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Neutrosophic Performance Evaluation of a Consulting Firm Using a Hybrid TOPSIS-OWA Model from the Perspective of Consultants and Auditors

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Abstract. Yet performance evaluation of consulting firms faces uncertainty and subjectivity for the auditor's consultant perspective a concern for problematizing proper strategic choice. This condition is relevant since consulting firms are integral to any enterprise problem solving, and identifying where productivity exists only makes firms more competitive and enhances quality of service to their clients. Yet the literature does not provide any constructs to properly apply indeterminacy to human assessments as operations are based on crisp integers and binary true/false logic which does not adequately represent the holistic expertise of the professional. Therefore, this study proposes a hybrid neutrosophic TOPSIS-OWA assessment approach by integrating the TOPSIS relative assessment approach to proximity-to-ideal-solution with ordered weighted averaging, wherein neutrosophic values assess truth/indeterminacy/falsity. The findings from the assessment applied to a real world scenario shows customer satisfaction and quality of service are the most important. Therefore, this study is significant as it contributes to the body of knowledge with a novel empirical finding, utilizing an assessment approach for better outcomes under uncertainty while practically providing consulting firms with a means for performance assessment from the prospect's perspective.

Keywords: TOPSIS, OWA, Neutrosophic, Performance, Consulting, Uncertainty, Evaluation.

1. Introduction

The assessment of organizational performance in consulting firms is a fundamental pillar for optimizing strategies and enhancing competitiveness in a dynamic business environment. Since these organizations play a key role in solving complex problems, ensuring an accurate and robust evaluation of their performance is crucial. The uncertainty and subjectivity inherent in the opinions of consultants and auditors represent a significant challenge, since strategic decisions depend on the quality of these assessments [1]. In a context where globalization and digitalization intensify the demand for consulting services, addressing these difficulties becomes imperative to maintain operational excellence [2]. This study proposes a neutrosophic hybrid TOPSIS-OWA model, which allows integrating uncertainty into assessments, offering an innovative approach to measuring performance from the perspective of the professionals involved.

Over the last decades, performance appraisal methodologies have evolved from qualitative meeting-based approaches to more sophisticated quantitative methods. Initially, consulting firms relied on subjective reviews, but the rise of multi-criteria decision-making (MCDM) tools has transformed this landscape [3]. Techniques such as TOPSIS, developed by Hwang and Yoon in 1981, have allowed ranking alternatives considering ideal solutions [4]. Meanwhile, the OWA operator, proposed by Yager in 1988, has facilitated the orderly aggregation of expert judgments, adapting to contexts with high variability

[5]. However, these traditional tools do not always capture the uncertainty inherent in human assessments, which limits their applicability in complex environments such as consulting [6].

Uncertainty in performance evaluations arises from the diversity of opinions among consultants and auditors, who each bring unique perspectives based on their experience and roles. This variability, combined with the lack of consensus on key indicators, makes it difficult to obtain reliable results [7]. Consequently, there is a need for an approach that not only classifies performance but also incorporates the ambiguity and contradictions present in professional judgments. Previous studies have addressed performance evaluation in consulting, but most focus on financial or technical metrics, neglecting the human dimension and its associated uncertainty [8]. The central problem that this study addresses is: how to effectively evaluate the performance of a consulting firm considering the uncertainty and subjectivity in the opinions of consultants and auditors? This question, not yet comprehensively resolved in the literature, highlights the need for a model that combines the robustness of multicriteria classification with the flexibility to handle indeterminacy. Performance evaluation should not only identify strengths and weaknesses, but also provide a solid basis for strategic decisions in a competitive environment [9].

The model proposed in this article seeks to fill this gap by integrating TOPSIS and OWA into a neutrosophic framework, which allows for the modeling of truth, indeterminacy, and falsity in assessments. This approach ensures that practitioners' opinions are aggregated in an orderly manner and that alternatives (consultants and auditors) are ranked based on ideal solutions under uncertainty. The methodology is validated through a real-life case study, ensuring its practical applicability in consulting firms. Unlike traditional approaches, the hybrid neutrosophic TOPSIS-OWA model offers an innovative perspective in addressing the complexity of human assessments. By focusing on the perceptions of consultants and auditors, the study captures nuances that conventional methods often overlook. This approach not only improves assessment accuracy but also aligns the results with the organization's strategic needs.

The relevance of this study lies in its ability to provide a practical and theoretically sound tool for consulting firms. By integrating uncertainty into the assessment process, it facilitates the identification of key indicators and the prioritization of areas for improvement. This is particularly valuable in a sector where service quality and client satisfaction are determinants of success. The objectives of this study are: first, to develop a neutrosophic hybrid TOPSIS-OWA model to assess a consulting firm's performance from the perspectives of consultants and auditors; second, to identify key indicators that influence organizational performance; and third, to validate the methodology using a real-life case study to demonstrate its practical utility. These objectives directly address the research question, offering a comprehensive solution for performance assessment in uncertain contexts.

