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Performance Evaluation of Venture Capital for Small and Medium-Sized Technology Startups under Uncertainty Environment

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Abstract

This study presents a novel approach to evaluating venture capital in an uncertain environment using a multi-criteria decision-making (MCDM) methodology integrated with the plithogenic framework. Venture capital decisions often involve numerous conflicting factors and vague information, making precise evaluations challenging. The MARCOS method was applied to rank eleven alternatives based on eight criteria, such as return on investment and market growth. The criteria weights were computed using normalized crisp values, and the plithogenic operator was utilized to handle uncertainty. Sensitivity analysis confirmed the stability of the results, showing that the proposed method effectively ranks alternatives under varying conditions. The findings highlight the robustness of the MARCOS approach when integrated with plithogenic sets in addressing complex decision-making scenarios.

Keywords: Venture Capital; Uncertainty Environment; Venture Capital; MCDM.

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1. Introduction

Venture capital, frequently shortened to VC, is a sort of private equity and startup finance that enables a new firm to provide a significant portion of its business to one or a small group of investors in exchange for money or other advantages like talent or mentorship. For both investors and businesses, venture capital can have both high risks and high returns. Through venture capital, startups can obtain funds without having to make monthly payments, but they might have to cede some degree of control over the company's administration and innovation. Although there is a significant chance that the firm will fail, investors also have the chance to profit if it succeeds[1], [2].

Depending on how new the company is, a startup may look for one of three primary forms of venture financing. For example, companies that are prepared to begin selling their goods or services may look for seed capital, whereas fresh startups that are still refining their concepts may seek pre-seed funding. Startups may attempt to obtain early-stage investment if they have already achieved some sales success and are prepared to increase production[3], [4].

Since venture capitalists usually seek long-term partnerships, the startup funding process for obtaining venture money might be drawn out. To thoroughly evaluate the startup and decide whether to invest, requires time[5], [6]. Although the exact time frame will differ from case to case, obtaining venture capital funding normally takes three to nine months from the time of initial contact to funding. After that, several years will pass between when the company or investor begins to provide funds and when they leave[7], [8].

Evaluating Venture Capital is difficult since there are many factors to consider, and these factors frequently contradict one another. Multi-criteria decision-making (MCDM), which is a component of Evaluating Venture Capital, requires decision-makers to evaluate both qualitative and quantitative considerations. The ability of MCDM to assess many options based on predetermined criteria makes it a highly useful tool for assessing complicated real-world issues. Using MCDM techniques, complicated issues are divided into manageable chunks that, upon analysis, can be combined to provide a comprehensive view of the issue[9], [10].

When it comes to solving difficulties in complex sectors, the decision-making process necessitates the prior definition and fulfillment of certain variables. In the scientific community, the notion of multi-criteria decision-making has a unique place. These approaches take advantage of the standards that characterize options for decision-making. Using predetermined criteria, a decision-maker uses MCDM techniques to analyze potential options and determine how well they meet the decision-making objective. The use of MCDM techniques to address a variety of issues has grown recently, and several new techniques have been created. All MCDM techniques fall into one of three categories: interactive, synthesis, or outranking techniques. Optimization problems are solved interactively, and a non-dominant solution is sought[11], [12].

Outranking techniques allow the ranking of options based on the preferences of the decision maker (DM). Making decisions when evaluating several, frequently opposing situations is made possible by synthesis procedures. By using the MCDM approaches, the decision-maker can establish a compromise between all potential conflicting factors by considering various criteria or goals[13], [14]. Finding the optimum MCDM method is nearly impossible, even though there are many different approaches available in the literature. However, researchers and practitioners typically choose the approach to be used based on the nature and complexity of the topic being studied[15], [16].

The Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS) is a novel approach that has been developed in this research. It consists of seven easy steps. The foundation of this approach is the ranking of options concerning a compromise solution once they have been measured. The compromise solution involves calculating utility functions based on the separation between ideal and anti-ideal solutions as well as their aggregations. This paper's primary contribution is to advance the field of decision-making by creating a novel approach that will assist decision-makers (DMs) in resolving complex issues[14], [17].

Uncertain, ambiguous, and incomplete information is a flaw that can result in a less-than-ideal choice, as is the case with many assessments and decision-making issues. Therefore, more accurate evaluation findings should be obtained by combining the plithogenic set with the triple components of the neutrosophic set (truth-membership, falsity-membership, and indeterminacy-membership). Plithogenic sets improve decision-making efficiency and accuracy. Plithogeny is a generalization of neutrosophy that was first proposed by Florentin Smarandache in 2017.

