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Creditworthiness of small and medium enterprises: a fuzzy decision-making approach

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Abstract

Small and medium enterprises (SMEs) play a crucial role in global economies but face significant challenges in accessing credit. Traditional credit assessment models often rely on statistical and artificial intelligence methods, which require extensive financial data usually unavailable for SMEs. This study aims to enhance creditworthiness evaluation by integrating financial and non-financial data using a Fuzzy decision-making approach. We apply this model to 33 Italian SMEs collaborating with a local cooperative credit bank (CCB), leveraging financial and strategic indicators such as internationalization and sustainability. This paper combined the fuzzy decision-making approach with the TOPSIS method, as it is easy to implement. However, our fuzzy-based tool can be integrated with other methods, similar to TOPSIS, such as PROMETHEE, VIKOR, or others. Implemented through a VBA & Excel-based template, the tool allows for flexible and gradual decision-making and accommodates financial and non-financial data. Moreover, the tool's ability to interpret results semantically and its design for processing native semantic data are two of its key strengths. Our empirical research shows that the Fuzzy approach improves credit risk assessment by handling heterogeneous data while maintaining ease of implementation. The proposed approach offers several advantages: its simplicity and modularity make it a valuable tool for CCBs to use as a complementary—rather than a substitute—assessment method alongside the existing system for identifying creditworthy companies. This study contributes to the literature on SME credit evaluation, offering a practical, cost-effective, and adaptable tool for financial institutions, particularly CCBs.

Keywords Credit assessment · Fuzzy decision making · Financial and non-financial information · SMEs

Extended author information available on the last page of the article

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1 Introduction

Small and medium enterprises (SMEs) play a crucial role in the world economy and in the development of society (Jackowicz and Kozlowski 2019; OECD 2024): they account for 90% of businesses, 60 to 70% of employment and 50% of GDP worldwide (World Bank 2020). Also, in Italy minor firms form the backbone of the national economy, accounting for 95% (ISTAT 2023), providing nearly 80% of the industrial and service labour force and generating about two-thirds of turnover and value added (OECD 2024). In a climate of radical instability and uncertainty caused by an endless succession of overlapping crises – economic and financial, health, and climate – the survival of these firms has become a significant issue for all economic systems (European Central Bank 2021; OECD 2024). In this sense, one of the most relevant and challenging issues regards credit access and creditworthiness assessment (Altman et al. 2020; Sun et al. 2022; Russo et al. 2024; Roy and Shaw 2023a,b). It is widely recognized that small enterprises are typically at a disadvantage compared with larger firms when accessing finance, owing to opacity, under-collateralization, incomplete financial information, and absence of strategic information about their activities (Sun et al. 2022; Russo et al. 2024). Consequently, SMEs generally face higher interest rates and tighter borrowing terms and are more likely to be credit-rationed than large firms, more so during periods of crisis (Kremp and Sevestre 2013; OECD 2022; Russo et al. 2024).

The last consideration draws attention to the financial institutions, especially banks which represent the primary financial source for SMEs (European Central Bank 2014 and 2021; McKillop et al. 2020; Russo et al. 2024). Financial organizations employ credit assessment systems to manage credit risk by quantifying it (Wang and Ku 2021; Roy and Shaw 2023a): in other words, banks evaluate the firm's capacity to meet financial obligations. Creditworthiness assessment is a multidimensional, and oftentimes, complex decision-making problem (Fahner 2012; Du Jardin 2016; Roy and Shaw 2023b). Loan institutions invest significant resources and labor in gathering and processing quantitative and qualitative information about the potential borrowers in order to mitigate the risk of pitfalls and losses (Roy and Shaw 2023a). Moreover, estimate credit rating is particularly difficult in the case of SMEs because of their nature and size (Sun et al. 2022; Russo et al. 2024).

The decision-making process which determines whether or not a company will receive funding can avail itself of one of a number of credit rating models (Abdou and Pointon 2011; Bai et al. 2019; Dastile et al. 2020) which include statistical, artificial intelligence or learning machine methods.

Most extant credit rating systems are based on statistical methods (Altman and Sabato 2008; Altman et al. 2020), such as regression analysis, discriminate analysis, logistic regression and multinomial regression. These parametric methods use stochastic probability approaches to measure the probability of enterprise default. Some problems related to their adoption concern the violation of assumptions underlying parametric methods, such as linearity and multiple interactions (Wang et al. 2011; Wang and Ku 2021). Thus, the application of this method could prove unreliable in the assessment process (Huang et al. 2004).

Recently, artificial intelligence techniques including artificial neural networks, the support vector machine (SVM), the decision tree SVM have been developed (Malhotra and Malhotra 2003; Abedin et al. 2018). Although these sophisticated new methods based on artificial intelligence have proved more accurate than statistical methods (Carmona et al. 2009; Abellán and Mantas 2014; Bai et al. 2019), their main limitation arises from the complexity of the configurations and simulations which makes it difficult to understand the results (Roy and Shaw 2023a,b).

Both the above methods require a data set, generally of a quantitative nature, at once vast, time-consuming and costly (García et al. 2013). Therefore, if – as is often the case with SMEs – the financial information is not always available, reliable, and appropriately kept, it becomes even more difficult to apply statistical and artificial intelligence methods to evaluate an enterprise's risk exposure (Roy and Shaw 2023a,b).

In order to overcome these difficulties, the banks often supplement financial data with data of a non-financial kind, taking into consideration aspects such as management quality, firm size, legal disputes, external environmental factors or lending relationship data collected over time by the credit institution itself (Bai et al. 2019; Cornée 2019; Maldonado et al. 2020; Medina-Olivares et al. 2022).

This happens especially in small banks like cooperative credit banks (CCB). Cooperative banks, as locally rooted institutions, are well-positioned to acquire specialized local knowledge by fostering relationships between bank staff and the local community, including SMEs (Zedda et al. 2024). These relationships enable the collection of 'soft information' (based on non-financial data), which can help reduce screening and monitoring costs and facilitate credit provision to borrowers with limited financial transparency –such as SMEs (McKillop et al. 2020; Agostino et al. 2023). It follows that cooperative banks' evaluation method differs from commercial ones. Commercial banks adopt a more standardized and quantitative approach, making it more difficult for some SMEs to obtain credit, especially if they have limited financial data (Roy and Shaw 2023b). The CCBs employ relationship-based lending evaluation methods. This means they rely on analyzing non-coded, non-financial soft information (Altman et al. 2010; Bhimani et al. 2013; Zedda et al. 2024). This approach enables them to gather qualitative and forward-looking information –about the firms' strategies, innovation, internationalization and sustainability –which can be crucial in assessing the reliability of small businesses. However, the main difficulty in processing this kind of information is the high level of subjectivity, which makes it complicated to incorporate such data into credit rating models (Sun et al. 2022). Scholars argue that one of the greatest challenges is to develop models that can handle heterogeneous information while guaranteeing efficiency and accurate estimates for SMEs (Meng and Yang 2007; Sun et al. 2022).

With this in mind, some researchers try to address the problem by introducing fuzzy logic (Roy and Shaw 2023a,b), in combination with statistical and multicriteria decision-making methods, such as TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) (Guo and Zhao 2017; Ignatius et al. 2018; Bai et al. 2019; Abdullah et al. 2023). The TOPSIS method provides the decision-maker with a ranking alternatives technique, which identifies solutions from a finite set of alternatives closest to the positive ideal solution and farthest from the negative solution.

It is simple and easy to use and can be applied to the problems with a large or small number of criteria and alternatives, and integrated with others methods due to its simplicity and ease of use (Behzadian et al. 2012). The Fuzzy sets theory proposed by Zadeh (1975) can be used to handle the ambiguity and vagueness inherent in decision-makers' judgments (Herrera et al. 2000; Syau et al. 2001; Ignatius et al. 2018; Guerra et al. 2022), such as in credit risk evaluation. The fuzzy approach in credit risk models has been shown to be more efficient in measuring an enterprise's risk in the event of insufficient and imprecise data (Hoffmann et al. 2007; Guo and Zhao 2017; Bai et al. 2019; Guerra and Sorini 2020; Guerra et al. 2020). Furthermore, scholars argue that the fuzzy approach may better analyze heterogeneous information and produce a reliable and accurate credit rating for enterprises (Chen and Chiou 1999; Syau et al. 2001; Meng and Yang 2007; Sun et al. 2022). Thus, fuzzy logic models can be effective in helping to assess and shed light on risks that are imperfectly understood, as is the case with the credit risk associated with SMEs (Sun et al. 2022).