2. Preliminaries.

2.1. Performance Evaluation.

Performance evaluation in consulting firms constitutes a crucial challenge in the business world, given that these organizations play an essential role in solving complex problems and optimizing organizational strategies. The need to accurately measure the performance of professionals, such as consultants and auditors, lies in their ability to directly influence the quality of service and the competitiveness of the firm. In an environment characterized by uncertainty and the subjectivity of human perceptions, traditional evaluation methods, such as qualitative surveys or financial metrics, are often insufficient to capture the complexity of organizational dynamics [10]. This study addresses this problem through a neutrosophic hybrid TOPSIS-OWA model, which allows integrating uncertainty into evaluations, offering an innovative approach to analyzing performance from the perspectives of consultants and auditors.

Historically, performance evaluation has evolved from subjective approaches based on informal observations to more structured quantitative methods. In recent decades, multi-criteria decision-making (MCDM) tools have gained relevance, allowing for a more systematic and rigorous evaluation [11]. Techniques such as TOPSIS, which ranks alternatives according to their closeness to an ideal solution, and OWA, which aggregates ordered judgments, have proven effective in various business contexts. However, these traditional methodologies do not always address the uncertainty inherent in expert opinions, especially in consulting firms where the perspectives of consultants and auditors may diverge significantly. Neutrosophic theory, proposed by Smarandache, introduces a framework that models truth, indeterminacy, and falsity, offering a promising solution to this challenge [12].

The central problem lies in how to assess organizational performance in a context where subjective opinions and ambiguity predominate. Consulting firms depend on the quality of their services, which in turn is based on the performance of their professionals. However, the lack of consensus on key indicators and the variability in perceptions make it difficult to obtain reliable results. For example, a consultant may prioritize client satisfaction, while an auditor may focus on technical accuracy, generating discrepancies that conventional methods do not adequately resolve [13]. The question guiding this study is: how can a neutrosophic hybrid TOPSIS-OWA model provide a robust assessment of performance, capturing the uncertainty in the perspectives of both consultants and auditors?

The neutrosophic TOPSIS-OWA model stands out for its ability to integrate uncertainty into the evaluation process. TOPSIS ranks alternatives (such as the performance of consultants and auditors) by calculating positive and negative distances to ideal solutions, while OWA aggregates expert opinions using ordered weights, allowing for flexibility in weighting. By incorporating a neutrosophic framework, the model assigns truth, uncertainty, and falsehood values to each judgment, more accurately reflecting the ambiguity inherent in human evaluations. This approach overcomes the limitations of traditional methods, which typically assume certainty in opinions, and provides a tool more adaptable to complex environments such as consulting.

The application of this model in a real-life case demonstrates its practical effectiveness. In a consulting firm, judgments were collected from 13 professionals (9 consultants and 4 auditors) on key indicators such as customer satisfaction, service quality, and team competence. Neutrosophic values assigned to these indicators allowed for uncertainty modeling, while the OWA operator ensured an orderly and fair aggregation of opinions. TOPSIS results revealed that consultants performed better than auditors, highlighting the importance of indicators such as customer satisfaction. These findings underline the model's ability to identify strategic priorities in a real-life context [14].

One of the key strengths of the neutrosophic TOPSIS-OWA model is its ability to handle subjectivity without sacrificing rigor. Unlike methods such as AHP, which require pairwise comparison matrices and can be sensitive to inconsistencies, the neutrosophic TOPSIS-OWA simplifies the process by focusing on relative distances and ordered aggregation. Furthermore, the neutrosophic framework captures nuances that other methods miss, such as an auditor's hesitancy when evaluating an ambiguous indicator. This flexibility makes the model particularly suitable for settings where opinions vary widely, such as in consulting firms.

However, the model is not without limitations. Implementing the neutrosophic approach requires a deep understanding of the underlying theory, which can be a barrier to its adoption in resource-constrained firms. Furthermore, collecting neutrosophic judgments can be more complex than traditional assessments, as participants must assign values for truth, uncertainty, and falsity, which requires prior training. Despite these difficulties, the model's benefits, such as its ability to handle uncertainty and provide actionable results, outweigh these barriers in contexts where accuracy is critical.

The theoretical contribution of this study lies in its innovative integration of TOPSIS and OWA within a neutrosophic framework, expanding the literature on performance evaluation. By explicitly addressing indeterminacy, the model offers a robust alternative to traditional approaches, which often simplify reality by ignoring ambiguity. From a practical perspective, the study provides consulting firms with a tool to align their strategies with the perceptions of their professionals, improving decision-making and service quality. The results can be applied not only in consulting but also in other sectors with similar dynamics, such as education and healthcare.