The plithogenic set is a collection of elements where each element x is distinguished by an appurtenance degree d(x, v) of element x to the plithogenic set and attribute values v that have a matching contradiction degree c(v, D) between them and a dominant attribute value D[18], [19].

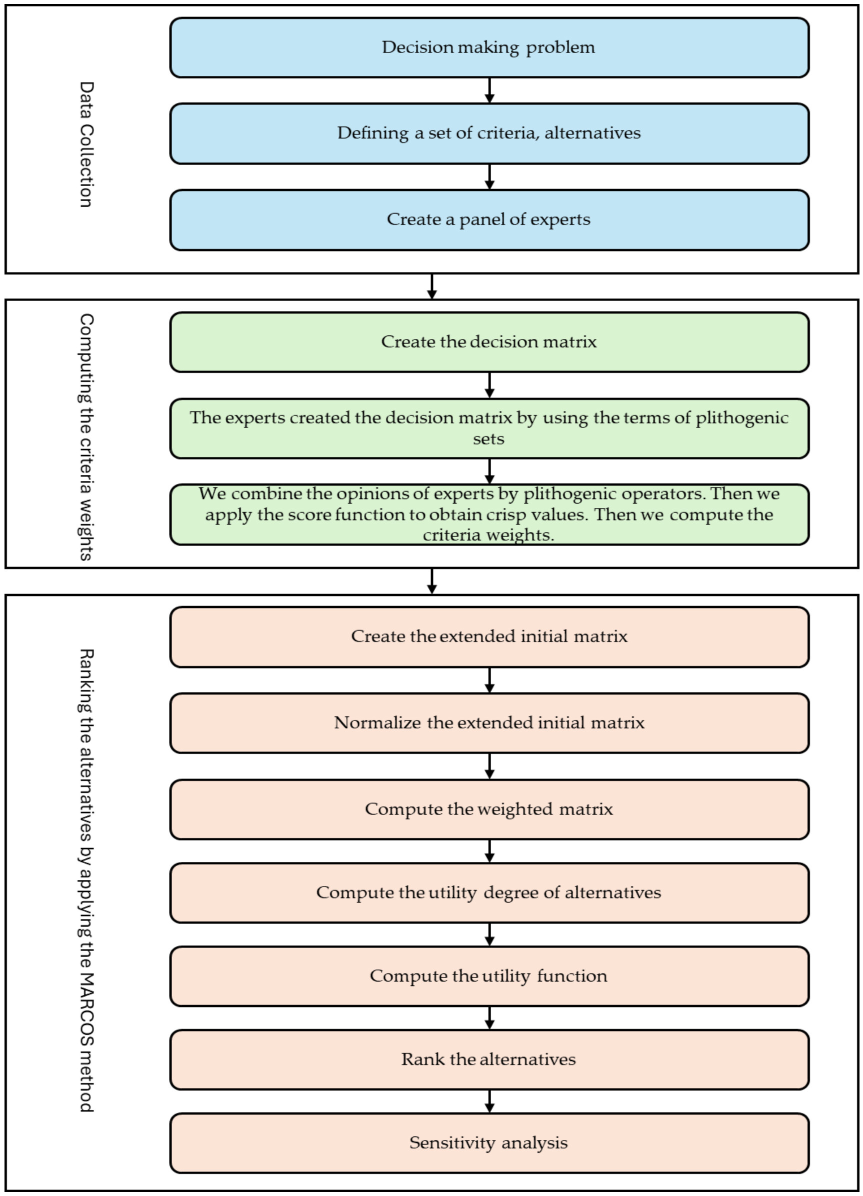

Figure 1. Details of the MARCOS method under plithogenic.

2. Methods

This section of the work presents the steps of the method to rank the alternatives as shown in Figure 1. This section shows the criteria weights and rank of alternatives.

2.1. Evaluation of Plithogenic Set Integration

In the context of evaluating venture capital for small and medium-sized technology startups, handling vague and uncertain information is critical due to fluctuating market conditions and subjective expert opinions. The integration of plithogenic sets into the decision-making process enhances the framework by accounting for these uncertainties. Unlike traditional fuzzy or neutrosophic sets, plithogenic sets introduce the concept of a contradiction degree, which quantifies inconsistencies between conflicting attributes.

2.1.1 Example Application

For instance, when evaluating the "Return on Investment" criterion, expert opinions might conflict due to differences in industry perspective. A plithogenic operator is used to combine these opinions into a comprehensive evaluation, as shown in the table below.

