Enhanced Supplier Evaluation in Digital Transformation: A BWM-Neutrosophic TOPSIS Approach for Decision-Making Under Uncertainty

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Abstract: In the context of comprehensive business systems engineering, manufacturers must establish and maintain robust relationships with suppliers and customers in order to remain competitive. This paper introduces a Neutrosophic BWM-TOPSIS framework for supplier evaluation, addressing the uncertainty inherent to multi-attribute decision-making (MADM) during digital transformation (DX). By integrating Neutrosophic sets, which extend fuzzy logic, this framework effectively deals with ambiguous, inconsistent, and incomplete data. Additionally, it incorporates the Best-Worst Method (BWM) with the purpose of determining the weights for decision-makers and deploys the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank supplier alternatives. A case study carried out for the metro rail coach manufacturing industry validates the framework's practical application, showcasing its ability to enhance decision-making accuracy. Moreover, this study compares the performance of the proposed framework to that of existing approaches in terms of informativeness and reliability. This research significantly contributes to the field of informatics by providing a scalable and systematic decision-making methodology, which can also be adapted to other MADM contexts in DX.

Keywords: Neutrosophic sets, Supplier evaluation, Digital transformation, Multi-participant decision-making, Information Technology deployment, BWM, TOPSIS.

1. Introduction

Digital Transformation (DX) has gained significant attention in recent years as organizations strive to enhance operational efficiency, value creation, and profitability by integrating advanced technologies into their processes. DX involves adopting innovative informatics systems and frameworks to enable seamless automation, data analysis, and decision-making, creating opportunities for organizations to modernize themselves and remain competitive. The predicted expansion of DX arises from the concerted efforts of organizations, corporations, and agencies to establish DX-centric business visions.

To successfully implement comprehensive production processes, companies must cultivate robust relationships with both suppliers and clients. In this regard, informatics tools play a crucial role in assessing and managing these relationships, particularly through data-driven evaluation methods. Companies are required to reevaluate their collaborators' procedures to adapt to DX-driven advances related both to products and processes, ensuring their alignment with the evolving technological demands. This necessity underscores the importance of supplier evaluation frameworks that are both dynamic and adaptable to Information Technology (IT) deployment, addressing the increasing complexity of decision-making.

DX has a profound impact on organizations and industries, as it demands adaptation to digital trends for maintaining competitiveness and innovation capabilities. Moreover, DX extends beyond technology to encompass organizational culture, strategy, and value creation (Nadkarni & Prügl, 2021). Among industries, DX is expected to

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have the most significant impact on communication services, where products such as mobile factories rely on thousands of components, many of which are electronic. These intricate systems highlight the importance of multi-participant decision-making frameworks, as diverse stakeholders must align their priorities when addressing supplier and component selection.

Innovation driven by DX leads to product and process updates, requiring manufacturers and their distributors to improve their operations and merchandising. At this stage, supplier assessment becomes a critical challenge, particularly for automakers. To address this, informatics-enabled supplier evaluation frameworks are essential for automating data collection, analysis, and decision-making, ensuring the alignment with DX requirements. One of the key drivers of DX is technology (Kraus et al., 2021), which is often sourced from suppliers.

The eight key components - digital technology, organizational structure, culture, processes, customer experience, data management, innovation capability, and strategy - work synergistically to help organizations address challenges and create value during the DX process (Vial, 2019). Effective informatics systems integrate these components, enabling organizations to streamline their supplier evaluations by providing real-time insights and robust decision support. For driving digital transformation, companies should consider the following four key aspects when selecting suppliers: (1) alignment with digital transformation needs, (2) integration and flexibility, (3) performance evaluation and risk management, and (4) ongoing support and collaboration (Morakanyane et al., 2017).

Under rapidly changing market conditions, the companies must adapt to new standards, which, in turn, must be adopted by their suppliers. Evaluating suppliers involves considering various factors such as cost, reliability, availability, and post-sales support. Multi-criteria analysis methods can be used to assess suppliers by weighing these factors. In specific situations, Multi-Attribute Decision-Making (MADM) techniques are invaluable tools for decision-makers to evaluate different options. Technological advancements have made these techniques more accessible and widely used in various business and administrative decision-making processes. Among the most commonly employed multi-criteria methods one should mention MAXMIN, MAXMAX, SAW, AHP, TOPSIS, SMART, VIKOR, and ELECTRE. The choice of the appropriate technique is largely dependent on the nature of the problem, whether it involves selection, sorting, or ranking.