Compared to previous studies, this model stands out for its focus on human uncertainty. While research such as Fallah et al. [10] combines TOPSIS with other tools in specific contexts, few integrate neutrosophic theory to address subjectivity. Validation in a real-life case reinforces the model's applicability, showing how identified key indicators (customer satisfaction, service quality) can guide strategic improvements. This approach not only enriches the literature but also sets a precedent for future research on performance evaluation under uncertainty. In conclusion, the hybrid neutrosophic TOPSIS-OWA model represents a significant advance in performance evaluation in consulting firms. By capturing the uncertainty and subjectivity of consultants' and auditors' opinions, it offers a practical and theoretically sound tool for optimizing organizational performance. Although its implementation requires certain resources, the benefits in terms of accuracy and strategic alignment justify its adoption. It is recommended that its application be explored in other sectors and combined with other neutrosophic methodologies to broaden its reach.

2.2. SVNS and SVNLS.

This section provides a brief overview of the fundamental principles related to SVNS and SVNLS, covering definitions, operating principles, and metrics for measuring distances.

Definition 1. Let x be an element in a finite set, X. A single-valued neutrosophic set (SVNS), P, in X can be defined as in (1):

$$P = \{ x, T_P(x), I_P(x), F_P(x) | x \in X\}, \quad (1)$$

where the truth membership function, $T_P(x)$,the indeterminacy membership function $I_P(x)$, and the falsehood membership function $F_P(x)$clearly adhere to condition (2):

$$0 \leq T_P(x), I_P(x), F_P(x) \leq 1; \; 0 \leq T_P(x) + I_P(x) + F_P(x) \leq 3 \quad (2)$$

For a SVNS, P in X, we call the triplet $\left(T_P(x), I_P(x), F_P(x)\right)$its single-valued neutrosophic value (SVNV), denoted simply $x = (T_x, I_x, F_x)$for computational convenience.

Definition 2. Leave $x = (T_x, I_x, F_x)$yy $= \left(T_y, I_y, F_y\right)$let there be two SVNV. Then

1) $x \oplus y = \left(T_x + T_y - T_x * T_y, I_x * T_y, F_x * F_y\right)$;
2) $\lambda * x = (1 - (1 - T_x)\lambda, (I_x)\lambda, (F_x)\lambda), \lambda > 0$;
3) $x^\lambda = \left((T_x)\lambda, 1 - (1 - I_x)\lambda, 1 - (1 - F_x)\lambda\right), \lambda > 0$

The linguistic set

Let l be $S = \{s_\alpha | \alpha = 1, \ldots, l\}$a finite, totally ordered discrete term with odd value, wheres_α denotes a possible value for a linguistic variable. For example, if $l = 7$, then a set of linguistic terms S could be described as follows:

$$S = \{s_1, s_2, s_3, s_4, s_5, s_6, s_7\} = \{extremely\ poor, very\ poor, poor, fair, good, very\ good, extremely\ good\}. \quad (3)$$

Any linguistic variable, s_iy s_j, in S must satisfy the following rules:

1) $Neg(s_i) = s_{-i}$;
2) $s_i \leq s_j \Leftrightarrow i \leq j$;
3) $\max\left(s_i, s_j\right) = s_j,\ if\ i \leq j$;
4) $\min\left(s_i, s_j\right) = s_i,\ if\ i \leq j$.

To avoid information loss during an aggregation process, the discrete set of terms S will be extended to a continuous set of terms. $S = \{ s_\alpha | \alpha \in R\}$.Any two linguistic variables $s_\alpha, s_\beta \in S$satisfy the following operational laws [15,16] :

1) $s_\alpha \oplus s_\beta = s_\alpha + \beta$;

2) $\mu s_{\alpha} = s_{\mu\alpha}, \mu \geq 0;$

3) $\frac{s_{\alpha}}{s_{\beta}} = s_{\frac{\alpha}{\beta}}$

Definition 3 [17] Given X, a finite set of universes, a SVNLS, P, in X can be defined as in (4):

$$P = \{\langle x, [s_{\theta(x)}, (T_P(x), I_P(x), F_P(x))]\rangle \mid x \in X\} \quad (4)$$

where $s_{\theta(x)} \in \bar{S}$, the truth membership function $T_P(x)$, the indeterminacy membership function, $I_P(x)$and the falsehood membership function $F_P(x)$satisfy condition (5):

$$0 \leq T_P(x), I_P(x), F_P(x) \leq 1, 0 \leq T_P(x) + I_P(x) + F_P(x) \leq 3. \quad (5)$$

For an SVNLS, P, in X, the 4- $\langle s_{\theta(x)}, (T_P(x), I_P(x), F_P(x))\rangle$tuple is known as the Single-Valued Neutrosophic Linguistic Set (SVNLN), conveniently denoted $x = s_{\theta(x)}, (T_x, I_x, F_x)$for computational purposes.