Criterion	Expert 1 Opinion	Expert 2 Opinion	Expert 3 Opinion	Plithogenic Value
Return on Investment (C1)	0.80	0.75	0.85	0.80 ± 0.05
Market Growth (C2)	0.70	0.65	0.75	0.70 ± 0.05
Innovation (C7)	0.90	0.85	0.88	0.88 ± 0.03

Figure 2 illustrates the variability in expert opinions for each criterion and the resulting plithogenic values. The red line represents the consolidated plithogenic values derived from the expert evaluations, showcasing how the framework incorporates varying opinions into a comprehensive assessment.

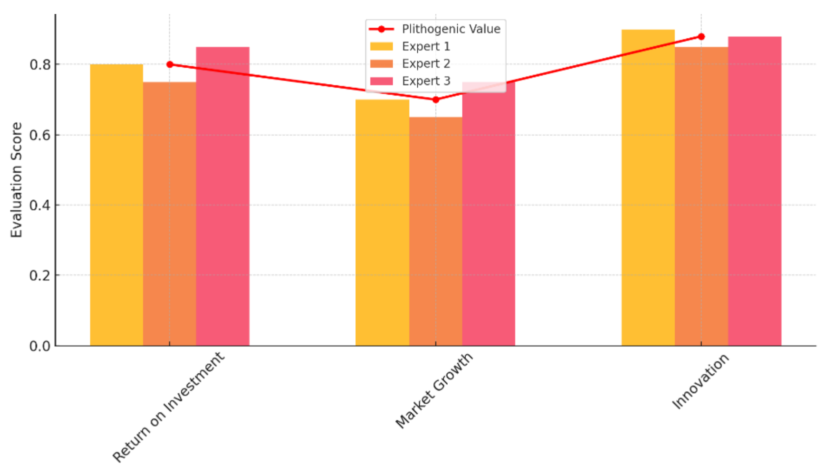

Figure 2.Variability in Expert Opinions and Resulting Plithogenic Values

2.2 Measurement of alternatives and ranking according to COmpromise solution (MARCOS)

In this part, the MARCOS method is described in detail (See Figuer 3). The MARCOS method is the MCDM method used to rank the alternatives. It is obtaining the relationship between the alternatives and reference values[20], [21], [22], [23]. The steps of MARCOS methodology as:

A) Create the decision matrix. Define a set of criteria and alternatives. The set of experts has evaluated the criteria and alternatives. The experts created the decision matrix by using the terms of plithogenic sets. We combine the opinions of experts by plithogenic operators. Then we apply the score function to obtain crisp values.

B) Create the extended initial matrix.

This step defines the ideal (AI) and anti-ideal (AAI) solution.

$$AAI = \min x_{ij} \ \ if\ j \in B\ and \max x_{ij} \ \ if\ j \in C \tag{1}$$

$$AI = \max x_{ij} \ \ if\ j \in B\ and \min x_{ij} \ \ if\ j \in C \tag{2}$$

Where C refers to the cost criteria and B refers to the positive criteria.

C) Normalize the extended initial matrix

$$q_{ij} = \frac{x_{ai}}{x_{ij}} \ \ if\ j \in C \tag{3}$$

$$q_{ij} = \frac{x_{ij}}{x_{ai}} \ \ if\ j \in B \tag{4}$$

D) Compute the weighted matrix.

$$y_{ij} = q_{ij} w_j \tag{5}$$

E) Compute the utility degree of alternatives

$$U_i^- = \frac{p_i}{p_{aai}} \tag{6}$$

$$U_i^+ = \frac{p_i}{p_{ai}} \tag{7}$$

$$p_i = \sum_{i=1}^{n} y_{ij} \tag{8}$$

F) Compute the utility function

$$f(U_i) = \frac{U_i^+ + U_i^-}{1 + \frac{1-f(U_i^+)}{f(U_i^+)} + \frac{1-f(U_i^-)}{f(U_i^-)}} \tag{9}$$

$$f(U_i^+) = \frac{U_i^-}{U_i^- + U_i^-} \quad (10)$$

$$f(U_i^-) = \frac{U_i^+}{U_i^- + U_i^-} \quad (11)$$

G) Rank the alternatives.

