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A Hybrid MAGDM Approach of Neutrosophic TOPSIS - LINMAP method for developing Enterprise Selection Criteria

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Abstract. Multi-attribute group decision-making (MAGDM) problems have traditionally been addressed using approaches like the standard LINMAP and TOPSIS. However, existing studies utilizing these methods often face challenges in handling uncertain, vague, and incomplete data, especially when working with fuzzy or intuitionistic environments. Additionally, traditional methods have limitations in modeling and computing with more complex, nuanced information such as neutrosophic numbers, which are better suited for capturing the indeterminacy inherent in real-world decision-making problems.

In this research, we provide a novel approach to handle MAGDM problems under a SVTN number framework, extending the classic LINMAP approach to the neutrosophic context. The new method overcomes the shortcomings of existing techniques by providing a more robust decision-making model that incorporates neutrosophic uncertainty. Furthermore, we propose an integrated approach combining neutrosophic LINMAP with TOPSIS, offering a comprehensive solution to MAGDM problems that is more adaptable to practical enterprise selection scenarios.

This method is intended to increase decision-making accuracy and dependability when faced with ambiguous and insufficient information. The usefulness of the suggested technique is illustrated by a real-world example that shows how the integrated neutrosophic LINMAP-TOPSIS strategy may be used for enterprise selection and produces better outcomes than standard techniques.

Keywords: Single valued trapezoidal neutrosophic number; decision making; Neutrosophic Linear programming technique for multidimensional analysis of preference; Hamming distance;Relative closeness coefficient; Consistency and inconsistency measurements; Borda's scores

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1. **Introduction**

The idea of the LINMAP approach under crisp values for solving MADM issues was first presented by Srinivasan and Shocker [65] in 1973. The TOPSIS method was developed by Hwang and Yoon [28] to address MCDM issues. A neutrosophic set, that permits membership degrees of truth, indeterminacy, and falsity, was introduced by Smarandache [66]. Fuzzy LINMAP was initially created by Xia et al. [11] for multiattribute decision making in fuzzy situations. In order to resolve decision-making difficulties, Amir et al. [3] transformed crisp LINMAP approach into the fuzzy LINMAP method. Deng and Wan [15] developed the probabilistic LINMAP strategy to address the MADM model difficulties with a range of attributes categories and inadequate weight data. Razavi et al. [63] expanded the LINMAP technique to MCDM problems, including grey numbers. An extended LINMAP technique was presented by Liu et al. [13] to handle the MAGDM issues in a linguistically hesitant fuzzy environment.

The fuzzy LINMAP approach was extended by Wan and Li [64] to deal with heterogeneous MADM issues. Adel et al. [1] have improved the LINMAP technique to tackle group choice issues that arise in an environment that is uncertain. The fuzzy LINMAP approach was created by Ali et al. [2] to solve supplier evaluation and company selection problems in the automobile industry. To solve a MCDM problem in an interval type-2 fuzzy environment, Chen [70] created the LINMAP approach. The neutrosophic simplified TOPSIS strategy, which is a continuation of the simple TOPSIS , has been offered by A. Elhassouny & F. Smarandache [21] and used to address MCDM problems. The TOPSIS approach was examined by Partha et al. [49] in order to solve MADM problems in a bi-polar neutrosophic environment. To handle MCDM difficulties, Sorin and Simona [68] introduced the neutrosophic TOPSIS approach. The game theory-based neutrosophic TOPSIS technique was suggested by Hagar G. The interval valued neutrosophic TOPSIS approach was suggested by Sharma et al. [26] to solve decision making difficulties. Peide The normal neutrosophic frank aggregation operator was created by Liu et al. [51] to solve MADM difficulties. Liu and Liu [50] addressed MADM issues and created a weighted power averaging operator.

Rana et al. [54], [57] presented neutrosophic TOPSIS for solving MCDM problems. The neutrosophic TOPSIS was created by Anh Duc Do et al. [4] to assess teachers' performance using an interval complex neutrosophic set. For SVNHFS and IVNHFS, B. C. Giri et al. created the TOPSIS [6] and applied MADM issues. Neutosophic hypersoft matrices were created by Rana et al. [56] in order to address multi-attributive decision-making issues. In order to solve decision-making problems under single-valued neutrosophic sets, Harish and Nancy [25] introduced a novel clustering distance measure and TOPSIS approach. For offshore wind farm site selection, M. Deveci et al. [44] suggested a type-2 neutrosophic number based on the multi-attributive border approximation area comparison (MABAC) model. In order to solve brand recognition challenges, J. Wu et al. [32] developed a similarity measure and a multi-person TOPSIS approach based on m-polar SVN sets. Muhammad et al. [45] used (α, β, γ) cuts and applied MCDM problems to build the TOPSIS method with interval type 2 trapezoidal neutrosophic numbers. In order to solve MAGDM difficulties, Geng et al. [30] developed the TOPSIS approach, which is a SVNLCWD measure. In many researchers([31], [20], [8], [23], [47], [36], [55], [41]) developed different methods for solving decision making problems. A novel approach to modeling Zero Base Budgeting in a fuzzy environment is presented by EI-Morsy [22]. Colombo et al. [7] investigate employs a novel, entropy-weighted MADM model to decipher these intricate relationships. Using a strong FIS, Venugopal et al. [71] suggested the urgent need for a groundbreaking indicator for daily stock trading. Lamrini et al. [37] Presented new distributed TOPSIS approach in MCDM methods with big data context. Mona Mohamed and Abduallah Gamal [40]constructed entrepreneurs in emerging economies face obstacles in implementing Industry 5.0, which are assessed using a neutrosophic AHP-based Appraisal Decision Framework (ADF) to identify and rank key barriers. The results highlight cost and funding as the most significant obstacles, followed by scalability, socio-technological planning, and security concerns.Sara Fawaz AL-baker et al. [58]

developed TreeSoft's new strategy using MCDM approaches aims to advise an exceptional online service provider based on QoS values.

1.1. *Research Gap and Motivation*

The arguments and research gaps that influenced the choice of the proposed structure are as follows:

Research gap: As of right now, there is no literature on the integrated TOPSIS-LINMAP technique in the SVTN context..

Motivation: We started researching the integrated technique in the SVTN environment in order to close the research gap.

- A LINMAP approach for reluctant fuzzy MADM issues was expanded by Liu et al. [12] and also developed integrating combination of TOPSIS and LINMAP. Donga and Wan [35] proposed integrating TOPSIS and LINMAP for applying the virtual enterprise partner selection problems. Wan et al. [9] proposed q-ROTFWA operator and establish LINMAP according to q- ROTFWA operators for resolving issues with collective decision-making.
- It is evident that the integrating techniques mentioned above address fuzzy number opinions. With inspiration from the aforementioned literature in general and the expanded LINMAP method, a novel strategy for solving the SVTN number to address MADM difficulties was developed. For SVTN numbers, a comprehensive approach combining the LINMAP and TOPSIS approaches is described along with its known ideal solutions in unknown conditions. We proposed metrics for consistency and inconsistency between the decision maker's preference relation and the ranking order of the alternatives, based on the definitions of ideal solutions and neutrosophic hamming distance. After estimating the weights of the attributes using a linear programming model, the TOPSIS approach is used to determine the optimal choice.

