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# A multicriteria credit scoring model for SMEs using hybrid BWM and TOPSIS

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## Abstract

Small- and medium-sized enterprises (SMEs) have a crucial influence on the economic development of every nation, but access to formal finance remains a barrier. Similarly, financial institutions encounter challenges in the assessment of SMEs' creditworthiness for the provision of financing. Financial institutions employ credit scoring models to identify potential borrowers and to determine loan pricing and collateral requirements. SMEs are perceived as unorganized in terms of financial data management compared to large corporations, making the assessment of credit risk based on inadequate financial data a cause for financial institutions' concern. The majority of existing models are data-driven and have faced criticism for failing to meet their assumptions. To address the issue of limited financial record keeping, this study developed and validated a system to predict SMEs' credit risk by introducing a multicriteria credit scoring model. The model was constructed using a hybrid best-worst method (BWM) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Initially, the BWM determines the weight criteria, and TOPSIS is applied to score SMEs. A real-life case study was examined to demonstrate the effectiveness of the proposed model, and a sensitivity analysis varying the weight of the criteria was performed to assess robustness against unpredictable financial situations. The findings indicated that SMEs' credit history, cash liquidity, and repayment period are the most crucial factors in lending, followed by return on capital, financial flexibility, and integrity. The proposed credit scoring model outperformed the existing commercial model in terms of its accuracy in predicting defaults. This model could assist financial institutions, providing a simple means for identifying potential SMEs to grant credit, and advance further research using alternative approaches.

**Keywords:** Credit scoring model, SME, Financial institutions, MCDM, BWM, TOPSIS

## Introduction

Credit scoring is an essential tool for financial institutions prior to granting credit to applicants (Chen and Chiou 1999). In the financial sector, credit may be defined as granting some form of financial resources to individuals or organizations with agreed terms and conditions for both the lenders and borrowers. Credit scoring enables financial institutions to assess borrowers' ability to repay loans on time. It is a relatively complex task with numerous risks that may result in the failure of a loan recipient in meeting payment obligations when due (Zhang et al. 2016). The entire process necessitates careful

scrutiny, and even minor mistakes can have serious consequences (Lando 2004). Financial institutions often choose the safer side and deny credit to risky firms to avoid pecuniary loss (Zhang et al. 2016). Even a small improvement in the credit scoring model could significantly facilitate earnings (Zhang et al. 2019).

The interest of financial institutions is estimating and mitigating the risks generated by various sources, particularly credit. Compared to large corporations, SMEs are significantly disadvantaged regarding financial data organization and planning (Batsaikhan 2015), which makes it challenging to predict defaults when sufficient financial data are unavailable. Financial institutions frequently rely on relationship-based lending to SMEs (Hasumi and Hirata 2014) as it is often difficult to assess SMEs' credit risk because of unorganized financial operating systems. As a result, SMEs face challenges in obtaining credit from financial institutions (Angilella and Mazzù 2015). According to a World Bank (2020) report, SMEs contribute to approximately 90% of businesses and more than 50% of global employment opportunities. Notably, half of these SMEs do not have access to traditional credit, and when uncounted informal SMEs are considered, the financing gap widens even further. In terms of its potential to unlock economic resources, financial institutions cannot afford to overlook the niche SME market (Campbell and Rogers 2012).

Following the introduction of Basel-II international business standards<sup>1</sup> by the Basel Committee on Banking Supervision (BCBS 2006), financial institutions emphasized both qualitative and quantitative techniques for credit scoring. Since then, many researchers, such as Dželihodžić et al. (2018), Shi et al. (2019), and Doumpos and Figueira (2019), have designed various credit scoring models that are primarily based on data-driven quantitative techniques like regression analysis and discriminant analysis. Beaver (1966) observed that financial ratio-based models alone are insufficient for predicting bankruptcy. Such techniques rely on certain assumptions, such as multivariate normality for independent variables, which are frequently violated (Wang et al. 2011). Furthermore, a large amount of default data is required, which is expensive and scarce (García et al. 2013). Identifying the beneficiaries of financial participation is challenging owing to a lack of credit history, a considerable number of applicants, and applicants' competing perspectives and characteristics (Chao et al. 2021). It is difficult to make credit lending decisions with limited data (Huang et al. 2004). Hence, it is a challenge to accurately predict the potential for default when sufficient financial information is unavailable, and data-driven methods may not perform well in such cases (Hasumi and Hirata 2014). This problem could be solved using a multiple criteria decision-making model (MCDM), which is expert-driven and can simultaneously assess financial and nonfinancial information with limited data available (Batsaikhan 2015). Thus, this study proposes applying this technique as SMEs are often inept at preserving financial data.

MCDM is a branch of operations research that integrates mathematics, management, informatics, and economics to solve multicriteria decision problems, incorporating the decision-maker's preferences into the model for a meaningful decision. The model is

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<sup>1</sup> The Basel Committee on Banking Supervision (The Basel committee) is a committee of bank governing authorities formed in 1975 by the group of ten central bank governors. It is made up of top officials from bank regulatory agencies and central banks. The Committee published a complete version of the Basel II Framework on July 4, 2006.

helpful in identifying a compromise solution while keeping the decision-maker at the core of the system. MCDM has been used to successfully resolve a variety of real-world problems (Ishizaka and Nemery 2013). The model's problems are classified into two categories, including multiobjective decision-making and multiattribute decision-making (MADM) (Kahraman et al. 2015). This study proposes a hybrid MCDM model under MADM to assist financial institutions in identifying suitable SMEs for granting credit. The model considers both financial and nonfinancial data without constraining assumptions, as with statistical techniques (García et al. 2013). By involving experts throughout the development and implementation of the model, MCDM can improve decision-making precision (Doumpos and Figueira 2019). The MCDM model does not necessarily require data into two groups (default and nondefault) in the credit lending process but can continuously estimate the possibility of default (Wang et al. 2011). This study presents a credit scoring model for SMEs based on the MCDM technique to address the research gaps. The model can simultaneously assess both subjective and financial criteria. In addition, the proposed model considers important nonfinancial factors when determining the SMEs' credit scoring. To the best of the author's knowledge, very few studies have addressed the simultaneous evaluation of these two factors for assessing creditworthiness. This study seeks to answer the following research questions.

- What are the financial and nonfinancial variables that influence SMEs' creditworthiness?
- How much weight should be given to various factors in the credit scoring process?
- How are various firms evaluated against the identified factors to obtain a credit risk score?
- What advantages does the proposed MCDM technique have over existing methods?

This study proposes a hybrid model combining the best–worst method (BWM) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The BWM is used to evaluate criteria weight (Rezaei 2015), whereas TOPSIS is applied to calculate SMEs' credit score. The primary rationale for using the BWM is the superior efficacy that the method has demonstrated over previous MCDA approaches (Rezaei 2015). Contrastingly, the TOPSIS fulfills the goal of credit scoring in finance by eliciting a relative score for the SME in comparison to ideal and worst creditworthy borrowers. A decision-maker can use TOPSIS to compare an applicant's performance to ideal performance standards. This procedure requires less time and data than conventional MCDAs. This study is the first to apply the BWM in the field of SME credit scoring to improve the identification and selection of potential SMEs for lending based on 30 criteria. It combines nonfinancial parameters, such as managerial quality, industry perspective, and conduct of accounts, with financial parameters because focusing only on financial aspects may lead to an incorrect decision.

This study makes a fourfold contribution to existing literature. It is assumed to be the first to use the BWM for credit scoring. Second, this study attempts to improve the current credit scoring system, which often assesses only financial information. The proposed model presents a novel integration of managerial, industrial, and ethical considerations with financial factors simultaneously. Finally, the study is innovative as it

uses an expert-driven multicriteria approach to credit scoring to solve an endemic issue of practical credit decision-making. The method explains how expert opinions can be included to make more viable decisions.

