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A Novel Approach for Commercial Opportunities Qualification Using the BANT Methodology under the Fuzzy Set Theory Framework.

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Abstract

Demand generation is crucial for organizations, supplying sales teams with well-qualified commercial opportunities. Despite the wide variety of existing opportunity qualification methodologies, the subjective nature of experts' final evaluation remains an obstacle to efficiency and productivity in the business process. This research investigated how Fuzzy Set Theory and Fuzzy Logic could be applied to the BANT methodology for qualifying commercial opportunities, aiming to replace these deliberative evaluations by experts to increase the sales cycle performance. A fuzzy inference system was developed to emulate the assessments of the experts. The analysis of the ratings obtained after processing a sample of commercial opportunities from 2022 and 2023 confirmed the system's effectiveness in aligning with expert perceptions. While the study indicated room for refinements in the model, the findings underscore the potential to streamline the qualification of opportunities and improve sales cycle performance.

Keywords: Fuzzy Set Theory, Fuzzy Logic, Decision Making, Commercial Opportunity Qualification, BANT Methodology, Sales Force Support, Commercial Process Optimization

1. Introduction

Demand generation stands out as an essential process for the sales divisions of organizations, intending to supply sales forces with well-qualified and high-potential business opportunities [1], [2]. Several opportunity qualification methodologies have been proposed to meet this objective. Among these, the BANT Methodology —an acronym for budget, authority, need, and Timing— is notably recognized in the Brazilian market. Developed by IBM, this multi-criteria methodology guides the assessment of a sales cycle's likelihood of success through questions tailored to the context of the business opportunity. Although the BANT Methodology efficiently captures situational aspects of ongoing business, it does not offer guidance on interpreting the results obtained. This limitation necessitates that organizations adopt a deliberative decision-based approach for analyzing, classifying, and grouping opportunities, potentially impacting sales cycle productivity [1], [5], [6], [12].

Automation approaches have been proposed to improve efficiency opportunity qualification. Machine learning algorithms are one of the most common approaches to predict lead conversion and sales success [20], [21], [22], [24]. Unified predictive models also leverage historical data to forecast the success of sales opportunities [23]. Additionally, decision support systems utilizing web tracking and AI solutions focus on data collection and enhancing the customer experience [25]. These approaches face challenges that prevent effective predictive modeling. Reliance on historical data and traditional lead scoring systems, which are error-prone and non-probabilistic, can lead to inaccurate predictions. Key challenges include the dynamic behavior of qualification in response to changes in the market, data ambiguity, subjectivity, and bias in expert assessments [20], [22]. In addition, the small number of B2B transactions and noisy data can compromise the model's efficiency [20], [23].

This study is mainly justified by the critical need to increase the productivity of commercial opportunity qualification. This challenge leads to exploring innovative approaches, including applying Fuzzy Set Theory and Fuzzy Logic to the BANT Methodology, to overcome the challenges posed by subjective evaluations in the sales cycle. Non-classical logic is increasingly recognized as an efficient approach for tackling complex decision-making challenges that require human-like judgment and reasoning skills [13]. In this context, fuzzy set theory and fuzzy logic are mathematical tools that capture human thought processes such as abstraction, information communication, and pattern recognition [3].

That being the case, this study addresses the gaps in current approaches to automating opportunity qualification. While previous works focusing on machine learning algorithms and predictive models face challenges due to their reliance on historical data [20], [26], this work stands out by capturing and systematizing the knowledge from experts through integrating Fuzzy Set Theory and Fuzzy Logic into the BANT Methodology. This approach mitigates the risks of subjective biases common in human evaluations [20], [22]. In addition, it also offers transparency and adaptability that traditional machine learning frameworks often fail to achieve [24]. Finally, the approach proposed in this work allows confrontation with historical data to identify initial biases in the data and refine qualification rules, providing greater precision and flexibility through a continuous cycle of improvement in the analysis of commercial opportunities, meeting the dynamism imposed by the market.

Given this, this study explores the integration of Fuzzy Set Theory and Fuzzy Logic with the BANT Methodology, investigating the hypothesis that this approach can significantly improve sales cycle performance. This leads to the central research question: Can fuzzy Set Theory and Fuzzy Logic effectively replace the deliberative decisions of experts in qualifying business opportunities, thus ensuring better sales cycle performance?