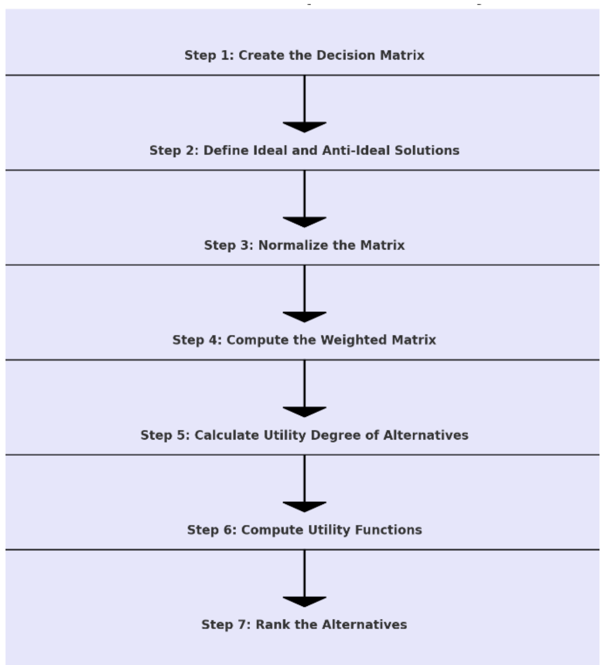

Figure 3. The main steps of MARCOS method

3. Case Study of Venture Capital

This study focuses on evaluating venture capital using a set of defined criteria and potential alternatives. To ensure accuracy and depth, three experts, each with over 20 years of experience in venture capital evaluation, were consulted. They assessed eight key criteria and eleven alternatives to determine the best investment options. The details of the criteria and alternatives are presented in Table 1.

Table 1. The criteria.

	Criteria	Alternatives
C_1	Exit Strategy Viability	A_1
C_2	Customer Base Growth and Retention	A_2
C_3	Quality of the Management Team	A_3
C_4	Market Growth and Scalability	A_4
C_5	Return on Investment	A_5
C_6	Risk Mitigation and Resilience	A_6
C_7	Innovation and Technological Advancement	A_7

C_8	Financial Stability and Liquidity	A_8
		A_9
		A_{10}
		A_{11}

4. Results

4.1 Overview of the Methodology

The evaluation of venture capital alternatives involved applying the MARCOS method to rank eleven alternatives based on eight criteria. Three decision-makers provided evaluations, which were aggregated using a plithogenic framework to account for vagueness and uncertainty. The results were systematically derived through a series of steps, including normalizing the decision matrix, calculating the weighted normalized matrix, determining utility degrees, and ranking the alternatives. The process and results are supported by detaile Tables 2–8 and Figure 4.

4.1 Expert Evaluations and Decision Matrix

The process began with gathering input from three decision-makers with expertise in venture capital evaluation. These experts evaluated the importance of eight criteria for each of the eleven alternatives. The criteria include Exit Strategy Viability (C1), Customer Base Growth and Retention (C2), Quality of the Management Team (C3), Market Growth and Scalability (C4), Return on Investment (C5), Risk Mitigation and Resilience (C6), Innovation and Technological Advancement (C7), and Financial Stability and Liquidity (C8).

The experts' evaluations were aggregated into a decision matrix using the plithogenic framework, which effectively manages vague and uncertain information. The evaluations from each expert are detailed in Tables 2–4.

Table 2 contains the evaluations provided by Decision-Maker 1. Table 3 Shows the assessments from Decision-Maker 2. Table 4 displays the input from Decision-Maker 3.

Table 2. The significance of the criteria of each alternative by decision maker 1.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.80, 0.10, 0.30)	(0.25, 0.60, 0.80)	(0.40, 0.70, 0.50)	(0.50, 0.40, 0.60)	(0.65, 0.30, 0.45)	(0.95, 0.05, 0.05)	(0.95, 0.05, 0.05)	(0.95, 0.05, 0.05)
A_2	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)	(0.95, 0.05, 0.05)	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.80, 0.10, 0.30)
A_3	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)	(0.25, 0.60, 0.80)	(0.40, 0.70, 0.50)	(0.95, 0.05, 0.05)
A_4	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.50, 0.40, 0.60)	(0.10, 0.75, 0.85)
A_5	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.25, 0.60, 0.80)
A_6	(0.95, 0.05, 0.05)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.40, 0.70, 0.50)
A_7	(0.95, 0.05, 0.05)	(0.95, 0.05, 0.05)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)
A_8	(0.10, 0.75, 0.85)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.40, 0.70, 0.50)	(0.95, 0.05, 0.05)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)
A_9	(0.25, 0.60, 0.80)	(0.25, 0.60, 0.80)	(0.25, 0.60, 0.80)	(0.95, 0.05, 0.05)	(0.95, 0.05, 0.05)	(0.95, 0.05, 0.05)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)
A_{10}	(0.40, 0.70, 0.50)	(0.40, 0.70, 0.50)	(0.40, 0.70, 0.50)	(0.10, 0.75, 0.85)	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.95, 0.05, 0.05)	(0.40, 0.70, 0.50)
A_{11}	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.25, 0.60, 0.80)	(0.40, 0.70, 0.50)	(0.50, 0.40, 0.60)	(0.50, 0.40, 0.60)