1.2. *Contributions*

By comparing with integrated methods (TOPSIS and LINMAP), has some advantages. The planned study will contribute the following:

- Firstly, it has been extended to neutrosophic environment.
- The integrated method considered both positive and negative ideal solution in neutrosophic environment and it over come the drawbacks for neutrosophic LINMAP because it consider only positive ideal solution.
- Neutosophic TOPSIS may suffer from the integrated approach, which is designed to establish objective weights for the qualities.

- Measures of consistency as well as inconsistency between the decision maker's preference relation for ideal solutions and the ranking order of the options are established in a neutrosophic setting.
- This paper's primary goal is to highlight the advantages of combining the LINMAP and TOPSIS approaches to solve neutrosophic MAGDM issues based on SVTN numbers.

1.3. *Paper Organization*

The structure of this document is as follows. The fundamental ideas of SVTN numbers are reviewed in Section 2. The MAGDM problem's structure is explained in Section 3. The hybrid MAGDM for combining the TOPSIS and LINMAP approaches to SVTN numbers is described in Section 4. The approach for the neutrosophic MAGDM problem is covered in Section 5, along with a summary of the comparison findings. The paper's conclusion is found in Section 6.

2. **Preliminaries**

We will review some fundamental ideas regarding the SVTN numbers in this part.

Definition 2.1. [39] Let $p_l, p_{m1}, p_{m2}, p_u \in R$ such that $p_l \leq p_{m1} \leq p_{m2} \leq p_u$. A SVTN number $\tilde{p} =< (p_l, p_{m1}, p_{m2}, p_u); T_{\tilde{p}}, I_{\tilde{p}}, F_{\tilde{p}} >$ is a unique set on the real number set R, with truth, indeterminacy, and falsity membership functions are defined by $\alpha_{\tilde{p}}(x), \beta_{\tilde{p}}(x)$ and $\gamma_{\tilde{p}}(x)$ respectively.

$$\alpha_{\tilde{p}}(x) = \begin{cases} \frac{x-p_l}{p_{m1}-p_l} T_{\tilde{p}}, & \text{for } p_l \leq x \leq p_{m1} \\ T_{\tilde{p}}, & \text{for } p_{m1} \leq x \leq p_{m2} \\ \frac{p_u-x}{p_u-p_{m2}} T_{\tilde{p}}, & \text{for} p_{m2} \leq x \leq p_u \\ 0, & \text{otherwise.} \end{cases}$$

$$\beta_{\tilde{p}}(x) = \begin{cases} \frac{p_{m1}-x+(x-p_l)I_{\tilde{p}}}{p_{m1}-p_l}, & \text{for } p_l \leq x \leq p_{m1} \\ I_{\tilde{p}}, & \text{for } p_{m1} \leq x \leq p_{m2} \\ \frac{x-p_{m2}+(p_u-x)I_{\tilde{p}}}{p_u-p_{m2}}, & \text{for} p_{m2} \leq x \leq p_u \\ 0, & \text{otherwise.} \end{cases}$$

$$\gamma_{\tilde{p}}(x) = \begin{cases} \frac{p_{m1}-x+(x-p_l)F_{\tilde{p}}}{p_{m1}-p_l}, & \text{for } p_l \leq x \leq p_{m1} \\ F_{\tilde{p}}, & \text{for } p_{m1} \leq x \leq p_{m2} \\ \frac{x-p_{m2}+(p_u-x)F_{\tilde{p}}}{p_u-p_{m2}}, & \text{for} p_{m2} \leq x \leq p_u \\ 0, & \text{otherwise.} \end{cases}$$

Definition 2.2. [62] Let $\tilde{p} =< (p_l, p_{m1}, p_{m2}, p_u); t_{\tilde{p}}, i_{\tilde{p}}, f_{\tilde{p}} >$ and $\tilde{q} =< (q_l, q_{m1}, q_{m2}, q_u); t_{\tilde{q}}, i_{\tilde{q}}, f_{\tilde{q}} >$ be two SVTN numbers. Then the hamming distance between SVTN numbers $\tilde{m}$ and $\tilde{n}$ is defined as

$$
\begin{aligned}
d(\tilde{p},\tilde{q}) = \tfrac{1}{12}\big(&\mid (2+t_{\tilde{p}}-i_{\tilde{p}}-f_{\tilde{p}})p_l-(2+t_{\tilde{q}}-i_{\tilde{q}}-f_{\tilde{q}})q_l \mid \\
&+\mid (2+t_{\tilde{p}}-i_{\tilde{p}}-f_{\tilde{p}})p_{m1}-(2+t_{\tilde{q}}-i_{\tilde{q}}-f_{\tilde{q}})q_{m1} \mid \\
&+\mid (2+t_{\tilde{p}}-i_{\tilde{p}}-f_{\tilde{p}})p_{m2}-(2+t_{\tilde{q}}-i_{\tilde{q}}-f_{\tilde{q}})q_{m2} \mid \\
&+\mid (2+t_{\tilde{p}}-i_{\tilde{p}}-f_{\tilde{p}})p_{u}-(2+t_{\tilde{q}}-i_{\tilde{q}}-f_{\tilde{q}})q_{u} \mid \big)
\end{aligned}
$$

Definition 2.3. [18] The Borda method's stages of issue solving are known as the rank order method. The value of m, which is the sum of the alternatives less 1, is the greatest rating value in an alternative sequence. The series up to the last order has a value of 0, and the second-highest place has a value of m-1. The value multiplies the noises that are derived from the relevant place. The most likely option chosen by the respondent is the one with the highest selection, according to Borda's functional, statistical analysis of its alternative.

3. Neutrosophic MAGDM problems with incomplete weight information

The Neutrosophic MAGDM problem and its normalization techniques are discussed in this section.

3.1. *Problem Description*

The Neutrosophic MAGDM problems under consideration are represented by the following symbols.