To this end, this study proposes a new approach for analyzing and qualifying commercial opportunities based on the criteria of the BANT Methodology. It also aims to present a prototype of a Fuzzy Inference System that emulates human reasoning and systematizes the analysis of these criteria. To validate this system, the study evaluates a sample of commercial opportunities from the Latin American subsidiary of a multinational information technology company, comparing the experts' assessments with those derived from using the Fuzzy inference system.

To achieve these objectives, the article is organized as follows: The Theoretical Framework reviews related works, establishing the research basis. Methodology describes the procedures, instruments, and techniques used. Results present the sample processing and analyses. Discussion interprets findings and discusses implications and limitations. The conclusion summarizes the main findings and suggests future research.

2. Theoretical Framework

The theoretical framework includes Commercial Opportunity Qualification, BANT Methodology, Behavioral Biases, Fuzzy Set Theory, Fuzzy Logic, and the Likert Scale.

2.1. Commercial Opportunity Qualification

The Business-to-Business Sales Cycle, or Lead to Cash, involves processes from prospecting to completing transactions, which is crucial for revenue and customer experience [1], [2]. It starts with demand generation, providing the sales team with well-qualified opportunities, which is a top priority over other marketing goals [1], [6], [7], [8]. This stage faces two challenges: generating interest through campaigns and managing leads to ensure the quality of business opportunities for the sales force [5], [12]. The marketing department supplies qualified leads to the sales team, which converts them into revenue and avoids wasted efforts on unpromising opportunities.

The quality of qualification, opportunity reliability, and sales process effectiveness are directly related [7], [8], [12]. Poor or imprecise qualifications cause uncertainty, impacting productivity and decision-making. Promising opportunities must continue to be developed, but unpromising prospects should be moved to a nurturing process to avoid wasting time and resources [8], [14].

Therefore, to guarantee maximum sales force efficiency, it is necessary to investigate each opportunity based on relevant criteria demonstrating the potential for converting a prospect into a revenue-generating customer. Companies have proposed several different methodologies to filter the opportunities with the most significant potential for success through sets of criteria and indicators that reflect the contextual aspects of the business [6]. Often referred to as the acronyms of their key criteria, these approaches mainly ascertain the customer's capacity and willingness to invest, the adherence of the product or service offered to their needs, and the deadline to complete the acquisition process [1].

2.2. The BANT Opportunity Qualification Methodology

Developed by IBM in the 1950s, the BANT methodology filters and prioritizes commercial opportunities based on the customers' interests and needs in the solution offered. IBM's sales teams initially applied BANT and delivered remarkable results, which explains its popularization.

The four criteria proposed by the BANT methodology focus on the following aspects:

- Budget: Investigates whether the customer already has an adequate budget to purchase the offer.
- Authority: Identifies whether contacts at the client can make decisions or influence them.
- Need: Indicates whether there is a real need in the customer and how much it aligns with the characteristics of the offer.
- Timing: Assess when the customer plans to purchase, indicating urgency and helping prioritize opportunities.

The main benefits of using BANT are the standardization of the process of scrutinizing the opportunities generated by marketing actions, the standardization of the registration of information about the opportunities' context, the standardization of the language between the Marketing and Sales teams, and the subsidies for the qualification of commercial opportunities [6], [7].

Even considering these benefits, the flexibility and capacity of the BANT methodology to deal with changes in the market and the absence of a proposal for interpreting the responses to the criteria are issues frequently debated by organizations.

In the absence of an interpretative approach to the results obtained in the investigations of their criteria, the organizations that adopted BANT initially proposed that the fulfillment of 75% of the criteria would validate a business prospect. Another frequent approach was to assign weights to the criteria to support the demand prioritization. However, the primary approach to decision-making among BANT users is based on joint deliberative decisions between the Marketing and Sales teams. Although this practice allows accuracy in the qualification and prioritization, it compromises the agility of the sales cycle, and this remains an open question for users of the BANT methodology [1], [7].

New approaches, including CHAMP, which revises BANT to prioritize customer needs, SCOTSMAN by the Advanced Selling Skills Academy with comprehensive criteria, and MEDDIC/MEDDPICC, focusing on enterprise sales with iterative qualification reviews, have emerged. Despite this, BANT remains widely accepted due to its familiarity with marketing and sales teams.

2.3. Behavioral Biases on Opportunity Qualification

Experts and decision-makers in commercial teams are often influenced by various behavioral factors that affect their objectivity. Research has shown that several types of bias can affect the entire sales process, including qualification opportunities [16], [17], [20].