Table 3. The significance of the criteria of each alternative by decision maker 2.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.50, 0.40, 0.60)	(0.25, 0.60, 0.80)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)	(0.95, 0.05, 0.05)	(0.10, 0.75, 0.85)
A_2	(0.65, 0.30, 0.45)	(0.25, 0.60, 0.80)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.95, 0.05, 0.05)	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.25, 0.60, 0.80)
A_3	(0.25, 0.60, 0.80)	(0.50, 0.40, 0.60)	(0.25, 0.60, 0.80)	(0.65, 0.30, 0.45)	(0.25, 0.60, 0.80)	(0.95, 0.05, 0.05)	(0.50, 0.40, 0.60)	(0.25, 0.60, 0.80)
A_4	(0.50, 0.40, 0.60)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.25, 0.60, 0.80)	(0.50, 0.40, 0.60)	(0.10, 0.75, 0.85)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)
A_5	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.25, 0.60, 0.80)	(0.25, 0.60, 0.80)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)
A_6	(0.80, 0.10, 0.30)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.25, 0.60, 0.80)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)
A_7	(0.95, 0.05, 0.05)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.25, 0.60, 0.80)	(0.95, 0.05, 0.05)
A_8	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.65, 0.30, 0.45)
A_9	(0.80, 0.10, 0.30)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.80, 0.10, 0.30)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)
A_{10}	(0.95, 0.05, 0.05)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.95, 0.05, 0.05)	(0.95, 0.05, 0.05)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.95, 0.05, 0.05)
A_{11}	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.10, 0.75, 0.85)	(0.10, 0.75, 0.85)	(0.65, 0.30, 0.45)	(0.95, 0.05, 0.05)	(0.10, 0.75, 0.85)

Table 4. The significance of the criteria of each alternative by decision maker 3.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.40, 0.70, 0.50)	(0.50, 0.40, 0.60)	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)	(0.95, 0.05, 0.05)	(0.10, 0.75, 0.85)
A_2	(0.40, 0.70, 0.50)	(0.10, 0.75, 0.85)	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)	(0.95, 0.05, 0.05)	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.25, 0.60, 0.80)
A_3	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)	(0.10, 0.75, 0.85)	(0.40, 0.70, 0.50)	(0.40, 0.70, 0.50)
A_4	(0.25, 0.60, 0.80)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.50, 0.40, 0.60)
A_5	(0.40, 0.70, 0.50)	(0.50, 0.40, 0.60)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.65, 0.30, 0.45)
A_6	(0.50, 0.40, 0.60)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.50, 0.40, 0.60)	(0.40, 0.70, 0.50)	(0.80, 0.10, 0.30)
A_7	(0.65, 0.30, 0.45)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.40, 0.70, 0.50)	(0.10, 0.75, 0.85)	(0.50, 0.40, 0.60)	(0.95, 0.05, 0.05)
A_8	(0.50, 0.40, 0.60)	(0.65, 0.30, 0.45)	(0.10, 0.75, 0.85)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.25, 0.60, 0.80)	(0.65, 0.30, 0.45)	(0.10, 0.75, 0.85)
A_9	(0.40, 0.70, 0.50)	(0.50, 0.40, 0.60)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.40, 0.70, 0.50)	(0.25, 0.60, 0.80)	(0.25, 0.60, 0.80)
A_{10}	(0.25, 0.60, 0.80)	(0.40, 0.70, 0.50)	(0.50, 0.40, 0.60)	(0.25, 0.60, 0.80)	(0.80, 0.10, 0.30)	(0.50, 0.40, 0.60)	(0.40, 0.70, 0.50)	(0.40, 0.70, 0.50)
A_{11}	(0.10, 0.75, 0.85)	(0.25, 0.60, 0.80)	(0.10, 0.75, 0.85)	(0.95, 0.05, 0.05)	(0.80, 0.10, 0.30)	(0.65, 0.30, 0.45)	(0.50, 0.40, 0.60)	(0.50, 0.40, 0.60)

4.2 Normalization of the Decision Matrix (Table 5)

The decision matrix was normalized to scale all values between 0 and 1, allowing for comparability across different criteria. Normalization was performed using Equations (3) and (4):

For benefit criteria, each value was divided by the maximum value in its column.