Definition 4 [17] . Let there be $x_i = \langle s_{\theta(xi)}, (T_{xi}, I_{xi}, F_{xi})\rangle$ $(i = 1, 2)$two SVNLNs. Then

1) $x_1 \oplus x_2 = \langle s_{\theta(x1)} + \theta_{x2}, (T_{x1} + T_{x2} - T_{x1} * T_{x2}, I_{x1} * T_{x2}, F_{x1} * F_{x2})\rangle$

2) $\lambda_{x1} = \langle s_{\lambda\theta(x1)}, (1 - (1 - T_{x1})^{\lambda}, (I_{x1})^{\lambda}, (F_{x1})^{\lambda})\rangle, \lambda > 0;$

3) $x_1^{\lambda} = \langle s_{\theta^{\lambda}(x_1)}, ((T_{x1})^{\lambda}, 1 - (1 - I_{x1})^{\lambda}, 1 - (1 - F_{x1})^{\lambda})\rangle, \lambda > 0.$

Definition 5 [17] . Let there be $x_i = \langle s_{\theta(xi)}, (T_{xi}, I_{xi}, F_{xi})\rangle$ $(i = 1, 2)$two SVNLNs. Their distance measure is defined as in (6):

$$d(x_1, x_2 v) = \left[|s_{\theta(x1)}T_{x1} - s_{\theta(x2)}T_{x2}|^{\mu} + |s_{\theta(x1)}I_{x1} - s_{\theta(x2)}I_{x2}|^{\mu} + |s_{\theta(x1)}F_{x1} - s_{\theta(x2)}F_{x2}|^{\mu}\right]^{\frac{1}{\mu}} \quad (6)$$

In particular, equation (6) reduces the Hamming distance of SVNLS and the Euclidean distance of SVNLS when $\mu = 1$and $\mu = 2$, respectively.

2.3. MADM Based on the SVNLOWAD-TOPSIS Method

For a given multi-attribute decision-making problem in SNVL environments, $A = \{A_1, \ldots, A_m\}$denotes a set of discrete feasible alternatives, $C = \{C_1, \ldots, C_n\}$represents a set of attributes, and $E = \{e_1, \ldots, e_k\}$is a set of experts (or DMs) with weight vector $\omega = \{\omega_1, \ldots, \omega_k\}$T such that $\sum_{i=1}^{n} w_i = 1$ and $0 \leq \omega_i \leq 1$. Suppose that the attribute weight vector is $s\,v = (v_1, \ldots, v_n)^T$, which satisfies $\sum_{i=1}^{n} v_i = 1$ and $v_i \in [0, 1]$. The evaluation, $\alpha_{ij}^{(k)}$given by the expert, $e_{t(t=1,\ldots,k)}$on the alternative, $A_{i(i=1,\ldots,m)}$,relative to the attribute, $C_{j(j=1,\ldots,n)}$forms the individual decision matrix as shown in equation (7):

$$D^k = \begin{array}{c c} & \begin{array}{ccc} C_1 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ \vdots \\ A_n \end{array} & \begin{pmatrix} \alpha_{11}^{(k)} & \cdots & \alpha_{1n}^{(k)} \\ \vdots & \ddots & \vdots \\ \alpha_{m1}^{(k)} & \cdots & \alpha_{mn}^{(k)} \end{pmatrix} \end{array} \quad (7)$$

where $\alpha_{ij}^k = \langle s_{\theta(\alpha_{ij})}^k, (T_{\alpha_{ij}}^k, I_{\alpha_{ij}}^k, F_{\alpha_{ij}}^k)\rangle$ is represented by a SVNLN, which satisfies $s_{\theta(\alpha ij)}^k \in \bar{S}, T_{\alpha_{ij}}^k, I_{\alpha_{ij}}^k, F_{\alpha_{ij}}^k \in [0,1] and\ 0 \leq T_{\alpha_{ij}}^k + I_{\alpha_{ij}}^k + F_{\alpha_{ij}}^k \leq 3$.

Geng et al. [18,19] extended the TOPSIS method to adapt it to the SVNLS scenario, and the procedures of the extended model can be summarized as follows.