The remainder of the paper is structured into five sections. First, the literature review discusses current SME credit rating models, the use of MCDM in credit scoring, and nonfinancial factors for determining SMEs' creditworthiness. Next, the methodology section proposes the model for scoring SMEs based on the BWM and TOPSIS. A real-life case study for rating SMEs is presented in the case study section, and the results and discussion section describes the proposed method's results compared to existing commercial SME ratings to evaluate the model's adeptness and accuracy using a sensitivity analysis. Finally, the conclusion ends the paper.

### **Literature review**

This section discusses previous literature on credit ratings for SMEs. The primary objective of this study is to develop an effective credit scoring model for SMEs. This literature review has been divided into three parts. The first section reviews the fundamental concepts of credit scoring and their significance in the context of SMEs. The second section discusses the application of MCDM in the field of SME credit scoring. Finally, the third part discusses the significance of various nonfinancial factors for determining SMEs' creditworthiness.

### **SMEs' credit scoring and its importance**

SMEs have an essential role in economic development and job creation around the world. According to a World Bank (2016) report, SMEs are responsible for 40% of the global gross domestic product (GDP). Several studies, including Jackowicz and Kozłowski (2019) and Yoshino (2016), have found that SMEs contribute significantly to economic development. Despite their significant contributions, SMEs' growth is hampered by the lack of availability of formal financing (Berger and Udell 2006). Financial institutions consider SMEs to be riskier lending prospects than large corporations due to a lack of reliable financial records (Berger et al. 2005a,b). According to Berger et al. (2005a, b), most SMEs do not maintain appropriate accounting records, making it difficult for banks to grant them credit. Furthermore, in a volatile business environment, the creditworthiness of SMEs can change rapidly. Culture can also impede SMEs' access to credit. For example, large corporate banks are often reluctant to lend to SMEs because of a lack of knowledge regarding them (Kumar and Rao 2016). Regardless of the risks associated with SME financing, banks can no longer ignore this sector when seeking to gain a significant share of the credit market. Financial institutions must use an accurate credit scoring model to make credit decisions and calculate capital following regulatory guidelines (Grunert et al. 2005). A scoring model facilitates the determination of loan pricing (Liu et al. 2019). Improving the process of assessing credit risk would help financial institutions make sound decisions and reduce the financial losses associated with loan defaults (Gonçalves et al. 2016). Recently, Kou et al. (2021) proposed a two-stage multiobjective feature-selection technique for evaluating SMEs' creditworthiness that relies on operational information and payment channel variables but does not include financial data. According to the findings, the suggested model obtained comparable

classification performance while significantly decreasing the number of nodes in the feature subset. The authors proposed that financial institutions could use the multiobjective approach to address concerns regarding model readability.

Basel-II provides a standard framework for assessing credit risk (Van Gool et al. 2012). Financial institutions use the standardized approach (TSA) and an internal rating-based (IRB) approach for calculating credit risk capital requirements. Under TSA, financial institutions engage with external credit rating agencies to measure credit risk, whereas the IRB approach allows financial institutions to build their internal credit risk rating model (Merikas et al. 2020). Financial institutions can use internal credit scoring to determine credit risk and identify potential borrowers. Bruno et al. (2015) and Cucinelli et al. (2018) explained the benefits of applying IRB over TSA. The IRB approach produces better risk management in comparison to TSA (Cummings and Durrani 2016). Moreover, the IRB approach has improved significantly in recent years (Gupta et al. 2015).

Credit scoring methods, such as statistical techniques, mainly apply logistic regression, multivariate discriminant analysis, and linear regression to predict default probability (Altman et al. 2018; Bedin et al. 2019). However, unlike the MCDM technique, this requires considerable default and nondefault data, which are costly and difficult to obtain (Dastile et al. 2020). Pang et al. (2021) suggested a credit scoring system based on extreme learning and the fuzzy c-means methodology to classify borrowers' credit characteristics. The research gathered sample data from 7706 debtors through the internet, categorizing them into seven classes. Furthermore, according to the Basel-II guidelines, credit evaluation should combine both qualitative and quantitative dimensions. Therefore, the MCDM-based method will integrate qualitative and quantitative data to determine a credit score (García et al. 2013).

#### **Application of MCDM in credit scoring**

Credit scoring can be modeled as an MCDM problem (Ishizaka and Nemery 2013). Kou et al. (2014) indicated that it may be modeled as an MCDM issue if the assessment involves various criteria. In MCDM, a complex problem is typically divided into multiple parts, which are then used to construct a decision tree. Following the calculation of the weights of each component, the individual parts are combined to reach a common decision (Mardani et al. 2015). MCDM techniques have drawn tremendous attention because of their ease of use and operational flexibility (Doumpos and Figueira 2019; Yu et al. 2021). The MCDM technique can simultaneously evaluate financial and nonfinancial aspects. Hence, this technique can be used as an alternative approach to traditional credit scoring for SMEs. Various scholars have applied combinations of MCDM techniques to develop credit scoring models (Gutiérrez-Nieto et al. 2016; Gastelum Chavira et al. 2017).

IÇ and Yurdakul (2010) established an MCDM-based credit decision support system using AHP and TOPSIS to determine firms' creditworthiness, with particular emphasis on industry influence and business ratings. The authors asserted that the weight of the criteria should be adjusted based on market conditions. Chi and Zhang (2017) proposed an entropy-based credit rating method, including both default and nondefault firms. Doumpos and Figueira (2019) developed an internal credit rating model using

the ELimination Et Choice Translating REality (ELECTRE) Tri-nC method to examine the deviation from external risk ratings. The authors observed that the use of multiple parameters could improve a rating model's accuracy and reduce ambiguity compared to external rating systems. Yang et al. (2019) developed a green credit rating mechanism by combining the Decision-Making Trial and Evaluation Laboratory technique (DEMATEL), grey relational analysis, analytic network process (ANP), and TOPSIS into a hybrid MCDM. The authors claimed that their study could assist the banking industry in Taiwan. Ji et al. (2020) proposed an interactive multicriteria decision-making model (TODIM) of personal default risk assessment for the peer-to-peer (P2P) credit lending process. According to the research, TODIM successfully integrates decision-makers' psychological behavior into credit lending considerations. Atmaca and Karadaş (2020) applied AHP to select the best financial instrument for investment. Recently, Roy and Shaw (2021a) suggested an AHP–TOPSIS-based model for SME credit scoring. Diverse MCDM approaches (such as AHP, ANP, DEMATEL, ELECTRE, PROMETHEE, TODIM, and TOPSIS) have been applied in the context of credit ratings. According to the findings, the application of MCDMs could help in alleviating decision-making challenges when granting credit to SMEs. Unfortunately, no studies have reported the use of the BWM for credit ratings.

#### **Nonfinancial factors relevant to deciding SMEs' creditworthiness**

Nonfinancial factors have an essential role in the credit scoring process, just as financials. Yurdakul and Iç (2004) made some noteworthy observations on the credit rating model in Turkey. Owing to the lack of dependable financials, the authors discovered that banks in Turkey rarely use financial ratio-based credit ratings; instead, banks use traditional asset-based lending and comprehensive business analysis. They constructed an AHP-based credit evaluation technique integrating both financial and nonfinancial criteria to establish creditworthiness based on decision-makers' information and expertise. In Turkey, the relationship and age of the company are essential factors in determining overall creditworthiness. Different researchers have investigated relationship lending to SMEs and have determined that the strength of the relationship affects the lending decision (Trönberg and Hemlin 2014). Relationship length was also found to be crucial for the collateral requirements for obtaining a loan (Steijvers et al. 2010). By investigating relationship lending, Bhimani et al. (2013) observed that businesses often perform well for the first two to three years before defaulting. However, firm survival rates differ depending on their size as large firms survive better than small firms (Gupta et al. 2018). Angilella and Mazzù (2015) investigated the role of nonfinancial factors, such as management efficiency and business, in credit default forecasting. The default of loans also depends on the type of industry as different sectors face different competition levels. According to Castrén et al. (2010), firms' default rate is influenced by macroeconomic factors, such as GDP, exchange rates, and short-term interest rates. Furthermore, financial institutions consider the borrower's character and honesty in the loan granting process, and trust reduces negotiation and agency costs when obtaining a loan from a financial institution (Hirsch et al. 2018). Tang et al. (2020) observed that one firm's default behavior could prompt others to default on their intentions because of defective disciplinary procedures in the system.