Various biases lead to positive evaluations without supporting evidence. These include optimism bias, commitment bias, loss aversion bias, social or organizational pressure bias, and incentive bias. Some biases can influence positive and negative evaluations due to beliefs or filters disregarding current conditions. This includes experience bias and confirmation bias. There are biases that lead to negative decisions by focusing on negative aspects, overestimating risks, and underestimating returns. These include negativity bias and conservatism bias [18], [19].

Strategies such as adopting structured and automated decision-making processes with peer reviews or using decision-making technologies can significantly mitigate these negative influences, improving the quality of decisions and the performance of business processes [17], [20].

2.4. Fuzzy Set Theory, Fuzzy Logic and Fuzzy Inference Systems

Lotfi Zadeh introduced the Fuzzy Set Theory in 1965. It extends the classical set theory to address imprecision and ambiguity, thereby modeling uncertainties in real-life phenomena. The classical set theory operates on clear boundaries, with elements either belonging to a set or not, defined by a membership function that returns 1 or 0 [3]. In contrast, fuzzy set theory allows for partial membership, where elements belong to a set to varying degrees between 0 and 1, better capturing the nuances of real-world situations [3].

Fuzzy logic builds on this theory by modifying traditional bivalent logic to handle partial truth, with proposition values ranging from 0 (false) to 1 (true), using fuzzy pertinence functions [3], [13].

Fuzzy Inference Systems integrate resources from Fuzzy Set Theory and Fuzzy Logic to emulate human reasoning. These systems consider the uncertainty associated with values through linguistic variables that store knowledge about the problem and decision rule bases derived from expert knowledge and contain cause and effect relationships [4], [13]. The process of fuzzy inference involves several stages: fuzzification of input values, evaluation of rules using fuzzy logic, aggregation of rule outputs, and finally, defuzzification to convert fuzzy output values back into precise quantities [4], [9], [10], [13].

Because of their ability to reflect decision-making based on the complexities of human cognition, Fuzzy Set Theory, Fuzzy Logic, and their application with Fuzzy Inference Systems have significantly influenced the construction of models and algorithms in systems that deal with imprecise data [10].

2.5. Likert and Likert-type scales

Named after Rensis Likert, the Likert scale is widely used in the Humanities and Applied Social Sciences to measure responses. As a psychometric response tool, it gauges agreement or disagreement with statements using multiple items with points and semantic differentials [11]. Initially applied in 1932, the scale had five response categories, with a midpoint indicating indifference. Responses were summed and averaged to analyze frequency distributions. Likert-type scales differ from the original ones by allowing individual questions with adaptable response categories and scores.

3. Methodology

This study used theoretical and empirical research methodologies. Theoretical research involved reviewing the literature on business opportunity qualification, the BANT Methodology, Fuzzy Set Theory, Fuzzy Logic, Fuzzy Inference Systems, and the Likert Scale.

The empirical research aimed to validate if Fuzzy Set Theory and Fuzzy Logic could replace specialists' decisions in qualifying opportunities using the BANT methodology. A fuzzy inference system was developed with Python and Scikit-Fuzzy. A sample of previously qualified opportunities by specialists from a multinational IT company was selected to validate the system. The system processed the sample, and the results were compared with expert qualifications. The final analysis discussed the ability of Fuzzy Set Theory and Fuzzy Logic to emulate human evaluation of BANT criteria.

3.1. Sample Selection and Preparation

The study analyzed 71 commercial opportunities from 2022-2023 developed by the marketing and sales team from the Latin American branch of a multinational software supplier. With over 50 years of experience, the organization extensively uses the BANT methodology for qualification.

The consistency of the sample was ensured by considering client characteristics (market segment and size) and offer characteristics (product and estimated value) to avoid deviations from unanalyzed variables.

The instruments used to collect the data were a search of the business opportunity qualification records and questionnaires with experts. The search aimed to select and group the business opportunities using similarity parameters. On the other hand, the questionnaires were structured in an electronic form with affirmative propositions aligned with the criteria of the BANT methodology, containing response alternatives on a Likert-type scale describing the degree of agreement with the proposition.

To meet confidentiality requirements, the data obtained from the survey and the questionnaires were anonymized beforehand without affecting the quality of the analyses.

3.2. Development of the Fuzzy Inference System

The approach proposed for developing the Fuzzy Inference System integrates several methods. The two initial stages focus on gathering knowledge about opportunity qualification according to the BANT. The third stage involves codifying this knowledge using programming languages and specialized libraries.

3.2.1. Linguistic Variables Elicitation

Linguistic Variables Elicitation. According to specialists' experience, the linguistic variables and their respective terms in a fuzzy inference system materialize the domain of the problem under analysis. The antecedent variables represent the system's inputs; the consequent variables are the processing results [4].