(1) Consider the following set of **neutrosophic decision matrix** wherein the alternative evaluation qualities' ratings are presented as SVTN numbers and define $D_p, (p = 1, 2, ..., t)$ is expressed as

$$
D_p = \left(\tilde{s}^p_{ij}\right)_{(m\times n)} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{pmatrix} \tilde{s}^p_{11} & \tilde{s}^p_{12} & \dots & \tilde{s}^p_{1n} \\ \tilde{s}^p_{21} & \tilde{s}^p_{22} & \dots & \tilde{s}^p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{s}^p_{m1} & \tilde{s}^p_{m2} & \dots & \tilde{s}^p_{mn} \end{pmatrix} \end{array}
$$

and $\omega = (\omega_1, \omega_2, ..., \omega_n)^T, \omega_j \in [0, 1]$, the weight component of the decision matrix. In this case, ω is entirely unknown and must be found.

(2) A_i denotes the i -th alternative $(i = 1, 2, ..., m)$ in the set of **alternatives** $A = (A_1, A_2, ..., A_m)$.

(3) $C = (C_1, C_2, ..., C_n)$ is the set of **attributes**, where C_j is the j -th attribute $(j = 1, 2, ..., n)$; $\omega = (\omega_1, \omega_2, ..., \omega_n)^T$ represents the weight vector of the attribute; this is not complete information and must be established.

(4) The rating $\tilde{s}_{ij}^{p}$ of alternatives A_i on attributes C_j given by the p^{th} decision maker is in the form of SVTN number and its defined by $\tilde{s}_{ij}^{p} =< (s_{ijl}^{p}, s_{ijm1}^{p}, s_{ijm2}^{p}, s_{iju}^{p}); T_{ij}^{p}, I_{ij}^{p}, F_{ij}^{p} >, (p = 1, 2, ..., t)$.

(5) Assume that the decision makers D_p derive their preference relations between alternatives from their knowledge and experience by using the formula $\Omega^{p} = \left\{(k,l) \mid A_k^p \geq A_l^p, (k,l = 1,2,3,\ldots,m)\right\}$. The symbol "$\geq$" indicates that the decision maker D_p either prefers A_k and A_l, or that they are indifferent between A_k and A_l.

3.2. *Normalization methods*

Normalization is not necessary if every rating in a decision matrix D_p is either profit or cost. If not, create the decision matrix that has been normalized. The value $\tilde{s}_{ij}^{p}$ must be normalized in the way indicated follows in order to remove any disturbance from the final results: $\tilde{r}_{ij}^{p} =< (r_{ijl}^{p}, r_{ijm1}^{p}, r_{ijm2}^{p}, r_{iju}^{p}); T_{ij}^{p}, I_{ij}^{p}, F_{ij}^{p} >, (p = 1, 2, ..., t)$.

$$\tilde{r}_{ij}^{p} = \begin{cases} \dfrac{\tilde{s}_{ij}^{p}}{\sum\limits_{k=1}^{n} \tilde{s}_{ik}^{p}}, & \text{if the rating is profit} \\ \dfrac{\frac{1}{\tilde{s}_{ij}^{p}}}{\sum\limits_{k=1}^{n} (\frac{1}{\tilde{s}_{ik}^{p}})}, & \text{if the rating is cost} \end{cases}$$

By using above form, $D_p = \left(\tilde{s}_{ij}^{p}\right)_{(m\times n)}$ can be normalized as $N_p = \left(\tilde{r}_{ij}^{p}\right)_{(m\times n)}, (p = 1, 2, ..., t)$ and the normalized decision matrix N_p expressed as follows:

$$N_p = \left(\tilde{r}_{ij}^{p}\right)_{(m\times n)} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{pmatrix} \tilde{r}_{11}^{p} & \tilde{r}_{12}^{p} & \ldots & \tilde{r}_{1n}^{p} \\ \tilde{r}_{21}^{p} & \tilde{r}_{22}^{p} & \ldots & \tilde{r}_{2n}^{p} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{r}_{m1}^{p} & \tilde{r}_{m2}^{p} & \ldots & \tilde{r}_{mn}^{p} \end{pmatrix} \end{array}$$

4. **A novel method for neutrosophic MAGDM problems**

We present a novel integration approach to answer the neutrosophic MAGDM problems using the relative closeness coefficient (RCC) and neutrosophic ideal solutions inside the framework of LINMAP and TOPSIS.

4.1. *Comprehensive relative closeness coefficient*

Let us define the neutrosophic positive & negative ideal solutions are $\tilde{p}_j^{+p}, \tilde{p}_j^{-p}$ defined by

$$\tilde{p}_j^{+p} =< (\tilde{p}_{jl}^{+p}, \tilde{p}_{jm1}^{+p}, \tilde{p}_{jm2}^{p+}, \tilde{p}_{ju}^{+p}); T_j^{+p}, I_j^{+p}, F_j^{+p} >$$

$$=< (\max_j\left(\tilde{r}_{ijl}^{p}\right), \max_j\left(\tilde{r}_{ijm1}^{p}\right), \max_j\left(\tilde{r}_{ijm2}^{p}\right), \max_j\left(\tilde{r}_{iju}^{p}\right)); \max_j\left(T_{ij}^{p}\right), \min_j\left(I_{ij}^{p}\right), \min_j\left(F_{ij}^{p}\right) >$$

and

$\tilde{p}_j^{-p} =< (\tilde{p}_{jl}^{-p}, \tilde{p}_{jm1}^{-p}, \tilde{p}_{jm2}^{-p}, \tilde{p}_{ju}^{-p}); T_j^{-p}, I_j^{-p}, F_j^{-p} >, j = 1, 2, ..., n; p = 1, 2, ..., t$

$=<$

$(\min_j \left(\tilde{r}_{ijl}^{p}\right), \min_j \left(\tilde{r}_{ijm1}^{p}\right), \min_j \left(\tilde{r}_{ijm2}^{p}\right), \min_j \left(\tilde{r}_{iju}^{p}\right)); \min_j \left(T_{ij}^{p}\right), \max_j \left(I_{ij}^{p}\right), \max_j \left(F_{ij}^{p}\right) >$

The squares of the weighted distances between $\tilde{r}_{ij}^{p}, \tilde{p}_j^{+p}$ and $\tilde{p}_j^{-p}$ can be calculated by using the Definition 3 as follows:

$$d_i^{+p} = \sum_{j=1}^{n} \omega_j [d\left(\tilde{r}_{ij}^{p}, \tilde{m}_j^{+p}\right)]^2 \tag{1}$$

and

$$d_i^{-p} = \sum_{j=1}^{n} \omega_j [d\left(\tilde{r}_{ij}^{p}, \tilde{m}_j^{-p}\right)]^2 \tag{2}$$

The relative closeness coefficient can be determined as follows:

$$R_i^p = \frac{d_i^{-p}}{(d_i^{+p} + d_i^{-p})}, i = 1, 2, ..., m, p = 1, 2, ..., t. \tag{3}$$