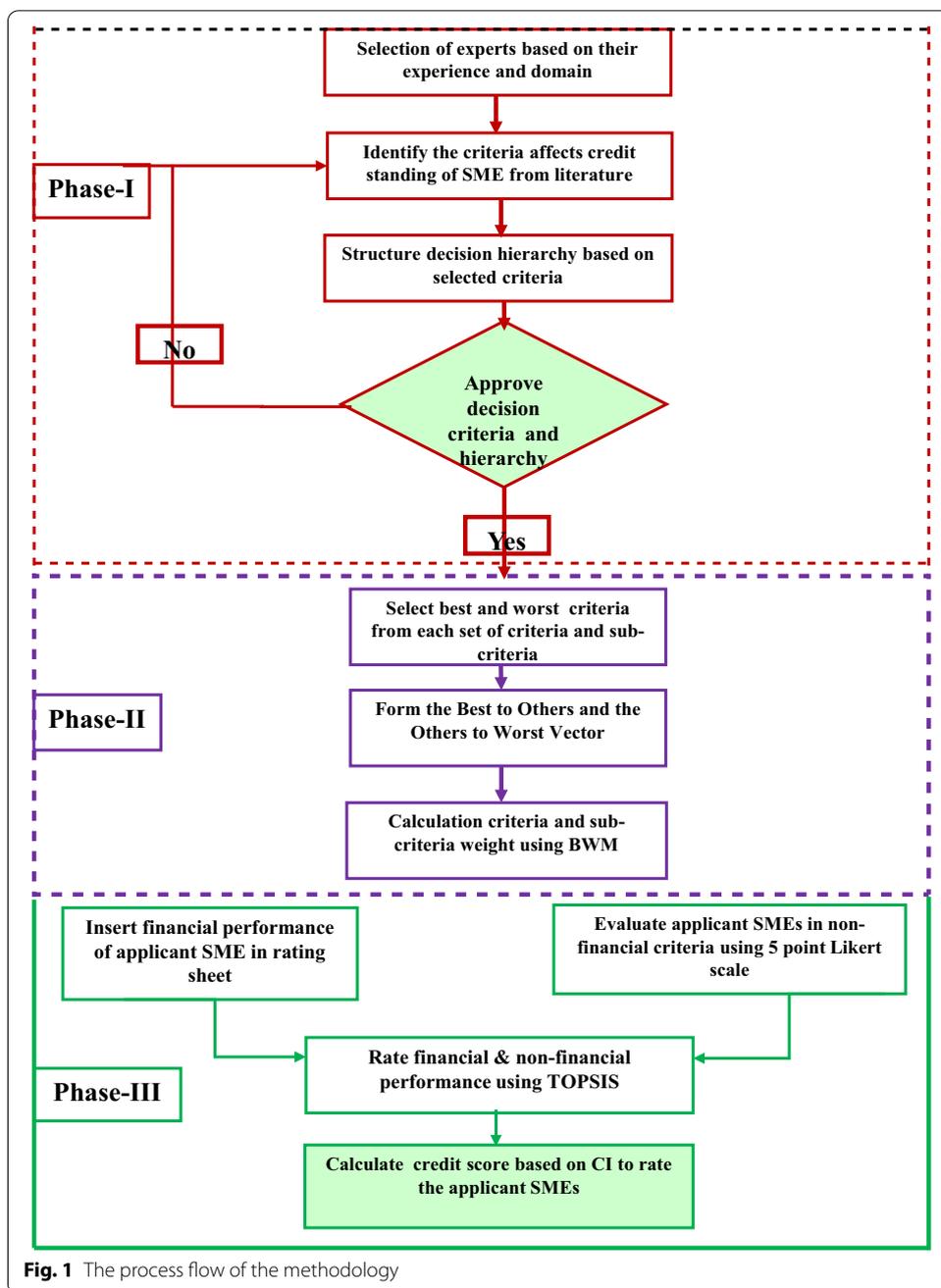
Collateral securities and personal or corporate guarantees have also been extensively used as a tool to reduce lending barriers between financial institutions and SMEs (Le and Nguyen 2019). According to the BCBS (2006), lenders should evaluate collateral as an essential independent criterion in the credit lending process for repayment and pay-back periods. As a result, financial institutions use credit scoring models to determine collateral requirements when identifying potential borrowers. This practice has been commonly used to reduce credit risk in times of adversity. Dias Duarte et al. (2017) indicated that obtaining collateral to secure loans is an essential feature of the credit lending process as financial institutions use collateral to mitigate credit risk. A prospective borrower with a credit score below a certain level necessitates collateral. Collateral and guarantees are not dependent on variables in credit ratings because lenders make credit judgments based on recipients' repayment ability. Collateral is now an important consideration in approving credit proposals (Le and Nguyen 2019). Lenders view collateral as a vital credit risk mitigation tool (BCBS 2006).

### Methodology

The credit lending process is a multistep process that begins with identifying the borrower and ends with credit approval or disapproval. The method of evaluating SMEs against multiple criteria can be classified as an MCDM problem (Ishizaka and Nemery 2013). As delineated above, researchers have shown tremendous interest in MCDM techniques due to their ability to manage complex situations. This study proposes a three-phase methodology for evaluating firms' creditworthiness by applying the hybrid BWM and TOPSIS. Initially, the factors are identified through literature review and expert opinions. Further, a decision hierarchy is developed using selected factors. The process flow of the methodology is shown in Fig. 1.

In this study, the criteria weights were determined using BWM to collect the opinions of loan sanctioning experts. Finally, the credit score of the SMEs was calculated by applying the TOPSIS method. Among the existing MCDM techniques, BWM is a new concept developed by Rezaei in 2015 that is found to have superior consistency. In this study, BWM was chosen because of its comparative advantages over other popular MCDM techniques. For example, BWM requires only  $2n - 3$  pairwise comparisons as opposed to  $n(n - 1)$  for AHP. As a result, experts need to work with fewer data and spend less time (Rezaei 2015).

Various researchers have used BWM to solve diverse MCDM problems. For example, Ijadi Maghsoodi et al. (2019) suggested a hierarchical community decision-making approach focused on BWM and axiomatic design principles to address a concept design selection challenge. In addition, Ijadi Maghsoodi et al. (2020) proposed a hybrid MADM approach integrating BWM and Combinative Distance-based Assessment for a site selection problem. Wu et al. (2019) developed an integrated model for green supplier selection using BWM and *VlseKriterijumska Optimizacija I Kompromisno Resenje* (VIKOR). In a similar direction, Roy and Shaw (2021d) recently proposed an integrated fuzzy model using BWM and TOPSIS. The study applied BWM to obtain the weight of the criteria affect selection of m-banking, and TOPSIS was applied to elicit m-banking applications rank. The methods have been successfully combined with other MCDM techniques such as PROMETHEE (Ishizaka and Resce 2021), TOPSIS (Roy and Shaw



2021b, c), and VIKOR (Cheraghali et al. 2018). However, BWM has not been used to investigate the credit lending process for SME. Taking inspiration from the above, this study extends the application of BWM with TOPSIS to the field of SME credit scoring.

**Description of the BWM approach**

In the BWM, experts first identify the best and worst criteria among all criteria, followed by a comparison of each criterion using a scale of 1–9, as suggested by Rezaei (2015).

Finally, the optimum weights of the parameters are determined through a pairwise comparison following the steps below.

- *Step 1* Identify a set of “n” number of decision criteria and subcriteria denoted as

$$C_1, C_2, \dots, C_n. \tag{1}$$

- *Step 2* Determine the best “B” (most important) and the worst “W” (least important) from each set of criteria and subcriteria based on expert opinions.
- *Step 3* A preference rating of the best criterion over other criteria is calculated applying a scale of 1–9. The weight vector, best-to-others, is denoted as

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}), \tag{2}$$

where  $a_{Bj}$  indicates the importance of the best criterion “B” over the criteria “j” and  $a_{BB} = 1$ .

