• U C • FEUC FACULDADE DE ECONOMIA UNIVERSIDADE DE COIMBRA

# Multicriteria Decision Analysis with AHP-TOPSIS

Ana Paula Ferrari Januário, uc2023140299@student.uc.pt

**Summary:** This article provides an analysis of "A credit scoring model for SMEs using AHP and TOPSIS" paper by Roy et al. (2021), presenting the theoretical foundations and evaluation of the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) as methods to provide credit scoring. Additionally, it conducts a comparative discussion of these methods with Multi-Attribute Value Theory (MAVT), critically highlighting their strengths, limitations, and applicability. The combination of AHP-TOPSIS methods is widely used to solve multi-criteria decision problems and has applications in various fields. In the case of the analyzed article, was identified some vulnerabilities in the methodologies' multi-criteria and statistical aspects.

**Key-words:** Multiple Criteria Decision Making, AHP, TOPSIS, MAVT

## 1.0 Introduction

Decision-making is crucial to most human activities, whether engaging in daily routines, professional tasks, or political work. Some decisions are relatively straightforward, especially when the consequences of a poor choice are minimal, while others are complex and carry significant implications (Govindan & Brandt Jepsen, 2015).

Credit for small and medium-sized enterprises (SMEs) is crucial, given that they constitute a significant portion of global businesses (Wendel & Harvey, 2006). However, the adoption of Small Business Credit Scoring (SBCS) tools faces several challenges, especially in developing countries (Roy et al., 2021). The main challenges include the limited availability of data, as timely, accurate, and reliable information on SMEs and their owners is often lacking. This scarcity complicates the development and maintenance of SBCS models (Wendel & Harvey, 2006).

Additionally, the high costs associated with developing custom SBCS models can be prohibitive for smaller banks. Furthermore, there is resistance to data sharing, with large lenders often unwilling to share their data with credit bureaus or other institutions, hindering the development of pooled data SBCS models. These challenges can impede the adoption of SBCS tools, which are designed to enhance the efficiency and accuracy of credit decisions for SMEs (Wendel & Harvey, 2006).

This article aims to conduct an analysis of the article "A credit score model for SMEs using AHP and TOPSIS", as well as present the theoretical foundations and evaluation of the applied methods, Analytic Hierarchy Process (AHP), and the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS), and perform a comparative evaluation of these methods with Multi-Attribute Value Theory (MAVT) critically highlighting their strengths, limitations, and applicability.

In the context of credit scoring models for SMEs, the decision actors are those who can directly or indirectly influence the decision-making process (Dias, 2022). The decision actors are, in our case, the financial institutions (loan officers), the SME owners – who bear the consequences of the decision, and the seven experts who helped identify the necessary criteria for the decision and assign weights to them (Roy et al., 2021).

The article is structured as follows: section 2 establishes the theoretical basis, presenting the background and principles underlying each of the four methods under consideration: AHP, TOPSIS, and MAVT. Section 3 illustrates a practical application of the methodology AHP-TOPSIS in the credit scoring model for SMEs. Section 4 presents a brief discussion of the article under analysis and Section 5 concludes the study.

## 2.0 Theoretical Background

To evaluate the multicriteria techniques discussed in the article, we will conduct a theoretical review of the AHP and TOPSIS techniques employed by the authors. Additionally, we will examine the Multi-Attribute Value Theory (MAVT) method to assess its applicability to the specific case under analysis.

### 2.1 Multi-Attribute Value Theory (MAVT)

MAVT (Multi-Attribute Value Theory) is a quantitative approach to decision-making that provides a framework for evaluating and ranking alternatives based on their performance across multiple relevant attributes. For each attribute ($a_x$), a value function $v(a_x)$ is defined, which maps performance levels to values between 0 and 1 (Belton & Stewart, 2002). An example is presented in Figure 1.

The most common method to obtain the value function is direct rating, where the value functions are directly elicited from the decision-maker, allowing them to assign specific values to each level of performance (Dias, 2022). The bisection method involves dividing the continuous scale into two points, enabling the decision-maker to compare and assign values to these points. In the standard difference method, the decision-maker evaluates the differences in attractiveness between pairs of performance levels (Dias, 2022). These differences are then used to construct the value function, ensuring that the assigned values are consistent with the judgments made (Beinat, 1997; Belton & Stewart, 2002; Dias, 2022).

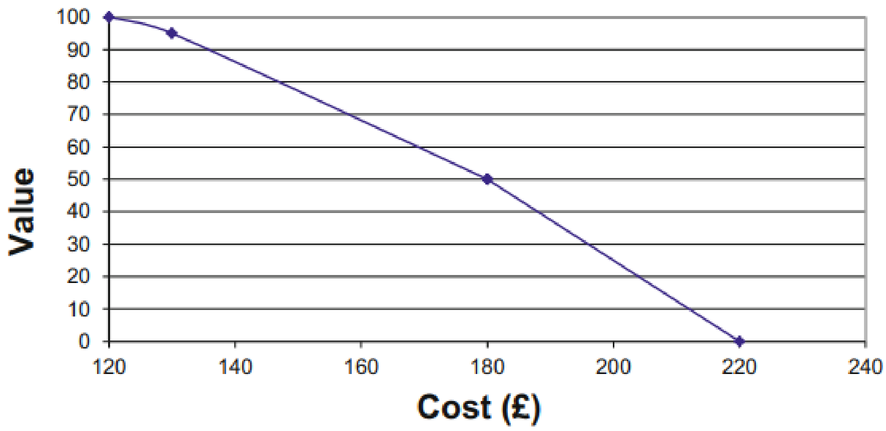


*Figure 1: example of a value function presented by Dias et al. (2018) – possible value function for Cost.*

Once the value function is constructed we compute the global value for each action. In practical terms, decision-makers use a system of preference (P) and indifference (I) to assess alternatives. This means they will either prefer one alternative over another or find them equally desirable when comparing any two value functions (Dias, 2022). So, the next step is to weigh the criteria, i.e., determine the coefficient scales. The reason for weighting is that although options have been scored, criteria scales are not commensurable: a unit of value on one criterion scale is not the same as a unit of value on another scale (Dias et al., 2018).