4.2. *Consistency and inconsistency measurements*

Srinivasan and Shocker introduced the classical LINMAP approach [65]. Numerous methods have been developed to address human judgments, including intuitionistic fuzzy sets (Atanssov 1986), fuzzy sets (Zadeh 1965), and others. As a result, the LINMAP approach has also been expanded to intuitionistic fuzzy [73] and fuzzy [27] environments. To handle the scenario where the input arguments take the form of a neutrosophic environment, we further enhance the LINMAP algorithm in this section. Assume that that unidentified weighted vector of attribute $C_j, (j = 1, 2, ..., n)$ is $\omega = (\omega_1, \omega_2, ..., \omega_n)$.By using the concept of neutrosophic hamming distance between each pair of alternatives $(k, l) \in \Omega^p$ and positive (negative) ideal solutions are defined as follows:

$S_i^p = \sum_{j=1}^{n} \omega_j [d\left(\tilde{r}_{ij}^{p}, \tilde{p}_j^{+p}\right)]^2, S_k^p = \sum_{j=1}^{n} \omega_j [d\left(\tilde{r}_{kj}^{p}, \tilde{p}_j^{+p}\right)]^2 (i = 1, 2, ..., m)$

$S_k^{p'} = \sum_{j=1}^{n} \omega_j [d\left(\tilde{r}_{kj}^{p}, \tilde{p}_j^{-p}\right)]^2$ and $S_l^{p'} = \sum_{j=1}^{n} \omega_j [d\left(\tilde{r}_{lj}^{p}, \tilde{p}_j^{-p}\right)]^2, (i = 1, 2, ..., m)$

Definition 4.1. The inconsistency (error) between the preference of alternatives A_l^p and A_k^p and the ranking order of alternatives A_l^p and A_k^p, which is defined by S_l^p and S_k^p, is measured by an index $(S_l^p - S_k^p)^-$, which is based on SVTN numbers.The following is an expression for the preference relation $p, (k, l) \in \Omega^p$ inconsistency index:

$$(S_l^p - S_k^p)^- = \begin{cases} (S_k^p - S_l^p), & (s_l^p < s_k^p) \\ 0, & (s_l^p \geq s_k^p). \end{cases}$$

Thus, inconsistency index

$(S_l^p - S_k^p)^- = \max\left\{0, (S_k^p - S_l^p)\right\}$.

A total inconsistency index of the decision maker is defined as

$B = \sum_{(k,l)\in\Omega^p} (S_l^p - S_k^p)^- = \sum_{(k,l)\in\Omega^p} \max\left\{0, \left(S_k^p - S_l^p\right)\right\}$

Definition 4.2. The consistency between the preference of alternatives A_l^p and A_k^p and the ranking order of alternatives A_l^p and A_k^p as defined by S_l^p and S_k^p is measured using an index $(S_l^p - S_k)^+$ based on SVTN numbers.The following is an expression for the consistency index for the preference relation $p, (k,l) \in \Omega^p$:

$$(S_l^p - S_k^p)^+ = \begin{cases} (S_l^p - S_k^p), & (s_l^p \geq s_k^p) \\ 0, & (s_l^p < s_k^p). \end{cases}$$

Thus, consistency index

$(S_l^p - S_k^p)^+ = \max\left\{0, \left(S_l^p - S_k^p\right)\right\}$.

The decision maker's overall consistency index is described as

$G = \sum_{(k,l)\in\Omega^p} (S_l^p - S_k^p)^+ = \sum_{(k,l)\in\Omega^p} \max\left\{0, \left(S_l^p - S_k^p\right)\right\}$

Definition 4.3. The ranking order of alternatives $A_l^{p'}$ and $A_k^{p'}$, which are determined by $S_l^{p'}$ and $S_k^{p'}$, and the preference of alternatives A_l^p and A_k^p are measured for consistency using an index $(S_k^{p'} - S_l^{p'})^-$ based on SVTN numbers.The preference relation $p, (k,l) \in \Omega^p$'s inconsistency index can be written as follows:

$$(S_k^{p'} - S_l^{p'})^- = \begin{cases} (S_l^{p'} - S_k^{p'}), & \text{if } S_l^{p'} > S_k^{p'} \\ 0, & \text{if } S_l^{p'} \leq S_k^{p'} \end{cases}$$

Thus, inconsistency index

$$(S_k^{p'} - S_l^{p'})^- = \max\left\{0, (S_l^{p'} - S_k^{p'})\right\}.$$

The overall inconsistency index can then be found as

$$B' = \sum_{(k,l)\in\Omega^p} (S_k^{p'} - S_l^{p'})^- = \sum_{(k,l)\in\Omega^p} \max\left\{0, \left(S_l^{p'} - S_k^{p'}\right)\right\}$$

Definition 4.4. The ranking order of alternatives $A_l^{p'}$ and $A_k^{p'}$, which are determined by $S_l^{p'}$ and $S_k^{p'}$, and the preference of alternatives A_l^p and A_k^p are measured for consistency using an index $(S_k^{p'} - S_l^{p'})^+$ based on SVTN numbers.The following is an expression for the consistency index for the preference relation $p, (k,l) \in \Omega^p$:

$$(S_k^{p'} - S_l^{p'})^+ = \begin{cases} (S_k^{p'} - S_l^{p'}), & \text{if } S_l^{p'} \leq S_k^{p'} \\ 0, & \text{if } S_l^{p'} > S_k^{p'} \end{cases}$$

Thus, consistency index

$$(S_k^{p'} - S_l^{p'})^+ = \max\left\{0, \left(S_k^{p'} - S_l^{p'}\right)\right\}.$$

The decision maker's overall consistency index is therefore defined as

$$G' = \sum_{(k,l)\in\Omega^p} (S_k^{p'} - S_l^{p'})^+ = \sum_{(k,l)\in\Omega^p} \max\left\{0, \left(S_k^{p'} - S_l^{p'}\right)\right\}$$

4.3. *LINMAP under neutrosophic environment*

A linear programming model is built in the following to ascertain the qualities' unknown weight ω.

$$\begin{aligned}&\min B\\ \text{Subject to }&G-B\geq h\\ &\sum_{j=1}^{n}\omega_j=1\\ &\omega_j\geq 0,(j=1,2,...n)\end{aligned}$$

where the decision maker provides h to guarantee that the overall consistency index G exceeds the total inconsistency index B.
On the other hand, a mathematical model, we can also obtained the minimize total inconsistency index $B^{'}$.

$$\begin{aligned}&\min B^{'}\\ \text{Subject to }&G^{'}-B^{'}\geq h^{'}\\ &\sum_{j=1}^{n}\omega_j=1\\ &\omega_j\geq 0,(j=1,2,...n)\end{aligned}$$