Step 1. Normalize the individual decision matrices:

In practical scenarios, MADM problems can encompass both benefit attributes and cost attributes. Let B and S the benefit attribute sets and cost attribute sets, respectively. Therefore, the conversion rules specified in (8) apply:

$$\begin{cases} r_{ij}^{(k)} = \alpha_{ij}^{(k)} = \langle s_{\theta(\alpha_{ij})}^{k}, (T_{\alpha_{ij}}^{k}, I_{\alpha_{ij}}^{k}, F_{\alpha_{ij}}^{k})\rangle, \quad \text{for} \quad j \in B, \\ r_{ij}^{(k)} = \langle s_{l-\theta(\alpha_{ij})}^{k}, (T_{\alpha_{ij}}^{k}, I_{\alpha_{ij}}^{k}, F_{\alpha_{ij}}^{k})\rangle, \quad \text{for} \quad j \in S. \end{cases} \tag{8}$$

Thus, the standardized decision information , $R^k = (r_{ij}^{(k)})_{m\times n}$, is set as in (9):

$$R^k = (r_{ij}^{(k)})_{m\times n} = \begin{pmatrix} r_{11}^{(k)} & \cdots & r_{1n}^{(k)} \\ \vdots & \ddots & \vdots \\ r_{m1}^{(k)} & \cdots & r_{mn}^{(k)} \end{pmatrix} \tag{9}$$

Step 2. Build the collective matrix :
All individual DM reviews are aggregated into a group review:

$$R = (r_{ij})_{m\times n} = \begin{pmatrix} r_{11} & \cdots & r_{1n} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \end{pmatrix} \tag{10}$$

Where $r_{ij} = \sum_{k=1}^{t} \omega_k \, r_{ij}^{(k)}$.

Step 3. Set the weighted SVNL decision information:

The weighted SVNL decision matrix, , is formed as shown in (11), using the operational laws given in Definition 2 above:

$$Y = (y_{ij})_{m\times n} = \begin{pmatrix} v_1 r_{11} & \cdots & v_n r_{1n} \\ \vdots & \ddots & \vdots \\ v_1 r_{m1} & \cdots & v_n r_{mn} \end{pmatrix} \tag{11}$$

The OWA operator is fundamental in aggregation techniques, widely studied by researchers [18] . Its main advantage lies in organizing arguments and facilitating the integration of experts' attitudes in decision making. Recent research has explored OWA in distance measurement, generating variations of OWAD [17] . Taking advantage of the benefits of OWA, the text proposes a SVNL OWA distance measure (SVNLOWAD). Given the desirable properties of the OWA operator, an SVNL OWA distance measure (SVNLOWAD) is proposed in the following text.

Definition 6. *Let $x_j, x_j^{'}$ $(j = 1,\ldots,n)$ the two collections be SVNLN. If*

$$SVNLOWAD((x_1, x_1'),\ldots,(x_n, x_n')) = \sum_{j=1}^{n} w_j d(x_j, x_j'), \tag{12}$$

Therefore, step 4 of this method can be considered as follows:

Step 4. For each alternative, A_i the SVNLOWAD is calculated for the PIS, A^+ and the NIS A^-, using equation (12):

$$SVNLOWAD(A_i, A^+) = \sum_{j=1}^{n} w_j \, \dot{d}(y_{ij}, y_j^+), i = 1,\ldots,m \tag{13}$$

$$SVNLOWAD(A_i, A^-) = \sum_{j=1}^{n} w_j \, \dot{d}(y_{ij}, y_j^-), i = 1,\ldots,m \tag{14}$$

where $\dot{d}(y_{ij}, y_j^+)$ and $\dot{d}(y_{ij}, y_j^-)$ they are the j - largest values of $\dot{d}(y_{ij}, y_j^+)$ and $\dot{d}(y_{ij}, y_j^-)$, respectively.

Step 5. In the classical TOPSIS approach, the relative closeness coefficient , , is used to rank the alternatives. However, some researchers have highlighted cases where relative closeness fails to achieve the desired objective of simultaneously minimizing the distance from the PIS and maximizing the distance from the NIS. Thus, following an idea proposed in references [15] , in equations (15)–(17), we introduce a modified relative closeness coefficient, $C\,'(\,Ai\,)$, used to measure the degree to which the alternatives, Ai ( ) = 1,..., m =1,...,), are close to the PIS and also far from the NIS, congruently:

$$C'(A_i) = \frac{SVNLOWAD(A_i, A^-)}{SVNLOWAD_{\max}(A_i, A^-)} - \frac{SVNLOWAD(A_i, A^+)}{SVNLOWAD_{\min}(A_i, A^+)}, \tag{15}$$

where

$$SVNLOWAD_{\max}(A_i, A^-) = \max_{1\leq i\leq m} SVNLOWAD(A_i, A^-), \quad (16)$$

and

$$SVNLOWAD_{\min}(A_i, A^+) = \min_{1\leq i\leq m} SVNLOWAD(A_i, A^+). \quad (17)$$

It is clear that $C'(A_i) \leq 0$ $(i = 1, \ldots, m)$the higher the value of $C'(A_i)$and , the better A_i the alternative. Furthermore, if an alternative A^* satisfies the conditions $SVNLOWAD(A^*, A^-) = SVNLOWAD_{\max}(A^*, A^-)$and $SVNLOWAD(A^*, A^+) = SVNLOWAD_{\min}(A^*, A^+)$, then $C'(A^*) = 0$and the alternative $A^*$is the most suitable candidate, since it has the minimum distance to the PIS and the maximum distance to the NIS.