However, although the literature on credit access and credit evaluation methods has increased in recent decades (Abdou and Pointon 2011; Dastile et al. 2020; Roy and Shaw 2023a,b), more empirical evidence is required, specially about the fuzzy and TOPSIS approach and its application in small firms (Sun et al. 2022; Roy and Shaw 2023b). To help fill this gap, the aim of our study is to propose an effective, scientific decision-making support tool for the creditworthiness assessment by adopting the Fuzzy-TOPSIS approach, one which includes financial and non-financial information, and which will hopefully provide financial institutions with an additional perspective from which to measure the creditworthiness of SMEs.

We apply the Fuzzy-TOPSIS decision-making approach to 33 small Italian firms and consult a local CCB – which has expressed an assessment regarding the degree of reliability of the companies being analysed. Drawing on two-fold sources (AIDA-BvD and ATOKA-CERVED database), financial (profitability and debt ratios) and non-financial information (internationalization, sustainability, and innovation) is collected in a fuzzy database. Financial and non-financial indicators jointly reflect different dimensions of managerial quality and strategic behavior, which are crucial indicators for assessing creditworthiness in SMEs. While metrics like ROA, EBITDA margin, and indebtedness capture efficiency, profitability, and prudence, non-financial aspects – such as sustainability, internationalization, and innovation – highlight the management's ability to lead complex, future-oriented initiatives. The tool is implemented in a VBA & Microsoft Excel-based template; the choice was driven by the fact that it is widely used in the banking sector as a support tool for: financial analysis and customized reporting, customer data and transaction management in spreadsheets, risk calculations and forecasting models, automation of repetitive processes through VBA (Visual Basic for Applications), integration with other banking software for data processing. Excel can be used to complement the credit risk management system, which traditionally does not take soft information into account: it is useful for optimising the use of such information, and is a highly valuable tool for prototyping, exploratory analysis, and early-stage development, offering flexibility and ease of use, as demonstrated in our study.

Starting with a set of quantitative and qualitative data the fuzzy logic is applied. We define fuzzy semantic and fuzzy query semantic (which responds to the question: *Which companies are creditworthy?*) and subsequently order output scores by proximity index.

Subsequently, we implement the TOPSIS method, by assigning a weight to the parameters, classifying them according to their distance from the ideal and worst solutions. A rank is obtained, expressing information with positional and not absolute value. This rank is normalized (adjusted rank) to maintain position information, making it comparable with the proximity index.

In the following step, we included the CCB's independent valuation; the decision-maker expressed their assessment by adopting the most preferred linguistic semantic. It is important to note that we didn't ask the bank to confirm whether the companies were their customers, but rather to assess their creditworthiness based on the information available to them, irrespective of any customer relationship.

Finally, all these methods are integrated according to the TOPSIS approach. The decision-maker can combine the different methods, assigning a weight for each one. Adjusted rank is calculated to permit the semantic interpretation of data.

The study offers several contributions to the literature regarding creditworthiness models. First, this paper experiments with a decision-making support tool based on fuzzy TOPSIS approach, extending these concepts in credit risk assessment for SMEs (Sun et al. 2022). We have adopted the fuzzy triangular numbers and defined query semantics on each single attribute/parameter taken into account, which allowed us to address the problem of data query and interpretation based solely numerical values, usually obtained with traditional credit scoring systems. Moreover, the definition of fuzzy semantic has made it possible to simultaneously analyze different types of data (financial and non-financial information) without encountering problems concerning the adaptability of the different scales on which the attributes, qualitative and quantitative, can be indicated – such as percentages, in euros, ratios, etc. Subsequently, with the fuzzy decision-making approach, the proposed method handles the vagueness of lenders' requests, implied in their natural language.

The key strength of this tool lies in its simplicity and flexibility, as it can integrate both quantitative and qualitative data and handle varying data volumes. These features make it particularly effective for evaluating SMEs. Additionally, the decision-maker (e.g., the CCBs) can choose to apply one or multiple methods (Fuzzy, TOPSIS, and/or the bank model) simultaneously. The model also allows for the inclusion of financial and non-financial indicators related to companies' strategic behaviours—such as innovation, internationalization, and sustainability—which can be essential in defining the most suitable credit policies for specific firms. The proposed approach offers key benefits: its simplicity and modularity make it a valuable complementary tool for CCBs, enhancing rather than replacing existing credit assessment methods, and enabling a gradual transition toward improved efficiency and effectiveness in decision-making and credit risk management. Additionally, its low adoption costs (including software maintenance and staff training) and easy implementation in an Excel-based template make it accessible even for small banks, allowing for experimental use.

This paper proceeds as follows: Sect. 2 presents the methodological framework adopted to implement the Fuzzy-TOPSIS decision-making tool; Sect. 3 illustrates the empirical analysis; and Sect. 4 presents conclusions and potential avenues for further research.

2 Methodological framework for developing a Fuzzy-TOPSIS decision support system

The application of fuzzy logic in the financial sector, particularly in the analysis of creditworthiness, represents an innovative and flexible approach to evaluating the solvency of companies (Ignatius et al. 2018; Roy and Shaw 2023b). While traditional credit scoring models often rely on absolute values and rigid criteria, fuzzy logic makes it possible to address the uncertainty and complexity of financial and non-financial information (Sun et al. 2022), enabling a valuation more in line with the economic reality of the borrowers. On the other hand, TOPSIS is a multicriteria decision method for ranking alternatives (Behzadian et al. 2012; Nadaban et al. 2016). It has received significant attention due to its simplicity and low mathematical calculation. It can be applied to problems with many criteria and alternatives, such as creditworthiness (Roy and Shaw 2021, 2023a,b). In this section, starting with a little introduction to the fuzzy sets theory, fuzzy numbers, and TOPSIS method, we describe each step in applying the proposed Fuzzy-TOPSIS decision support system.

2.1 Fuzzy logic approach

Fuzzy logic was the first (and probably the most successful) attempt to formalize in a sound mathematical framework the way humans 'compute' with words (Zadeh 1999). This flexibility can be used to 'fuzzify' existing mathematical frameworks and/or connect them to address multiple sources of uncertainty. Unlike common numerical variables, linguistic variables can take the form of words or sentences in a natural or artificial language (Zadeh 1975).

Thus, the primary aim of fuzzy logic is to represent the mechanisms underlying the approximate modes of reasoning that are common in everyday language. Fuzzy logic is a mathematical framework that can be used to bridge the gap between the qualitative world of words and the quantitative world of measurements. Therefore, it is not a statistical tool that requires representative samples.

Fuzzy logic differs from classical (or binary) logic in that it allows for a more flexible and nuanced representation of information which has proven to be very reliable and promising in several application areas and contexts of economics, finance, engineering, decision making, social sciences among others.

While classical logic assigns strictly binary truth values (true/false) to propositions, fuzzy logic allows for the assignment of truth degrees ranging from 0 to 1, enabling a more detailed representation of nuances or uncertainty in data (Sun et al. 2022). Rules in fuzzy logic are defined so that input and output variables are described through membership functions. These rules can be defined in natural language and may involve fuzzy logical connectors such as 'and', or, 'not', etc. (Zadeh et al. 1996). Fuzzy sets are a fundamental part of fuzzy logic and provide a way to represent concepts that do not have precise boundaries but are characterized by degrees of membership. In a fuzzy set, an element can belong to the set with a membership degree ranging from 0 to 1. Therefore, instead of stating that an element 'is' or 'is not' in the set, we say that an element has a certain degree of membership in the set. Membership functions can be defined in various ways, such as triangular curves (Fig. 1), bell curves (similar to the shape of a normal distribution curve), step curves, etc.