The two objectives can be added to the following linear programming model with equal weights since there are no preference relations on them:

$$\begin{aligned}&\min B+B^{'}\\ \text{Subject to }&G-B\geq h\\ &G^{'}-B^{'}\geq h^{'}\\ &\sum_{i=1}^{n}\omega_j=1\\ &\omega_j\geq 0,(j=1,2,...n)\end{aligned}$$

i.e., $\min\left\{\sum_{(k,l)\in\Omega^p}\max\left\{0,\left(S_k^p-S_l^p\right)\right\}+\sum_{(k,l)\in\Omega^p}\max\left\{0,\left(S_l^{p^{'}}-S_k^{p^{'}}\right)\right\}\right\}$
Subject to
$\sum_{(k,l)\in\Omega^p}\max\left\{0,\left(S_l^p-S_k^p\right)\right\}-\sum_{(k,l)\in\Omega^p}\max\left\{0,\left(S_k^p-S_l^p\right)\right\}\geq h$
$\sum_{(k,l)\in\Omega^p}\max\left\{0,\left(S_k^{p^{'}}-S_l^{p^{'}}\right)\right\}-\sum_{(k,l)\in\Omega^p}\max\left\{0,\left(S_l^{p^{'}}-S_k^{p^{'}}\right)\right\}\geq h^{'}$
$\omega_1+\omega_2+...+\omega_n=1$
$\omega_j\geq 0,(j=1,2,...n)$

For every $(k,l)\in\Omega^p$ pair.
Let $\lambda_{kl}^p=\max\left\{0,\left(S_k^p-S_l^p\right)\right\}$ and $\lambda_{lk}^{p^{'}}=\max\left\{0,\left(S_l^{p^{'}}-S_k^{p^{'}}\right)\right\}$
Hence, $\lambda_{kl}^p\geq S_k^p-S_l^p$ & $\lambda_{kl}^p\geq 0$ and $\lambda_{lk}^{p^{'}}\geq S_l^{p^{'}}-S_k^{p^{'}}$ & $\lambda_{lk}^{'p}\geq 0$

Therefore, the aforementioned model can be converted into the LPP that follows:

$$\min \sum_{P=1}^{t} \left\{ \sum_{(k,l)\in\Omega^p} \lambda_{kl}^{p} + \sum_{(k,l)\in\Omega^p} \lambda_{lk}^{p'} \right\}$$

Subject to

$$S_l^p - S_k^p + \lambda_{kl}^p \geq 0, ((k,l) \in \Omega^p, p = 1,2,...t)$$
$$\sum_{(k,l)\in\Omega^p} (S_l^p - S_k^p) \geq h$$
$$\sum_{(k,l)\in\Omega^p} (S_k^{p'} - S_l^{p'}) \geq h'$$
$$\lambda_{kl}^p \geq 0, \lambda_{lk}^{p'} \geq 0, ((k,l) \in \Omega^p, p = 1,2,...t)$$
$$\omega_1 + \omega_2 + ... + \omega_j = 1$$
$$\omega_j \geq 0, (j = 1,2,...n)$$

The weight vector $\omega = (\omega_1, \omega_2, ..., \omega_n)^T$ was acquired while solving the previously discussed linear programming model with LINGO.

5. MAGDM method under neutrosophic environment

In this part, we construct a strategy for solving MAGDM issues by combining the neutrosophic TOPSIS and LINMAP approaches. The weights of the qualities are established by the use of integrated approaches. The following steps make up the operational process of the suggested approach to the neutrosophic MAGDM problem: Figure 1 displays the suggested method's flow diagram.

Step 1: The evaluation m qualities and n alternatives are determined by the decision makers.

Step 2: The decision-maker D_p gives the alternatives' preference relations by
$\Omega^p = \left\{(k,l) \mid A_k^p \geq A_l^p, (k,l = 1,2,3,\ldots,m)\right\} (p = 1,2,\ldots,t)$

Step 3: If required, create the normalization decision matrix $\tilde{r}_{ij}^p$..

Step 4: Find neutrosophic positive $\tilde{p}_j^{+p}$ and negative $\tilde{p}_j^{-p}$ ideal solutions by using the section 4.1.

Step 5: Form the linear programming problems (Sec. 4.3)and obtain the weighted vector ω_j

Step 6: Using equations (1) and (2), calculate the separation measures d_i^{+p} and d_i^{-p}.

Step 7: Use equation (3) to calculate the relative closeness coefficient R_i^p.

Step 8: The best selection option from the alternative set A_i is identified by generating the ranking order of the alternatives using the Borda's score values.

5.1. *Illustrative Example*

To demonstrate the new method, we will create a business selection and investment problem in this part. Pramanik and Mallick [59] and Das and Guha [14] have adapted the following issues and applied them to single valued trapezoidal neutrosophic numbers using the suggested

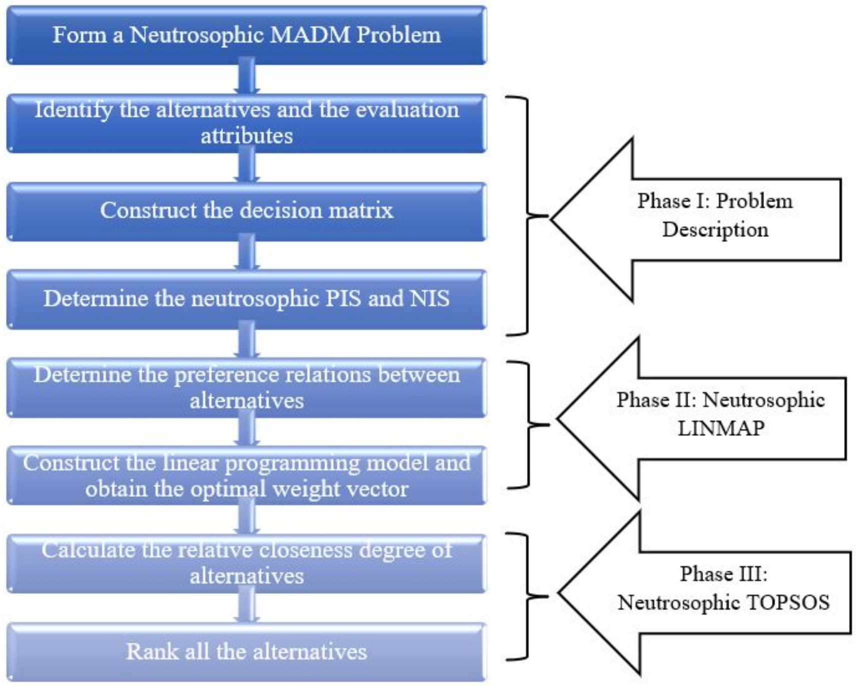

Figure 1. The flow diagram of the proposed method

method.

Enterprise Selection Problem: In order to meet market demand, a corporation wishes to establish a cooperative partnership with a few possible businesses. Three businesses $A_i, (i = 1, 2, 3)$ are chosen for additional assessment following pre-evaluation. The following four criteria are used by the expert unit to choose the best business: C_1-Producing ability, C_2-Technological competence, Capital money is C_3, and research ability is C_4.