The most popular weighting method in MAVT is swing, which is typically defined as a measure that quantifies an attribute's value change when one alternative has improved its performance relative to another (Dias et al., 2018). For example, if an attribute is rated on a scale of 0 to 10, a 2-point swing means that one alternative improved its performance by 2 points relative to the other.

Conventionally, the weight of the most valued swing is set to 1 and the weights of the other swings are defined as fractions of the most valued swing, so in the case of the example, if the swing is 2 points and the maximum possible value is 10, the weight would be 2/10 = 0.2. To reach these conclusions, swing weighting involves asking questions to decision-makers about hypothetical changes in options (Dias et al., 2018).

Another alternative procedure, called trade-off, involves a series of comparative judgments made by the decision-maker about the relative importance of different criteria. The first step is to order the criteria from least important to most important. This ordering serves as the basis for subsequent comparisons. For each pair of adjacent criteria in order, the decision maker is asked how much performance on the least important criterion he or she is willing to trade for a small improvement on the most important criterion, holding the other criteria constant. These trade-off judgments are expressed numerically. Based on trade-off judgments, it is possible to calculate the relative weights of the criteria. (Dias et al., 2018).

In trade-off, it is necessary to make compromises between different important aspects or criteria to reach a satisfactory decision. For example, when choosing between cost and quality, you can opt for a cheaper product, accepting possible compromises in quality. In other words, this technique involves weighing the advantages and disadvantages of each available option. This helps to understand which benefits are most important and which sacrifices are acceptable to achieve a desired outcome (Dias et al., 2018).

After defining the value functions and their weights, the next step is to aggregate the scores of each criterion into a single function. The most straightforward approach for decision-makers is the weighted additive model (Dias, 2022), which sums the values through a weighted sum:

$$V(a_i) = \sum_{j=1}^{n} w_j v_j(a_i)$$

Where $V(a_i)$ is the overall value of alternative $i$, $w_j$ is the weight (importance) of criterion $j$, and $v_j(a_i)$ is the score alternative *i* on criterion *j* (Belton & Stewart, 2002).

Value functions in Multi-Attribute Value Theory (MAVT) must satisfy certain conditions, including:

- Transitivity of preference: If a is preferred to b, and b is preferred to c, then a is preferred to c.
- Transitivity of indifference: If a is indifferent to b, and b is indifferent to c, then a is indifferent to c.

Additionally, the chosen aggregation method imposes further conditions. For instance, the weighted sum method has limitations such as complete compensation and exclusion of convexly dominated alternatives. These characteristics should be carefully considered when selecting a multi-criteria method (Dias, 2022).

Von Winterfeldt and Edwards (1986) emphasize that well-structured problems should feature value functions that are smooth and continuous. Conversely, Belton and Stewart (2002) caution against oversimplifying problems with linear value functions, as this can lead to misleading conclusions. They argue that assumptions of linearity often fail to capture the complexities of real-world decisions, necessitating alternative techniques.

MAVT also requires a deep understanding of attributes and decision-makers preferences, which can be time-consuming (Dias, 2022). The validity of MAVT's weighted additive model depends on assumptions such as mutual preference independence; failing to meet these assumptions can result in erroneous conclusions (Belton & Stewart, 2002).

However, the MAVT advantages relay that by creating value functions and assigning weights to attributes, MAVT enhances transparency and clarity in decision-making processes. This method directly incorporates decision-makers' preferences and perceptions, promoting decisions that align closely with organizational values and objectives (Dias, 2022). MAVT also simplifies complex decision-making by facilitating direct comparisons among alternatives based on a unified measure of value (Belton & Stewart, 2002).

### 2.2 Analytic Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP), a method for MCDA developed by Saaty in the ’70s is used to structure complex decisions, dividing them into a hierarchy of criteria and alternatives that are compared in pairs. In the standard AHP procedure, alternatives are not distinguished from criteria, but are treated as the lowest level of the hierarchy, and all comparisons follow the same procedure (Belton & Stewart, 2002). The decision maker is required to answer a series of pairwise comparison questions that lead to an implicit numerical evaluation of the alternatives according to each criterion (Saaty, 1978, 1990).

After identifying the relevant criteria, experts perform a pairwise comparison between the criteria using Saaty's nine-point scale (table 1), where 1 means that one alternative is equal to the other and 9 means that one alternative is much better than the other (Saaty, 1990).

*Table 1: Nine-point scale presented by Saaty.*

| Intensity of Importance | Definition |
|---|---|
| 1 | Equal importance |
| 2 | Weak or slight |
| 3 | Moderate importance |
| 4 | Moderate plus |
| 5 | Strong importance |
| 6 | Strong plus |
| 7 | Very strong or demonstrated importance |
| 8 | Very, very strong |
| 9 | Extreme importance |

The pairwise comparisons are used to construct a decision matrix *X* of dimension $n \times n$, where $n$ represents the number of criteria or alternatives (Saaty, 1990). The matrix contains the relative weights of each element compared to others, denoted by $c_{ij}$. For comparisons to be consistent, the matrix must satisfy certain mathematical properties:

$$c_{ii} = 1, c_{ij} = \frac{1}{c_{ji}}, c_{ij} \neq 0$$

where the relative weight of an element compared to itself is always 1. Additionally, there is a reciprocal relationship between the relative weights of two elements. If element *i* is *x* times more important than element *j*, then element *j* is *1/x* times more important than element *i*. The relative weights between any two elements cannot be zero, indicating that all elements must have some non-zero relative importance compared to each other.