For cost criteria, the minimum value in the column was divided by each value.

4.2.1 *Example from Table 5*

For C1 (a benefit criterion), where the maximum value is 0.95 and x_{11}=0.80, the normalized value for A1 is N_{11}=0.842

For C2 (a cost criterion), where the minimum value is 0.10 and x_{12}= 0.25, the normalized value for A1 is N_{12} = 0.400

The complete normalized decision matrix is shown in Table 5, where each entry represents the scaled value of an alternative for a specific criterion.

4.3 Computation of the Weighted Normalized Matrix (Table 6)

After normalization, the criteria weights were incorporated into the matrix to reflect their relative importance. This was done using Equation (5).

4.3.1 *Example from Table 6*

For C1 , with N_{11}=0.842 and w1=0.20, the weighted normalized value for A1 is: W11=0.1684

The resulting weighted normalized matrix, which aggregates the relative contributions of each criterion to the performance of alternatives, is presented in Table 6.

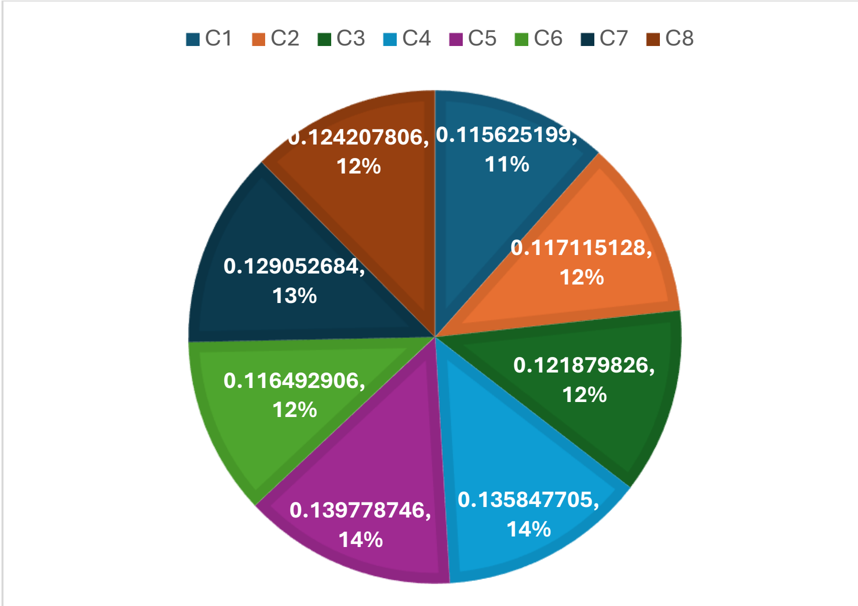

Figure 4. The criteria weights.

Table 5. The normalization matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.686291	0.399358	0.572889	0.576918	0.800064	1	1	0.594608
A_2	0.855007	0.664704	0.915644	0.898623	1	0.146852	0.337556	0.614678
A_3	0.217822	0.915742	0.643003	0.822098	0.821442	0.66682	0.553925	0.717294
A_4	0.474384	0.621442	0.885846	0.577311	0.943778	0.577311	0.577664	0.508998
A_5	0.63353	0.832314	0.601154	0.795344	0.20919	0.737049	0.821442	0.684716
A_6	0.953153	0.971461	0.805142	0.539738	0.455584	0.407738	0.903063	0.829355
A_7	1	1	0.939746	0.722885	0.608424	0.407738	0.396809	1
A_8	0.601502	0.848094	0.680507	0.843738	0.91538	0.591475	0.626101	0.413114
A_9	0.677786	0.915742	1	1	0.96037	0.895344	0.575622	0.614678
A_{10}	0.746893	0.482144	0.896874	0.66682	0.845246	0.795344	0.871347	0.730185
A_{11}	0.148814	0.399358	0.163563	0.66682	0.561838	0.729115	0.834588	0.508998