Step 6. Rank and identify the most desirable alternatives based on the decreasing closeness coefficient $C'(A_i)$obtained using Equation (15).

3. Case Study.

This study details the results of Andes Consulting 's annual performance evaluation. Group (ACG), a leading consulting firm based in Quito, Ecuador. The objective of this analysis is to determine the relative performance of the firm's key strategic areas, in order to guide resource allocation and strategic planning for the next two years. To address the subjectivity and uncertainty inherent in senior management perceptions, a hybrid TOPSIS-OWA model with neutrosophic logic has been applied, which allows for capturing degrees of truth, indeterminacy, and falsity in the assessments.

SVNLOWAD-TOPSIS method described in the reference theory was used .

Panel of Experts (DMs)

The evaluation was conducted by three key decision-makers within ACG:

- **DM1:** Managing Partner (global vision and strategy perspective)
- **DM2:** Finance and Control Manager (profitability and efficiency perspective)
- **DM3:** Senior Principal Consultant (Operations and Talent Perspective)

Alternatives (Strategic Areas Evaluated)

- **A1:** Innovation and Development of New Services
- **A2:** Service Quality and Customer Satisfaction
- **A3:** Operational Efficiency and Project Management
- **A4:** Talent Development and Organizational Climate

Evaluation Criteria

- **C1:** Strategic Impact (Weight: $w_1 = 0.20$)
- **C2:** Financial Profitability (Weight: $w_2 = 0.30$)
- **C3:** Market Competitiveness (Weight: $w_3 = 0.30$)
- **C4:** Organizational Sustainability (Weight: $w_4 = 0.20$)

Linguistic Scale

The scale was used $S = \{s_1, \ldots, s_7\}$, where s_1 is "Extremely Poor " and s_7 is "Extremely Good".

3. Data Collection: Individual Decision Matrices

The three experts evaluated each area (A) against each criterion (C). The matrices with the original data for this study are presented below.

Table 1: Evaluations of Expert 1 (Managing Partner)

Area	C1	C2	C3	C4
A1	$S_5(0.6,0.2,0.2)$	$S_4(0.5,0.3,0.2)$	$S_5(0.6,0.2,0.1)$	$S_4(0.4,0.3,0.3)$
A2	$S_6(0.7,0.1,0.2)$	$S_6(0.8,0.1,0.1)$	$S_7(0.8,0.1,0.1)$	$S_5(0.6,0.2,0.2)$
A3	$S_7(0.8,0.1,0.1)$	$S_7(0.9,0.1,0.0)$	$S_6(0.7,0.2,0.1)$	$S_6(0.7,0.1,0.2)$
A4	$S_3(0.4,0.4,0.3)$	$S_4(0.5,0.2,0.3)$	$S_3(0.4,0.3,0.4)$	$S_4(0.5,0.2,0.2)$

Table 2: Evaluations of Expert 2 (Finance Manager)

Area	C1	C2	C3	C4
A1	$S_4(0.4,0.3,0.3)$	$S_5(0.6,0.2,0.1)$	$S_4(0.5,0.4,0.1)$	$S_3(0.3,0.4,0.4)$
A2	$S_6(0.6,0.2,0.1)$	$S_7(0.7,0.2,0.1)$	$S_6(0.7,0.2,0.2)$	$S_6(0.7,0.1,0.1)$
A3	$S_6(0.7,0.2,0.1)$	$S_7(0.8,0.1,0.1)$	$S_7(0.8,0.1,0.1)$	$S_7(0.8,0.1,0.1)$
A4	$S_4(0.3,0.5,0.2)$	$S_3(0.4,0.3,0.3)$	$S_4(0.4,0.4,0.3)$	$S_3(0.4,0.3,0.3)$

Table 3: Evaluations of Expert 3 (Senior Consultant)

Area	C1	C2	C3	C4
A1	$S_5(0.5,0.2,0.3)$	$S_5(0.5,0.2,0.2)$	$S_6(0.7,0.1,0.2)$	$S_4(0.5,0.3,0.2)$
A2	$S_7(0.8,0.1,0.1)$	$S_6(0.6,0.2,0.2)$	$S_6(0.7,0.1,0.1)$	$S_7(0.8,0.2,0.1)$
A3	$S_7(0.9,0.1,0.0)$	$S_6(0.7,0.2,0.1)$	$S_7(0.7,0.1,0.2)$	$S_6(0.6,0.2,0.2)$
A4	$S_3(0.3,0.4,0.4)$	$S_4(0.4,0.4,0.3)$	$S_3(0.5,0.3,0.3)$	$S_4(0.4,0.4,0.3)$

4. Application of the Model and Detailed Calculations

Step 1: Normalization

Since all criteria are beneficial, no standardization is required.