The inputs in the decision matrix $X$ are then normalized to ensure consistency:

$c'_{ij} = \frac{c_{ij}}{\sum_{i=1}^{n} c_{ij}}$ for i, j= 1, 2, …, n

After, The consistency index (CI) is calculated by evaluating the consistency of the pairwise comparisons. This involves calculating the largest eigenvalue ($\lambda_{max}$) and the eigenvector and eigenvalue $W$ and $W'$:

$W = \begin{bmatrix} W_1 \\ \dots \\ W_n \end{bmatrix}$ and $W_i = \frac{\sum_{i=1}^{n} c'_{ij}}{n}$ and $W' = \begin{bmatrix} W'_1 \\ \dots \\ W'_n \end{bmatrix}$

The largest eigenvalue is calculated as:

$$\lambda_{max} = \frac{1}{n}\left(\frac{W'_1}{W_1} + \frac{W'_n}{W_n}\right)$$

The Consistency Index (CI) is calculated using the following equation:

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

The consistency of judgment is calculated by the Consistency Ratio (CR) using the following equation.

$$CR = \frac{CI}{RI}$$

where RI is the Random Index for the *n*th rank, as suggested by Saaty (1978). In this case, the rank used in the article is a little different than that proposed by Saaty (Roy et al., 2021).

*Table 2: Index used by Roy et al. (2021)*

| n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| RI | 0 | 0 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 |

The matrix is considered consistently acceptable if the consistency ratio (CR) is less than 0.1. The eigenvector corresponding to the largest eigenvalue ($\lambda_{max}$) of the pairwise comparison matrix provides the relative priorities of the criteria or alternatives. These priorities are essential for decision-making, as they reflect the weight or relative importance of each criterion or alternative about the others.

The AHP offers several advantages in decision-making. Firstly, it provides a clear and organized framework for complex decisions by decomposing them into a hierarchy of criteria and alternatives (Belton & Stewart, 2002). This structure allows a systematic analysis of the decision problem.

Secondly, AHP enables the quantification of criteria and alternatives, setting it apart from other decision-making techniques (Belton & Stewart, 2002). This feature helps to objectify the decision-making process and reduce ambiguity. Thirdly, the pairwise comparison process in AHP systematically elicits decision-makers preferences and priorities (Saaty, 2004). Lastly, AHP encourages the involvement of multiple stakeholders, leading to more informed and widely accepted decisions (Saaty, 1979). By incorporating diverse perspectives, AHP enhances the legitimacy and credibility of the decision-making process.

However, AHP has certain limitations, one of which is the time-intensive pairwise comparison process. This process can be particularly burdensome when dealing with a substantial number of criteria and alternatives. Additionally, AHP is susceptible to the rank reversal phenomenon, where the ranking of alternatives shifts when a new alternative is introduced or an existing one is removed (Belton & Stewart, 2002).

Another limitation is the subjectivity inherent in pairwise comparisons and the resulting weights, which are based on the decision-maker's judgments. This subjectivity can introduce biases and preferences that influence the outcome. Establishing appropriate weights for the criteria can be challenging, especially when there are many criteria or alternatives, or when the criteria are interdependent. Furthermore, the pairwise comparisons made by the decision-maker may not always be entirely consistent, leading to inconsistencies in the final results (Belton & Stewart, 2002).

To mitigate these limitations, it is essential to ensure that the decision-making process is transparent, well-structured, and involves multiple stakeholders to minimize individual biases. Additionally, sensitivity analyses can be conducted to assess the robustness of the results and the impact of changes in criteria weights or the addition or removal of alternatives (Belton & Stewart, 2002).

### 2.3 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS, developed by Hwang and Yoon (1981), is a simple ranking method in conception and application. The standard TOPSIS method attempts to choose alternatives that simultaneously have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution (Bilbao-Terol et al., 2014).

The positive ideal solution maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria. To apply this technique, attribute values must be numeric, monotonically increasing or decreasing, and have commensurable units (Behzadian et al., 2012).

The stepwise procedure to implement TOPSIS begins with the construction of a decision matrix (X) with $m$ alternatives and $n$ criteria. The element $x_{ij}$ represents the performance score of the ith alternative concerning the jth criterion(Behzadian et al., 2012). To ensure that all criteria are comparable, the decision matrix is normalized using the following formula (which has the same normalization idea as step 2.2):

$r_{ij} = \frac{x_{ij}}{\sqrt{\sum(x_{ij}^2)}}$ for i= 1, …m; j= 1, …, n

Where $x_{ij}$ and $r_{ij}$ are the original and normalized scores of the decision matrix, respectively. This is followed by building the weighted normalized decision matrix (V) multiplying each normalized score by its associated weight.:

$$v_{ij} = w_j r_{ij}$$

Where $w_j$ is the weight for $j$ criterion. This way it is possible to determine the ideal positive and negative solution.