Table 6. The weighted normalization matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.079353	0.046771	0.069824	0.078373	0.111832	0.116493	0.129053	0.073855
A_2	0.09886	0.077847	0.111599	0.122076	0.139779	0.017107	0.043562	0.076348
A_3	0.025186	0.107247	0.078369	0.11168	0.11482	0.07768	0.071485	0.089094
A_4	0.054851	0.07278	0.107967	0.078426	0.13192	0.067253	0.074549	0.063222
A_5	0.073252	0.097477	0.073269	0.108046	0.02924	0.085861	0.106009	0.085047
A_6	0.110209	0.113773	0.098131	0.073322	0.063681	0.047499	0.116543	0.103012
A_7	0.115625	0.117115	0.114536	0.098202	0.085045	0.047499	0.051209	0.124208
A_8	0.069549	0.099325	0.08294	0.11462	0.127951	0.068903	0.0808	0.051312

A_9	0.078369	0.107247	0.12188	0.135848	0.134239	0.104301	0.074286	0.076348
A_{10}	0.08636	0.056466	0.109311	0.090586	0.118147	0.092652	0.11245	0.090695
A_{11}	0.017207	0.046771	0.019935	0.090586	0.078533	0.084937	0.107706	0.063222

4.4 Utility Degree Calculation and Ranking of Alternatives (Table 7)

The utility degree of each alternative was calculated by comparing its weighted normalized values to the ideal solution (AI) and the anti-ideal solution (AAI). The utility degree measures the proximity of each alternative to the ideal solution, as determined by Equations (6), (7), and (8).

Ideal Solution: Represents the best possible performance for all criteria.

Anti-Ideal Solution: Represents the worst possible performance for all criteria.

4.4.1 *Example from Table 7*

Alternative 9 achieved the highest utility degree (U9=1.635931), indicating it is the closest to the ideal solution.

Alternative 11 had the lowest utility degree (U11=1.0), indicating it is the farthest from the ideal solution.

The computed utility degrees for all alternatives and their corresponding rankings are detailed in Table 7. The table shows that Alternative 9 consistently outperformed the others, while Alternative 11 performed the weakest.

Table 7. The MARCOS results.

	U_i^-	U_i^+	$f(U_i^-)$	$f(U_i^+)$	$f(U_i)$	**Rank**
A_1	1.386439	0.847492	0.379373	0.620627	0.644244	5
A_2	1.350332	0.825421	0.379373	0.620627	0.627466	7
A_3	1.327505	0.811467	0.379373	0.620627	0.616859	8
A_4	1.279177	0.781926	0.379373	0.620627	0.594402	10
A_5	1.29339	0.790614	0.379373	0.620627	0.601007	9
A_6	1.42695	0.872256	0.379373	0.620627	0.663069	4
A_7	1.480538	0.905013	0.379373	0.620627	0.687969	3
A_8	1.366486	0.835296	0.379373	0.620627	0.634972	6

A9	1.635931	1	0.379373	0.620627	0.760177	1
A10	1.48688	0.908889	0.379373	0.620627	0.690916	2
A11	1	0.611273	0.379373	0.620627	0.464675	11

The results demonstrate that the MARCOS method, combined with the plithogenic framework, provides a robust and systematic approach for evaluating venture capital alternatives under uncertainty. By incorporating expert evaluations, normalization, weighted aggregation, and sensitivity analysis, the methodology ensures that the final rankings are comprehensive and reliable. This structured approach enables decision-makers to identify the most favorable alternatives with confidence.

5. Result Validation

We validated the results by conducting a sensitivity analysis to show the different ranks of alternatives. We performed nine cases in criteria weights as shown in Figure 5. We increased the criteria weights by 20% and reduced other criteria. Then we applied the MARCOS method to show different ranks of alternatives as shown in Table 8. We show that alternative 11 is the best and alternative 9 is the worst.