Definition 1 A real fuzzy set $\widetilde{a}$ is defined to be any function $\mu_{\underset{a}{\sim}}(x) \in [0,1]$ for $x \in R$; it is called a fuzzy number if the membership function $\mu_{\underset{a}{\sim}}$ satisfies:
(1) $\exists x_0 \in \mathbb{R}$ such that $\mu_{\underset{a}{\sim}}(x_0) = 1$;
(2) $\forall \alpha \in (0,1]$, the level set $\widetilde{a}_\alpha = \{x, \mu_{\underset{a}{\sim}}(x) \geq \alpha\}$ is a closed interval.

Here, $\mathbb{R}$ is the set of real numbers, and $F(\mathbb{R})$ represents the set of all fuzzy numbers.

Definition 2 A fuzzy number $\widetilde{a}$ is said to be a triangular fuzzy number (TFN) if its membership function $\mu_{\underset{a}{\sim}}(x) : [a,b] \subseteq \mathbb{R} \to [0,1]$ is equal to:

$$\mu_{\underset{a}{\sim}}(x) = \begin{cases} 0, & if\ x < a \\ \frac{x-a}{m-a}, & if\ a \leq x < m \\ 1, & if\ x = m \\ \frac{b-x}{b-m}, & if\ m < x \leq b \\ 0, & if\ b < x \end{cases}$$

where a and b represent the lower and upper values of the support of $\widetilde{a}$, all of which are real numbers $(-\infty < a \leq m \leq b < +\infty)$. A TFN can be represented as a triplet $(\boldsymbol{a}, \boldsymbol{m}, \boldsymbol{b})$.

2.1.1 Application of the proposed method

Among the various applications of fuzzy logic, there is the managing of uncertainty in decision support systems and processing linguistic information (Guo and Zhao 2017; Ignatius et al. 2018). Through the use of fuzzy sets, linguistic rules, and member-

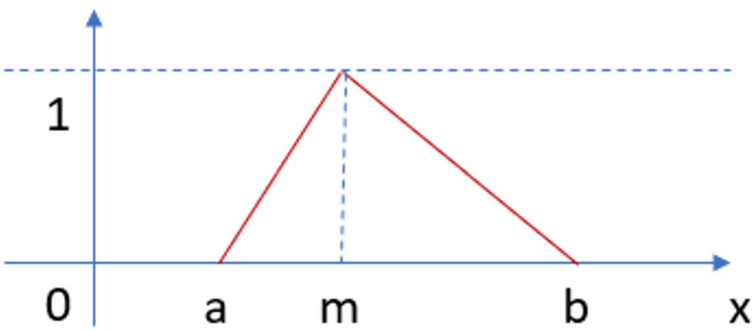


Fig. 1 Representation of a triangular fuzzy number (TFN)

ship functions, fuzzy logic allows for a more precise modeling of complex concepts such as 'good creditworthiness' or 'moderate risk'. This approach proves particularly useful in situations where available information is vague or subject to variations, providing credit institutions with a more sophisticated and effective tool for conducting the decision-making process leading to the determination of business risk. In the following subsections, we describe the steps to follow in order to apply fuzzy logic in the company assessment process.

2.1.2 First step: identifying the group of firms, gathering information and constructing the fuzzy database

In the first phase, we identify a group of 33 small companies – defined according to the European Union Commission Recommendation of 2003, based on the number of employees and annual revenues – operating in the commerce sector, as classified by the the Italian National Institute of Statistics (ISTAT), and located in the province of Pesaro-Urbino in Central Italy. For those firms we verify the availability of both financial information – such as profitability, indebtedness and productivity ratios– from the AIDA-BvD database and, also non-financial information – i.e. foreign market affinity, sustainability, and innovation scores from the ATOKA-CERVED database.

All these financial and non-financial indicators offer information about the quality of management, and its strategic actions from different points of view. The Return on assets indicates whether resources are being used efficiently by management (Maharani et al. 2025); the Ebitda margin suggests whether the company management succeeds in achieving good operating margins and having a cost structure under control (Bouwens et al. 2019); the indebtedness is a sign of prudent management, which tends to reduce financial risk (Kijkasiwat et al. 2022). On the side, non-financial indicators, such as the sustainability engagement reveals a sensitive and active management capable of balancing financial performance with corporate social responsibility (Grimaldi et al. 2020). A company's international presence is also often considered an indicator of high managerial quality: in fact, operating successfully on a global scale requires strategic expertise, cultural adaptability, and the ability to handle greater organizational complexities (Floris et al. 2022). Finally, a highly innovative organization typically reflects quality management, capable of driving change and adopting a long-term strategic vision (Jiang et al. 2024). Table 1 shows the description of variables.

All information was collected in a fuzzy database having the following structure: field, in rows, contains enterprises, and records, in columns, showing attributes or variables analyzed.

2.1.3 Second step: definition of fuzzy semantic

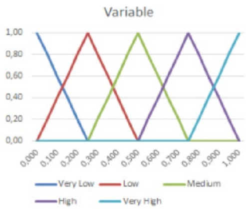
In this phase the fuzzy semantic was created, i.e. the linguistic semantics most suited to the decision-maker. Specifically, via expert input, we adopted a twofold semantic with three words (low, medium and high) and five terms (very low, low, medium, high, and very high) (see Table 2). The locution needs to be simple to read and understand. Then for each variable the grade of categorization was identified, in other words we created a set of semantic rules.

Table 1 Description of variables

Variables	Abbreviations	Measurements	Type of information	Sources
Return on assets	ROA	As a ratio of operating income and total assets.	**Financial**	AIDA-BvD database
Ebitda profit margin	Ebitda margin	As a ratio of earnings before interest, tax, depreciation and amortisation (Ebitda) and total turnover	**Financial**	AIDA-BvD database
Financial independence	Indebtedness	As ratio of equity and total assets	**Financial**	AIDA-BvD database
Sustainability engagement	SDG score	The SDG score provides an indication of the company's sensitivity and commitment to the SDG objectives. The score is calculated based on three main aspects: *(i)* a profile baseline defines such as aggregate statistics and analysis on the sector/segment to which the company belongs (ISTAT data, EU sustainable finance taxonomy, etc.); *(ii)* detailed information (granular data) collected from thousands of sources (certifications, news, websites, sustainability reports, etc.) concerning the individual company; *(iii)* a network effect at the group level and along the supply and value chains. The score assumes values between 1 (low) and 100 (high).	**Non-financial**	ATOKA-CERVED database
Internationalization propensity	ITZ propensity	The export propensity score measures the likelihood of a company to have relations with foreign countries' markets. The score assumes values between 1 (low) and 100 (high).	**Non-financial**	ATOKA-CERVED database
Innovation score	Innovation	A score given to the company based on the content of its website that measures the innovation factors of a company. The score assumes values between 1 (low) and 100 (high).	**Non-financial**	ATOKA-CERVED database

Table 2 Fuzzy triangular numbers used

Linguistic Terms	**Symbol**	**Fuzzy Triangular Numbers**
Very low	VL	(0.00, 0.00, 0.25)
Low	L	(0.00, 0.25, 0.50)
Medium	M	(0.25, 0.50, 0.75)
High	H	(0.50, 0.75, 1.00)
Very high	VH	(0.75, 1.00, 1.00)