$A *= \{v_1^*, \ldots, v_n^*\}$ Positive ideal solution

Where $v_i^* = \{max\ (v_{ij})\ if\ \ j\ \in\ J;\ min(v_{ij})\ if\ \ j\ \in\ J'\}$

$A' = \{v_1', \ldots, v_n'\}$ Negative ideal solution

Where $v_i' = \{min\ (v_{ij})\ if\ \ j\ \in\ J;\ max(v_{ij})\ if\ \ j\ \in\ J'\}$

We can calculate the separation measures for each alternative using the Euclidean distance. The separation from positive ideal alternative is:

$S_i^* = \sqrt{\sum_{i=1}^{m}(v_i^* - v_{ij})^2}$

Similarly, the separation from negative ideal alternative is:

$S_i' = \sqrt{\sum_{i=1}^{m}(v_i' - v_{ij})^2}$

The procedure ends by computing the relative closeness coefficient to the ideal solution $C_i^*$. The set of alternatives (or candidates) can be ranked according to the descending order of the closeness coefficient.

$C_i^* = {S_i'}/{(S_i^* + S_i')}$ , $0 < C_i^* < 1$

TOPSIS is a simple and logical method that is easy to implement and understand, with the advantage that it can handle both quantitative and qualitative criteria in the decision-making process. This method provides a scalar value that accounts for both the best and worst alternative solutions, allowing for a more realistic assessment. Also, it can rank the alternatives from the best to the worst option and provide a compromise solution, as it considers both the ideal and anti-ideal solutions (Behzadian et al., 2012).

As a weakness, the method can be sensitive to the weights assigned to the criteria, and the ranking results can be influenced by the choice of reference alternatives (Abushark et al., 2022). TOPSIS requires that the criteria be monotonically increasing or decreasing, which may not always be the case in real-world problems, and also, assumes that the relative importance of the distances from the positive and negative ideal solutions is equal, which may not always be appropriate. The method does not provide a clear guideline for determining the weights of the criteria, which can be a subjective process (Behzadian et al., 2012).

Additionally, TOPSIS can suffer from the rank reversal problem, where the ranking of alternatives can change if a new alternative is added or an existing alternative is removed, which is an undesirable property. The method also assumes independence between the criteria, which may not always be the case in real-world decision-making problems (Bilbao-Terol et al., 2014).
Furthermore, the TOPSIS method is limited in its ability to handle uncertainty and ambiguity in the input data. The classical TOPSIS method assumes precise, crisp input data, which may not be realistic in many decision-making situations involving uncertainty (Tansel & Iç, 2014). Extending the TOPSIS method to handle fuzzy or interval data can help address this limitation.

## 2.5 Considerations of the methods

The methods for multi-criteria decision-making in analysis - Analytic Hierarchy Process (AHP), Multi-Attribute Value Theory (MAVT), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) differ in their underlying principles and approaches to evaluating alternatives.
AHP and MAVT are based on the value principle, assessing alternatives across multiple criteria. However, they differ in their aggregation approach. AHP aggregates pairwise comparisons between alternatives, while MAVT aggregates performance scores independently for each alternative. TOPSIS, on the other hand, uses the distance principle, ranking alternatives based on their proximity to ideal and anti-ideal solutions (Dias, 2022).
The degree of independence in evaluating alternatives also varies among these methods. AHP's evaluations depend on other alternatives in the hierarchy due to its pairwise comparison approach. MAVT offers independent assessment based solely on criteria performance. TOPSIS falls somewhere in between, assessing alternatives against ideal or threshold-based criteria without direct comparisons to other options (Dias, 2022).
Rank reversal and sensitivity are important considerations when comparing MAVT, AHP, and TOPSIS. MAVT is less prone to rank reversal, as the ranking is based on the aggregate value of the alternatives (Bottero et al., 2014). AHP is known to suffer from rank reversal, where the ranking of alternatives can change if a new alternative is added or an existing one is removed (Saaty, 1990). TOPSIS also has the potential for rank reversal, although it is less common compared to AHP (Bilbao-Terol et al., 2014).
Regarding interpretability and transparency, MAVT provides a straightforward and interpretable ranking of alternatives based on their aggregate value (Bottero et al., 2014). AHP provides a hierarchical structure that can be easier to interpret, but the weights and rankings can be sensitive to the judgments of the decision-makers. TOPSIS provides a clear ranking based on the closeness to the ideal solution, but the interpretation of the results can be less straightforward compared to MAVT (Martino Neto et al., 2023).

In summary, while all MCDM methods aim to facilitate decision-making across multiple criteria, they diverge significantly in their fundamental principles, and level of independence in evaluating alternatives. Understanding these differences is essential for selecting the most suitable method for a given decision-making scenario, considering factors such as the nature of criteria, complexity of alternatives, and desired level of decision independence.

## 3.0 Application AHP-TOPSIS

In Roy et al. (2021) paper, the authors affirms that assessing credit risks for small and medium-sized companies is a challenge, mainly due to the lack of financial data. To solve this situation, the authors propose a new method using two combined multi-criteria decision techniques, AHP-TOPSIS. The study proposes a three-phase methodology available in Figure 1.

To choose the scoring criteria in phase one, seven credit rating experts were selected and picked out five criteria, namely liquidity, leverage, coverage, efficiency, and profitability, the criteria also was verified in the literature review.

