [17]. This is considering the need to predict the creditworthiness of clients and determine who is granted financing, which is a crucial skill for the success of these operations [18], [19]. Traditionally, both financial institutions and informal lenders have employed risk assessment techniques to identify reliable clients [18], [20]. However, these techniques are not always accurate and can be influenced by external factors, such as incorrect, imprecise, or missing information [21]. Therefore, it is essential for the financial sector to have decision support tools that enable the identification of reliable clients, thus reducing the risk of unpaid loans and, consequently, capital losses.

In accordance with the aforementioned, this study proposed a contribution in the form of a software

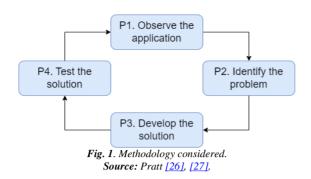
tool based on fuzzy logic and sentiment analysis. This tool takes as inputs the perceived level of trust by the lender, the perception of the borrower's responsibility, and the perception of the borrower's reliability. Based on these inputs, the output is determined as the degree of borrower reliability. To obtain these data, a structured interview was utilized as the method of information collection, as it allows for reliable and organized results due to the standardization provided by this interview modality [22]. Meanwhile, sentiment analysis techniques are employed in this research for analyzing the polarity of the borrower's responses. In this regard, these techniques can be defined as a branch of affective computing, which enables the automatic extraction of subjective information expressed in texts, allowing the identification of positive or negative connotations present in them [23], [24]. Finally, fuzzy logic was used to determine the degree of borrower reliability. Fuzzy logic can be understood as a branch of artificial intelligence based on multivalued logic that mathematically represents uncertainty values, providing formal tools for their study. This enables the classification of ambiguous, imprecise, or vague values [25].

The rest of the paper is organized as follows: Section 2 introduces the methodological phases considered for the development of this research. In Section 3, the results obtained in this study are presented, which include the development of a tool for estimating the reliability of financial clients using sentiment analysis and fuzzy logic technologies. Additionally, the verification and validation of the tool's proper functioning are demonstrated through a case study conducted with financial client data from the city of Cartagena. Finally, in Section 4, conclusions and future work arising from this research are presented.

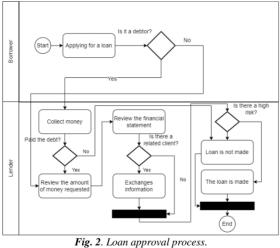
2. METHODOLOGY

The current applied research was conducted using the iterative research model proposed by Pratt [26], [27], as illustrated in Figure 1. This methodology consists of four phases: observe the application, identify the problem, develop the solution, and test the solution.





In the first phase of the methodology, technologies and sentiment analysis techniques were explored, along with methods for assessing reliability in individuals. Likewise, a characterization of the loan granting processes in informal lenders and financial companies in Cartagena was developed, finding that the loan granting process involves two actors: the borrower, who is the person requesting the money, and the lender, who is the person to whom the money is requested. The process begins with the borrower having the need for a loan and contacting the lender. Subsequently, the lender verifies if the applicant has any previous debt; if so, they proceed to collect it before initiating a new loan. In the absence of a previous debt, the lender conducts a series of reviews of the borrower's financial background and economic situation to assess the risk in the loan. If it is not a high-risk situation, the loan proceeds. The aforementioned process is illustrated in Figure 2.



Source: Own.

Phase 2 of the methodology involved the design of the necessary process for estimating the reliability of financial clients. This process was divided into eight stages, including: questionnaire for lenders, questionnaire for borrowers, sentiment analysis, determination of perception levels, fuzzification, inference, and defuzzification. Finally, the stage of report generation or reporting is concluded, as depicted in Figure 3.

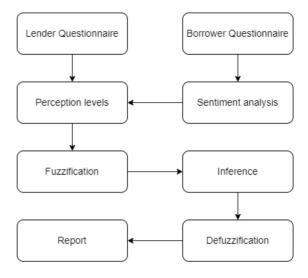


Fig. 3. Process defined for reliability estimation. Source: Own.