Step 1: Identify the evaluation attributes and alternatives.

Tables 1, 2, and 3 list the three experts who made the decisions.

Step 2: Assume that experts who make decisions give the following preference connections between options:

$$\Omega^1 = \{(1, 2), (1, 3)\}$$
$$\Omega^2 = \{(2, 1), (2, 3)\}$$
$$\Omega^3 = \{(3, 1), (3, 2)\}$$

Step 3: Create the choice matrix for normalization.

Tables 4,5 and 6 provide the results of the normalizing decision matrix computations.

Step 4: Determine neutrosophic positive & negative ideal solutions.

Each p^{th} decision maker's neutrosophic positive & negative ideal solutions are defined as follows:

TABLE 1. Decision matrix provided by expert d_1

DM	C_1	C_2	C_3	C_4
A_1	$<(2,4,6,8); 0.5,0.4,0.8>$	$<(2,4,6,7); 0.7,0.2,0.5>$	$<(17,18,19,20); 0.6,0.3,0.4>$	$<(3,4,6,7); 0.7,0.1,0.4>$
A_2	$<(3,5,6,7); 0.6,0.3,0.4>$	$<(15,17,19,20); 0.7,0.2,0.4>$	$<(3,4,5,6); 0.7,0.2,0.6>$	$<(4,5,6,7); 0.6,0.4,0.3>$
A_3	$<(1,2,3,4); 0.7,0.2,0.5>$	$<(2,3,4,5); 0.5,0.4,0.3>$	$<(2,4,5,6); 0.6,0.4,0.2>$	$<(15,16,18,20); 0.8,0.1,0.2>$

TABLE 2. Decision matrix provided by expert d_2

DM	C_1	C_2	C_3	C_4
A_1	$<(15,16,17,20); 0.9,0.1,0.4>$	$<(2,4,5,7); 0.5,0.3,0.6>$	$<(2,5,6,8); 0.7,0.2,0.5>$	$<(3,5,6,7); 0.8,0.1,0.3>$
A_2	$<(4,5,6,7); 0.6,0.3,0.4>$	$<(16,17,19,20); 0.8,0.2,0.1>$	$<(3,4,5,6); 0.7,0.2,0.5>$	$<(4,5,6,9); 0.6,0.3,0.5>$
A_3	$<(1,3,5,6); 0.6,0.4,0.3>$	$<(2,3,4,6); 0.6,0.3,0.4>$	$<(2,3,4,5); 0.6,0.4,0.2>$	$<(17,18,19,20); 0.6,0.3,0.7>$

TABLE 3. Decision matrix provided by expert d_3

DM	C_1	C_2	C_3	C_4
A_1	$<(4,5,6,8); 0.5,0.4,0.3>$	$<(1,2,3,4); 0.7,0.2,0.5>$	$<(17,18,19,20); 0.6,0.25,0.3>$	$<(3,4,5,6); 0.7,0.1,0.4>$
A_2	$<(3,5,6,7); 0.6,0.2,0.4>$	$<(2,3,4,6); 0.6,0.3,0.8>$	$<(3,4,5,6); 0.7,0.2,0.6>$	$<(16,17,19,20); 0.8,0.2,0.1>$
A_3	$<(16,17,18,20); 0.8,0.1,0.3>$	$<(4,5,6,7); 0.5,0.4,0.3>$	$<(2,4,5,6); 0.6,0.4,0.1>$	$<(3,4,6,7); 0.7,0.2,0.5>$

For expert 1,

$\tilde{p}_1^{+1} =< (0.08, 0.139, 0.2, 0.33); 0.6, 0.4, 0.5 >$

$\tilde{p}_1^{+2} =< (0.38, 0.47, 0.613, 0.8); 0.6, 0.4, 0.5 >$

$\tilde{p}_1^{+3} =< (0.405, 0.49, 0.63, 0.83); 0.6, 0.4, 0.5 >$

$\tilde{p}_1^{+4} =< (0.33, 0.53, 0.72, 0.8); 0.6, 0.4, 0.5 >$

$\tilde{p}_1^{-1} =< (0.02, 0.07, 0.12, 0.2); 0.5, 0.4, 0.8 >$

$\tilde{p}_1^{-2} =< (0.04, 0.1, 0.16, 0.25); 0.5, 0.4, 0.8 >$

$\tilde{p}_1^{-3} =< (0.04, 0.11, 0.16, 0.24); 0.5, 0.4, 0.8 >$

$\tilde{p}_1^{-4} =< (0.07, 0.108, 0.194, 0.28); 0.5, 0.4, 0.8 >$

TABLE 4. Expert-provided normalized decision matrix d_1

DM	C_1	C_2	C_3	C_4
A_1	$<(0.05, 0.108, 0.2, 0.33); 0.5, 0.4, 0.8>$	$<(0.05, 0.108, 0.2, 0.29); 0.5, 0.4, 0.8>$	$<(0.405, 0.49, 0.63, 0.83); 0.5, 0.4, 0.8>$	$<(0.07, 0.108, 0.2, 0.29); 0.5, 0.4, 0.8>$
A_2	$<(0.08, 0.139, 0.194, 0.28); 0.6, 0.4, 0.6>$	$<(0.38, 0.47, 0.613, 0.8); 0.6, 0.4, 0.6>$	$<(0.08, 0.11, 0.16, 0.24); 0.6, 0.4, 0.6>$	$<(0.1, 0.139, 0.194, 0.28); 0.6, 0.4, 0.6>$
A_3	$<(0.02, 0.07, 0.12, 0.2); 0.5, 0.4, 0.5>$	$<(0.04, 0.1, 0.16, 0.25); 0.5, 0.4, 0.5>$	$<(0.04, 0.13, 0.2, 0.3); 0.5, 0.4, 0.5>$	$<(0.33, 0.53, 0.72, 0.8); 0.5, 0.4, 0.5>$

TABLE 5. Expert-provided normalized decision matrix d_2

DM	C_1	C_2	C_3	C_4
A_1	$<(0.36, 0.47, 0.57, 0.91); 0.5, 0.3, 0.6>$	$<(0.048, 0.12, 0.17, 0.32); 0.5, 0.3, 0.6>$	$<(0.048, 0.147, 0.2, 0.364); 0.5, 0.3, 0.6>$	$<(0.07, 0.15, 0.2, 0.32); 0.5, 0.3, 0.6>$
A_2	$<(0.1, 0.139, 0.194, 0.26); 0.6, 0.3, 0.5>$	$<(0.4, 0.47, 0.61, 0.7); 0.6, 0.3, 0.5>$	$<(0.07, 0.111, 0.16, 0.22); 0.6, 0.3, 0.5>$	$<(0.1, 0.139, 0.194, 0.33); 0.6, 0.3, 0.5>$
A_3	$<(0.027, 0.09, 0.185, 0.273); 0.6, 0.4, 0.7>$	$<(0.05, 0.09, 0.148, 0.273); 0.6, 0.4, 0.7>$	$<(0.05, 0.09, 0.148, 0.227); 0.6, 0.4, 0.7>$	$<(0.459, 0.563, 0.704, 0.91); 0.6, 0.4, 0.7>$