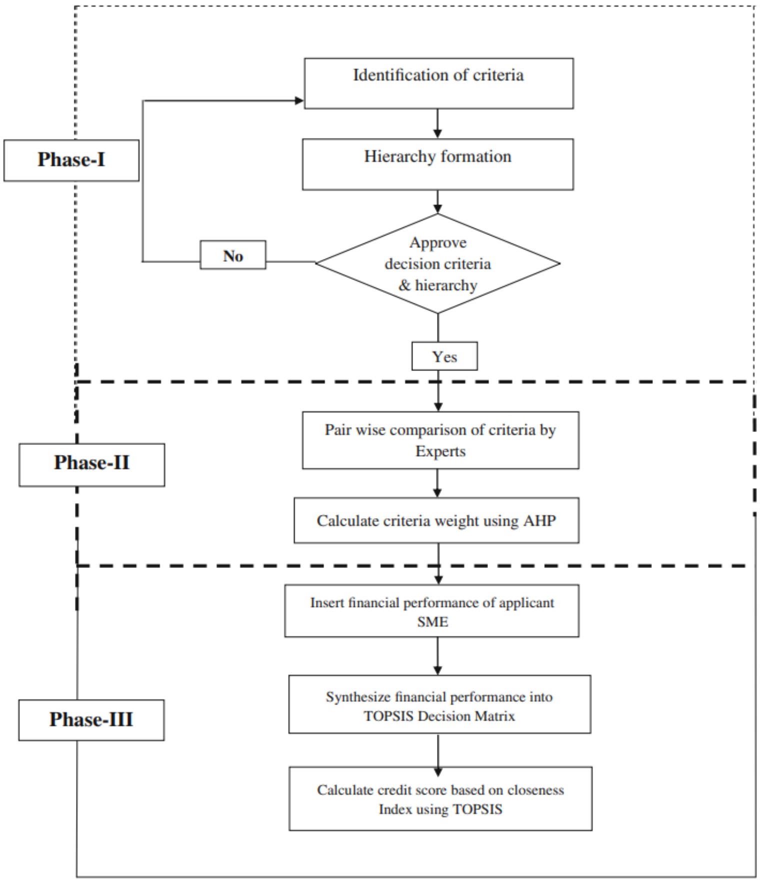


*Figure 2: Methodology developed on paper under analysis*

Each of the criteria presented three sub-criteria using relevant financial ratios considering six small and medium-sized Indian companies as alternatives (figure 2). The considered ratios by Roy et al. (2021) were:

I) Liquidity:

- Current ratio
- Quick ratio
- Cash ratio

II) Leverage:

- Debt Equity Ratio (DER)
- Total outside liabilities/ Tangible net worth (TOL/TNW)
- Proprietary Ratio

III) Coverage:

- Debt Service Coverage Ratio (DSCR)
- Interest Coverage Ratio (ICR)
- Fixed Charges Coverage Ratio (FCCR)

IV) Efficiency:

- Stock turnover (STR)
- Debtors/receivables turnover (DTR)
- Creditors turnover (CTR)

V) Profitability:

- Return on Capital Employed (ROCE)
- Operating profit ratio (OPR)
- Net Profit Ratio (NPR)

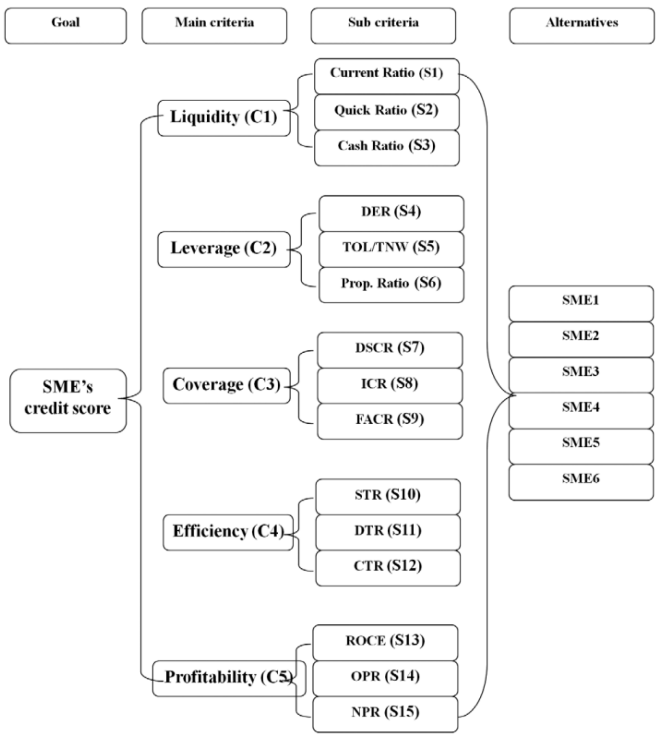


*Figure 3: Hierarchy of selected criteria to obtain SME's credit score*

After identifying the criteria and developing the decision hierarchy, experts perform pairwise comparisons using a scale of 1 to 9 to assess the relative importance of each criterion to the others. Based on these comparisons, the decision matrix is constructed and then normalized to ensure the values are comparable. The eigenvalue is calculated to determine the consistency of the comparisons, and the consistency ratio is evaluated to assess the reliability of these comparisons. In the case of the article, the consistency coefficients found were below the indicated value (0.1), which suggests good consistency in comparisons (Roy et al., 2021).

The local and global weights of criteria and sub-criteria are presented in Figure 3. The liquidity condition of the borrower (31.30%) emerged as the most important factor, followed by profitability (29.30%), coverage (17.65%), efficiency (11.88%), and leverage (9.86%). Among the global weights of the sub-criteria, the Quick Ratio was identified as a key factor with a weight of 16.88%, followed by ROCE (16.07%), ICR (11.44%), Cash Ratio (9.30%), OPR (7.06%), NPR (6.17%), and DER (5.31%).