Two sources were considered to identify the variables: the best practices associated with the BANT criteria identified in the theoretical research and the knowledge of the experts collected in the interviews [1], [7]. The antecedent variables are affirmative propositions, and the linguistic terms of their fuzzy answer sets follow a 5-point Likert-type table.

The only consequent variable in the system is an interrogative sentence that determines the evaluation of the opportunity in terms of its potential to convert it into a sale. A second 5-point Likert-type table determines its possible linguistic terms. The universe of discourse of the fuzzy sets of antecedent and consequent linguistic variables is a continuous range from 0 to 100.

The syntactic and semantic rules for generating the fuzzified values as a composition of terms for the variables follow the triangular and trapezoidal membership functions as identified in theoretical research and by experts' knowledge.

Defuzzification of the resulting value uses the Centroid method, and the syntactic and semantic rules follow the triangular and trapezoidal pertinence functions.

3.2.2. Knowledge Based Rule Definition

Determining knowledge-based rules is crucial for capturing the nuanced expertise of specialists in a fuzzy inference system [4].

The product of the number of linguistic terms in each input variable gives the maximum number of rules in a fuzzy inference system. A 5-point Likert-type scale for the four variables corresponding to the BANT criteria results in 625 potential rules. However, not all these rules are relevant or necessary in practical applications. Involving experts in the selection process can identify a more manageable and pertinent subset of rules.

In this study, experts have distilled this comprehensive set down to 16 essential rules that accurately reflect real evaluation scenarios.

This approach ensures that the fuzzy inference system is efficient and aligned with the actual decision-making processes, thereby enhancing the system's reliability and effectiveness in qualifying business opportunities.

3.2.3. System Development

The fuzzy inference system proposed in this article followed the algorithm proposed by Mamdani and Assilian [4]. The development used the Google Colab Notebook with Python programming language and the Scikit-Fuzzy library from Logica Fuzzy for scientific computing. The source code is available in the GitHub repository [27].

4. Results

The fuzzy inference system processed the sample dataset, including expert-assessed commercial opportunities, and produced outcomes scrutinized using a structured testing framework. The following sections, "Sample Processing with the Fuzzy Inference System" and "Evaluating the Fuzzy Inference System's Effectiveness Compared to Expert Assessments," thoroughly explain these processes.

4.1. Sample Processing with the Fuzzy Inference System

The study analyzed the sample data from 71 commercial opportunities in 2022 and 2023, evaluating them against BANT criteria through a Fuzzy Inference System. This process assigned each opportunity a precise score and a classification reflecting its potential. The input data and results are available in the GitHub repository [27].

Table 1 presents a detailed comparison of expert and fuzzy analyses for opportunity evaluations. The confusion matrix includes five classes. Each cell displays the count of occurrences followed by an indication of whether the fuzzy analysis was equivalent to the expert analysis ("="), more optimistic (" ↑ "), or more pessimistic (" ↓ ").

Table 1. Comparison Matrix with Values and Analyses: Expert vs. Fuzzy Analysis Comparison.

	Fuzzy Analysis					
Expert Analysis	Very poor	Bad	Neutral	Good	Excellent	Total
Very poor	0 (=)	0 (↑)	0 (↑)	0 (↑)	0 (↑)	0
Bad	1 (↓)	6 (=)	0 (↑)	0 (↑)	0 (↑)	7
Neutral	0 (↓)	6 (↓)	0 (=)	0 (↑)	0 (↑)	6
Good	0 (↓)	17 (↓)	0 (↓)	15 (=)	13 (↑)	45
Excellent	0 (↓)	0 (↓)	0 (↓)	1 (↓)	12 (=)	13
Total	1	29	0	16	25	71

4.2. Evaluating the Efficacy of the Fuzzy Inference System Against Expert Assessments

The fuzzy inference system's evaluation against expert assessments employed a strategy that treated rating scores as continuous quantitative variables. This comprehensive approach assessed the relationship between the fuzzy system's outputs and expert ratings, agreement levels, predictive capabilities, discrepancies, and statistical significance. The analysis included Descriptive Analysis, Correlation Analysis, Concordance Analysis, Regression Analysis, Error Analysis, and Hypothesis Testing, ensuring a rigorous evaluation. This method validated the system's effectiveness and reliability in practical applications [13].

Descriptive statistics was the first analytical approach to evaluate the alignment between expert and fuzzy system rating scores. Table 2 provides a statistical summary of the scores to understand the overall distribution of the data.