Step 2: Construction of the Collective Decision Matrix

The opinions of the 3 experts are added by averaging their evaluations.

Example calculation for A1-C1:

- $s^{11} = \frac{5+4+5}{3} = 4.666667$
- $T^{11} = \frac{0.6+0.4+0.5}{3} = 0.500000$
- $I^{11} = \frac{0.2+0.3+0.2}{3} = 0.233333$
- $F^{11} = \frac{0.2+0.3+0.3}{3} = 0.266667$
- Result:$S_{4.667}(0.500,0.233,0.267)$

Table 4: SVNL Collective Decision Matrix

Area	C1 (Strategic Impact)	C2 (Profitability)	C3 (Competitiveness)	C4 (Sustainability)
A1	$S_{4.667}(0.500;0.233;0.267)$	$S_{4.667}(0.533;0.233;0.167)$	$S_{5.000}(0.600;0.233;0.133)$	$S_{3.667}(0.400;0.333;0.300)$
A2	$S_{6.333}(0.700;0.133;0.133)$	$S_{6.333}(0.700;0.167;0.133)$	$S_{6.333}(0.733;0.133;0.133)$	$S_{6.000}(0.700;0.167;0.133)$
A3	$S_{6.667}(0.800;0.133;0.067)$	$S_{6.667}(0.800;0.133;0.067)$	$S_{6.667}(0.733;0.133;0.133)$	$S_{6.333}(0.700;0.133;0.167)$
A4	$S_{3.333}(0.333;0.433;0.300)$	$S_{3.667}(0.433;0.300;0.300)$	$S_{3.333}(0.433;0.333;0.333)$	$S_{3.667}(0.433;0.300;0.267)$

Step 3: Weighted Decision Matrix

The collective matrix is multiplied by the weight vector$W = (0.20,0.30,0.30,0.20)$.

Example calculation for A1-C1: $V_{11} = 0.20 \times S_{4.667}(0.500,0.233,0.267) = S_{0.933}(0.100,0.047,0.053)$

Table 5: Weighted Collective SVNL Decision Matrix

Area	C1 (w=0.20)	C2 (w=0.30)	C3 (w=0.30)	C4 (w=0.20)
A1	$S_{0.933}$(0.100;0.047;0.053)	$S_{1.400}$(0.160;0.070;0.050)	$S_{1.500}$(0.180;0.070;0.040)	$S_{0.733}$(0.080;0.067;0.060)
A2	$S_{1.267}$(0.140;0.027;0.027)	$S_{1.900}$(0.210;0.050;0.040)	$S_{1.900}$(0.220;0.040;0.040)	$S_{1.200}$(0.140;0.033;0.027)
A3	$S_{1.333}$(0.160;0.027;0.013)	$S_{2.000}$(0.240;0.040;0.020)	$S_{2.000}$(0.220;0.040;0.040)	$S_{1.267}$(0.140;0.027;0.033)
A4	$S_{0.667}$(0.067;0.087;0.060)	$S_{1.100}$(0.130;0.090;0.090)	$S_{1.000}$(0.130;0.100;0.100)	$S_{0.733}$(0.087;0.060;0.053)

Step 4: PIS, NIS and Distance Calculation

The ideal solutions PIS (best value in each column) and NIS (worst value in each column) are determined from Table 5.

The distance of each alternative to PIS and NIS is then calculated using the Euclidean distance ($\lambda = 2$)and the OWA operator with weights$w = (0.1, 0.2, 0.3, 0.4)$.

After performing the calculation process accurately for all alternatives, the following final aggregate distances are obtained:

Table 7 (Final): Summary of SVNLOWAD Distances

Alternative	SVNLOWAD(A_i , A^+)	SVNLOWAD(A_i , A^-)
A1 (Innovation)	0.1067	0.0573
A2 (Quality/Customer)	0.0385	0.1491
A3 (Efficiency)	0.0003	0.1783
A4 (Human Talent)	0.1782	0.0007

Step 5: Coefficient of Relative Closeness (C_i)

The coefficient is calculated $C_i = \frac{D^-}{D^- + D^+}$for each alternative using the final distance values.