In the 'Lender Questionnaire' stage, the lender completes a form expressing their perception of the client's reliability, considering both the structured interview conducted with the borrower and the assessment of their background. The questions designed for this interview utilized a Likert scalemeasured question model [28]. Thus, from the information of this questionnaire, the variable prest_perc_client is obtained. Subsequently, in the 'Borrower Questionnaire' stage, the borrower selfreports their perception of reliability and payment responsibility using a perception questionnaire. Similarly, in the 'Sentiment Analysis' stage, sentiment analysis is performed using the ParallelDots library on responses provided by potential clients regarding their self-perception of reliability and responsibility in payments, and the polarities of the responses are obtained. Following this, in the 'Perception Levels' stage, the compound scoring formula proposed by the VADER library [29], is applied, through which the perception level is obtained concerning their responsibility in payments (client_perc_res variable) and their reliability (client_perc_conf variable), as shown in (1)

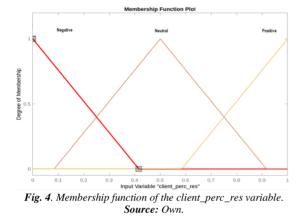
$$client_perc = \left(\frac{x}{\sqrt{x^2 + a}} + \frac{\sqrt{1 + a} - 1}{\sqrt{1 + a}}\right) * 100$$

$$Equation. \ 1. \ Perception formula for the variables client perc res and client perc conf.$$
(1)

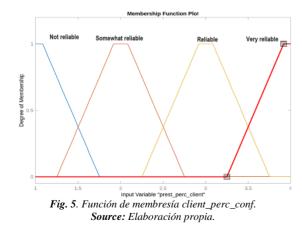
In equation (1), "x" refers to (2), which differentiates between positive and negative polarity.

$$x = pol_{pos} - pol_{neg}$$
(2)

During the 'fuzzification' stage, the conversion of input levels related to payment responsibility (client_perc_res) and customer reliability (client_perc_conf), obtained in the previous stage, is performed through a membership function. This function comprises fuzzy sets such as "Negative", "Positive", and "Neutral", as illustrated in Figure 4.



The lender's perception level regarding the borrower's reliability (prest_perc_client) is also converted from numerical values to values represented on a fuzzy scale within the system, using the membership function associated with this variable. This membership function encompasses the fuzzy sets: "Not reliable", "Somewhat reliable", "Reliable", and finally "Very reliable", as depicted in Figure 5.



In the 'inference' stage of the process, the inference rules designed in the Fuzzy Control Logic (FCL) language are applied to the different levels presented by the fuzzy sets associated with the variables client_perc_res. client perc conf, and loan perc client. The objective is to obtain the output level of the system corresponding to the estimating customer variable reliability (conf level). This variable includes in its membership function the fuzzy sets: 'Not reliable,' 'Somewhat reliable,' 'Reliable,' and 'Very reliable.' The result is a fuzzy system with 3 inputs and 1 output, comprising 36 inference rules, as illustrated in Table 1.

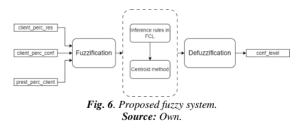
Table 1	1: De	fined	inferen	ce rules

Rule	Defined rules
	IF client_perc_res IS Negativo AND
1	client_perc_conf IS Negativo AND
	prest_perc_client IS Nada confiable
	THEN conf_level IS Nada confiable
	IF client_perc_res IS Neutral AND
•	client perc conf IS Negativo AND
2	prest_perc_client IS Nada confiable
	THEN conf_level IS Nada confiable
	IF client_perc_res IS Positivo AND
2	client_perc_conf IS Negativo AND
3	prest_perc_client IS Nada confiable
	THEN conf_level IS Nada confiable
	IF client_perc_res IS Negativo AND
	client_perc_conf IS Negativo AND
4	prest_perc_client IS Algo confiable THEN
	conf_level IS Nada confiable
5	IF client_perc_res IS Neutral AND
	client_perc_conf IS Negativo AND
	prest_perc_client IS Algo confiable THEN
	conf_level IS Nada confiable
	IF client_perc_res IS Positivo AND
	client_perc_conf IS Negativo AND
6	prest_perc_client IS Algo confiable THEN
	conf_level IS Algo confiable
	IF client_perc_res IS Negativo AND
_	client_perc_conf IS Negativo AND
7	prest_perc_client IS Confiable THEN
	conf_level IS Nada confiable
	IF client_perc_res IS Neutral AND
0	client_perc_conf IS Negativo AND
8	prest_perc_client IS Confiable THEN
	conf_level IS Algo confiable
	IF client_perc_res IS Positivo AND
•	client_perc_conf IS Negativo AND
9	prest_perc_client IS Confiable THEN
	conf_level IS Algo confiable
	IF client_perc_res IS Negativo AND
10	client_perc_conf IS Negativo AND
10	prest_perc_client IS Muy confiable THEN
	conf_level IS Nada confiable
	IF client_perc_res IS Neutral AND
	client_perc_conf IS Negativo AND
11	chem_perc_com is negativo AND
11	
11	prest_perc_client IS Muy confiable THEN conf_level IS Algo confiable
11	prest_perc_client IS Muy confiable THEN conf_level IS Algo confiable
	prest_perc_client IS Muy confiable THEN conf_level IS Algo confiable IF client_perc_res IS Positivo AND
11 12	prest_perc_client IS Muy confiable THEN conf_level IS Algo confiable