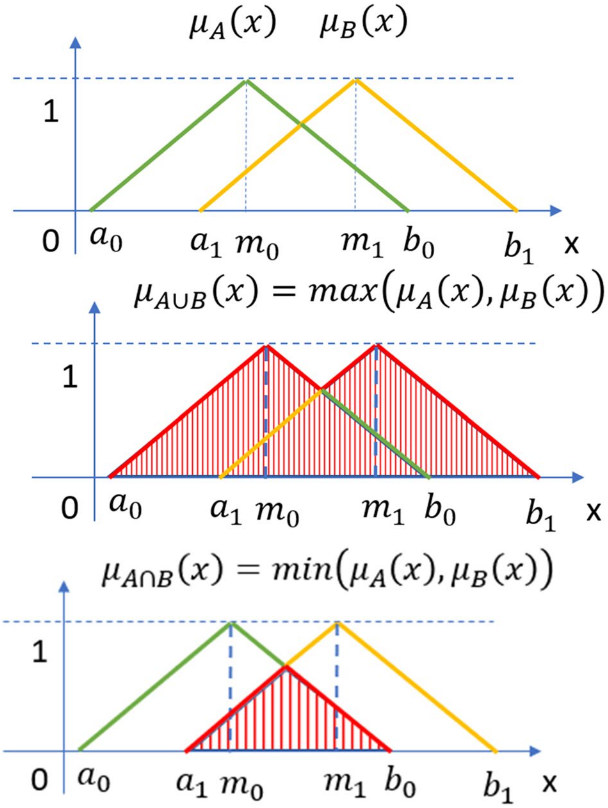
In our case, we have used triangular fuzzy numbers that sum to one, so for every variable the scheme will be as follows:

2.1.4 Third step: definition of fuzzy query semantic and the rules

The next step consisted in building the fuzzy query semantic, in other words formulating a request for information so the system understands the semantic meaning. To do this, we used twofold connectives: *'is not' or 'is at least'* to refer to a specific fuzzy semantic (e.g. *'is not'* low, *'is at least'* medium*)*; and logical connectives like *'and'* (another is *'or'*) to combine the different query variables (e.g. SDG score is at least high *'and'* Ebitda margin is not low). Figure 2 displays the fuzzy query identified in this study.

2.1.5 The rules

The usual logical operators AND and OR for fuzzy numbers are computed as follows:



Non-Financial variables								AND	Financial variables							
ITZ propensity (SEMANTIC 5)		AND	SDG Score (SEMANTIC 5)		AND	Innovation (SEMANTIC 3)			Ebidta margin (SEMANTIC 3)		AND	ROA (SEMANTIC 5)		AND	Indebtedness (SEMANTIC 3)	
IS AT LEAST	MEDIUM		IS AT LEAST	MEDIUM		IS NOT	LOW		IS NOT	LOW		IS AT LEAST	MEDIUM		IS NOT	LOW

Fig. 2 Definition of semantic fuzzy query

2.1.6 Fourth step: order by proximity function

Once the queries were formulated and performed, scores for each firm were calculated. The scores measuring between 0 and 1 indicate the degree of membership of the specific unit of analysis (firm) to my request (the query semantic). The set of scores obtained are ordered on the basis of the proximity function, so the first case, at the top of the rank, is the one that is closest to our request/query. Figure 3 shows how the creation of the fuzzy query semantic takes place in a circular manner:

2.2 Topsis

The Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), developed by Hwang and Yoon (1981), is a well-established multi-criteria decision-making method. Its main principle is to identify the alternative that is simultaneously closest to the positive ideal solution (PIS) and farthest from the negative-ideal solution (NIS). TOPSIS is widely applied in domains such as engineering, management, and environmental studies (Çelikbilek and Tüysüz 2020; Roy and Shaw 2021).

The method involves: (1) normalizing the decision matrix; (2) applying criteria weights to obtain the weighted normalized matrix; (3) determining the PIS and NIS; (4) calculating each alternative's distance to PIS and NIS; (5) computing the relative closeness to the ideal solution; and (6) ranking the alternatives accordingly.

In our analysis, six input variables were considered, grouped into non-financial variables – ITZ propensity, SDG score, and Innovation – and financial variables – EBITDA margin, ROA, and Indebtedness. Each variable was assigned equal weight, reflecting a balanced consideration of financial and non-financial performance dimensions.

The resulting closeness index, which ranges between 0 and 1, was further rescaled to the [0,1] interval by setting the highest value to 1, the lowest to 0, and proportionally adjusting all intermediate values. This normalization facilitates comparability with other methods. Moreover, the resulting vector can be interpreted using fuzzy semantics with 3, 5, 7, 9, or 11 linguistic terms, enabling a more nuanced, qualitative reading of the results.

Fuzzy and TOPSIS methods are decision-making tools but fundamentally differ in their approach and applications (Guo and Zhao 2017; Ignatius et al. 2018). The Fuzzy method is based on fuzzy logic and allows the decision-maker to manage uncertainty and imprecision in data, easily including subjective data of a qualitative nature in the analyses. For instance, it transforms words such as 'high', 'medium' or 'low' into fuzzy numbers, through the use of triangular or non-linear numbers (Stefanini et al. 2008; Sun et al. 2022). This approach results in a more realistic solution in the presence of uncertainty by assigning and combining fuzzy membership values

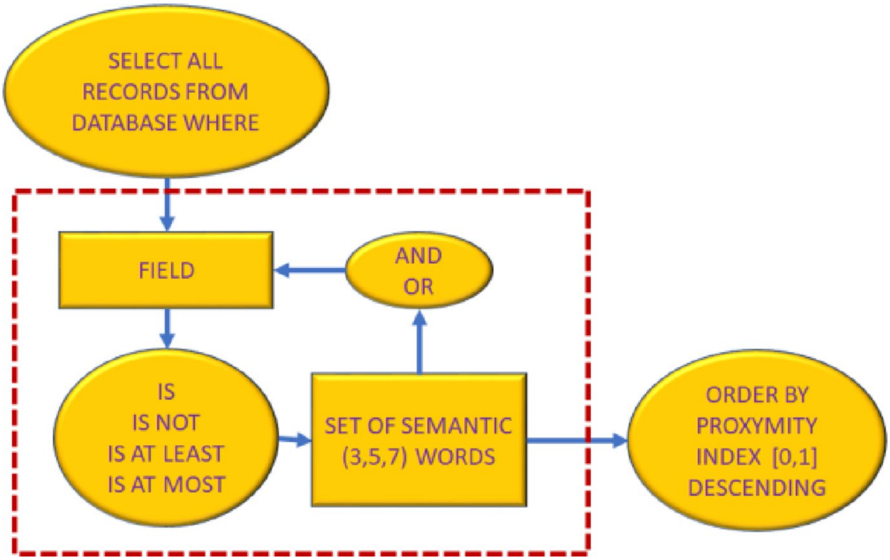


Fig. 3 Circular creation of fuzzy query semantic

to the evaluation criteria. On the other hand, based on the theory of distance from extremes, the TOPSIS method provides the decision-maker with a technique of ranking alternatives, which identifies solutions from a finite set of alternatives closest to the positive ideal solution and farthest from the negative solution, classifying them according to their relative distance. This method requires precise numerical values for each criterion and alternative and, therefore, is unsuitable in cases of ambiguity and subjectivity management. However, it presents itself as a simple and intuitive method that requires a low number of computations.

3 Empirical analysis

The results in the graph provide an interesting picture of fuzzy method performance, useful in helping financial institutions to manage credit risk. Our decision-making tool comprised financial and non-financial information. Applying fuzzy logic, we applied a fuzzy query semantic which corresponds to a promising scenario in which banks could decide to adopt ad-hoc credit policies.

Promising scenario means that these firms are in good financial health –measuring by ROA, Ebitda margin and indebtedness– and also that they invest in long term projects, such as foreign markets, sustainability strategies and innovativeness, calculated by ITZ propensity, SDG score and innovation score. Under these circumstances the bank should adopt an enterprising credit policy. Some of these firms are betting on long-term projects which need financial support in the present. Moreover, the current robust state of health in terms of financial performance indicates a good performance forecast.