From the study, it can be inferred that a high Quick Ratio indicates the smooth running of operations during a crisis or less liquid market conditions. Conversely, the profitability position of the borrower is a good indicator of the firm's overall future performance. Additionally, lenders are interested in the overall return on investment, making the ROCE an important metric as it represents the opportunity cost for investors.

| Main-criteria | Local weight in % | Sub-criteria | Local weight in % | Global weight in % |
|---|---|---|---|---|
| Liquidity | 31.30 | Current Ratio | 16.37 | 5.12 |
| | | Quick Ratio | 53.91 | 16.88 |
| | | Cash Ratio | 29.72 | 9.30 |
| Leverage | 9.86 | Debt Equity Ratio | 53.90 | 5.31 |
| | | TOL/TNW | 16.38 | 1.61 |
| | | Prop. Ratio | 29.73 | 2.93 |
| Coverage | 17.65 | DSCR | 22.99 | 4.06 |
| | | ICR | 64.79 | 11.44 |
| | | FACR | 12.22 | 2.16 |
| Efficiency | 11.88 | STR | 16.94 | 2.01 |
| | | DTR | 44.31 | 5.26 |
| | | CTR | 38.75 | 4.60 |
| Profitability | 29.30 | ROCE | 54.85 | 16.07 |
| | | OPR | 24.09 | 7.06 |
| | | NPR | 21.06 | 6.17 |

*Figure 4: Final weights of criteria and sub-criteria using AHP by Roy et al. (2021)*

After calculating the criterion weight using AHP, the SME is rated using the TOPSIS method, which requires estimating cutoff values for factors. For this, a Likert-like scale was adopted to map these cutoff values, determined through discussions with loan sanctioning experts, considering various factors' effects on the firm's credit score. The scale ranges from 0 (below the minimum level) to 4 (well above the benchmark level).

Six Indian SMEs listed on the Bombay Stock Exchange (BSE)/National Stock Exchange (NSE) were selected as alternatives to receive the credit score. The step-by-step procedures for implementing TOPSIS are outlined below.

The first step involved collecting various financial information from the candidate SMEs. The raw data is then cleaned and prepared for calculating financial ratios. In this study, liquidity, efficiency, and profitability are considered attributes to maximize (i.e., higher values are desirable), while coverage and leverage are considered attributes to minimize (i.e., lower values are desirable).

In the second step, financial ratios are calculated for the six SMEs. The financial ratio data is then mapped using a performance rating scale for each criterion for the candidate SME. To make the model ideal for industrial use, two fictitious SMEs (best and worst) are considered. DPI_SME and DNI_SME represent the positive SME dummy and the negative SME dummy, respectively. DPI_SME and DNI_SME performances are taken to mean the highest score (100 percent) and the lowest possible score (0 percent), respectively. The data are normalized following the equation presented in section 2.3.

The Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) were calculated from the weighted matrix. The distance between each alternative and the SIP is first calculated using the Euclidean distance formula. Similarly, the distance between each alternative and the SIN is determined using the same formula. Next, the Closeness Coefficient (CC) for each alternative is computed as the ratio of the distance to the SIP to the distance to the SIN. Alternatives are then ranked based on their CC values, with the highest CC indicating the best option. The final ranking of companies, as presented in the article, is shown below.

| | $S_i^* = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^*\right)^2}$ | $S_i^- = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^-\right)^2}$ | $C_i^* = \frac{S_i^-}{S_i^- + S_i^*}$ | **Final ranking** |
|---|---|---|---|---|
| DPI_SME | 0.00 | 0.19 | 1.00 | PIS |
| SME1 | 0.11 | 0.12 | 0.51 | 2nd |
| SME2 | 0.12 | 0.15 | 0.54 | 1st |
| SME3 | 0.15 | 0.09 | 0.36 | 4th |
| SME4 | 0.16 | 0.09 | 0.36 | 5th |
| SME5 | 0.12 | 0.09 | 0.43 | 3rd |
| SME6 | 0.19 | 0.04 | 0.18 | 6th |
| DNI_SME | 0.19 | 0.00 | 0.00 | NIS |

*Figure 5: Final score of the SMEs based on CI (Roy et al., 2021)*

As this is a model proposal, the authors carried out validation by correlating (Spearman correlation) the results obtained with the AHP-TOPSIS scores of SMEs with their commercially available external risk ratings (ERR). The result suggested a strong positive correlation, therefore, it can be conjectured that the credit scoring model proposed by the authors has a performance in line with the external rating model.

## 4.0 Discussion

The article under analysis used the AHP method to assign weights and evaluate the importance of each criterion according to experts and confirmed by the literature review. They then calculated the ideal point and the distance of each company from it using the TOPSIS method. The combined application of AHP-TOPSIS offers several advantages and disadvantages that must be considered. The AHP-TOPSIS is a flexible approach, suitable for complex problems with multiple criteria and alternatives. Its flexibility allows adaptation to different contexts and scenarios. Additionally, its customization capability is a strong point, as experts can define criteria and weights according to the specific needs of the problem, ensuring relevance and specificity.

Another advantage is the ease of interpreting the results. The criteria weights are calculated clearly and transparently, facilitating communication and understanding among stakeholders. The scalability of AHP-TOPSIS allows it to be applied to problems of varying sizes and complexities, from simple to highly complex issues. Finally, the method allows for customization, adjusting criteria and weights as needed to improve the accuracy and suitability of the proposed solutions.

However, AHP-TOPSIS also has some disadvantages. One of them is the complexity of the method, which requires advanced knowledge in Multi-Criteria decision analysis, potentially posing a challenge for inexperienced users.