13	IF client_perc_res IS Negativo AND client_perc_conf IS Neutral AND prest_perc_client IS Nada confiable
	THEN conf_level IS Nada confiable IF client_perc_res IS Neutral AND
14	client_perc_conf IS Neutral AND
	prest_perc_client IS Nada confiable THEN conf_level IS Nada confiable
	IF client_perc_res IS Positivo AND
15	client_perc_conf IS Neutral AND prest_perc_client IS Nada confiable
	THEN conf_level IS Nada confiable
	IF client_perc_res IS Negativo AND
16	client_perc_conf IS Neutral AND prest_perc_client IS Algo confiable THEN
	conf_level IS Nada confiable
	IF client_perc_res IS Neutral AND client_perc_conf IS Neutral AND
17	prest_perc_client IS Algo confiable THEN
	conf_level IS Algo confiable
	IF client_perc_res IS Positivo AND client_perc_conf IS Neutral AND
18	prest_perc_client IS Algo confiable THEN
	conf_level IS Algo confiable IF client_perc_res IS Negativo AND
10	client_perc_conf IS Neutral AND
19	prest_perc_client IS Confiable THEN
	conf_level IS Algo confiable IF client_perc_res IS Neutral AND
20	client_perc_conf IS Neutral AND
20	prest_perc_client IS Confiable THEN conf_level IS Confiable
	IF client_perc_res IS Positivo AND
21	client_perc_conf IS Neutral AND
	prest_perc_client IS Confiable THEN conf_level IS Confiable
	IF client_perc_res IS Negativo AND
22	client_perc_conf IS Neutral AND prest_perc_client IS Muy confiable THEN
	conf_level IS Algo confiable
	IF client_perc_res IS Neutral AND
23	client_perc_conf IS Neutral AND prest_perc_client IS Muy confiable THEN
	conf_level IS Muy confiable
	IF client_perc_res IS Positivo AND client_perc_conf IS Neutral AND
24	prest_perc_client IS Muy confiable THEN
	conf_level IS Muy confiable
	IF client_perc_res IS Negativo AND client_perc_conf IS Positivo AND
25	prest_perc_client IS Nada confiable
	THEN conf_level IS Nada confiable IF client_perc_res IS Neutral AND
26	client_perc_conf IS Positivo AND
26	prest_perc_client IS Nada confiable
	THEN conf_level IS Nada confiable IF client_perc_res IS Positivo AND
27	client_perc_conf IS Positivo AND
	prest_perc_client IS Nada confiable THEN conf_level IS Algo confiable
	IF client_perc_res IS Negativo AND
28	client_perc_conf IS Positivo AND prest_perc_client IS Algo confiable THEN
	conf_level IS Algo confiable
	IF client_perc_res IS Neutral AND
29	client_perc_conf IS Positivo AND prest_perc_client IS Algo confiable THEN
	conf level IS Algo confiable