TOPSIS has emerged as a highly effective method among these techniques due to its distinct advantages. Based on previous studies and certain observations, the benefits of TOPSIS include: (1) a logical approach that explains individual choices; (2) a process that accounts for both the best and worst possible outcomes; (3) a simple data processing method that can be easily implemented on a spreadsheet; and (4) the ability to visualize the impact of each option on multiple criteria, at least with regard to two factors.

TOPSIS is a practical tool for evaluating alternatives based on the data provided in initial rankings and classifications. Therefore, it has been chosen as the primary software platform for this study. MADM is widely applicable as it helps identify and rank multiple options. In the Asia-Pacific region, TOPSIS is regarded as one of the most important decision-making tools. Over the past few years, TOPSIS has been successfully applied in various fields, including human resource management, transportation, systems engineering, manufacturing, flood control, and product testing (GIS). Qi (2023) proposed an extended TOPSIS model integrated with the Full Consistency Method (FUCOM) within a probabilistic hesitant fuzzy context to evaluate the public charging service quality, a typical MAGDM issue. Radulescu et al. (2023) proposed a Multi-Criteria Weighting Approach (MCWA) for analyzing the diverse and interdependent security requirements of Internet of Things (IoT) systems. Recognizing that IoT systems face both critical application-related needs and a variety of security threats, the authors address the problem of evaluating and weighting IoT security requirements (IoT-SR), which is inherently multi-criteria in nature. Gurmani et al. (2023) proposed a MAGDM model to select the most suitable construction company, considering the complexities of human judgment and the hybrid uncertainty of fuzziness and probability.

Zavadskas et al. (2022) examined the robustness of the Weighted Influence Nonlinear Gauge

System (WISP) method, which traditionally uses the maximum normalization procedure, by exploring its performance through the square root and sum normalization procedures. To evaluate the similarity of the obtained results, they conducted analyses using the Python programming language and measured similarity through the cosine similarity measure. Liu (2011) suggested an extended TOPSIS method for multi-attribute group decision-making (MAGDM) problems, where the criteria weights are determined by decision-makers using interval-valued fuzzy sets. Mohammadi et al. (2012) introduced a TOPSIS method under an uncertain environment to select an effective security mechanism in e-business processes. Petrovas et al. (2022) proposed a novel approach to creative procedural generation by combining the Combined Compromise Solution (CoCoSo) multi-criteria decision algorithm with a genetic algorithm to generate game scenes that satisfy game rules while enhancing the aesthetic value of visuals. By incorporating fuzzy neutrosophic sets, this method increases nondeterminism, a crucial aspect of creativity, ensuring that each output is unique and adheres to the replayability principle. Nafei et al. (2024) proposed an extension of TOPSIS and Autocratic decision-making methods for dealing with neutrosophic fuzzy sets that consider membership as a separate function of the truth membership function. Lee (2023) proposed an autocratic decision-making strategy for multi-attribute group decision-making under a neutrosophic environment. The method transforms multiple management decisions and weight matrices into a unified aggregated assessment matrix, addressing uncertainties inherent to real-life systems. Using single-valued neutrosophic triplets, the approach prioritizes recreation areas in the tourism sector, enabling the selection of optimal tourist destinations based on key attributes and sustainable growth considerations.

The neutrosophic set, introduced by Smarandache (1998), has emerged as a valuable framework for handling indeterminate, inconsistent, and incomplete information by introducing three parameters: truth, indeterminacy, and falsity. However, despite the advantages of neutrosophic sets, the integration of these sets into MADM for supplier evaluation within the context of digital transformation has not been fully explored. Conventional methods, such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Analytic Hierarchy Process (AHP), are often inadequate for handling high levels of uncertainty, a common challenge in digital transformation contexts. These traditional methods also struggle with processing ambiguous and inconsistent data, which can lead to inaccuracies in supplier ranking and selection. Moreover, there is a lack of frameworks capable of addressing complex, multi-dimensional decision-making scenarios within the digital transformation landscape. To overcome these challenges, this study proposes an advanced Neutrosophic TOPSIS method tailored for supplier evaluation in digital transformation applications. The proposed approach leverages the strengths of neutrosophic logic to effectively manage uncertainty, indeterminacy, and ambiguity, thus providing a robust and flexible framework for MADM.

To address these challenges, this study employs a neutrosophic TOPSIS approach, effectively managing indeterminacy and ambiguity through neutrosophic logic. Neutrosophic Set (NS) theory, an extension of the fuzzy set theory, provides a robust framework for handling inconsistent and imprecise information by incorporating the three aforementioned parameters: truth, indeterminacy, and falsity. This enables a more nuanced approach to decision-making, especially in scenarios involving complex and uncertain data.