- *Step 4* Similarly, the rating of all other criteria is based on the worst criterion, applying a scale of 1–9. The weight vector, other-to-worst, is

$$A_w = (a_{1W}, a_{2W}, \dots, a_{nW})^T, \tag{3}$$

where  $a_{jW}$  indicates the importance of criteria “j” over the worst criteria “W” and  $a_{WW} = 1$ .

- *Step 5* The optimum weights of the criteria ( $w_1^*, w_2^*, w_3^*, \dots, w_n^*$ ) are calculated by minimizing the absolute differences as below:

$$\left| \frac{w_B}{w_j} - a_{Bj} \right| \quad \text{and} \quad \left| \frac{w_j}{w_W} - a_{jW} \right| \quad \text{for all } j. \tag{4}$$

The weights are obtained by solving the following min–max model.

$$\min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \text{ s.t. } \sum_j w_j = 1, w_j \geq 0, \text{ for all } j. \tag{5}$$

- *Step 6* The above model can be reformulated in reference to Rezaei’s (2015) theory.

$$\min \xi^l \text{ s.t. } \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi^l \text{ for all } j; \tag{6}$$

$$\left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi^l \text{ for all } j \quad \sum_j w_j = 1, w_j \geq 0 \text{ for all } j, \tag{7}$$

where  $\xi^l$  denotes the consistency of decision-making.

- *Step 7* The optimal weights  $w_1^*, w_2^*, w_3^*, \dots, w_n^*$  and consistency  $\xi^l$  of the pairwise comparisons are obtained by solving the above linear model.

**Table 1** Consistency indices for BWM (Rezaei 2015)

$a_{BW}$	1	2	3	4	5	6	7	8	9
CI max	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

In the BWM, a comparison is considered fully consistent if  $a_{Bj} \times a_{jW} = a_{BW}$  for all  $j$ . However, while judging, a decision-maker may not always exhibit consistency for every criterion (i.e., for every “j”), and inconsistency arises when  $a_{Bj} \times a_{jW} \neq a_{BW}$  for all  $j$ . Maximum inconsistency occurs when  $a_{Bj}$  and  $a_{jW}$  become the highest (i.e., equal to  $a_{BW}$ ). Hence, a consistency ratio must be computed from the derived  $\xi^l$  to assess pairwise comparisons’ overall consistency and the decision for different values,  $a_{BW} \in (1, 2, \dots, 9)$ , as suggested by Rezaei (2015). The author’s consistency indexes for every maximum possible value,  $a_{BW} \in (1, 2, \dots, 9)$ , are presented in Table 1. From this, the consistency ratio of the pairwise comparisons is calculated as follows:

$$\text{Consistency Ratio}(CR) = \frac{\xi^l}{\text{Consistency Index}}.$$

As per Rezaei (2015), the closer the value  $\xi^l$  to zero, the higher are the consistency and accuracy of the comparison.

**SME evaluation using TOPSIS to obtain credit score**

The weights of the variables that affect credit quality, derived from the BWM, are used in TOPSIS to obtain SMEs’ credit score. TOPSIS was developed by Hwang and Yoon (1981), and it presents an approach by which a decision-maker can choose the best option from a set of alternatives (Gumus 2009). To arrive at a decision, the system calculates the distances between the best and worst solutions. A preferable solution must have little space from the best solution and the farthest distance from the worst solution. The relative closeness of an alternative to the optimal solution can be used to rate it (Joshi et al. 2011). Hsieh et al. (2006) demonstrated that the use of TOPSIS after any MCDM approach results in a superior ranking of alternatives than a single MCDM. The technique has been successfully used to address various decision-making problems. TOPSIS can be integrated with other MCDM techniques because of its mathematical simplicity and ease of use (Chen 2021). Multiple researchers, such as Behzadian et al. (2012) and Tian et al. (2019), have applied TOPSIS in different domains to solve numerous problems. Iç (2014) combined design of experiment (DoE) and the TOPSIS approaches (DoE–TOPSIS) to assess firms’ ranking in a real-time financial context. The findings reported using the DoE–TOPSIS approach were substantially identical to those obtained using traditional methods. Recently, Liu et al. (2021) proposed a hybrid MCDM approach integrating variable weight, correlation coefficient, and TOPSIS to choose the most appropriate alternative. Researchers have also used TOPSIS and AHP in credit scoring for SMEs. Roy and Shaw (2021a, c) demonstrated that TOPSIS and its different versions can evaluate firms in terms of positive and negative ideal solutions and can offer a relative credit score that is commensurate with borrowers’ credit rating. TOPSIS has

been used in this analysis to determine the credit score of the applicant SMEs. Below is the step-by-step procedure for using TOPSIS.

**Description of TOPSIS**

- *Step 1* Suppose a decision problem consists of  $m$  alternatives  $A_1, A_2 \dots A_m$  and  $n$  criteria  $C_1, C_2 \dots C_n$ . The evaluation of alternatives against the criteria forms a matrix  $A_{ij}$  (Hwang and Yoon 1981).

$$A_{ij} = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix}, \tag{9}$$

where  $A_i$  denotes the  $i$ th alternatives,  $i = 1, 2, \dots m$ ;  $C_j$  represents the  $j$ th criterion used for rating,  $j = 1, 2, \dots n$ ; and  $a_{ij}$  is a crisp value representing the rating of an alternative  $A_i$  with respect to criterion  $C_j$ .

- *Step 2* The matrix  $A_{ij}$  is normalized using the equation

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^m a_{ij}^2}}, \text{ where } i = 1, 2, \dots m \text{ and } j = 1, 2, \dots n, \tag{10}$$

and the normalized matrix is represented as  $W_{ij}$ :

$$W_{ij} = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \vdots & \vdots & & \vdots \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix} \tag{11}$$

- *Step 3* Next, weighted normalized matrix ( $V_{ij}$ ) can be calculated by multiplying BWM weights of criteria  $w_i$  with  $r_{ij}$ . Therefore,

$$v_{ij} = w_i \times r_{ij}, \text{ where } i = 1, 2, \dots m \text{ and } j = 1, 2, \dots n,$$

$$V_{ij} = \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ w_1 r_{11} & w_2 r_{12} & \dots & w_n r_{1n} \\ w_2 r_{21} & w_2 r_{22} & \dots & w_2 r_{2n} \\ \vdots & \vdots & & \vdots \\ w_n r_{m1} & w_n r_{m2} & \dots & w_n r_{mn} \end{bmatrix}. \tag{12}$$

- *Step 4* The positive ideal solution (PIS  $A^*$ ) and negative ideal solution (NIS  $A^-$ ) can be determined as follows (Hwang and Yoon 1981):

$$A^* = \{[\max(v_{ij}|i = 1, 2, \dots, m)|j \in J_+], [\min(v_{ij}|i = 1, 2, \dots, m)|j_-]\} = \{v_1^*, v_2^* \dots v_n^*\}, \quad (13)$$

$$A^- = \{[\min(v_{ij}|i = 1, 2, \dots, m)|j \in J_+], [\max(v_{ij}|j = 1, 2, \dots, n)|j_-]\} = \{v_1^-, v_2^- \dots v_n^-\}, \quad (14)$$

where

$J_+ = \{j = 1, 2, \dots, n|j \text{ associated with positive criteria}\}$ ,

$J_- = \{j = 1, 2, \dots, n|j \text{ associated with negative criteria}\}$ .