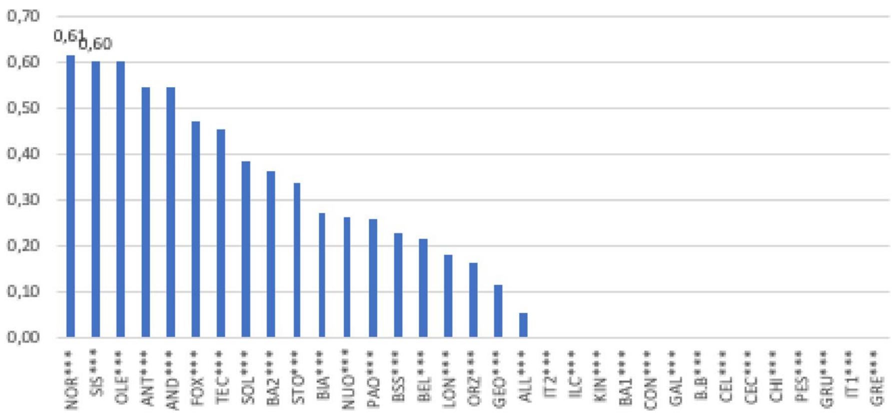
In graph 1, the first firm, from the right, is the one which most closely corresponds to the fuzzy query formulated, in other words it shows the highest financial and non-financial values; whereas the last firm, from the left, with the low proximity index, is the one which least satisfies the conditions of the query. For these firms, such as NOR* or SIS*, the bank can adopt a favorable credit policy because of the low risk of default.

In the next step we applied the TOPSIS method. Results show a ranking of firms based on their creditworthiness scores, offering insights into their financial and non-financial reliability and alignment with ideal credit standards. As required by the TOPSIS method, each parameter analyzed was assigned a weight; in this case we indicated 0.166, calculated as the ratio between 1 (the total sum of weights) and 6 (the total number of indicators), i.e. giving equal importance to all parameters in the credit rating assessment. The calibration of the parameters can vary according to the needs of the decision-maker, who can choose to assign a higher weight to parameters that are given greater relevance.

In graph 2 we can see the ranking. As we illustrate above (par. 2.1), this method ranks the alternatives on the basis of their proximity to the ideal solution and their distance from the worst solution. Thus, the alternatives with the highest scores (i.e., SOL* and BA2*) are the ones closest to the ideal solution while those with low scores (i.e., GAL* and CHI*) are less desirable.

The TOPSIS method thus provides a ranking which is meaningful only in terms of position. In order to make the data from the fuzzy method comparable (proximity index between 0 and 1), the TOPSIS data was normalized in the interval [0,1] (adjusted rank). This procedure allowed us to retain the position information while making it comparable with the proximity index.

In the following step a Cooperative Credit Bank (CCB) was consulted. As usually happens, cooperative banks differ from commercial banks in their SMEs credit rating models due to the lack of information on the part of these firms (Roy and Shaw 2021), a deficit which results in the credit institutions themselves having less formal scoring systems which also include non-codified information (i.e., relationship-based lending) and subjective parameters (i.e., the borrowers' characters, capital, capacity and

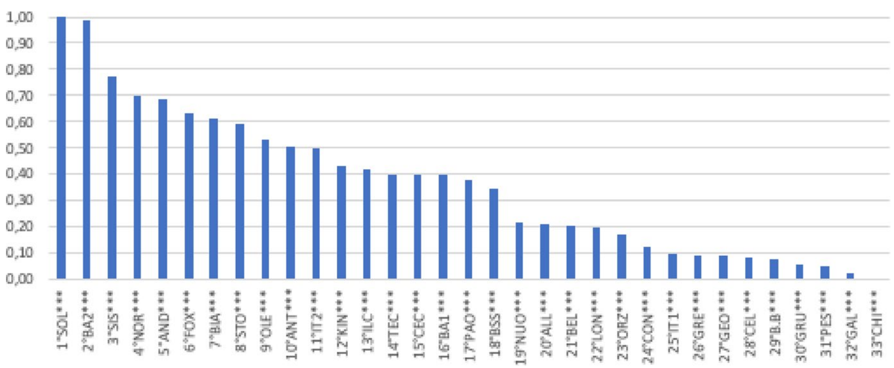


Graph 1 Fuzzy logic output: promising scenario (proximity index)

collateral). Similarly, our CCB operates under these conditions. Therefore, they were asked to make an assessment of the trustworthiness of a group of small businesses by using their favorite linguistics semantics (at 3, 5 or 7). So, we didn't ask the bank to confirm whether the companies were their customers, but rather to assess their creditworthiness based on the information available to them, irrespective of any customer relationship. The decision-maker opted for the semantics at 5: where 1 is not at all creditworthy and 5 is very creditworthy. (Tables 3 and 4 shows, also, the CCB score).

With regard to the fuzzy method, Table 3 illustrates how the relative positioning of firms – measured through the proximity index derived from the adopted query (see Fig. 2) – can vary significantly depending on the evaluation criteria considered. Specifically, the columns 'NF rank', 'F rank', and 'NF + F rank' indicate the position of each company based respectively on: non-financial indicators (NF), financial indicators (F), and a combination of both (F + NF). The column labeled 'CCB Score' reports the level of trustworthiness assigned by financial institutions. In order to compare the bank's rankings with those obtained using the fuzzy method, the last column 'CCB rank' shows the bank's evaluation converted into a ranking.

The analysis shows that some firms experience a notable improvement in their ranking when transitioning from a purely financial evaluation to a more comprehensive one that includes non-financial dimensions. In contrast, other firms drop in the ranking. These shifts highlight the significant impact that the inclusion – or exclusion – of different types of indicators can have on the resulting classification. This evidence reinforces the argument that incorporating qualitative and non-financial factors can substantially influence the perception of corporate performance, leading to different ranking outcomes depending on the evaluation approach adopted. To support this point, the Kendall distance (Fagin et al. 2006; Cicirello 2019) was calculated – a metric used to assess how different two rankings are: 0 indicates minimum distance, 1 maximum distance – between the CCB F, NF, F + NF rankings; a graph reporting all the distances resulting from the fuzzy method are illustrated in the left side of Fig. 4. For example, the distances of pairs (CCB, NF), (CCB, F) and (CCB, NF + F) are, respectively, 0.730, 0.794 and 0.921, indicating a substantial distance between them. Thus, from a sensitivity test perspective, the value of Kendall distance indicates that the rankings are different from each other.



Graph 2 Ranking TOPSIS

Table 3 – Fuzzy method comparison

Firm	NF*	F*	F*+NF*	NF rank	F rank	F + NF rank	CCB Score (1–5)	CCB rank
NOR***	0.61	0.83	0.61	7	5	1	1	18
SIS***	0.60	0.98	0.60	9	2	2	1	18
OLE***	0.60	0.62	0.60	8	10	3	1	18
ANT***	0.55	0.66	0.55	11	6	4	1	18
AND***	0.55	0.65	0.55	10	7	5	3	10
FOX***	0.80	0.47	0.47	1	14	6	1	18
TEC***	0.46	0.53	0.46	14	13	7	4	7
SOL***	0.39	0.94	0.39	15	3	8	5	1
BA2***	0.36	1.00	0.36	16	1	9	5	1
STO***	0.70	0.34	0.34	4	16	10	3	10
BIA***	0.27	0.56	0.27	19	12	11	1	18
NUO***	0.77	0.26	0.26	2	20	12	1	18
PAO***	0.46	0.26	0.26	13	21	13	3	10
BSS***	0.55	0.23	0.23	12	22	14	1	18
BEL***	0.61	0.21	0.21	6	23	15	4	7
LON***	0.18	0.21	0.18	20	24	16	1	18
ORZ***	0.32	0.16	0.16	18	25	17	1	18
GEO***	0.36	0.11	0.11	17	30	18	3	10
ALL***	0.68	0.06	0.06	5	31	19	1	18
IT2***	0.00	0.91	0.00	31	4	20	3	10
ILC***	0.00	0.65	0.00	30	8	21	4	7
KIN***	0.00	0.63	0.00	32	9	22	5	1
BA1***	0.00	0.60	0.00	22	11	23	3	10
CON***	0.00	0.35	0.00	26	15	24	5	1
GAL***	0.00	0.31	0.00	27	17	25	5	1
B.B***	0.00	0.30	0.00	21	18	26	1	18
CEL***	0.00	0.28	0.00	24	19	27	1	18
CEC***	0.00	0.16	0.00	23	26	28	5	1
CHI***	0.00	0.16	0.00	25	27	29	3	10
PES***	0.00	0.13	0.00	33	28	30	2	17
GRU***	0.00	0.12	0.00	29	29	31	1	18
IT1***	0.70	0.00	0.00	3	32	32	1	18
GRE***	0.00	0.00	0.00	28	33	33	1	18

* Proximity index, calculated respectively using non-financial data, financial data, and a combination of both

As with the fuzzy method, Table 4 presents a comparison of firms' rankings based on the TOPSIS approach, which assigns equal weight to all parameters in the credit rating assessment. The analysis shows that, once again, firms' positions vary significantly depending on the evaluation criteria applied (i.e., non-financial, financial, and combined), confirming the strong influence of indicator selection on the final classification. The Kendall distances between the CCB, F, NF, F + NF rankings, obtained from the TOPSIS approach, are given in the right side of the graph in Figura 4. For example, for the pairs (CCB, NF), (CCB, F) and (CCB, NF + F) we obtain values of values 0.653, 0.771 and 0.921, respectively, highlighting the strong misalignments between them.