The primary contributions of this study are as follows:

1. The development of an Extended Neutrosophic TOPSIS Framework: this study extends the TOPSIS method by integrating neutrosophic logic, which enhances its capacity to manage ambiguous and uncertain data in supplier evaluation.

2. The optimization of the Ranking Algorithm for Neutrosophic Numbers: the study uses an innovative algorithm based on score, access, and certainty functions for accurately ranking Single-Valued Neutrosophic Numbers (SVNNs).

3. Its application to the Metro Rail Coach Industry: the proposed methodology is applied for a case study focused on supplier selection in the metro rail coach industry, which illustrates its practical applicability and effectiveness.

4. This study integrates the Best-Worst Method (BWM) and TOPSIS for an enhanced decision-making process. BWM is utilized to determine the weights of decision-makers within a multi-group decision-making (MGDM) framework, capturing their relative influence accurately.

5. Robust IT Deployment Potential: this framework demonstrates a strong capability for integration into informatics systems, such as decision support tools and enterprise resource planning (ERP) platforms, enabling the implementation of dynamic and real-time supplier evaluation processes.

The structure of this paper is outlined as follows. Section 2 introduces the fundamental concepts related to Neutrosophic Sets. Section 3 proposes an algorithm for ranking Single-Valued Neutrosophic Numbers (SVNNs), while Section 4 presents an extended BWM-TOPSIS strategy for dealing with neutrosophic MADM problems. In Section 5, the proposed methodology is applied to a numerical case study addressing supplier selection issues in the metro rail coach industry, demonstrating the validity of this method. Finally, Section 6 concludes this paper.

2. Basic Definitions for Neutrosophic Sets

This section outlines the key concepts related to Single-Valued Neutrosophic Sets (SVNS) that are relevant to this study.

Definition 1. (Smarandache, 1998): A neutrosophic set (NS) N in a universal set O is defined by three membership functions, namely truth: $T_N : O \rightarrow]\,0^-,1^+[$, indeterminacy: $I_N : O \rightarrow]\,0^-,1^+[$ and falsity: $F_N : O \rightarrow]\,0^-,1^+[$. One can easily see that these functions satisfy the condition $0^- \leq T_N(o) + I_N(o) + F_N(o) \leq 3^+ \, \forall\, o \in O$.

Definition 2. (Wang et al., 2010): Let X be the universe of discourse. A Single-Valued Neutrosophic Set (SVNS) N is mapped as $N = \{\langle x, T_N(x), I_N(x), F_N(x)\rangle; x \in X\}$, where $T_N : X \rightarrow [0,1]$, $I_N : X \rightarrow [0,1]$ and $F_N : X \rightarrow [0,1]$. It should be noted that the condition$0 \leq T_N(x) + F_N(x) + I_N(x) \leq 3,\ \forall\, x \in X$ is always satisfied. In the context of the SVNS N, the trinary $(T_N(x), I_N(x), F_N(x))$ is called a neutrosophic triplet (NT). For simplicity purposes, this trinary is often represented by the symbol (T, I, F).

Definition 3. (Eroğlu & Şahin, 2020): It shall be assumed that $N = (T_1, I_1, F_1)$ and $M = (T_2, I_2, F_2)$. N is a subset of M, denoted as $N \subseteq M$ if and only if $T_1 \leq T_2$, $I_1 \geq I_2$, and $F_1 \geq F_2$. In this case, N is considered a subset of M because N is less true, more indeterminate, and no less false than M.

Definition 4. (Kaur & Garg, 2022): The complement of a neutrosophic set N is represented as $c(N)$ where each membership function is transformed as follows: the truth membership becomes $T_{c(N)}(o) = \{1^+\} \ominus T_N(o)$, the indeterminacy membership becomes $I_{c(N)}(o) = \{1^+\} \ominus I_N(o)$ and the falsity membership becomes $F_{c(N)}(o) = \{1^+\} \ominus F_N(o)$ for every element $o \in O$.