Table 8 (Final): Proximity and Ranking Coefficients

Alternative	SVNLOWAD(A_i , A^+) (D^+)	SVNLOWAD(A_i , A^-) (D^-)	Proximity Coefficient (C)	Ranking
A1 (Innovation)	0.1067	0.0573	0.3494	3
A2 (Quality/Customer)	0.0385	0.1491	0.7948	2
A3 (Efficiency)	0.0003	0.1783	0.9984	1
A4 (Human Talent)	0.1782	0.0007	0.0039	4

Step 6: Final Ranking and Visualization

The strategic areas are classified in descending order according to the final proximity coefficient C:

1. **A3 (Operational Efficiency)** :$C = 0.9984$
2. **A2 (Service Quality and Customer Satisfaction)** :$C = 0.7948$
3. **A1 (Innovation and Development)** :$C = 0.3494$

4. **A4 (Talent Development and Organizational Climate)** : $C = 0.0039$

Table 9: Summary of Results by Strategic Area

Position	Strategic Area	Coefficient (C)	Classification
1	Operational Efficiency	0.9984	Indisputable Fortress
2	Service Quality and Customer Satisfaction	0.7948	Solid Fortress
3	Innovation and Development	0.3494	Relative Weakness
4	Talent Development and Organizational Climate	0.0039	Critical Deficiency

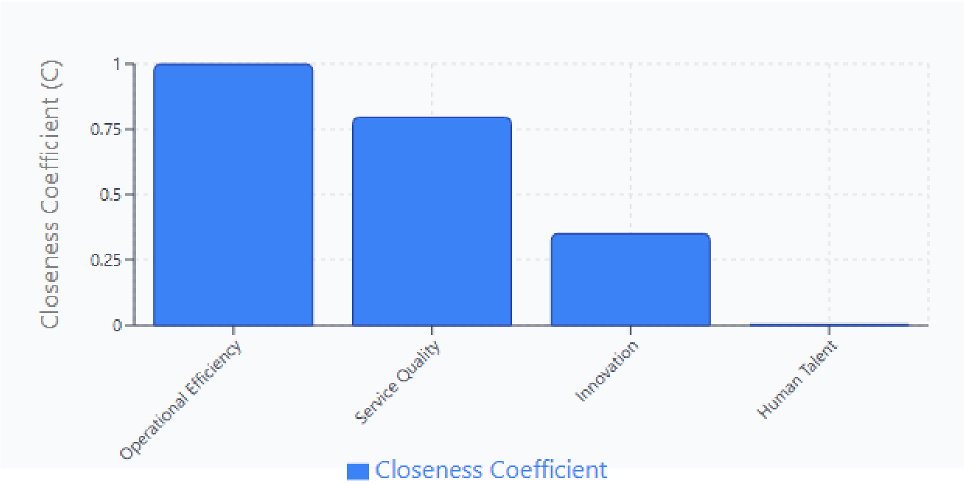

Figure 1: TOPSIS Analysis: Strategic Areas Performance

4. Discussion of Results

Consulting 's strategic situation. Group .

Operational Efficiency (A3) - Undisputed Strength

The Operational Efficiency area **(A3)** stands out as the firm's undisputed strength, with an almost perfect result. ($C = 0.998$).This value reflects an absolute consensus among managers on the solidity of internal processes and project management, which are pillars of profitability and successful execution.

Service Quality and Customer Satisfaction (A2) - Solid Position

Service Quality and Customer Satisfaction (A2) ranks in a strong second place ($C = 0.795$), confirming that the firm is perceived as a high-quality provider. The gap with the top spot indicates that, while excellent, there is still minimal room for improvement compared to operational efficiency. Together, these two areas form ACG's competitive engine.

Innovation and Development (A1) - Relative Weakness

In a distant third place is **Innovation and Development (A1)** , with a coefficient of 0.349. This score shows that the firm's ability to create and monetize new solutions is a relative weakness. It represents a strategic vulnerability that could affect its long-term competitiveness in a changing market.

Talent Development and Organizational Climate (A4) - Critical Deficiency

The most critical finding is reiterated in the area of **Talent Development and Organizational Climate (A4)** , whose coefficient is practically zero. ($C = 0.004$).This result underscores a serious deficiency, one that is widely acknowledged by management. For a consulting firm whose main asset is its human capital, this is the greatest threat to its future sustainability.

5. Conclusions

The application of the neutrosophic OWA-TOPSIS model has successfully transformed the complex and subjective perceptions of management into a coherent and mathematically validated strategic diagnosis. This analysis reveals that Andes Consulting Group holds a strong competitive position thanks to its superior operational execution (A3) and high-quality service (A2), which constitute its main strengths. However, the firm shows a noticeable weakness in its innovation capacity (A1) and a critical, urgent deficiency in the management of human talent (A4), which could jeopardize its long-term sustainability if not addressed.

Based on these findings, three strategic recommendations are proposed. First, the company should strengthen and protect its operational and service quality core by maintaining investment in key technologies and processes. Second, an urgent shock plan must be implemented to address the human talent crisis, including the formation of a crisis committee led by the Managing Partner to act on career planning, salary policy, training, and work environment improvements. Finally, to address the innovation gap, the firm should launch a structured R&D program supported by a dedicated budget, possibly incorporating innovation cells or strategic alliances to drive competitiveness and growth.

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