Table 2. Descriptive statistics for Expert Rating Scores and Fuzzy Rating Scores

	Expert Rating Score	Fuzzy Rating Score
Count	71.000	71.000
Mean	75.197	69.296
Std	11.888	20.787
Min	37.000	22.000
Q1 (25%)	67.500	50.000
Median (50%)	77.000	71.000
Q3 (75%)	82.000	94.000
Max	100.000	94.000

The Shapiro-Wilk test determined non-normal distribution in both score sets, leading to the selection of Spearman's correlation for assessing score association. Lin's Concordance Coefficient provided a comprehensive view of their concordance to gauge the agreement level between scores. A linear regression model explored the predictive relationship between variables, incorporating various statistical measures for an in-depth analysis. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) evaluated the fuzzy system's score accuracy by measuring deviation from expert scores, showcasing precision and reliability. As confirmed by Levene's test, non-normal distribution and non-homogeneous variances necessitated the Wilcoxon Signed-Rank Test for hypothesis testing, ensuring a thorough analysis (Table 3).

Table 3. Results for Alignment Between Expert and Fuzzy System Rating Scores

Analysis/Test	Indicator	Value
Test of normality (Shapiro-Wilk) for Expert Rating Score	Test Statistic	0.959
	P-value:	0.021
Test of normality (Shapiro-Wilk) for Fuzzy Rating Score	Test Statistic	0.824
	P-value:	9.22e-08
Correlation Analysis	Spearman Correlation	0.783
	P-value:	7.60e-16
Concordance Analysis	Lin's Concordance Coefficient	0.631
Regression Analysis	Slope	1.358
	Intercept	32.798
	Standard error	0.133
	R-value	0.776
	R^2	0.603
	P-Value	1.772
Error Analysis	MAE	10.601
	RMSE	13.006
Test for Homogeneity (Levene)	Test Statistic	33.156
	P-Value	5.167
Hypothesis Testing (Wilcoxon Signed-Rank)	Test Statistic	725.500
	P-Value	0.002

Four graphs illustrated the relationships between datasets containing expert and fuzzy system rating scores (Fig.1). The histogram enabled comparative visualization of frequencies. The box plot offered a visual summary of the two datasets' value variability. The scatter plot with regression line depicted the strength of the relationship between the two variables. The density plot provided a comparative summary of the distribution of the two sets.

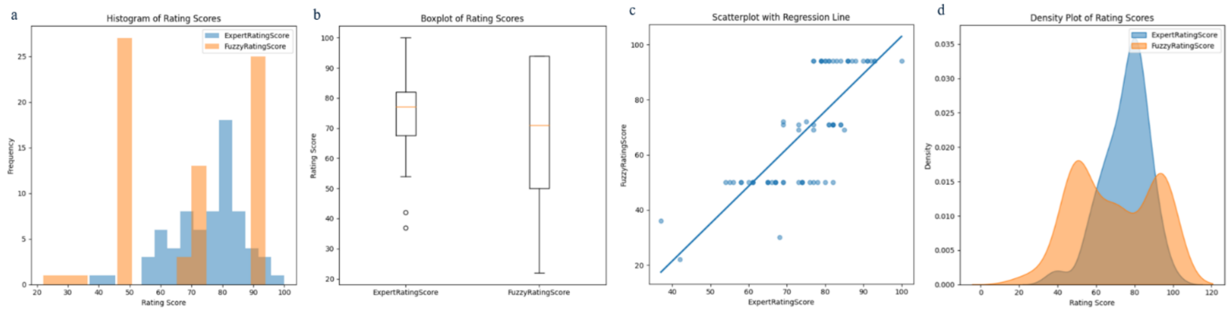

Fig. 1. Analysis of Rating Scores: (a) histogram, (b) box plot, (c) scatter plot with regression line, and (d) density plot.

5. Discussion

Using different statistical techniques to compare the results of the Fuzzy Inference System with the experts' evaluations made it possible to identify the system's capabilities, points for improvement, and biases in the experts' evaluations (Table 2, Table 3). This approach aligns with the need to address biases and improve qualification systems [16], [20], [22].

The descriptive statistical analysis of the two sets of evaluations revealed a consistency in the central tendency of the average values of the two sets of assessments (Table 1, Fig.1b). The fuzzy system's standard deviation indicated more significant variability, suggesting more sensitivity to specific BANT criteria not considered necessary by the experts. This addresses the importance of precision in sales forecasting [21].