Definition 5. (Smarandache, 1998): Arithmetic operations on neutrosophic triplets $e = (T_1, I_1, F_1)$ and $f = (T_2, I_2, F_2)$ include:

$$e \oplus f = \left(T_1 + T_2 - T_1 T_2, I_1 I_2, F_1 F_2\right), \tag{1}$$

$$e \otimes f = \left(T_1 T_2, I_1 + I_2 - I_1 I_2, F_1 + F_2 - F_1 F_2\right), \tag{2}$$

$$e \overset{N}{-} f = \left(\frac{T_1 - T_2}{1 - T_2}, \frac{I_1}{I_2}, \frac{F_1}{F_2}\right), \tag{3}$$

$$e \overset{N}{\div} f = \left(\frac{T_1}{T_2}, \frac{I_1 - I_2}{1 - I_2}, \frac{F_1 - F_2}{1 - F_2}\right), \tag{4}$$

$$\lambda e = \left(1 - (1 - T_1)^\lambda, I_1^\lambda, F_1^\lambda\right), \quad \lambda > 0, \tag{5}$$

$$e^\lambda = \left(T_1^\lambda, 1 - (1 - I_1)^\lambda, 1 - (1 - F_1)^\lambda\right), \quad \lambda > 0. \tag{6}$$

3. Discussion

This section initially explores the existing score functions employed for the evaluation of single-valued neutrosophic numbers. Subsequently, a more effective ranking technique for neutrosophic values is presented, which was developed by critically analyzing and addressing the limitations of the current methodologies.

Şahin (2014) proposed a score function for SVNNs. Let $A = (a, b, c)$ be a neutrosophic triplet. The score function S for ranking the single-valued neutrosophic number A is expressed as follows:

$$S(A) = \frac{1 + a - 2b - c}{2}; \quad S(A) \in [-1, 1], \tag{7}$$

However, in some instances, the suggested function is unable to provide adequate information. For example, if $N_1 = (0.5,0.2,0.6)$ and $N_2 = (0.2,0.2,0.3)$, then $S(N_1) = S(N_2) = 0.25$ Consequently, this scoring system is unable to identify the optimal option in a few exceptional circumstances. Nancy & Garg (2016) suggested an optimized score function G for $A = (a,b,c)$ as follows:

$$G(A) = \frac{1+(a-2b-c)(2-a-c)}{2} \tag{8}$$

Now, by applying this score function to the previous particular case, $G(N_1) = 0.275$ and $G(N_2) = 0.125$ can be obtained. This means A_1 is a better alternative than A_2

The examination of the ranking function G reveals that some numbers cannot be rated by using this function. Let $N_1 = (0.5,0.25,0.0)$ and $N_2 = (0.5,0.0,0.5)$ be two different SVNNs. Using the score function, G, $G(N_1) = G(N_2) = 0.5$ can be obtained.

Consequently, it cannot achieve the optimal selection in this situation. This circumstance motivates the search for an appropriate solution to this issue.

Taking into consideration the uniqueness property and exceptional cases associated with different sets of single-valued neutrosophic numbers, it is necessary to refine the existing score functions in order to develop a more efficient method that fully accounts for all neutrosophic number characteristics. This refinement is crucial for accurately ranking alternatives in decision-making processes. The investigation carried out reveals that the primary limitation stems from the fact that current ranking methods are typically based on a single function, despite neutrosophic sets being composed of three distinct components.

Relying on a single function to rank neutrosophic numbers, which are inherently defined by triplets, introduces significant disadvantages in the ranking process, particularly in exceptional cases. In this regard, an algorithm is used which consists of three functions, namely the score, accuracy, and certainty functions that were structured by Smarandache (2020).

The proposed algorithm is as follows:

Algorithm 1.

Assume that $A_1 = (a_1,b_1,c_1)$ and $A_2 = (a_2,b_2,c_2)$ are two different neutrosophic triplets.

Step 1. Apply the score function $S(A) = \frac{1+a-2b-c}{2}$, for ranking neutrosophic triplets.

If $S(A_1) > S(A_2)$,then $A_1 > A_2$.

If $S(A_1) < S(A_2)$, then $A_1 < A_2$.

If $S(A_1) = S(A_2)$, then go to the next step.

Step 2. Apply the accuracy function $AC(A) = 1+2a-b$ for ranking SVNNs.

If $AC(A_1) > AC(A_2)$, then $A_1 > A_2$.

If $AC(A_1) < AC(A_2)$, then $A_1 < A_2$.

If $AC(A_1) = AC(A_2)$, then go to the next step.

Step 3. Apply the certainty function $C(A) = 2a$ for ranking SVNNs.

If $C(A_1) > C(A_2)$, then $A_1 > A_2$.

If $C(A_1) < C(A_2)$, then $A_1 < A_2$.

4. The BWM-TOPSIS Method

By considering N alternatives and M attributes, it is assumed that the decision-making committee consists of L experts. It shall be assumed that $w_l = \left[w_1^l, w_2^l, ..., w_m^l\right]$ is a set of criteria weights given by the decision maker D_l. Further on, $1 \le m \le M$, $1 \le n \le N$ and $1 \le l \le L$.