30	IF client_perc_res IS Positivo AND
	client_perc_conf IS Positivo AND
	prest_perc_client IS Algo confiable THEN
	conf_level IS Algo confiable
31	IF client_perc_res IS Negativo AND
	client_perc_conf IS Positivo AND
	prest_perc_client IS Confiable THEN
	conf_level IS Algo confiable
32	IF client_perc_res IS Neutral AND
	client_perc_conf IS Positivo AND
	prest_perc_client IS Confiable THEN
	conf_level IS Confiable
	IF client_perc_res IS Positivo AND
22	client_perc_conf IS Positivo AND
33	prest_perc_client IS Confiable THEN
	conf_level IS Muy confiable
	IF client_perc_res IS Negativo AND
24	client_perc_conf IS Positivo AND
34	prest_perc_client IS Muy confiable THEN
	conf_level IS Algo confiable
	IF client_perc_res IS Neutral AND
25	client_perc_conf IS Positivo AND
35	prest_perc_client IS Muy confiable THEN
	conf_level IS Confiable
	IF client_perc_res IS Positivo AND
26	client_perc_conf IS Positivo AND
36	prest_perc_client IS Muy confiable THEN

After the aforementioned steps, the process continues with the 'defuzzification' stage, wherein the fuzzy level obtained in the variable conf_level (after applying the inference rules) is converted into a numerical value. This conversion utilizes the center of gravity method. The resulting numerical value represents the perception level of customer reliability obtained by the system from the three inputs. The fuzzy system, composed of the fuzzification and defuzzification modules, is depicted in Figure 6. Finally, in the 'report' stage, the process concludes with the generation of a report on the perception level obtained by the system for the client, along with the inference rules activated during the defuzzification process.



Por último, en la etapa "informe", se finaliza el proceso al generar un reporte de con todos los niveles de percepción, de las reglas de inferencia y de la información del prestatario.

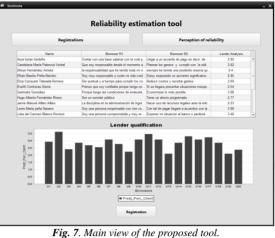
Continuing with the methodology, in phase 3, a set of techniques and technologies were initially selected for use in implementing the tool. Following this, the tool was constructed using the Java programming language, utilizing the JFuzzyLogic library for the implementation and definition of the established membership functions and inference rules, as well as the commons-math library for calculations. The javacsy library was employed for processing surveys conducted with lenders regarding their opinions on the reliability of borrowers under analysis, and with borrowers regarding their self-perceived reliability and responsibility with payments. Additionally, a Python script was utilized for sentiment analysis based on the borrower questionnaire responses, employing the Paralleldots library. Furthermore, the itextpdf library was used for generating reports in PDF format, the ifreechart library for creating graphs, and the JTattoo library for the tool's interface.

In the final phase (Phase 4) of the methodology, a dataset was assembled using Google Forms, consisting of responses to a questionnaire from financial clients in the city of Cartagena, Colombia. Subsequently, a case study was conducted based on this dataset to analyze and verify the proper functioning of the designed tool. The results were then compared with the opinion of an expert in the financial sector.

3. RESULTS

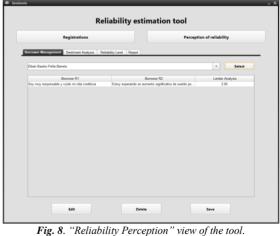
In this section, the results obtained in the current research are presented, including the description of the interfaces of the proposed fuzzy logic tool and the outcomes of the conducted study. The implementation of the tool for estimating the reliability of potential financial clients was developed in the Java programming language and features two views: the registration view and the reliability perception view. Throughout this section, the structure and operation of these views are presented. Upon initiating the tool, the registration view is displayed (see Figure 7), which is composed of a table storing the responses provided by borrowers to the conducted questionnaire, as well as a bar chart representing the lender's confidence level toward the borrower, and a button labeled "Register".





Source: Own.

Specifically, it is noted that the table presented in Figure 7 includes 4 columns. The first column displays the borrower's name, followed by the columns "Borrower R1" and "Borrower R2", where the borrowers' responses regarding their perception of trust and their responsibility in debt repayment are stored, respectively. Finally, the "Lender Analysis" column contains the rating provided by the lender regarding their perception of trust in the borrower. Once the data is loaded, the lender navigates to the "Reliability Perception" view (see Figure 8), which comprises 4 tabs: "Borrower Management", "Sentiment Analysis", "Reliability Level", and "Report".



ig. 8. "Reliability Perception" view of the tool. **Source:** Own.

Likewise, in Figure 8, there is an dropdown list containing the names of registered lenders, followed by the "Select" button, which allows fixing the borrower to carry out management and sentiment analysis processes. At the bottom of the "Borrower Management" tab, the "Edit" and "Delete" buttons are located, enabling the updating of borrower



information and the removal of their record, respectively. Finally, the "Save" button updates the persistence of borrower records. Similarly, to perform sentiment analysis on borrower responses, the lender selects the borrower and navigates to the "Sentiment Analysis" tab (see Figure 9).