The broader range of values with low minimum scores in the fuzzy system implies a better ability to differentiate between opportunities (Fig.1d). On the other hand, the narrower range with relatively higher minimum scores may indicate a more conservative approach in the experts' assessments (Fig.1d). Experts tend to rate opportunities as "Good" more often. In contrast, the fuzzy system distributed more ratings in the "Bad" and "Excellent" categories (Fig.1a; Fig.1d). This may confirm the tendency towards a more conservative approach by experts who see opportunities as more viable. This bias can be explained by a desire to avoid discarding potentially valuable opportunities. These results indicate that the fuzzy inference system can more accurately differentiate between advantageous or disadvantageous opportunities based on the rules defined [18], [22].

The Spearman coefficient resulting from the correlation analysis strongly indicates the alignment between the two sets of evaluations. This strong and statistically significant correlation suggests a consensus between the fuzzy inference system and experts regarding which opportunities can and cannot be considered promising. On the other hand, the Concordance Analysis revealed moderate consensus between the fuzzy system and the experts. The value of Lin's Coefficient of Concordance indicates that the system can evaluate opportunities in good alignment with the experts. Still, there are slight divergences in the interpretation of the BANT criteria. The combined Spearman and Lin coefficients show a strong correlation and moderate agreement, which implies that the evaluations of the fuzzy system and the experts move together but does not necessarily imply that the assessments are close in absolute terms. In other words, although the ratings tend to rise and fall together, they don't necessarily correspond precisely to each other at every opportunity.

The regression analysis revealed a strong positive correlation, with statistical significance and precision in the estimate, which indicates a positive linear relationship between the two sets (Fig.1c). This strong correlation suggests consistency between the evaluation sets, which gives confidence that new evaluation sets from the experts and the fuzzy inference system will behave similarly to those observed. This finding aligns with the importance of consistent predictive modeling in sales forecasting [22].

The error analysis reinforced the differences between the sets compared. The Mean Absolute Error and Root Mean Square Error values indicate cases where the fuzzy system diverges considerably from the experts' assessments. Similarly, the hypothesis test revealed that despite the alignment and correlation, a direct comparison of the experts' assessments and the fuzzy inference system reveals significant discrepancies and differences in their overall distributions. This highlights the importance of addressing subjectivity in human evaluations [20].

In conclusion, the analyses show both the ability of the Fuzzy Inference System to mirror the judgment of experts with solid alignment and moderate agreement [4], [9], and the room for refinements that can increase its accuracy. These findings suggest validation of the affirmative hypothesis for the research question, indicating that Fuzzy Set Theory and Fuzzy Logic can effectively replace the deliberative decisions of experts in qualifying business opportunities, thus ensuring better sales cycle performance. This aligns with automated qualification systems' need for continuous improvement and adaptability [25].

In general, it was clear that there is consensus among the evaluations on which opportunities may or may not be considered promising. The discrepancies observed suggest a greater sensitivity of the system in evaluating the criteria of the BANT methodology and a conservative bias in the experts' analyses that is not adequately translated into the system's rule bases [17], [18]. These opportunities for refinement do not contradict the positive answer to the research question; on the contrary, they highlight ways to improve the agreement between the Fuzzy Inference System and the expert evaluations, reinforcing the validity of the positive hypothesis.

6. Conclusion

This article introduced the application of Fuzzy Set Theory and Fuzzy Logic to the BANT Methodology in an innovative proposal for qualifying commercial opportunities. The motivation for this approach was the need to increase the sales cycle's productivity without compromising the qualification's quality.

To this end, a Fuzzy Inference System was developed to translate the experts' knowledge. Analyzing the results of using this system to process a sample of commercial opportunities showed the system's viability as a replacement for experts' judgment and highlighted areas for future improvement that could increase its accuracy.

These findings validate the hypothesis that the proposed approach can potentially improve sales cycle performance and should be used to qualify commercial opportunities.

The study lays the foundations for further research and future work that can contribute to the continuous evolution of organizational sales practices. Evaluating the impact of this approach on subsequent stages of the sales cycle would provide important insights into the value of the proposed approach. There is potential to explore the comparative use of other non-classical logic, such as Paraconsistent Annotated Evidential Logic Eτ, to evaluate the criteria of the Bant Methodology. There is also room to explore the use of Fuzzy Set Theory and Fuzzy Logic, as well as other non-classical logic, with other opportunity qualification methodologies such as the CHAMP, SCOTSMAN, MEDDIC, and MEDDPICC methodologies.

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