In group decision-making, assigning the appropriate weights to decision-makers is essential for achieving accurate results. To accomplish this, an Extended Best-Worst Method (BWM) is presented to determine the weights of the decision-makers. The process of using the BWM is explained as follows:

A. Identify the best and the worst decision-maker

An analyst selects the most important (best) and the least important (worst) decision-maker from the set of decision-makers.

B. Pairwise comparison matrices

The decision-makers conduct pairwise comparisons between the best decision-maker and each of the other decision-makers, and similarly for the worst decision-maker. These comparisons are rated on a scale from 1 (equal importance) to 9 (extreme importance).

- α_{Bl} represents the comparison of the best decision-maker D_b with decision-maker D_l.
- α_{lW} represents the comparison of decision-maker D_l with the worst decision-maker D_w.

Two vectors are constructed based on these comparisons:

$$\alpha_B = (\alpha_{B1}, \alpha_{B2}, ..., \alpha_{BL}),\ \alpha_W = (\alpha_{1W}, \alpha_{2W}, ..., \alpha_{LW}).$$

C. Optimization for weight calculation

The optimization problem for obtaining the crisp weights for decision-makers is formulated to minimize the largest absolute differences between the pairwise comparisons and the calculated weights. This optimization problem is expressed as:

$$\min \max \left[\max_l |W_B - \alpha_{Bl} W_l|,\ \max_l |W_l - \alpha_{lW} W_W| \right] \quad (9)$$

where:

- W_B and W_W are the weights of the best and worst decision-makers, respectively.
- W_l represents the weight of the decision-maker D_l.
- the solution provides the crisp weight vector $W = (W_1, W_2, ..., W_L)$, where $\sum_{l=1}^{L} W_l = 1,\ l = 1, 2, ..., L.$

It is assumed that EV_l is an evaluating matrix of alternatives for criteria that is given by D_l based on SVNNs as follows:

$$EV_l = \begin{array}{c} \\ a_1 \\ a_2 \\ \vdots \\ a_N \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & \cdots & c_M \end{array} \\ \begin{bmatrix} ev_{11}^l & ev_{12}^l & \ldots & ev_{1M}^l \\ ev_{21}^l & ev_{22}^l & \ldots & ev_{2M}^l \\ \vdots & \vdots & \ddots & \vdots \\ ev_{N1}^l & ev_{N2}^l & \ldots & ev_{NM}^l \end{bmatrix} \end{array}, \quad (10)$$

where the components of EV_l are considered to be neutrosophic triplets such that $ev_{nm}^l = (T_{nm}^l, I_{nm}^l, F_{nm}^l)$.

Step 1. The weighted evaluation matrix is created as follows:

$$WEV_l = \begin{bmatrix} wev_{11}^l & wev_{12}^l & \ldots & wev_{1M}^l \\ wev_{21}^l & wev_{22}^l & \ldots & wev_{2M}^l \\ \vdots & \vdots & \ddots & \vdots \\ wev_{N1}^l & wev_{N2}^l & \ldots & wev_{NM}^l \end{bmatrix}, \quad (11)$$

where $wev_{nm}^l = ev_{nm}^l \otimes w_m^l$.

Step 2. The aggregated evaluation matrix F is created as follows:

$$F = \begin{array}{c} \\ a_1 \\ a_2 \\ \vdots \\ a_N \end{array} \begin{array}{c} \begin{array}{cccc} D_1 & D_2 & \cdots & D_L \end{array} \\ \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1L} \\ f_{21} & f_{22} & \cdots & f_{2L} \\ \vdots & \vdots & \ddots & \vdots \\ f_{N1} & f_{N2} & \cdots & f_{NL} \end{bmatrix} \end{array}, \quad (12)$$

where $f_{nl} = W_l [wev_{n1}^l \oplus wev_{n2}^l \oplus \cdots \oplus wev_{nM}^l]$, and $1 \le n \le N$, $1 \le l \le L$. Also, W_l is the weight of the decision maker D_l.