Table 4 – TOPSIS method comparison

Firm	NF adj*	F adj*	F+NF adj*	NF rank	F rank	F+NF rank	CCB Score (1–5)	CCB rank
SOL***	0.40	0.89	1.00	18	2	1	5	1
BA2***	0.24	1.00	0.99	21	1	2	5	1
SIS***	0.72	0.55	0.77	5	3	3	1	18
NOR***	0.64	0.51	0.70	9	5	4	1	18
AND***	0.55	0.52	0.68	13	4	5	3	10
FOX***	0.95	0.41	0.63	2	10	6	1	18
BIA***	0.69	0.43	0.61	7	8	7	1	18
STO***	0.62	0.43	0.59	10	7	8	3	10
OLE***	0.73	0.34	0.53	4	13	9	1	18
ANT***	1.00	0.26	0.51	1	15	10	1	18
IT2***	0.04	0.48	0.50	32	6	11	3	10
KIN***	0.15	0.41	0.43	25	9	12	5	1
ILC***	0.13	0.39	0.42	27	11	13	4	7
TEC***	0.28	0.34	0.40	20	14	14	4	7
CEC***	0.62	0.21	0.40	11	17	15	5	1
BA1***	0.21	0.36	0.40	24	12	16	3	10
PAO***	0.64	0.22	0.38	8	16	17	3	10
BSS***	0.85	0.08	0.35	3	26	18	1	18
NUO***	0.61	0.08	0.22	12	25	19	1	18
ALL***	0.71	0.05	0.21	6	30	20	1	18
BEL***	0.49	0.09	0.20	15	24	21	4	7
LON***	0.54	0.07	0.20	14	27	22	1	18
ORZ***	0.22	0.17	0.17	23	18	23	1	18
CON***	0.15	0.15	0.13	26	19	24	5	1
IT1***	0.46	0.00	0.10	16	33	25	1	18
GRE***	0.42	0.00	0.09	17	32	26	1	18
GEO***	0.35	0.02	0.09	19	31	27	3	10
CEL***	0.09	0.12	0.08	28	20	28	1	18
B.B***	0.24	0.07	0.08	22	28	29	1	18
GRU***	0.08	0.11	0.06	29	21	30	1	18
PES***	0.08	0.10	0.05	30	22	31	2	17
GAL***	0.00	0.10	0.03	33	23	32	5	1
CHI***	0.07	0.06	0.00	31	29	33	3	10

* Ranking TOPSIS adjusted, calculated respectively using non-financial data, financial data, and a combination of both

Figure 5 shows our proposed fuzzy TOPSIS decision-making tool, which integrates all three methods described above. It represents the operating logic of the tool, based on the use of quantitative and qualitative data to define the parameters to be considered in the decision-making process. Both categories of information can be analyzed using both methods, although qualitative parameters are better analyzed through fuzzy logic.

Starting with this information pool, we have applied the Fuzzy method by identifying the fuzzy semantic query (in our case, at 3 and 5 words), using the twofold connectives 'is not' and 'is at least' and the logic connective 'and'. The proximity index (between 0 and 1) is the output of the fuzzy logic, i.e., the company that obtains

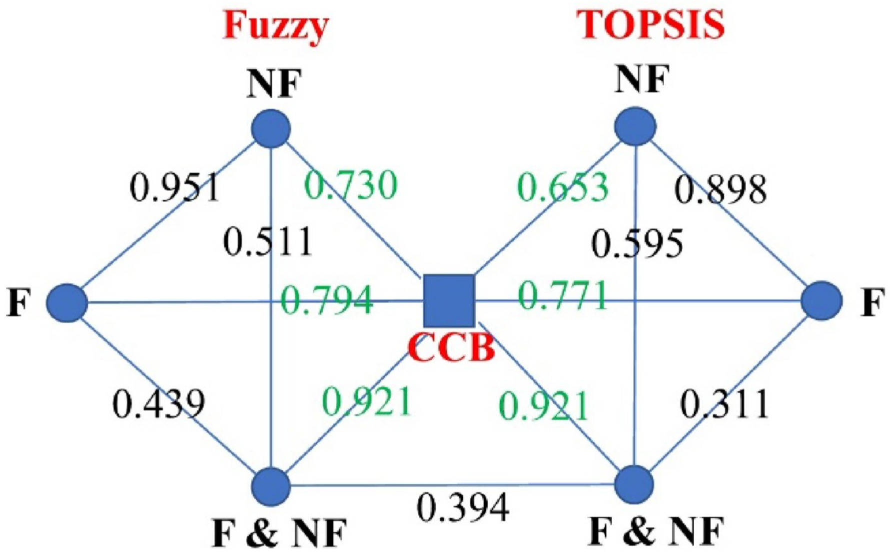


Fig. 4 Graphical representation of Kendall distances between all rankings

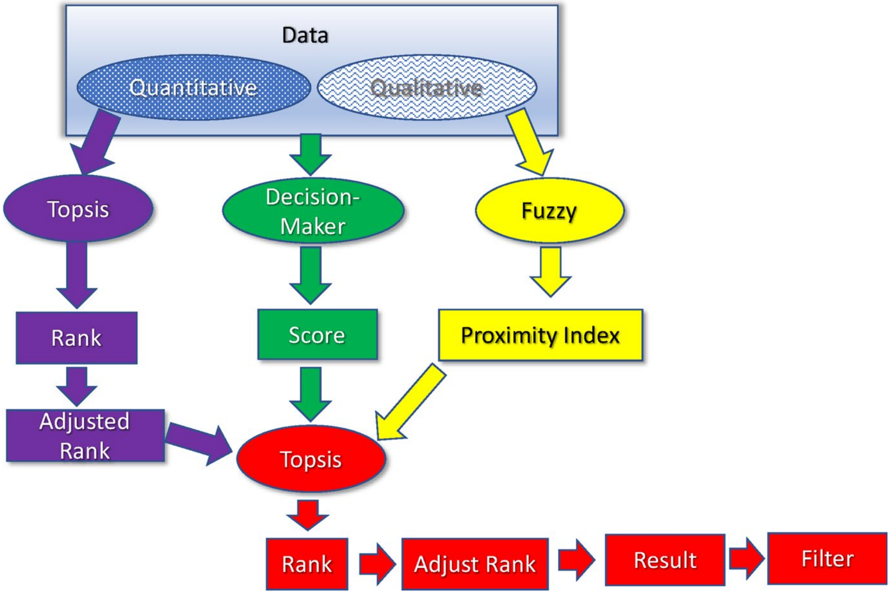


Fig. 5 – Fuzzy TOPSIS decision-making tool

greater proximity is the company that comes closest to the request formulated through the fuzzy semantic query, in this case, *'Which companies are most creditworthy?'*.

Then, the TOPSIS method could be adopted, assigning a weight to each parameter according to the degree of importance the decision-maker intends to give to each criterion. This method ranks the alternatives based on their closeness to the ideal solution and their separation from the worst solution, expressing information with positional and not absolute value. The ranking obtained was normalized (in the interval 0–1), and by doing this procedure we can integrate the ranking in the final step.