- *Step 5* Calculate the Euclidean distance of the alternatives between PIS and NIS:

$$S_i^* = \sqrt{\sum_{j=1}^m (v_{ij} - v_j^*)^2}, \quad (15)$$

$$S_i^- = \sqrt{\sum_{j=1}^m (v_{ij} - v_j^-)^2}. \quad (16)$$

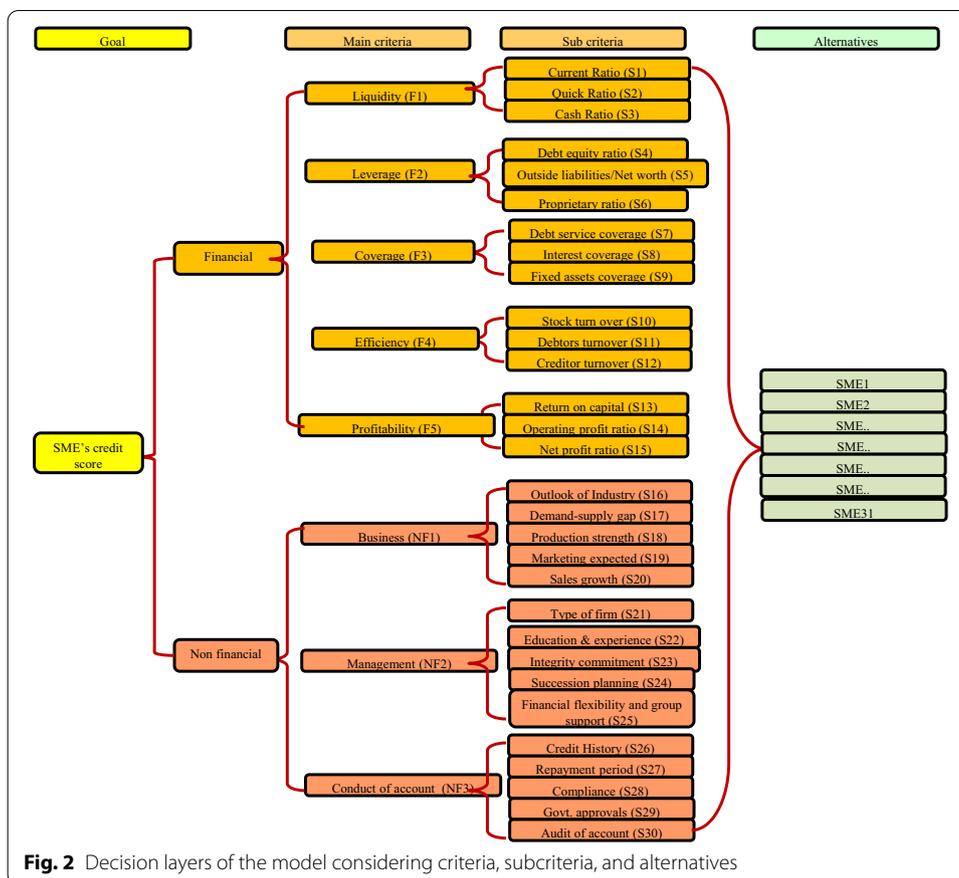
- *Step 6* Calculate the relative closeness to the ideal solution:

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*}. \quad (17)$$

- *Step 7* Rank the alternatives by arranging ( $C_i^*$ ) values from highest to lowest value.

### Case study

Most banks are interested in incorporating various models into credit scoring systems, but policymakers continue to believe that credit scoring methods should be public. As a result, to increase transparency, MCDA systems are gaining momentum in credit scoring to reduce the lack of transparency and rationalize forecasts. Following the 2006 introduction of the Basel-II framework, financial institutions are no longer limited to relying on external credit rating models due to the lack of reproducibility and high cost (Cucinelli et al. 2018). Because SMEs lack standard financial information, commercial agencies' ratings may not be appropriate for this context. Hence, the model proposed in this study can be used as an internal credit scoring mechanism for the evaluation of SMEs' credit score for potential lending based on both qualitative and quantitative criteria. The proposed model is affordable and adaptable, and decision-makers can easily apply it to SMEs. The effectiveness and practicality of this proposed model are demonstrated through a real-life case study. This research aims to find prospective SMEs by evaluating them against the identified criteria and determining their credit scores relative to ideal best and worst borrowers. The case study was developed in three stages. First, a decision hierarchy was established using goals, identified criteria, and alternatives. The study's goal was to determine the credit scores of SMEs that were in the first layer. Then, the main criteria and subcriteria were placed second, and alternatives were in the last layer. The decision hierarchy of the proposed model is presented in Fig. 2.



**Fig. 2** Decision layers of the model considering criteria, subcriteria, and alternatives

**Phase-I: Selection of criteria for rating SMEs**

Prior to constructing the credit scoring model, the possible criteria and subcriteria that affect SMEs’ creditworthiness must be identified. The IRB approach under Basel-II principles requires that banks develop and use an internal rating system to manage credit risk that is appropriate to its operation’s nature, size, and complexity. Furthermore, while examining individual credit and credit portfolios, banks should consider anticipated future changes in financial conditions in addition to potential credit risk exposure under stressful situations (BCBS 2000). Keeping the Basel-II principles for credit risk management in mind, the current study identified the financial and nonfinancial criteria shown in Fig. 2. The criteria were finalized by collecting the opinions of a panel of experts. In this study, a team of 12 respondents from SMEs and the financial sector was selected as experts. Of the 12 experts, seven had vast experience in banking and SME lending. Bank experts were chosen because they were active in SME lending processes and familiar with SMEs’ financial needs. In addition, five experts were from SMEs that have successfully obtained credit from financial institutions to support business operations. Although some initial disagreements arose, a consensus was eventually reached. Finally, 30 subcriteria were finalized.

This study adopted relevant financial ratios from a few significant studies, including Altman and Sabato (2007), Barboza et al. (2017), Chi and Zhang (2017), Altman et al. (2018), and Georgios (2019). The financial criteria were divided into five categories, as

**Table 2** Best-to-others vector under the main criteria

Best criteria	Other criteria			
	Financial evaluation	Industry evaluation	Management evaluation	Conduct of account evaluation
Financial evaluation	1	4	3	1

**Table 3** Others-to-worst vector

Other criteria	Worst criteria Industry evaluation
Financial evaluation	4
Industry evaluation	1
Management evaluation	3
Conduct of account evaluation	2

shown in Fig. 2, including liquidity, leverage, coverage, performance, and profitability. Financial criteria were further subdivided into relevant financial ratios for example liquidity was calculated in terms of current ratio, quick ratio and cash ratio that can be computed from SMEs’ financial statements. Similarly, the nonfinancial criteria were grouped into three main categories of industry and business evaluation, management evaluation, and conduct of account evaluation and were further subdivided into relevant nonfinancial information. In addition, this study adopted an approach to the relevant nonfinancial information based on studies like Kim and Sohn (2004), Angilella and Mazzù (2015), Ignatius et al. (2018), Gaganis et al. (2020), and Froelich and Hajek (2020). A complete description of each criterion is presented in Additional file 1: Supplementary A.

**Phase-II: Criteria weight calculation using BWM**

After identifying the relevant criteria, it is imperative to determine the weights. In this study, the weights of all criteria and subcriteria were calculated using the BWM suggested by Rezaei (2015). In the BWM process, experts were asked to identify the best (most important) and the worst (least important) among each set of criteria and subcriteria. Further, experts were asked to conduct pairwise comparisons of the criteria and subcriteria using a number ranging from 1 to 9. The intent of involving a panel of experts is the attainment of better decision-making than that available from a single expert (Hirschey 1979). In this study, initially, varying responses were received from experts when comparing the criteria, but a consensus was reached following a detailed discussion. The local weights of criteria and subcriteria were determined using BWM. The calculation of BWM was performed on Microsoft Excel. Tables 2 and 3 present the pairwise comparison to obtain best-to-others and others-to-worst vectors among the main criteria.

Table 4 indicates that respondents deemed financial evaluation of the utmost importance, followed by the conduct of account management and industry evaluation. The experts responded that financial evaluation was four and three times more important than industrial and management evaluations. Compared with the worst criterion,

**Table 4** Optimal weights for the main criteria

Weights (%)	Financial evaluation	Industry evaluation	Management evaluation	Conduct of account evaluation
	41.67	8.33	16.67	33.33
$\xi^*$	0.08			

respondents asserted that financial position and management situation are four and three times more important than industry condition. Similarly, the conduct of account evaluation was rated two times more important than industry evaluation. The results elicit an average consistency ratio ( $\xi^*$ ) of 0.08, which is very close to zero and satisfies the norms of below 0.10 for BWM (Rezaei 2015). After obtaining the weights of different main criteria, a similar procedure was followed for subcriteria. The local and global weights of criteria and subcriteria are presented in Table 5. The calculation of weights for every subcriterion set is available in Additional file 1: Supplementary B.