Step 3. The feature matrix $S(F)$ is generated based on the suggested strategy for ranking the SVNNs as it is outlined below:

$$S(F) = \begin{array}{c} \\ a_1 \\ a_2 \\ \vdots \\ a_N \end{array} \begin{array}{c} \begin{array}{cccc} D_1 & D_2 & \cdots & D_L \end{array} \\ \begin{bmatrix} Score(f_{11}) & Score(f_{12}) & \cdots & Score(f_{1L}) \\ Score(f_{21}) & Score(f_{22}) & \cdots & Score(f_{2L}) \\ \vdots & \vdots & \ddots & \vdots \\ Score(f_{N1}) & Score(f_{N2}) & \cdots & Score(f_{NL}) \end{bmatrix} \end{array} \quad (13)$$

Step 4. The positive and negative ideal solutions are determined as follows:

$$\begin{aligned} F_l^+ &= \max_n (Score(f_{nl})), l = 1, ..., L, \\ F_l^- &= \min_n (Score(f_{nl})), l = 1, ..., L. \end{aligned} \quad (14)$$

Step 5. The distance between the alternatives and PIS and NIS is calculated using the distance measure d as follows:

$$\begin{aligned} d_n^+ &= \sum_{l=1}^{L} f_{nl} - F_l^+ = \sum_{l=1}^{L} \left[\frac{\left(|T_{nl} - T_l^+| + |I_{nl} - I_l^+| + |F_{nl} - F_n^+| \right)}{6} \right] \\ d_n^- &= \sum_{l=1}^{L} f_{nl} - F_l^- = \sum_{l=1}^{L} \left[\frac{\left(|T_{nl} - T_l^-| + |I_{nl} - I_l^-| + |F_{nl} - F_n^-| \right)}{6} \right] \end{aligned} \quad (15)$$

Step 6. The values of the relative closeness ratios are calculated as follows:

$$RCR_n^* = \frac{d_n^-}{d_n^+ + d_n^-}. \quad (16)$$

Step 7. The alternatives are ranked by ordering them according to the increasing values of RCR.

5. Numerical Case Study

As a case study for this research, it is assumed that there exist four different suppliers, namely (a_1,a_2,a_3,a_4) that provide the main parts of metro rail coaches and which should be compared with each other. In this regard, a multitude of various criteria/ indicators is chosen after an evaluation of the relevant literature. These indicators include Mobility-As-a-Service (c_1), Predictive Maintenance (c_2), and Data Security and Protection (c_3). To conduct this comparison, a group of three specialists was formed. The advisory panel determined the characteristics to be included as the foundation. In the context of describing the neutrosophic theory's features, the professionals were requested to express their views using neutrosophic numbers. The evaluations which were carried out are represented as follows:

$$EV_1 = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} \begin{array}{c} \begin{array}{ccc} \quad c_1 \quad & \quad c_2 \quad & \quad c_3 \quad \end{array} \\ \begin{bmatrix} [0.4,0.8,0.2] & [0.9,1.0,0.2] & [0.6,0.0,0.4] \\ [0.0,1.0,0.4] & [0.9,0.8,0.9] & [0.2,0.1,0.6] \\ [0.2,0.7,0.4] & [0.5,0.9,0.5] & [0.1,0.2,0.5] \\ [0.5,0.6,0.4] & [0.6,0.4,0.6] & [0.8,0.2,0.4] \end{bmatrix} \end{array},$$

$$EV_2 = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} \begin{array}{c} \begin{array}{ccc} \quad c_1 \quad & \quad c_2 \quad & \quad c_3 \quad \end{array} \\ \begin{bmatrix} [0.5,0.7,0.8] & [0.4,0.1,0.3] & [0.9,0.2,0.5] \\ [0.9,0.0,0.6] & [1.0,0.2,0.5] & [0.9,0.1,0.5] \\ [0.8,0.7,0.5] & [0.2,0.5,0.4] & [0.5,0.4,0.8] \\ [0.8,0.3,0.6] & [0.3,0.5,0.4] & [0.7,0.4,0.5] \end{bmatrix} \end{array},$$

$$EV_3 = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} \begin{array}{c} \begin{array}{ccc} \quad c_1 \quad & \quad c_2 \quad & \quad c_3 \quad \end{array} \\ \begin{bmatrix} [0.5,0.6,0.5] & [0.8,0.7,0.6] & [0.4,0.3,1.0] \\ [0.3,0.2,0.1] & [1.0,0.1,0.3] & [0.1,0.2,0.4] \\ [0.9,0.3,1.0] & [0.0,0.4,0.4] & [0.8,0.9,0.3] \\ [0.4,0.3,0.8] & [0.6,0.1,0.6] & [0.8,0.0,0.5] \end{bmatrix} \end{array}.$$