Fig. 9. "Sentiment analysis" tab of the tool. Source: Own.

In the "Sentiment Analysis" tab of Figure 9, polarities (positive, Positive, and neutral) present in the borrower's responses are computed. Utilizing these polarities and employing Equation 1, the perception of sentiment (sent_perc) for each response is identified. The aforementioned information is displayed in the table in Figure 9 alongside the borrower's responses. Additionally, a bar chart illustrating the satisfaction level of sentiment analysis is presented, depicting the composite values of emotions found in the borrower's responses. With the data obtained from the sentiment analysis, the next step is to determine the confidence level of the borrower. For this purpose, the lender selects the "Reliability Level" tab, as depicted in Figure 10.

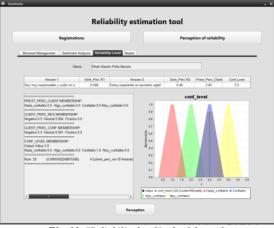


Fig. 10. "Reliability level" tab of the tool. Source: Own.

In the "Reliability Level" tab presented in Figure 10, the process of estimating the borrower's reliability level is carried out, utilizing fuzzy logic and the inference rules presented in Table 1. This results in the estimation of the borrower's reliability degree. Finally, the lender can view and download a report containing the obtained reliability level, the membership functions with fuzzified inputs and the fuzzified output, and the activated inference rules, as illustrated in Figure 11.

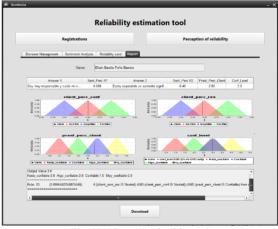


Fig. 11. "Report" tab of the tool. Source: Own.

3.1 CASE STUDY

To validate the functionality of the proposed fuzzy system, a case study was conducted, in which a dataset was compiled for a total of 20 borrowers from the city of Cartagena. The dataset is presented in Table 2, consisting of 6 columns ("User", "PPC", "CPR", "CPC", "CL" and "Rules"). The "User" column corresponds to the identifier of the analyzed borrower. In the "PPC" ("prest_perc_client")

column, the values of the confidence level perceived by the lender towards the borrower are recorded. Similarly, in the "CPR" ("client_perc_res") and "CPC" ("client_perc_conf") columns, the results of sentiment analysis on the lender's responses regarding their degree of responsibility towards payments and self-perceived reliability are displayed, respectively. The "CL" ("conf_level") column shows the confidence level generated by the fuzzy tool, and finally, in the "Rules" column, the activated inference rules are presented, determining the borrower's reliability level.

Tabla 2: Case study results

User	PPC	CPR	CPC	CL	Rules
					Rule 20
1	2.02	0.701	0.526	a 000	(0,518)
	2,92	0,701	0,536	3,000	Rule 32
					(0,282)
					Rule 20
		o -			(0, 195)
2	3,62	0,544	0,500	3,719	Rule 23
					(0,555)
					Rule 17
_					(0,525)
3	2,40	0,500	0,535	2,319	Rule 20
					(0,225)
					Rule 20
4	2,85	0,500	0,500	3,000	(0,900)
					Rule 17
					(0,090)
					(0,0)0) Rule 20
					(0,578)
5	2,69	0,676	0,57	2,850	Rule 29
					(0,090)
					(0,090) Rule 32
					(0,224)
					Rule 17
					(0,315)
					Rule 18
6	2,54	0,574	0,666	2,571	(0,198)
	2,51	0,071	.,		Rule 20
					(0,435)
					Rule 21
					(0,198)
7	3,08	0,500	0,500	3,000	Rule 20
	2,00	0,000	0,200	5,000	(1,000)
8	2,77	0,565	0,537	3,000	Rule 20
v	_,	0,000	0,007		(0,780)
	2,23	0,596	0,500	2,000	Rule 17
9					(0,770)
y					Rule 29
					(0,030)
	3,08				Rule 20
		0,500	0,614	3,000	(0,726)
10					(0,720) Rule 21
					(0,074)
					Rule 20
11	3,46			3,429	
		0,53	0,648		(0,435) Dula 21
					Rule 21
					(0,155)
					Rule 23 (0,315)