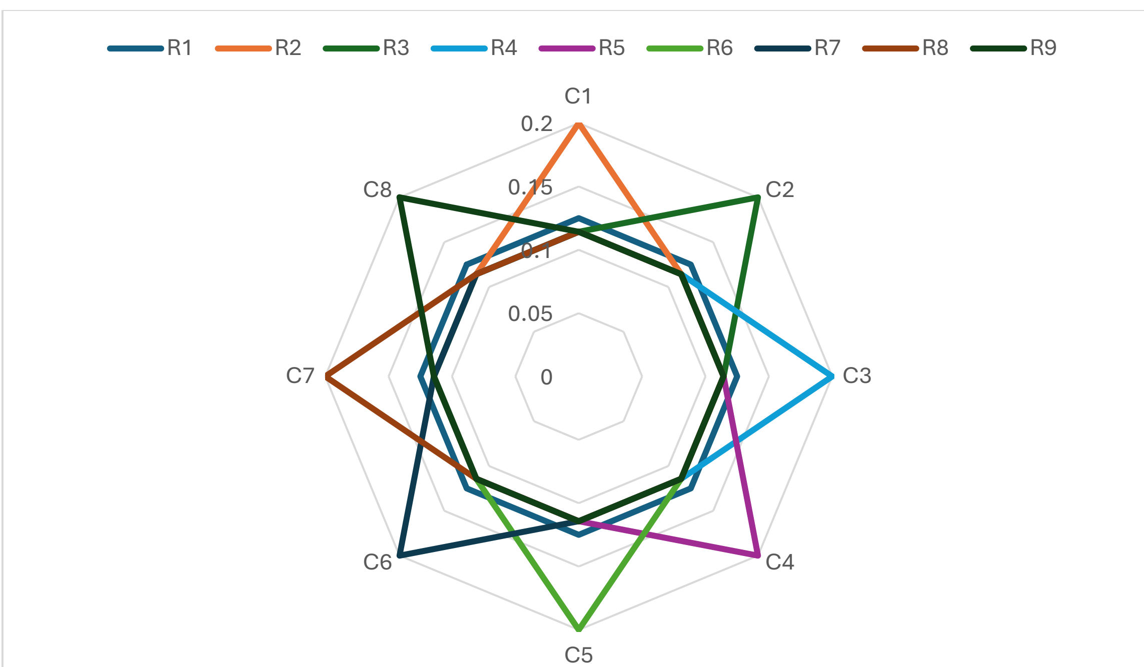

Figure 5. The change in criteria weights.

Table 8. The rank of alternatives under different criteria weights.

	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9
A_1	5	5	9	6	7	4	4	4	5
A_2	7	6	8	5	6	7	10	9	7
A_3	8	10	6	8	8	8	8	8	6
A_4	10	9	10	9	10	9	9	10	10
A_5	9	8	7	10	9	10	7	7	9
A_6	4	4	3	4	4	5	5	3	4
A_7	2	2	2	2	2	3	3	5	2
A_8	6	7	5	7	5	6	6	6	8
A_9	1	1	1	1	1	1	1	1	1
A_{10}	3	3	4	3	3	2	2	2	3
A_{11}	11	11	11	11	11	11	11	11	11

The stability of the rankings was validated through sensitivity analysis. This involved varying the weights of the criteria by ±20% and observing the impact on the rankings. The results, summarized in Table 8, indicate that the rankings remained consistent under different weighting scenarios:

Alternative 9 consistently ranked first across all scenarios.

Alternative 11 consistently ranked last.

Figure 3 provides a visual representation of how changes in criteria weights influence the rankings. The figure highlights the robustness of the MARCOS methodology, as the rankings are largely unaffected by moderate changes in weight distributions.

6. Discussion and Advantage of the Proposed Method

The multi-criteria aspect of decisions is stressed at the managerial level when objectives are established and the best options are chosen. Decision-makers at the managerial level have the authority to approve or disapprove of the engineering-level solution. Sometimes political factors, rather than just technical ones, determine the structure of preferences. By using thorough analysis and highlighting key features of non-inferior and/or compromised solutions, the system analyst can support the decision-making process in these circumstances.

When there are competing criteria, a compromise solution might aid decision-makers in reaching a final choice. Zeleny laid the groundwork for the compromise solution. A compromise is an agreement reached via mutual concessions, and a compromise solution is a workable solution that is closest to the ideal.

7. Conclusions and Future Works

This research successfully developed an MCDM methodology using the MARCOS method integrated with the plithogenic framework to evaluate venture capital options for small and medium-sized technology startups. By employing eight criteria and analyzing eleven alternatives, the approach demonstrated its capability to handle uncertainty and vague information effectively. The results revealed that return on investment carried the highest weight among the criteria, while exit strategy viability had the lowest. The rankings of the alternatives remained stable under various sensitivity analyses, confirming the robustness of the proposed method.

Future research can expand on this study by exploring additional decision-making frameworks or hybrid approaches to further improve the accuracy of venture capital evaluations. Incorporating machine learning algorithms into the MCDM process could enhance the adaptability and predictive capabilities of the framework. Furthermore, applying this methodology to real-world case studies across diverse industries can validate its effectiveness and highlight sector-specific criteria.

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