At this point, we have also included the evaluation made by the consulted bank, i.e. the score assigned to each company. The evaluation was formulated using a 5-word semantics (where 1 is not at all creditworthy and 5 is very creditworthy).

Finally, the identified tool provides that the methods are integrated according to the TOPSIS approach. Specifically, the final use of the TOPSIS method makes it possible to define a weighted ranking, which can combine, in customizable proportions, the bank's original evaluation with the outputs from the fuzzy and TOPSIS models. Therefore, the decision-maker can choose what weight to assign to each method for the final assessment of the companies' creditworthiness (for example, assign equal weight to all evaluation parameters-methods; exclude one or more, etc.). The output, as already seen, is a positional rank that indicates the firm closest to the optimal solution. The adjusted rank (normalized in the interval $[0,1]$) is calculated in order to making the ranking readable with the fuzzy semantic. For instance, in the case of 5-word semantics: it possible to ask to the system (by drop-down menu): *'show me the firms with maximun values'* (high values or medium values, etc.).

4 Conclusions

Small enterprises form the core of the economy and society worldwide, and yet in accessing credit they face major constraints which jeopardize their growth and continuity on the market. To evaluate an enterprise's credit risk exposure, financial institutions usually adopt methods mainly focused on financial data; however, SMEs are often deficient in reliable and structured financial indicators. Consequently, the creditworthiness assessment of SMEs is different from that of large enterprises (Sun et al. 2022; Row and Shaw 2023b). Hence the importance of taking into account supplementary data such as non-financial information in order to guarantee trustworthy and consistent estimates for small business.

Moreover, credit rating models based on exclusively quantitative approaches usually require a data set, generally of a quantitative nature, at once vast, time-consuming and costly, which may not be appropriate for the financial institutions that adopt them, as could be the case for cooperative financial institutions. Indeed, unlike shareholder-based commercial banks, cooperative banks –as locally based institutions– adopt relationship-based lending evaluation methods: that is, they rely on the analysis of non-coded information *–soft information–* of a non-financial character (Zedda et al. 2024). This allows them to obtain information of a qualitative and prospective nature which can be of significant importance for evaluating the reliability of small businesses.

Despite the particular importance of credit rating for SMEs, it remains a little explored field (Sun et al. 2022; Roy and Shaw 2023a, b). From this viewpoint, the current research proposes a decision-making support tool for creditworthiness assessment, including financial and non-financial variables to appraise the SMEs' risk more accurately.

This study set itself the task of developing a practical creditworthiness assessment tool by adopting a Fuzzy-TOPSIS decision-making approach. The main advantage of this tool lies in its simplicity and adaptability, (i.e., the inclusion of qualitative and quantitative data, the analysis of large and small amounts of data), characteristics which make it particularly suitable for assessing SMEs. Furthermore, the decision-maker, i.e. the CCB, may decide to use one or more methods (i.e., fuzzy and/or TOPSIS and/or bank model) at the same time, as well as incorporate in the model financial and non-financial indicators relating to the companies' strategic behaviour –such as innovation, internationalization and sustainability– which may prove crucial in identifying the best credit policy towards certain companies.

This study is intended to break new ground. The proposed approach has several advantages: its simplicity and modularity could make it a helpful tool for CCBs to use as a complementary (and not a substitute) assessment method to the existing system for identifying creditworthy companies. This would allow the bank to initiate a gradual process of change that could bring significant improvements in terms of effectiveness and efficiency in the decision-making process and credit risk management. Moreover, the potential cost of adopting this tool (such as costs related to the introduction and maintenance of the software and staff training) is relatively low, besides its being easy to implement in Microsoft-Excel-based template – all of which makes it accessible to small banks, even on an experimental basis.

Financial institutions can exploit the scalability of the proposed decision-making tool, i.e. based on their information needs, the decision-makers can decide to change the settings of the assessment model. On the fuzzy method side, it is possible: to supplement qualitative information (so called, *soft-information*), by using a linguistic semantic in keeping with the natural language of the decision-maker; to reduce or expand the granularity of semantics (e.g., 3, 5 or 7 words); to change logical operators (or/and) logical connectors (is, is not, is at least, is at most). On the TOPSIS method side it is possible: to modify the weights of parameters, assigning greater importance to some indicators than to others (for instance: ROA weighs twice as much as the SDG propensity, or vice versa; the SDG propensity has more weight than the Ebitda margin indicator, etc.). All these features can increase the effectiveness of the analysis and assessment of credit risk for SMEs.

As with any study, this work has some limitations, which point the direction for the future stages of research. The fuzzy-model proposed adopted triangular fuzzy numbers with a sum equal to 1 to analyze the linguistic semantic (i.e., 'strongly low,' 'low,' 'medium', 'high', 'strongly high'); however, future research could take into account more complex options of fuzzy numbers: triangular with a sum greater or less than 1; trapezoidal or another form (i.e., non-linear). Furthermore, we adopt only six parameters (from AIDA and ATOKA databases) of which three relate to the financial health of companies, while the other three are non-financial indicators linked to the strategic vision of companies in terms of sustainability and internationalization. Future work should include new data (financial and/or non-financial) stemming from the financial institution background. To test the effectiveness of the Fuzzy-Topsis model, it would be useful to apply it to other decision-making contexts, such as choosing between foreign markets, investment projects, or green or social investments. The aim of this work is not to generalise the results obtained from applying the fuzzy-Topsis model to SME creditworthiness, but rather to demonstrate the validity and opportunity of a decision support system within a specific decision-making context, such as the banking sector.

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Declarations

Competing interests The authors declare no competing interests.

References

Abdou HA, Pointon J (2011) Credit scoring, statistical techniques and evaluation criteria: a review of the literature. Intell Syst Account Finance Manage 18(2–3):59–88

Abdullah FM, Al-Ahmari AM, Anwar S (2023) An integrated fuzzy DEMATEL and fuzzy TOPSIS method for analyzing smart manufacturing technologies. Processes 11(3):906

Abedin MZ, Chi GT, Colombage S, Moula FE (2018) Credit default prediction using a support vector machine and a probabilistic neural network. J Credit Risk 14(2):1–27

Abellán J, Mantas CJ (2014) Improving experimental studies about ensembles of classifiers for bankruptcy prediction and credit scoring. Expert Syst Appl 41(8):3825–3830

Agostino M, Ruberto S, Trivieri F (2023) The role of local institutions in cooperative banks’ efficiency. The case of Italy. Int Rev Econ Finance 84:84–103

Altman EI, Sabato G (2008) Modeling credit risk for SMEs: evidence from the US market. J Acc Finance Bus Stud 43(3):332–357

Altman EI, Sabato G, Wilson N (2010) The value of non-financial information in small and medium-sized enterprise risk management. J Credit Risk 6(2):95–127

Altman EI, Esentato M, Sabato G (2020) Assessing the credit worthiness of Italian SMEs and mini-bond issuers. Glob Financ J 43:100450

Bai C, Shi B, Liu F, Sarkis J (2019) Banking credit worthiness: evaluating the complex relationships. Omega 83:26–38

Behzadian M, Otaghsara SK, Yazdani M, Ignatius J (2012) A state-of the-art survey of TOPSIS applications. Expert Syst Appl 39(17):13051–13069

Bhimani A, Gulamhussen MA, Lopes SDR (2013) The role of financial, macroeconomic, and non-financial information in bank loan default timing prediction. Eur Account Rev 22(4):739–763