For expert 2,

$$\tilde{p}_2^{+1} =<(0.36, 0.47, 0.57, 0.91); 0.6, 0.3, 0.5>$$
$$\tilde{p}_2^{+2} =<(0.4, 0.47, 0.61, 0.7); 0.6, 0.3, 0.5>$$
$$\tilde{p}_2^{+3} =<(0.07, 0.147, 0.2, 0.364); 0.6, 0.3, 0.5>$$
$$\tilde{p}_2^{+4} =<(0.459, 0.563, 0.704, 0.91); 0.6, 0.3, 0.5>$$
$$\tilde{p}_2^{-1} =<(0.027, 0.09, 0.185, 0.273); 0.5, 0.4, 0.7>$$
$$\tilde{p}_2^{-2} =<(0.048, 0.09, 0.148, 0.273); 0.5, 0.4, 0.7>$$
$$\tilde{p}_2^{-3} =<(0.048, 0.09, 0.148, 0.22); 0.5, 0.4, 0.7>$$
$$\tilde{p}_2^{-4} =<(0.07, 0.139, 0.194, 0.32); 0.5, 0.4, 0.7>$$

For expert 3,

TABLE 6. Expert-provided normalized decision matrix d_3

DM	C_1	C_2	C_3	C_4
A_1	$<(0.11, 0.15, 0.21, 0.32); 0.5, 0.4, 0.5>$	$<(0.03, 0.06, 0.1, 0.16); 0.5, 0.4, 0.5>$	$<(0.45, 0.55, 0.66, 0.8); 0.5, 0.4, 0.5>$	$<(0.08, 0.12, 0.17, 0.24); 0.5, 0.4, 0.5>$
A_2	$<(0.08, 0.15, 0.21, 0.29); 0.6, 0.3, 0.8>$	$<(0.05, 0.09, 0.14, 0.25); 0.6, 0.3, 0.8>$	$<(0.08, 0.12, 0.17, 0.25); 0.6, 0.3, 0.8>$	$<(0.4, 0.59, 0.66, 0.83); 0.6, 0.3, 0.8>$
A_3	$<(0.4, 0.49, 0.6, 0.8); 0.5, 0.4, 0.5>$	$<(0.1, 0.14, 0.2, 0.28); 0.5, 0.4, 0.5>$	$<(0.05, 0.11, 0.167, 0.24); 0.5, 0.4, 0.5>$	$<(0.08, 0.11, 0.2, 0.28); 0.5, 0.4, 0.5>$

$$\tilde{p}_3^{+1} =< (0.4, 0.49, 0.6, 0.8); 0.6, 0.3, 0.5 >$$
$$\tilde{p}_3^{+2} =< (0.1, 0.14, 0.2, 0.28); 0.6, 0.3, 0.5 >$$
$$\tilde{p}_3^{+3} =< (0.45, 0.55, 0.66, 0.8); 0.6, 0.3, 0.5 >$$
$$\tilde{p}_3^{+4} =< (0.4, 0.59, 0.66, 0.83); 0.6, 0.3, 0.5 >$$
$$\tilde{p}_3^{-1} =< (0.08, 0.15, 0.21, 0.29); 0.5, 0.4, 0.8 >$$
$$\tilde{p}_3^{-2} =< (0.03, 0.06, 0.1, 0.16); 0.5, 0.4, 0.8 >$$
$$\tilde{p}_3^{-3} =< (0.05, 0.11, 0.167, 0.24); 0.5, 0.4, 0.8 >$$
$$\tilde{p}_3^{-4} =< (0.08, 0.11, 0.17, 0.24); 0.5, 0.4, 0.8 >$$

Step 5: Build the model for linear programming.

$\min \lambda_{12}^1 + \lambda_{13}^1 + \lambda_{21}^2 + \lambda_{23}^2 + \lambda_{31}^3 + \lambda_{32}^3 + \lambda_{21}^{1'} + \lambda_{31}^{1'} + \lambda_{12}^{2'} + \lambda_{32}^{2'} + \lambda_{13}^{3'} + \lambda_{23}^{3'}$

Subject to

$$\lambda_{12}^1 + 0.00081\omega_1 + 0.0623\omega_2 - 0.061\omega_3 + 0.0115\omega_4 \geq 0$$
$$\lambda_{13}^1 - 0.00046\omega_1 + 0.063\omega_2 - 0.0799\omega_3 - 0.0098\omega_4 \geq 0$$
$$\lambda_{21}^2 + 0.057\omega_1 - 0.0573\omega_2 + 0.00083\omega_3 - 0.0091\omega_4 \geq 0$$
$$\lambda_{23}^2 - 0.0166\omega_1 - 0.066\omega_2 - 0.00169\omega_3 + 0.0746\omega_4 \geq 0$$
$$\lambda_{31}^3 - 0.0553\omega_1 - 0.0036\omega_2 + 0.08\omega_3 - 0.0046\omega_4 \geq 0$$
$$\lambda_{32}^3 - 0.062\omega_1 - 0.0016\omega_2 + 0.0011\omega_3 + 0.076\omega_4 \geq 0$$
$$\lambda_{21}^{1'} - 0.0014\omega_1 - 0.0585\omega_2 + 0.038\omega_3 - 0.00059\omega_4 \geq 0$$
$$\lambda_{31}^{1'} - 0.05\omega_1 - 0.0033\omega_2 + 0.038\omega_3 - 0.000588\omega_4 \geq 0$$
$$\lambda_{12}^{2'} - 0.057\omega_1 + 0.068\omega_2 - 0.0012\omega_3 + 0.0007\omega_4 \geq 0$$
$$\lambda_{32}^{2'} + 0.00139\omega_1 + 0.069\omega_2 0.0006\omega_3 - 0.059\omega_4 \geq 0$$
$$\lambda_{13}^{3'} + 0.051\omega_1 + 0.0033\omega_2 - 0.071\omega_3 + 0.00031\omega_4 \geq 0$$
$$\lambda_{23}^{3'} + 0.051\omega_1 + 0.0026\omega_2 - 0.0001\omega_3 - 0.059\omega_4 \geq 0$$

$$-0.0766\omega_1 - 0.0032\omega_2 - 0.053\omega_3 + 0.1386\omega_4 \geq h$$
$$-0.005\omega_1 + 0.0811\omega_2 + 0.0043\omega_3 - 0.1182\omega_4 \geq h'$$
$$\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1$$
$$\omega_1 \geq 0, \omega_2 \geq 0, \omega_3 \geq 0, \omega_4 \geq 0$$
$$\lambda_{12}^1 \geq 0, \lambda_{13}^1 \geq 0, \lambda_{21}^2 \geq 0, \lambda_{23}^2 \geq 0$$
$$\lambda_{31}^3 \geq 0, \lambda_{32}^3 \geq 0, \lambda_{21}^{1'} \geq 0, \lambda_{31}^{1'} \geq 0$$
$$\lambda_{12}^{2'} \geq 0, \lambda_{32}^{2'} \geq 0, \lambda_{13}^{3'} \geq 0, \lambda_{23}^{3'} \geq 0$$