In this case study, the supply chain manager, with extensive expertise in evaluating suppliers and ensuring alignment with production schedules, cost requirements, and quality standards, serves as the analyst responsible for applying the BWM-Neutrosophic TOPSIS framework to assess and rank the potential suppliers. Given that D_2 is more important than D_1, and D_1 is more important than D_3 and by using the BWM the weights of decision-makers are obtained, with the values 0.3, 0.5, and 0.2, respectively. Furthermore, the weights of the attributes assigned by multiple experts are expressed as follows:

$$w_1 = \big[[1.0,0.7,1.0],[0.5,0.7,0.0],[1.0,0.2,0.3]\big],$$
$$w_2 = \big[[0.1,0.7,0.5],[0.8,1.0,0.1],[0.4,0.5,0.3]\big],$$
$$w_3 = \big[[0.9,0.5,0.4],[1.0,0.2,0.4],[0.9,0.0,0.5]\big].$$

In this regard, the weighted evaluation matrices can be created as follows:

$$WEV_1 = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} \begin{array}{c} \begin{array}{ccc} \quad c_1 \quad & \quad c_2 \quad & \quad c_3 \quad \end{array} \\ \begin{bmatrix} [0.4,0.94,1.0] & [0.45,1.0,0.20] & [0.60,0.2,0.58] \\ [0.00,1.0,1.0] & [0.45,0.94,0.9] & [0.2,0.28,0.72] \\ [0.2,0.91,1.0] & [0.25,0.97,0.5] & [0.1,0.36,0.65] \\ [0.5,0.88,1.0] & [0.3,0.82,0.60] & [0.8,0.36,0.58] \end{bmatrix} \end{array},$$

$$WEV_2 = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} \begin{array}{c} \begin{array}{ccc} \quad c_1 \quad & \quad c_2 \quad & \quad c_3 \quad \end{array} \\ \begin{bmatrix} [0.05,0.91,0.9] & [0.32,1.0,0.37] & [0.36,0.6,0.65] \\ [0.09,0.7,0.8] & [0.8,1.0,0.55] & [0.36,0.55,0.65] \\ [0.08,0.91,0.75] & [0.16,1.0,0.46] & [0.20,0.7,0.86] \\ [0.08,0.79,0.8] & [0.24,1.0,0.46] & [0.28,0.7,0.65] \end{bmatrix} \end{array},$$

$$WEV_3 = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} \begin{array}{c} \begin{array}{ccc} \quad c_1 \quad & \quad c_2 \quad & \quad c_3 \quad \end{array} \\ \begin{bmatrix} [0.45,0.80,0.70] & [0.80,0.76,0.76] & [0.36,0.30,1.00] \\ [0.27,0.60,0.46] & [1.00,0.28,0.58] & [0.09,0.20,0.70] \\ [0.81,0.65,1.00] & [0.00,0.52,0.64] & [0.72,0.90,0.65] \\ [0.36,0.65,0.88] & [0.60,0.28,0.76] & [0.72,0.00,0.75] \end{bmatrix} \end{array}.$$

Therefore, based on the values obtained in the last step and the weight of the decision-makers, the aggregated evaluating matrix F can be calculated as follows:

$$F = \begin{array}{c} \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} \begin{array}{c} \begin{array}{ccc} \quad E_1 \quad & \quad E_2 \quad & \quad E_3 \quad \end{array} \\ \begin{bmatrix} [0.18,0.84,0.80] & [0.35,0.73,0.46] & [0.65,0.50,0.77] \\ [0.07,0.87,0.95] & [0.65,0.62,0.53] & [1.00,0.25,0.51] \\ [0.05,0.89,0.89] & [0.21,0.79,0.54] & [0.69,0.62,0.70] \\ [0.23,0.87,0.89] & [0.29,0.74,0.48] & [0.65,0.00,0.75] \end{bmatrix} \end{array}$$

Subsequently, the feature matrix $S(F)$ is created as follows:

$$S(F) = \begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} \begin{bmatrix} -0.6575 & -0.2930 & -0.0677 \\ -0.8144 & -0.0585 & 0.4870 \\ -0.8086 & -0.4636 & -0.1279 \\ -0.7070 & -0.3429 & 0.4463 \end{bmatrix}$$

Based on the obtained score values, the positive and negative ideal solutions can be determined.

The distance between the alternatives and F^+ and F^- is calculated as follows:

$$d^+ = \big[0.2250,\ 0.0474,\ 0.2925,\ 0.2603\big],$$
$$d^- = \big[0.1318,\ 0.2497,\ 0.0165,\ 0.1859\big].$$

Finally, the values of the relative closeness ratio can be obtained as follows:

$$RCR_1^* = 0.369, RCR_2^* = 0.8403,$$
$$RCR_3^* = 0.0536, RCR_4^* = 0.4165.$$

Therefore, the selected suppliers' priority order is Supplier 2, Supplier 4, Supplier 1, and Supplier 3.