The method is sensitive to the inputs provided, meaning that inaccurate or incomplete data can compromise the validity and effectiveness of the analysis. Additionally, despite its scalability, AHP-TOPSIS may face limitations when dealing with large datasets or numerous criteria, making the evaluation process more time-consuming and complex.

Another point is the difficulty of generalization. The effectiveness of the method depends on the choice of criteria and the hierarchical structure, which can limit its universal application and require specific adaptations for different contexts.

If the authors had chosen the MAVT (Multi-Attribute Value Theory) method instead of AHP-TOPSIS, the credit evaluation model would have some significant differences. Assuming the use of the trade-off technique to define weights, the analyst's work would likely be more extensive and complex. This is because, in addition to adjusting the weights, it would be necessary to manage the fluctuation of values. Although MAVT offers a robust method, defining value functions and assigning weights is complex, requiring a deep understanding of the attributes and preferences of the decision-makers. This process can be time-consuming.

MAVT allows for the consideration of different value scales and aggregation methods, which can be useful in situations where criteria are complex or have different units of measurement. However, it is crucial to assess whether the complexity required by MAVT is compatible with the availability and resources of the decision-makers. The choice of method should balance the precision of the analysis with the practicality of its application.

In ranking problems, the goal is to order all alternatives from best to worst based on multiple criteria. AHP, MAVT, and TOPSIS excel at this task, each using different approaches to produce a full ranking of alternatives.

The AHP-TOPSIS methodology, including its fuzzy version, has been applied in various fields, such as cybersecurity (Abushark, 2002) and the textile industry (Bathrinath, 2021), demonstrating its broad utility and applicability. However, certain aspects highlighted by Roy et al. (2021) require attention.

One of these aspects is the subjective assignment of weights based on interactions with experts, which can introduce biases and impact the generalization of the model. This subjectivity is an inherent characteristic of the AHP method and is a risk assumed when opting for this methodology. Additionally, Likert-like scales were used to map the different cutoff values for subsequent TOPSIS applications.

These scales are ordinal and commonly used to measure attitudes and subjective elements, with response categories having a ranking order (Joshi et al., 2015). The cutoff values for evaluating SMEs were decided based on discussions with loan-sanctioning experts, adding another layer of subjectivity. As presented in Figure 5, the experts assessed the various criteria (with their different units) according to the Likert scale.

Another factor that warrants attention is the authors' choice to validate the model using only Spearman's correlation. Given that the external risk classifications are ordinal, this correlation was appropriately applied (Afonso & Nunes, 2019). However, other tests could have been performed to verify the association between the results and the ERR, such as Kendall's Tau, which also measures the association between ordinal variables. Furthermore, correspondence analysis or ordinal regression models could have been explored to provide a more robust and detailed view of the relationships between the criteria and risk classifications. Incorporating these additional tests could enhance the robustness and credibility of the results (Afonso & Nunes, 2019).

| **→Score**<br>**↓Criteria** | | **0** | **1** | **2** | **3** | **4** |
|---|---|---|---|---|---|---|
| S1 | Current Ratio | ≤1.00 | 1.01–≤ 1.10 | 1.11–≤1.33 | 1.34–≤1.5 | ≥1.50 |
| S2 | Quick Ratio | ≤1.00 | 1.01–≤1.05 | 1.06–≤1.1 | 1.11–≤1.2 | ≥1.20 |
| S3 | Cash Ratio | ≤0.75 | 0.76–≤0.80 | 0.81–≤0.9 | 0.91–≤1.0 | ≥1.00 |
| S4 | DER | >3.01 | 2.01–≤3.00 | 1.01–≤2.00 | 0.5–≤1.01 | ≤0.50 |
| S5 | TOL/TNW | >5.00 | 4.01–≤5.00 | 3.01–≤4.00 | 2.01–≤3.00 | 1.00–≤2.0 |
| S6 | Proprietary Ratio | ≤0.20 | 0.20–≤0.50 | 0.51–≤0.60 | 0.61–≤0.75 | ≥0.75 |
| S7 | ICR | ≤1.00 | 1.01–≤1.50 | 1.51–≤2.00 | 2.01–≤2.5 | >2.50 |
| S8 | DSCR | ≤1.00 | 1.01–≤1.25 | 1.26–≤1.50 | 1.51–≤2.00 | >2.00 |
| S9 | FACR | ≤1.00 | 1.01–≤1.50 | 1.51–≤2.00 | 2.01–≤3.00 | >3.00 |
| S10 | STR | > 5 months | 4–≤5 months | 3.5–≤4 months | 2–≤3 months | ≤2 months |
| S11 | DTR | ≥5 months | 4–≤5 months | 3.5–≤4 months | 2–≤3 months | ≤2 months |
| S12 | CTR | ≥3 months | 2.5–≤3 months | 2–≤2.5 months | 1–≤2months | ≤1 month |
| S13 | ROCE in % | ≤6.00 | 6.01–≤9.00 | 9.10–≤12.00 | 12.10–≤15.00 | >15.00 |
| S14 | OPR in % | ≤10.00 | 10.01–≤15.00 | 15.01–≤20.0 | 20.00–≤25.00 | >25.00 |
| S15 | NPR in% | ≤5.00 | 5.00–≤7.00 | 7.00–≤10.0 | 10.01–≤12.00 | ≥12.00 |

*Figure 6: cutoffs by Roy et al. (2021)*

## 5.0 Conclusion

This article has provided an in-depth examination of the paper "A credit Scoring Model for SMEs using AHP and TOPSIS" by Roy et al. (2021) and compared it with alternative multi-criteria decision-making methods, MAVT.