Bouwens J, De Kok T, Verriest A (2019) The prevalence and validity of EBITDA as a performance measure. Comptabilite Controle Audit 25(1):55–105
Carmona R, Fouque JP, Vestal D (2009) Interacting particle systems for the computation of rare credit portfolio losses. Finance Stoch 13:613–633
Çelikbilek Y, Tüysüz F (2020) An in-depth review of theory of the TOPSIS method: an experimental analysis. J Manag Anal 7(2):281–300
Chen LH, Chiou TW (1999) A fuzzy credit-rating approach for commercial loans: a Taiwan case. Omega 27(4):407–419
Cicirello VA (2019) Kendall Tau sequence distance: extending Kendall Tau from ranks to sequences. EAI Endorsed Trans Ind Netw Intell Syst 7(23):1–23
Cornée S (2019) The relevance of soft information for predicting small business credit default: evidence from a social bank. J Small Bus Manage 57(3):699–719
Dastile X, Celik T, Potsane M (2020) Statistical and machine learning models in credit scoring: a systematic literature survey. Appl Soft Comput 91:106263
Du Jardin P (2016) A two-stage classification technique for bankruptcy prediction. Eur J Oper Res 254(1):236–252
European Central Bank (2021) Survey on the Access to Finance of Enterprises in the euro area, November. https://www.ecb.europa.eu/stats/accesstofinancesofenterprises/pdf/ecb.safe202111~0380b0c0a2.en.pdf
European Central Bank (2014) SME access to finance in the Euro area: barriers and potential policy remedies. Monthly bulletin, pp 79–97
Fagin R, Kumar R, Mahdian M, Sivakumar D, Vee E (2006) Comparing partial rankings. SIAM J Discrete Math 20(3):628
Fahner G (2012) Estimating causal effects of credit decisions. Int J Forecast 28(1):248–260
Floris M, Marongiu M, Dessi C, Dettori A (2022) Total quality management as driver for internationalization: a case study of a small family firm. J Fam Bus Manag 12(4):614–636
García F, Giménez V, Guijarro F (2013) Credit risk management: a multicriteria approach to assess creditworthiness. Math Comput Model 57(7–8):2009–2015
Grimaldi F, Caragnano A, Zito M, Mariani M (2020) Sustainability engagement and earnings management: the Italian context. Sustainability 12(12):4881
Guerra ML, Sorini L (2020) Value at risk based on fuzzy numbers. Axioms 9(3):98
Guerra ML, Sorini L, Stefanini L (2020) Bitcoin forecasting through fuzzy transform. Axioms 9(4):139
Guerra ML, Magni CA, Stefanini L (2022) A fuzzy sensitivity analysis for measuring uncertainty and financial efficiency in project financing transactions. Int J Inform Technol Decis Mak 21(06):1683–1714
Guo S, Zhao H (2017) Fuzzy best-worst multi-criteria decision-making method and its applications. Knowledge-Based Systems 121:23–31
Herrera F, Herrera-Viedma E, Martínez L (2000) A fusion approach for managing multi-granularity linguistic term sets in decision making. Fuzzy Sets Syst 114(1):43–58
Hoffmann F, Baesens B, Mues C, Van Gestel T, Vanthienen J (2007) Inferring descriptive and approximate fuzzy rules for credit scoring using evolutionary algorithms. Eur J Oper Res 177(1):540–555
Huang Z, Chen H, Hsu CJ, Chen WH, Wu S (2004) Credit rating analysis with support vector machines and neural networks: a market comparative study. Decis Support Syst 37(4):543–558
Hwang CL, Yoon K (1981) Multiple Attribute Decision Making Methods and Applications A State-of- the-Art Survey. In Lecture Notes in Economics and Mathematical Systems (Vol. 186). Springer. https://doi.org/10.1007/978-3-642-48318-9
Ignatius J, Hatami-Marbini A, Rahman A, Dhamotharan L, Khoshnevis P (2018) A fuzzy decision support system for credit scoring. Neural Comput Appl 29(10):921–937
Istat Annuario Statistico italiano, Capitolo n. 14, Imprese (2023) https://www.istat.it/storage/ASI/2023/capitoli/C14.pdf. Accessed on 15 January 2025
Jackowicz K, Kozłowski Ł (2019) Social ties between SME managers and bank employees: financial consequences vs. SME managers' perceptions. Emerg Mark Rev 40:100619
Jiang Y, Cai W, Wang Y (2024) Change starts within: does managerial ability matter to green innovation? Humanit Soc Sci Commun 11(1):1–14
Kijkasiwat P, Hussain A, Mumtaz A (2022) Corporate governance, firm performance and financial leverage across developed and emerging economies. Risks (Basel) 10(10):185
Kremp E, Sevestre P (2013) Did the crisis induce credit rationing for French smes? J Bank Finance 37(10):3757–3772

Maharani A, Putri YSK, Khairany DG (2025) Optimizing corporate financial performance through good corporate governance and leverage: a literature review. Dinasti Acc Rev 2(2):87–93

Maldonado S, Peters G, Weber R (2020) Credit scoring using three-way decisions with probabilistic rough sets. Inf Sci 507:700–714

Malhotra R, Malhotra DK (2003) Evaluating consumer loans using neural networks. Omega 31(2):83–96

McKillop D, French D, Quinn B, Sobiech AL, Wilson JO (2020) Cooperative financial institutions: a review of the literature. Int Rev Financ Anal 71:101520

Medina-Olivares V, Calabrese R, Dong Y, Shi B (2022) Spatial dependence in microfinance credit default. Int J Forecast 38(3):1071–1085

Meng D, Yang X (2007) SMEs Credit Rating Method with Heterogeneous Information: a Chinese Case. In International Conference on Intelligent Systems and Knowledge Engineering, 706–712. Atlantis Press

Nadaban S, Dzitac S, Dzitac I (2016) Fuzzy TOPSIS: a general view. Procedia Comput Sci 91:823–831

OECD (2022) Updated G20/OECD High-Level Principles on SMEs Financing, July 2020, Indonesia

Financing SMEs and Entrepreneurs 2024: An OECD Scoreboard, OECD, Publishing OECD (2024) Paris. https://www.oecd.org/en/publications/financing-smes-and-entrepreneurs-2024_fa521246-en.html. Accessed 15 January 2025

Roy PK, Shaw K (2021) A multicriteria credit scoring model for SMEs using hybrid BWM and TOPSIS. Financ Innov 7(1):77

Roy PK, Shaw K (2023a) A credit scoring model for SMEs using AHP and TOPSIS. Int J Finance Econ 28(1):372–391

Roy PK, Shaw K (2023b) An integrated fuzzy credit rating model using fuzzy-BWM and new fuzzy-TOPSIS-sort-C. Complex Intell Syst 9(4):3581–3600

Russo PF, Nigro V, Pastorelli S (2024) Bank lending to small firms: metamorphosis of a financing model. Int Rev Econ Finance 90:13–31

Stefanini L, Sorini L, Guerra ML (2008) Fuzzy numbers and fuzzy arithmetic. In: Pedrycz A, Pedrycz W, Skowron A (eds) Handbook of granular computing. Wiley, New York, NY, pp 249–284

Sun Y, Chai N, Dong Y, Shi B (2022) Assessing and predicting small industrial enterprises' credit ratings: a fuzzy decision-making approach. Int J Forecast 38(3):1158–1172

Syau YR, Hsieh HT, Lee ES (2001) Fuzzy numbers in the credit rating of enterprise financial condition. Rev Quant Finan Account 17:351–360

Wang M, Ku H (2021) Utilizing historical data for corporate credit rating assessment. Expert Syst Appl 165:113925

Wang G, Hao J, Ma J, Jiang H (2011) A comparative assessment of ensemble learning for credit scoring. Expert Syst Appl 38(1):223–230

World Bank (2020) World Bank SME Finance, In World Bank. https://www.worldbank.org/en/topic/smefinance. Accessed on 30 January 2025

Zadeh LA (1975) The concept of a linguistic variable and its application to approximate reasoning – I. Inf Sci 8(3):199–249

Zadeh LA (1999) Fuzzy logic = computing with words. *Computing with Words in Information/Intelligent Systems*, 1, Springer, 3–23

Zadeh LA, Klir GJ, Yuan B (1996) Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers, vol 6. World scientific

Zedda S, Modina M, Gallucci C (2024) Cooperative credit banks and sustainability: towards a social credit scoring. Res Int Bus Finance 68:102186

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