The numerical analysis not only validates the performance of the proposed framework but it also highlights its adaptability for integration into informatics systems. By leveraging the modular structure of its related methodology, the proposed approach can be seamlessly deployed in the context of decision support tools and enterprise resource planning (ERP) platforms. This integration allows for a dynamic, real-time supplier evaluation, ensuring that decision-makers can adapt quickly to changing conditions and data inputs. Additionally, the ability to incorporate multi-participant decision-making ensures a balanced and comprehensive evaluation process, addressing the diverse needs and perspectives of stakeholders. These features underscore the robustness and practical applicability of the proposed framework in supporting data-driven decision-making in digital transformation scenarios.

By utilizing a distinct set of inputs outlined in this case study, a detailed evaluation is conducted for the proposed methods in comparison with other decision-making approaches that build on neutrosophic sets and their advancements. The results of this evaluation are included in Table 1.

Table 1. A comparison of decision-making methods

Methods	**The order of alternatives**
The proposed BWM-TOPSIS Method	$a_2 < a_3 < a_4 < a_1$
BWM-VIKOR Method (Tanaji & Roychowdhury, 2024)	$a_2 < a_4 < a_3 < a_1$
VIKOR Method (Eroğlu & Şahin, 2020)	$a_3 = a_2 < a_4 < a_1$
Autocratic Method (Nafei et al., 2019)	$a_2 < a_4 < a_3 < a_1$
BWM-VIKOR (Tanaji & Roychowdhury, 2024)	$a_3 < a_2 < a_1 = a_4$
Neutrosophic TOPSIS Method (Nabeeh et al., 2019)	$a_2 < a_3 < a_1 < a_4$
Autocratic Method (Lee, 2023)	$a_2 < a_4 < a_3 < a_1$

The methods in Table 1 yield different orders, highlighting their varied approaches to ranking based on criteria weighting, proximity to ideal solutions, and handling of uncertainty. Methods like Neutrosophic TOPSIS and BWM-TOPSIS are advantageous in complex, uncertain scenarios, while VIKOR-based methods emphasize compromise. The choice among them depends on the decision context, available data, and priority with regard to balancing ideal proximity and robustness against uncertainty.

6. Conclusion

This paper presents a comprehensive framework for supplier evaluation in the context of Digital Transformation (DX), combining the Best-Worst Method (BWM) with Neutrosophic TOPSIS. By using neutrosophic sets, the proposed framework effectively addresses the uncertainty and ambiguity inherent to multi-attribute decision-making (MADM), especially in complex industries like metro rail coach manufacturing, where supplier quality is critical for product reliability.

This methodology incorporates expert assessments to determine criteria weights and evaluates suppliers using Single-Valued Neutrosophic Sets (SVNS), which enhances its decision accuracy and consistency compared to traditional MADM-based methods like TOPSIS and AHP. The integration of BWM strengthens this framework by enabling a refined prioritization of expert opinions. The presented case study demonstrates the proposed model's practicality and effectiveness, providing actionable rankings for supplier selection, which is essential for strategic decision-making in DX.

The BWM-Neutrosophic TOPSIS method offers multiple benefits. It provides a nuanced view of the decision-makers' judgments by accounting for the related degrees of truth, indeterminacy, and falsity, and it can represent real-world uncertainties more accurately. The framework's flexibility makes it applicable to other MADM contexts, including technology adoption and risk assessment in the context of DX initiatives. The positive outcomes related to the metro rail coach sector suggest that this framework can be adapted across industries where DX is crucial for competitiveness, as it represents a valuable tool for supplier evaluation that addresses ambiguous and imprecise information effectively. Furthermore, the proposed framework demonstrated a significant potential for deployment within informatics systems, such as decision support tools and enterprise resource planning (ERP) platforms. Its modular design allows a seamless integration into these systems, enabling a dynamic, real-time supplier evaluation and ensuring its adaptability to evolving data and decision-making needs. By incorporating multi-participant decision-making capabilities, this framework enhances collaboration between the stakeholders and ensures a balanced representation of diverse stakeholder perspectives. These attributes not only strengthen its utility in digital transformation scenarios but they also open avenues for broader applications in industries requiring complex decision-making processes, making this framework a valuable tool for both researchers and practitioners.

Although this framework demonstrated its effectiveness, it relies heavily on expert judgments for determining criteria weights and evaluating alternatives, which can introduce subjective biases into the decision-making process. Future research could explore hybrid models integrating machine learning for a reduced reliance on expert input and optimize this framework by enhancing its scalability to also make it suitable for larger datasets. By expanding the application of this framework to other industries and integrating dynamic, real-time data its relevance would be further enhanced.

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