Table 5 demonstrates that applicants' credit history is the most essential factor, with a weightage of 12.82%, followed by cash ratio (8.75%), repayment period (7.69%), ROCA (6.35%), financial flexibility and group support (5.81%), government approvals (5.13%), and compliance (5.13%). According to the findings, borrowers' past performance can be considered a good predictor of future performance. However, a cash liquidity position can be vital for running an operation during a crisis or less liquid market. Furthermore, as financial institutions are looking for excellent overall investment returns, government approvals and audit compliance have emerged as two critical factors in running a successful company. Before sanctioning a loan, financial institutions consider financial flexibility and group support. The global weights of the subcriteria measured using the BWM were then used in TOPSIS to determine the final credit score of SMEs in this analysis. For calculating the final scoring, each SME was scored against those 30 derived subcriteria given in Table 5.

### Phase-III: Evaluation of applicant SMEs against each criterion

After calculating the criteria weights using BWM, applicant SMEs are next rated using the TOPSIS method. Before applying the process, it is necessary to estimate the factors' cut-off values. A Likert scale was adopted to map the cut-off values onto the scale value in consultation with the previously noted experts. In addition, due consideration was given to various factors and their effect on firms' credit standing (Ignatius et al. 2018). Table 6 presents this adopted scale, with 0 denoting the lowest level, or below the benchmark, and 4 indicating the highest level, or well above it.

In this study, a firm could be rated 4 if it was found to be above the benchmarked performance, or lowest credit risk, level for every positive attribute. Contrastingly, a score of 0 can be assigned if a firm's performance is below the threshold, or the highest credit risk, level for every negative attribute. For example, current assets' level over current liabilities represents a current ratio, and a positive attribute indicates higher and is good. A ratio of 1.33 is treated as the benchmark level at which a firm can smoothly function in literature, whereas a ratio of 1.00 is treated as a threshold at which current assets match

**Table 5** Final weights of criteria and sub-criteria using BWM

Main criteria	Local weight in %	Sub criteria under financial	Local weight in%	Global weight of financial criteria	Sub-criteria	Local weight in %	Global weight in %
Financial	41.67	Liquidity	38.79	16.16	Current ratio	16.67	2.69
					Quick ratio	29.17	4.71
					Cash ratio	54.17	8.75
		Leverage	6.06	2.53	Debt equity ratio	22.86	0.58
					Outside liabilities/Net worth	62.86	1.59
					Proprietary ratio	14.29	0.36
					Debt service coverage	53.85	3.54
		Coverage	15.76	6.57	Interest coverage	30.77	2.02
					Fixed assets coverage	15.38	1.01
					Stock turn over	24.44	1.60
		Efficiency	15.76	6.57	Debtors turnover	64.44	4.23
					Creditor turnover	11.11	0.73
					Return on capital	64.44	6.35
					Operating profit ratio	24.44	2.41
					Net profit ratio	11.11	1.09
Industry/business	8.33				Outlook of industry	7.69	0.64
					Demand–supply gap	15.38	1.28
					Production strength	15.38	1.28
					Marketing strength	23.08	1.92
					Sales growth	38.46	3.21
Managerial	16.67				Type of firm	5.45	0.91
					Education and experience	14.17	2.36
					Integrity and commitment	34.88	5.81
					Succession planning	10.63	1.77
					Financial flexibility and group support	34.88	5.81

**Table 5** (continued)

Main criteria	Local weight in %	Sub criteria under financial	Local weight in%	Global weight of financial criteria	Sub-criteria	Local weight in %	Global weight in %
Conduct of account	33.33				Credit history	38.46	12.82
					Repayment period	23.08	7.69
					Compliance	15.38	5.13
					Government approvals	15.38	5.13
					Audit of accounts	7.69	2.56

the position of current liabilities, and a ratio below 1.00 indicates a firm is managing its day-to-day working capital with the creditor’s funds (Roy and Shaw 2021a).

**The final scoring of SMEs using the proposed BWM–TOPSIS model**

After estimating the cut-off values for the various factors, the SMEs are rated using TOPSIS. In this process, the weight calculated by BWM was used. Thirty-one SMEs consisting of 24 nondefaulted (ND) and seven defaulted (DT) enterprises were scored and classified into different grades for the case study. The selected SMEs’ names are not disclosed to preserve anonymity and confidentiality. The step-by-step procedure for SME’s rating using TOPSIS is discussed below.

- *Step 1—Information collection* The information needed for the SMEs chosen for credit scoring was collected from the Capitaline database, and nonfinancial information was gathered from industry, audit reports, company websites, and archival data. In practice, financial institutions may seek these data from prospective borrowers when they request a loan from a financial institution in a prescribed format.
- *Step 2—Feeding data* Financial ratios were calculated from the financial data collected. Financial ratios such as efficiency, profitability, and liquidity are considered positive attributions in this case study, indicating that higher is better. Contrastingly, coverage and leverage are considered negative attributives, which means lower is better. In this case, subcriteria ranging from S1 to S15 represent financial criteria, and S16 to S30 represent nonfinancial criteria. The financial data are depicted in Table 7.

The data presented in Table 7 were mapped using the five-point Likert scale displayed in Table 6. The converted data from Table 7 are depicted in Table 8.

Following the financial evaluation, the corresponding nonfinancial information was assessed. Table 9 presents the comparative number of nonfinancial data using the cut-off values shown in Table 6.

In this study, two dummy SMEs (best and worst) were assumed to make the model ideal for industrial use. In this case, DPI\_SME and DNI\_SME signify the dummy positive SME and the dummy negative SME. The performances of the DPI\_SME

**Table 6** The 5-point Likert scale

Score	0	1	2	3	4
Basis	Below the minimum level or threshold	Just above the threshold	Below the benchmark level	Just above the benchmark level	Well above the benchmark level

**Table 7** Financial data of the selected SMEs for sub-criteria

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15
SME1	1.5	0.08	0.02	1.55	1.61	0.38	3.19	0.824	1.207	5.28	2.60	1.60	24.01	6.61	3.27
SME2	1.18	1.04	0.01	0.07	0.12	0.89	45.25	0.290	1.145	21.18	3.57	2.80	8.23	0.53	0.36
↓															
SME31	1.48	0.99	0.31	0.92	1.00	0.50	2.46	0.88	7.39	6.55	3.97	1.97	17.67	8.73	3.54

**Table 8** Conversion of the data of Table 7 by using the scale

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15
DPI_SME	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
SME1	4	0	0	2	2	1	4	0	1	4	3	4	4	0	2
SME2	2	3	0	4	4	4	4	0	1	4	2	3	1	0	1
↓															
SME31	3	0	2	4	3	1	3	0	4	4	2	4	4	0	2
DNI_SME	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

**Table 9** Comparative number of non-financial data converted using Likert scale

	S16	S17	S18	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29	S30
DPI_SME	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
SME1	3	4	4	4	4	4	4	4	4	3	4	2	4	4	4
SME2	2	1	3	2	2	4	4	3	1	2	4	3	4	3	4
↓															
SME31	0	1	1	2	2	2	2	1	3	2	3	2	0	1	0
DNI_SME	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

and DNI\_SME represent the highest (100%) and lowest possible credit scores (0%), respectively.

The data depicted in Tables 8 and 9 are normalized using Eq. 10. After normalization, the weighted average value of different parameters for different SMEs was calculated. The weights calculated using the BWM were multiplied with the decision matrix to obtain the normalized weighted values as per Eq. 12. Subsequently, PIS and NIS were calculated based on variable types using Eqs. 13 and 14. Further, the distances from PIS ( $S_i^*$ ) and NIS ( $S_i^-$ ) were calculated using Eqs. 15 and 16, respectively, suggested in TOPSIS. Finally, the SMEs' final credit score was obtained based on its closeness index  $C_i^*$  derived from  $S_i^*$  and  $S_i^-$  using Eq. 17.