The AHP method offers several advantages, such as a clear structure for organizing and analyzing complex decisions, quantifying criteria and alternatives, and encouraging multiple stakeholder involvement. However, its limitations include the time-consuming nature of the pairwise comparison process, dealing with subjectivities, and the potential for rank reversal.

The TOPSIS method is simple and logical, making it easy to implement and understand. It can handle both quantitative and qualitative criteria and provides a scalar value that considers the best and worst alternative solutions. Nevertheless, its weaknesses include sensitivity to the weights assigned to the criteria and the influence of the choice of reference alternatives on the ranking results.

It would be possible to restructure the problem and apply the MAVT method, instead of the methods chosen by the author. As a consequence, we would have more objectivity in attributing weights. However, the disadvantage would be mainly the increase in complexity. By using MAVT, the author could provide a more straightforward and transparent ranking of alternatives based on their aggregate value. MAVT does not require explicit criteria weights, as the attributes are assumed to be equally important, which could lead to more objective results compared to the subjective pairwise comparisons required in AHP. Additionally, MAVT is less prone to rank reversal issues, ensuring more stable rankings of alternatives.

In our analysis, we identified some vulnerabilities in the multi-criteria approach and statistical aspects. Specifically, we suggested an ordinal model to provide a more robust and detailed view of the relationships between the criteria and risk classifications. Furthermore, we pointed out that the Likert-type scale might not be the optimal choice for defining the cutoffs in the TOPSIS method. By addressing these issues, future research can enhance the robustness and credibility of the results, ultimately leading to more informed and effective decision-making processes.

## References


Abushark, Y. B., Khan, A. I., Alsolami, F., Almalawi, A., Alam, M. M., Agrawal, A., Kumar, R., & Khan, R. A. (2022). Cyber Security Analysis and Evaluation for Intrusion Detection Systems. *Computers, Materials and Continua*, *72*(1), 1765–1783. https://doi.org/10.32604/cmc.2022.025604

Behzadian, M., Khanmohammadi Otaghsara, S., Yazdani, M., & Ignatius, J. (2012). A state-of the-art survey of TOPSIS applications. *Expert Systems with Applications*, *39*(17), 13051–13069. https://doi.org/10.1016/J.ESWA.2012.05.056

Beinat, E. (1997). *VALUE FUNCTIONS FOR ENVIRONMENTAL MANAGEMENT* (Vol. 7). https://doi.org/10.1007/978-94-015-8885-0

Belton, V., & Stewart, T. J. (2002). Multiple Criteria Decision Analysis: An Integrated Approach. In *Multiple Criteria Decision Analysis*. Springer US. https://doi.org/10.1007/978-1-4615-1495-4

Bilbao-Terol, A., Arenas-Parra, M., Cañal-Fernández, V., & Antomil-Ibias, J. (2014). Using TOPSIS for assessing the sustainability of government bond funds. *Omega*, *49*, 1–17. https://doi.org/10.1016/J.OMEGA.2014.04.005

Bottero, M., Ferretti, V., & Mondini, G. (2014). Constructing Multi-attribute Value Functions for Sustainability Assessment of Urban Projects. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *8581 LNCS*(PART 3), 51–64. https://doi.org/10.1007/978-3-319-09150-1_5

Dias, L. C. (2022). *Avaliação Multicritério em Processos de Decisão*. Imprensa da Universidade de Coimbra. https://doi.org/10.14195/978-989-26-2279-8

Dias, L. C., Quigley, J., & Morton, A. (2018). *Elicitation The Science and Art of Structuring Judgement* (UC Teaching Material, Vol. 261, pp. 1–33). http://www.springer.com/series/6161

Govindan, K., & Brandt Jepsen, M. (2015). ELECTRE: A comprehensive literature review on methodologies and applications. *European Journal of Operational Research*, *250*, 1–29. https://doi.org/10.1016/j.ejor.2015.07.019

Hwang, C.-L., & Yoon, K. (1981). *Multiple Attribute Decision Making* (Vol. 186). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-48318-9

Martino Neto, J., Salomon, V. A. P., Ortiz-Barrios, M. A., & Petrillo, A. (2023). Compatibility and correlation of multi-attribute decision making: a case of industrial relocation. *Annals of Operations Research*, *326*(2), 831–852. https://doi.org/10.1007/S10479-022-04603-9/TABLES/17

Roy, P. K., Shaw, K., & Pranith Roy, C. K. (2021). *A credit scoring model for SMEs using AHP and TOPSIS*. https://doi.org/10.1002/ijfe.2425

Saaty, T. L. (1978). Modeling unstructured decision problems — the theory of analytical hierarchies. *Mathematics and Computers in Simulation*, *20*(3), 147–158. https://doi.org/10.1016/0378-4754(78)90064-2

Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research*, *48*(1), 9–26. https://doi.org/10.1016/0377-2217(90)90057-I

Tansel, Y., & Iç, _. (2014). A TOPSIS based design of experiment approach to assess company ranking. *Applied Mathematics and Computation*. https://doi.org/10.1016/j.amc.2013.11.043

von Winterfeldt, D., & Edwards, W. (1986). *Decision Analysis and Behavioral Research* (Cambridge University Press, Ed.).

Wendel, C. B., & Harvey, M. (2006). *SME credit scoring : key initiatives, opportunities, and issues*. https://documents.worldbank.org/pt/publication/documents-reports/documentdetail/221231468339556964/sme-credit-scoring-key-initiatives-opportunities-and-issues