					_
					Rule 24
					(0,155)
12	3,08	0,581	0,500	3,000	Rule 20
14	5,00	0,501	0,500	5,000	(0,806)
					Rule 16
13	2,10	0,577	0,312	1,665	(0,251)
10	2,10	0,077			Rule 17
					(0,549)
14	2,85	0,500	0,494	3,000	Rule 20
	2,00	0,500	0,171	5,000	(0,900)
				3,139	Rule 20
15	3,31	0,505	0,543		(0,660)
	0,01	0,000	0,010		Rule 23
					(0,090)
					Rule 8
16	3,08	0,328	0,500	2,709	(0,213)
10	5,00	0,520	0,500		Rule 20
					(0,587)
17	3,23	0,500	0,500	3,000	Rule 20
	- , -	- ,	- ,	-)	(0,780)
	2,85	0,670	0,555	3,000	Rule 20
18					(0,592)
10					Rule 32
					(0,208)
19	2,09	0,532	0,500	2,000	Rule 17
20					(0,923) Rule 17
			0,429	2,281	(0,555)
					(0,333) Rule 20
	2,38	0,594			(0,195)
					(0,193) Rule 29
					(0,026)
					(0,020) Rule 30
					(0,026)
		Course	e: Own		(0,020)

Source: Own

According to the results obtained from the case study, it is observed that 14 borrowers were classified in the "Reliable" category, 5 borrowers were considered "Somewhat reliable" and only one borrower was classified as "Very reliable". Additionally, it was found that the client_perc_res values remain in an average range close to 0.549 and the clien_perc_conf values were close to the average value 0.522, these values indicate that borrowers have a moderate self-perception of trust and responsibility for payments. Finally, it was observed that the tool tends to agree with the expert lender's rating, obtaining reliability levels close to those reported by the borrower, but with small variations which allow us to demonstrate the relevance of the tool when evaluating the reliability of borrowers from their opinions.

4. CONCLUSIONS

This article addresses the need to assess the reliability of potential financial clients at the loan approval stage, proposing a contribution to the automation and simplification of this process. The proposed approach employs sentiment analysis to determine polarities, gathering perceptions from loan applicants' responses along with the lender's confidence estimation as inputs to the system. Subsequently, using a fuzzy logic system that incorporates the mentioned three inputs and 36 inference rules, it generates an output equivalent to the estimation of the borrower's confidence level. It is essential to emphasize that the solution presented in this article does not aim to replace the traditional method employed by informal lenders in Cartagena for making decisions about trust in new clients. Instead, it is conceived as a complement that enhances the lender's decision-making security, enriching the existing process.

This work made use of various open-source and freely available libraries, which can be considered for replication in the academic and financial sectors. In this regard, to implement the research approach, this tool was developed in Java and utilizes a Python script for sentiment analysis using the Paralleldots library. The identified polarities, along with the compound scoring formula used by the VADER library, establish the sentiment perception in borrower responses. These values, combined with the lender's confidence perception, become inputs that are fuzzified to form a fuzzy set estimating the confidence level. Finally, through inference rules, this fuzzy set is defuzzified to obtain the borrower's confidence level. All of this fuzzification and defuzzification process is achieved using the JFuzzyLogic library in Java.

In the case study developed with the 20 borrowers evaluated, it was observed that the tool tends to agree with the expert lender's rating, obtaining levels of reliability close to those expected by the lender, but with small variations which allow to demonstrate the relevance of the tool when evaluating the reliability of the borrowers from their opinions.

When comparing this research work with others of a similar nature, such as the proposal presented in [30], which focuses on determining satisfaction levels in usability tests, it is found that the combination of fuzzy logic and sentiment analysis proves effective in evaluating subjective data and determining perception levels. Both investigations employ a similar methodological approach, although they focus on different contexts, yet achieving equally satisfactory results. Therefore, one could anticipate further research utilizing the sentiment analysis combined with fuzzy logic approach for determining perception levels in other areas such as social research, public opinion, education, among others.

As a future work stemming from the current research, the implementation of an additional module for the tool is proposed, utilizing voice-to-

text transcription technologies to facilitate the collection of responses in structured interviews. This approach aims to make the gathering of borrower responses smoother, potentially yielding more candid responses for subsequent analysis.

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