**Table 10** The 5-point rating scale

Score	0.0–0.20	0.21–0.40	0.41–0.60	0.61–0.80	0.81–1.00
Basis	Below the minimum level or threshold	Just above the threshold	Below the benchmark level	Just above the benchmark level	Well above the benchmark level
Rating (rank)	E (5)	D (4)	C (3)	B (2)	A (1)

**Results and discussions**

Following the processes indicated, SMEs’ credit score can be accurately computed using the BWM–TOPSIS technique. SMEs’ credit score was derived based on closeness index ( $C_i^*$ ) from  $S_i^*$  and  $S_i^-$  using Eq. 17. Because standard binary classifications are ineffective for credit rating as there are diverse credit categories and misclassification costs vary significantly between classes (Wang et al. 2021), SMEs were organized into several categories based on  $C_i^*$  value, as shown in Table 10. This article classified credit quality into five categories using a credit score equivalent to a five-point rating system in line with criteria evaluation. The TOPSIS was used to classify borrowers with comparable credit quality status and characterize them based on credit score. In the pragmatic implementation of the proposed BWM–TOPSIS, interactions with credit experts concluded that a higher score represents a prolific, well-managed, and well-positioned corporation in a profitable market that is expected to pay its debts. Conversely, a lower-scoring firm within its industry is expected to have difficulty meeting its financial responsibilities. With the assistance of credit specialists, ideal best and worst values were computed to establish SMEs’ scoring. Finally, the threshold values split the companies into five distinct groups, which were then organized from A to E. A practical case study was used to demonstrate the efficacy of the method.

Accordingly, SMEs with a closeness coefficient ranging from 0.0 to 0.20 are allocated to rating E. Contrastingly, if an SME’s closeness coefficient ranged between 0.21 and 0.40, it was assigned a grade of D. Similarly, all SMEs were classified into five grades between A to E as per Table 10. The identified SMEs, their category, commercial rating, and corresponding BWM–TOPSIS rating and rank based on the TOPSIS coefficient ( $C_i^*$ ) are presented in Table 11.

Table 11 shows that out of 31 SMEs, one was rated E and eight were rated D, suggesting that they are just above or below the default category’s benchmark standard, but seven of these nine SMEs landed in the default group. The commercial agency reported five of these as D rated, indicating a default category, and the remaining two were not in the default category.

This study developed a BWM–TOPSIS credit scoring system for SMEs that may be easily implemented in real-life situations. Subsequently, the model results and performance must be compared and contrasted with commercially available ratings to ascertain its validity. To accomplish this task, the BWM–TOPSIS scoring model’s results were correlated with the commercially available risk ratings (CRISIL, India 2018–19) shown in Table 11. Spearman’s rank correlation coefficient was measured to assess the relationship between BWM–TOPSIS ratings’ rank and the commercial ratings’ rank (Roy and Shaw 2021a). The correlation was calculated using Eq. 18.

**Table 11** Final credit score and rating of the selected SMEs based on closeness index

SME	Category	Commercial rating	Commercial rating rank	$C_{ai}^* = \frac{S_{ai}^-}{S_{ai}^- + S_{ai}^+}$	BWM-TOPSIS rating	BWM-TOPSIS rank	$d_i$	$d_i^2$
DPI_SME	–	–		1.00	–			
SME1	ND	BB	4	0.50	C	3	1	1
SME2	ND	BBB	3	0.51	C	3	0	0
SME3	ND	BB+	4	0.45	C	3	1	1
SME4	ND	A	2	0.61	B	2	0	0
SME5	ND	BBB	3	0.41	C	3	0	0
SME6	DT	BB	4	0.30	D	4	0	0
SME7	ND	BB+	4	0.33	D	4	0	0
SME8	ND	BBB	3	0.50	C	3	0	0
SME9	ND	BB	4	0.44	C	3	1	1
SME10	ND	D	5	0.22	D	4	1	1
SME11	DT	B	4	0.20	E	5	1	1
SME12	ND	BBB+	3	0.59	C	3	0	0
SME13	ND	BBB	3	0.45	C	3	0	0
SME14	ND	A	2	0.34	D	4	2	4
SME15	ND	BB	4	0.43	C	3	1	1
SME16	ND	BBB+	3	0.41	C	3	0	0
SME17	ND	BBB	3	0.46	C	3	0	0
SME18	DT	D	5	0.24	D	4	1	1
SME19	DT	BB	4	0.35	D	4	0	0
SME20	ND	BB	4	0.40	C	3	1	1
SME21	ND	BBB	3	0.48	C	3	0	0
SME22	ND	BB	4	0.61	B	2	2	4
SME23	DT	D	5	0.32	D	4	1	1
SME24	ND	BB	4	0.56	C	3	1	1
SME25	ND	BB	4	0.47	C	3	1	1
SME26	ND	BBB	3	0.49	C	3	0	0
SME27	ND	BB	4	0.44	C	3	1	1
SME28	ND	BB	4	0.50	C	3	1	1
SME29	DT	D	5	0.31	D	4	1	1
SME30	DT	D	5	0.34	D	4	1	1
SME31	ND	BB	4	0.46	C	3	1	1
DNI_SME	–	–		0.00	–	–	17	23

$$\rho = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n(n^2 - 1)}, \tag{18}$$

where  $n$  represents the number of rating classes in the study and  $d_i$  is the difference between the corresponding ratings derived using BWM–TOPSIS and commercial ratings. The Spearman’s correlation coefficient value for the comparisons elicits 0.95, signifying a well-built affirmative relationship between the BWM–TOPSIS model and the commercial model. As a result, it can be asserted that the proposed BWM–TOPSIS credit scoring model potentially outperforms the commercial model and is suitable for useful implementation as an internal rating model.

Apart from the Spearman’s correlation, the accuracy rate of the proposed BWM–TOPSIS model was also checked. Furthermore, Type-I error (i.e., the probability of predicting

**Table 12** Definitive matrix

Model results	Actual number	
	Not DEFAULT (ND)	Default (DT)
ND	True negative (TN)	False negative (FN)
DT	False positive (FP)	True positive (TP)

**Table 13** Type-I, Type-II error and accuracy rate compared to a commercial model

Model	Type-I error rate (%)	Type-II error rate (%)	Accuracy rate (%)
BWM-TOPSIS model	8.33	14.28	90.32
Commercial model	4.17	28.57	83.87

a defaulted firm as a nondefaulted one) and Type-II error (i.e., the likelihood of predicting a nondefaulted firm as defaulted) were calculated using Eqs. 19, 20, and 21 using the information based on the definitive matrix shown in Table 12 to examine the efficacy of the proposed model.

$$Accuracy\ rate = \frac{(True\ Positive + True\ Negative)}{(True\ Positive + False\ Positive + False\ Negative + True\ Negative)}, \tag{19}$$

$$Type - I\ error = \frac{False\ Negative}{(True\ Positive + False\ Negative)}, \tag{20}$$

$$Type - II\ error = \frac{False\ Positive}{(True\ Negative + False\ Positive)}. \tag{21}$$

The reliability of the proposed model was tested using area under the receiver operating characteristics (AUC) as suggested by Dželihodžić et al. (2018). Table 12 summarizes the accuracy rate and the results in terms of Type-I and Type-II errors. Table 13 summarizes the proposed model’s true positive rate, false positives, and reliability rate (AUC) compared to the commercial model.

Table 13 reveals that the proposed model’s accuracy rate is 90.32%, indicating that it is healthy and accurate. Although the commercial model’s Type-I error is lower than that of the proposed model’s, the Type-II error, which is more serious (i.e., misclassifying a defaulted firm as a nondefaulted one), is lower (14.28% for the proposed model versus 28.57% for the commercial model). The reduction of Type-II errors indicates the proposed model’s ability to assess applicant SMEs’ eligibility while avoiding the inclusion of likely defaulting firms in the qualified group. Further, AUC is presented in Table 14, confirming the accuracy and reliability of the proposed model in credit risk assessment as well as fewer Type-I and Type-II errors. Therefore, the proposed BWM–TOPSIS model is demonstrated to perform well in predicting future default probability.