We determine the ideal weight values for the qualities by solving the previously discussed model with the LINGO.

$$\omega_1 = 0.2811, \omega_2 = 0.3079, \omega_3 = 0.2154, \omega_4 = 0.1955$$

Step 6: Compute the distance separation measures d_i^{+p} and d_i^{-p} as shown in Table 7.

Step 7: Calculate the RCC R_i^p as given by Table 8.

TABLE 7. d_i^{+p} and d_i^{-p} are separation measures.

d_i^{+p}	d_i^{-p}
$d_1^{+1} = 0.0346, d_1^{+2} = 0.0353, d_1^{+3} = 0.0340$	$d_1^{-1} = 0.0085, d_1^{-2} = 0.0169, d_1^{-3} = 0.0156$
$d_2^{+1} = 0.0261, d_2^{+2} = 0.0322, d_2^{+3} = 0.0375$	$d_2^{-1} = 0.0189, d_2^{-2} = 0.0218, d_2^{-3} = 0.0121$
$d_3^{+1} = 0.0346, d_3^{+2} = 0.0430, d_3^{+3} = 0.0346$	$d_3^{-1} = 0.0156, d_3^{-2} = 0.0156, d_3^{-3} = 0.0156$

Step 8: Rank the alternatives.

TABLE 8. Relative closeness coefficient

Expert	R_i^p
1	$R_1^1 = 0.1972, R_2^1 = 0.42, R_3^1 = 0.3108$
2	$R_1^2 = 0.3238, R_2^2 = 0.4037, R_3^2 = 0.02662$
3	$R_1^3 = 0.3145, R_2^3 = 0.244, R_3^3 = 0.3108$

Borda's scores for the three businesses can be found in Table 9 below.Three businesses are ranked as follows: $A_2 > A_1 > A_3$, with A_2 being the best option.

TABLE 9. Borda's scores for alternatives

Experts Alternatives	d_1	d_2	d_3	Borda's Score
A_1	0	1	2	3
A_2	2	2	0	4
A_3	1	0	1	2

5.2. *Analysis of comparison with current techniques*

In this work, proposed method is more valuable to compare with some relevant papers. Initially, we contrast our suggested work with the Jun Ye [33],Bharatraj and Anand [34], Chiranjibe et al. [29], Pramanik and Mallick [60], [61] and Paulraj and Tamilarasi [52]. Similar ranking results were achieved when we examined the same MADM problem in a neutrophic environment. A detailed comparison with the existing methods is listed in Table 10. In order to compare Solairaju and Shajahan [67] imprecision membership and defuzzification methods. The comparison result shown in Table 11.
The suggested integrate LINMAP and TOPSIS approach is consistent and comparable to the

Table 10. Decision-making results of existing methods

Method	Ranking Order	Best Alternative
Jun Ye [33]	$A_2 > A_1 > A_3$	A_2
Pramanik and Mallick [60]	$A_2 > A_1 > A_3$	A_2
Bharatraj and Anand [34]	$A_2 > A_1 > A_3$	A_2
Chiranjibe et al [29]	$A_2 > A_1 > A_3$	A_2
Pramanik and Mallick [61]	$A_2 > A_1 > A_3$	A_2
Paulraj and Tamilarasi [52]	$A_2 > A_1 > A_3$	A_2
Proposed Method	$A_2 > A_1 > A_3$	A_2

Table 11. Ranking order of alternatives for precise set

Precise set	Ranking Order	Best Alternative
Fuzzy Set	$A_2 > A_1 > A_3$	A_2
Intuitionistic Fuzzy Set	$A_2 > A_1 > A_3$	A_2
Neutrosophic Set	$A_2 > A_1 > A_3$	A_2

current ones, according to the information shown in Tables 10 and 11. The suggested approach also offers the following benefits:

(1) The existing methods [[33], [34], [29], [52]] provide the same option for various procedures, as indicated in Table 10, but the recently suggested method consistently provides the same option for the integrated method, which has been demonstrated to work.
(2) The proposed Method also applied for COVID 19 problem [52] and we get the same alternatives.
(3) The suggested approach to decision-making in SVTN numbers is more generic and more practical than the current approaches since it extends some of the existing approaches.

(4) From Table 10 and 11 demonstrates that the optimal option is A_2. Next, the proposed method investigate the impact of the neutrosophic parameter in the ranking of imprecision membership and defuzzification methods in decision making. It is interesting to see that without considering the indeterminacy and falsity information also we got the same result. So, it can conclude that with neutrosophic information, we can obtain realistic results.

6. Conclusion

This study extends the neutrosophic LINMAP method to solve SVTN number MAGDM issues. The decision maker's preferences between two options are taken into consideration while defining the consistency & inconsistency measure indices. To ascertain the attribute weights, a linear programming model is built by reducing the inconsistency index. The optimal solution is then selected using the neutrosophic TOPSIS technique. To handle MAGDM difficulties, the suggested approach integrates the LINMAP and TOPSIS methodologies in a neutrosophic setting. One of the drawbacks of our proposed approach is that the decision makers might offer preference relationships between options that are consistent with the alternatives' rank-order. But this creates a big demand for the caliber of the decision makers. It is frequently not possible to infer the decision's rating of the options makers' preference relations since they show conflicting preference relations between the alternatives. Considering the possibilities' conflicting preference relations, the suggested approach might be more suitable. Future extensions of our proposed approach will apply other sets applied heterogeneous MAGDM issues .

Furthermore, applying the integrated neutrosophic LINMAP-TOPSIS approach across various sectors such as healthcare, manufacturing, or finance could broaden its utility and demonstrate its generalizability. Comparative studies with traditional methods or other advanced techniques could also enhance comprehension of the suggested model's advantages and disadvantages in a range of real-world contexts.

By extending these results to other decision-making frameworks, industries, and real-time applications, the proposed method could significantly enhance enterprise selection, risk assessment, and strategic planning processes, contributing to the overall success and sustainability of enterprises in competitive and rapidly evolving markets.

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