The key benefit of the proposed model is its low cost, flexibility, and ease of implementation in a simple, Microsoft Excel-based template. Conversely, financial institutions

**Table 14** Comparisons of AUC results with the commercial model

Model	Category of SME	True positive rate (TPR) (%)	False positive rate (FPR) (%)	AUC (1-FPR) * TPR (%)
BWM-TOPSIS model	Non defaulted SMEs	91.67	8.33	84.03
	Defaulted SMEs	85.71	14.29	73.46
Commercial model	Non defaulted SMEs	95.83	4.17	91.83
	Defaulted SMEs	71.42	28.57	51.00



spend significant amounts of money to acquire and implement commercial rating systems. Cost is a determining factor for any financial institution seeking to increase profitability. In addition, financial institutions can apply an internal rating process up to a particular loan limit as time and human capital use remain the same when comparing SME loans to corporate loans. As a result, the proportionate processing expense of an SME loan is considerably higher than that of a corporate loan. Thus, the proposed model could aid in reducing rating expenditures. It is also notable that the commercial model’s operational algorithm is not correctly known, and a simple algorithm can reliably assess a credit score to disburse loans up to a certain amount.

**Sensitivity analysis**

The weights of various criteria have a major influence on SMEs’ credit scoring. This study sought to assess the effects of multiple factors on final credit scoring (de Lima Silva et al. 2020). A sensitivity analysis was conducted by increasing or decreasing the weight of each main criteria (Financial—F+/-; Industrial—I+/-; Managerial M+/-; and Accounts Conduct—C+/-) by 10% or 20% at a time, recording the impact of the weighting variations on credit scores and related rankings for all SMEs. A total of 16 experiments were conducted (four for each main criterion), as shown in Fig. 3.

The sensitivity analysis demonstrates how changes in the weighting of the main criteria affect SMEs' ranking. A significant difference in ranking was revealed between weighted and unweighted SMEs, as shown in Fig. 3. As a result, it can be argued that the weight of the parameters is a deciding factor in the credit score and ranking of a small business.

However, when the sensitivity analysis was performed using different weights of parameters, it was noticed that SMEs' ratings did not change much. When the weight of the conduct of accounts ( $C + 20\%$ ) was increased to the extent of  $+/- 20\%$ , SMEs' rankings affected a few SMEs (SME6, SME10, and SME11). It is also notable that the remaining SMEs' ranking was observed to be the same.

## Conclusion

Financial institutions face significant challenges in predicting financial risk. The ability of financial institutions to anticipate risks determines their profitability. Numerous studies have assessed the likelihood of default using empirical approaches and complex mathematical models, but such techniques may not be suitable for SMEs because of an inherent lack of extensive data (García et al. 2013). SMEs' credit evaluation requires more attention, given the lack of studies. The credit rating of SMEs using nonfinancial variables has not been widely reported in archived literature. To fill the research gaps, this study endeavored to develop a credit scoring model for SMEs using the BWM and TOPSIS. To make the model robust, financial and nonfinancial variables were considered during the development process. Furthermore, by creating an MCDM system, the study attempted to simplify the currently complex rating process.

The analyses of the proposed approach are unique. According to the authors' knowledge, this is the first research to combine a newly developed BWM with TOPSIS to quantify SMEs' credit risks. By combining the BWM with other MCDM approaches like TOPSIS for application to a real-world problem, the current study addressed Rezaei's (2015) proposed future research directions, successfully to credit scoring, which has been unexamined by existing literature. Using a new MCDM to solve credit scoring, the proposed model also answered the recommended future research directions of Ignatius et al. (2018) and Roy and Shaw (2021a). The model is also unique in terms of the variables used. This research facilitates financial institutions' identification of a set of financial and nonfinancial parameters for rating SMEs. The proposed credit rating method is both cost effective and simple. The sensitivity analysis confirmed the proposed model's robustness in the face of unpredictability in financial situations. It is fascinating to examine how different conditions affect SMEs' credit scores.

The proposed model's main advantage is that it does not require any assumptions, as in statistical models, making it more flexible for application. The lower Type-II error indicating accurate superior default prediction accuracy signifies the practical usefulness of the proposed model. Furthermore, a minimal amount of data is required. Owing to its simplicity and low calculation cost, financial institutions may adopt it as an internal scoring model following regulatory approval to screen loan applications. As the processing costs of SME loans are significantly higher than those of large corporate loans, the proposed model can reduce costs. Furthermore, financial institutions can customize the model parameters based on the existing risk appetite. For example, a financial institution can add or remove a factor as per its requirements.

Financial institutions may apply the model for capital requirement calculation and for determining collateral requirements. The proposed BWM–TOPSIS model can also be programmed into DSS software. SMEs seeking credit from financial institutions may also use the model to assist in identifying and improving weak areas.

This research, like previous studies, has certain limitations. One of the limitations of the suggested technique is that expert biases and decision ambiguity may be of influence. Building consensus was difficult in group decision-making exercises, as it is in any MCDA technique. Furthermore, the study is based on financial statements made by recognized businesses in previous years. The findings might change over time. These issues could be addressed in future research using systematic evaluation and by including additional information regarding firms’ dynamic performance. In the future, other data sets may be examined to evaluate the predictability of the BWM–TOPSIS credit scoring model. The decision ambiguity while evaluating firms against multiple criteria may be managed using fuzzy set theory. Finally, future studies might employ other techniques, such as Bayesian BWM, PROMETHEE, TODIM, DEMATEL, and other potentially relevant applications, while addressing additional criteria that might affect SMEs’ credit standing.

**List of symbols**

$C_B$ : Best criteria in the set of criteria;  $A_B$ : Best-to-others criteria weight vector;  $a_B$ : Importance of the best criterion “B” over the criteria “j”;  $A_W$ : Other to the worst criteria weight vector;  $a_W$ : Importance of criteria “j” over the worst criterion “W”;  $A_{jW}$ : Other to the worst criteria, weight vector;  $a_{jW}$ : Importance or weight of criteria “j” over the worst criterion “W”;  $w_B$ : Optimal weight of criteria;  $\xi^l$ : Consistency of decision making;  $CR$ : Consistency Ratio ( $CR = \frac{\xi^l}{Consistency\ Index}$ );  $C_j$ : The criteria  $j = 1, 2, \dots, n$ ;  $A_i$ : The alternatives  $i = 1, 2, \dots, m$ ;  $A_{ij}$ : Evaluation matrix of alternative against the criteria;  $a_{ij}$ : A crisp value representing the rating of alternative  $A_i$  with respect to criterion  $C_j$ ;  $r_{ij}$ : Normalised weight of crisp weight  $a_{ij}$ ;  $v_{ij}$ : Weighted normalised weight of crisp weight  $a_{ij}$ ;  $W_{ij}$ : Normalised matrix of evaluation matrix  $A_{ij}$ ;  $V_{ij}$ : Weighted normalised matrix;  $A^+$ : Positive ideal solution (PIS);  $A^-$ : Negative ideal solution (NIS);  $J_+$ :  $\{j = 1, 2, \dots, n\}$  Associated with positive criteria;  $J_-$ :  $\{j = 1, 2, \dots, n\}$  Associated with negative criteria;  $S_i^+$ : Euclidian distance of alternative from PIS;  $S_i^-$ : Euclidian distance of alternative from NIS;  $C_i^*$ : Closeness coefficient of alternative.

**Supplementary Information**

The online version contains supplementary material available at <https://doi.org/10.1186/s40854-021-00295-5>.

**Additional file 1. A.** A complete description of criteria affect the creditworthiness of SMEs. **B.** Complete BWM calculation to determine the weight of every criterion.

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**Authors’ contributions**

PKR designed and developed the model, analysed the results and drafted this research work. While KS supervised and redrafted the paper. Both authors read and approved the final manuscript.

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**Availability of data and materials**

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

**Declaration**

**Competing interests**

The authors have no conflict of interest/competing interest to declare relevant to this article’s content.

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