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Intuitionistic Fuzzy Score and Distance-Based Hybrid Decision Framework for Analysing Sustainable Lean Six Sigma Enablers in the Manufacturing Sector

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Abstract. Lean Six Sigma (LSS) is defined as an innovative business strategy for achieving operational excellence through continuous improvement in the manufacturing sector. By embracing LSS principles, manufacturers can create an adaptable and capable system to preserve a competitive positioning, while reducing waste and defects in the business processes. The integration of sustainability with LSS has contributed to the upward attention among scholars and practitioners worldwide by advancing knowledge of how manufacturers can improve their sustainable performance through LSS practices. For any manufacturing firm, the challenge lies in exploring enablers that support successful adoption of sustainable LSS. Consequently, this study aims to develop an intuitionistic fuzzy decision-making framework for identifying and assessing the enablers influencing an integrated sustainable LSS in electric manufacturing companies. The proposed framework integrates the Weight by Envelope and Slope (WENSLO) and Modified Preference Selection Index (MPSI) models taking into account the developed score and distance formulae under the setting of intuitionistic fuzzy sets. Using an integrated intuitionistic fuzzy WENSLO-MPSI model, this study further evaluated thirteen sustainable LSS enablers of five electric manufacturing companies, followed by sensitivity and comparative analyses. The findings indicated that "Linking SLSS to business strategies", "Green design principles" and "Effective scheduling" are the most significant enablers to implement sustainable LSS in an electrical manufacturing company.

Key words: Lean Six Sigma, sustainability, manufacturing, decision-making, intuitionistic fuzzy set.

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1. Introduction

Manufacturing companies contribute significantly to the economic evolution of any country. Due to rapid globalization, scarcity of resources and variations in demand patterns, manufacturing companies are gradually focusing toward innovative strategies for meeting the customer demands in today's competitive and resource-constrained global landscape (Saha *et al.*, 2025), while minimizing waste generation and maximizing resource efficiency (Sakib *et al.*, 2025). In this context, Lean Six Sigma (LSS) has garnered increasing attention as a strategic methodology for improving quality, efficiency, responsiveness and environmental performance of a manufacturing organization (Ngouono *et al.*, 2025; Widiwati *et al.*, 2025). It combines Lean and Six Sigma principles to improve employee and company performance by eliminating resource waste and process/product flaws. The successful implementation of LSS enables organizations to enhance their performance by improving quality, reducing cycle time, minimizing wastes, along with creating value for customers (Cabeça *et al.*, 2025; Corredor-Rojas *et al.*, 2025).

In the recent past, Sustainable Lean Six Sigma (SLSS) comes to stand out as an innovative strategy for managing organizational sustainability performance, while optimizing their operations and reducing the waste materials and product defects (Utama and Abirfatin, 2023). The integration of sustainability and LSS results in SLSS, which has emerged as an effective methodology that focuses on economic, environmental and social aspects of a company together with the waste minimization and defects reduction in the business processes. Despite its importance, manufacturing companies encounter challenges when adopting SLSS into their business operations (Parmar and Desai, 2021). In this regard, manufacturers need to identify and prioritize the enablers for the effective operation of SLSS into business operations. Consequently, there is a need to assess and rank the enablers influencing SLSS adoption within a manufacturing organization.

Evaluating enablers requires an effective method to help the manufacturing organizations in implementing SLSS. Moreover, uncertainty significantly impacts the decision-making process, which necessitates the embracing of more advanced models able to managing such imprecise data. Zadeh (1965) offered a conceptual framework, namely Fuzzy Set (FS), for handling uncertainty in decision-making applications. It is characterized by the membership function that ranges from '0' to '1', signifying the degree of membership of an element in a set. The emergence of FS theory provided a potent tool for addressing ambiguity and uncertainty in practical issues (Alaoui *et al.*, 2024; Adali and Tuş, 2025). Later, the theory of intuitionistic fuzzy set (IFS) has been introduced by Atanassov (1986). In IFS, an element is portrayed by the membership and non-membership degrees with their sum restricted to 1. As a generalization of FS theory, an IFS is regarded as a more effective way to confront uncertainty and ambiguity of real-world applications (Miliauskaitė and Kalibatiene, 2025).

Existing studies have documented the efforts to the development of theories and applications of IFS theory. Li *et al.* (2023) suggested a combined intuitionistic fuzzy (IF) decision-making model to distinguish and rank the key challenges for collaborative innovation projects. For the purpose, they incorporated the entropy model, Stepwise Weight

Assessment Ratio Analysis (SWARA) and Measurement of Alternatives and Ranking according to the Compromise Solution (MARCOS) models under the context of IFSs. Deb *et al.* (2023) integrated the Weighted Aggregated Sum Product Assessment (WASPAS) and consensus reaching with IFSs, along with its application in open-source software learning management systems evaluation. Rani and Kumar (2023) presented new measures for finding the degree of discrimination and similarity between IFSs with their applicability in online shopping websites assessment. Salimian *et al.* (2023) introduced a collective IF-based decision-making model for assessing the sustainable construction projects under uncertain background. Hezam *et al.* (2023) identified the sustainability indicators using IFSs-based Symmetry Point of Criterion (SPC) and Rank-Sum (RS) models for the evaluation of biomass resources for biofuel formation. Kumar and Kumar (2024) presented new score and distance formulae in the setting of IFSs. Based on these measures, they proposed a combined IF-decision framework and utilized to deal with uncertainty of sustainable biomass crop selection problem. Within the framework of IFSs, Rani *et al.* (2025) developed a new distance based decision-making framework by combining MEthod based on the Removal Effects of Criteria (MEREC) and RS models with its relevance in the embracing of blockchain technology within the logistics sector. Ziquan *et al.* (2025) integrated the SWARA and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approaches within the IF environment and further used to rank the risk factors of e-commerce supply chain. Mishra *et al.* (2025) developed an intuitionistic fuzzy extension of multi-attribute multi-objective optimisation based on the ratio analysis model considering score and distance measures, along with its application in solar power plant location selection problem.

Considering the advantages of IFS theory, this paper proposes an integrated IF-decision support model for estimating and ranking the enablers of SLSS adoption in Indian electric manufacturing companies. To this aim, we integrate the Weights by ENvelope and SLOpe (WENSLO) and Modified Preference Selection Index (MPSI) models under the context of IFSs, and develop a combined ranking framework, which has not yet been presented in the literature. Pamucar *et al.* (2023) proposed the idea of WENSLO method to determine the objective weighting, while Gligorić *et al.* (2022) developed the concept of MPSI model to derive the subjective weighting. A WENSLO is mainly effective for finding weight of attributes as it combines slope and envelope axioms of the decision-matrix. By uniting these two dimensions, the approach alleviates subjective bias and gives a more stable illustration of the relative significance of criteria. Contrasting purely judgment-based approaches, WENSLO originates weights directly from the decision-matrix, improving both robustness and transparency. This mixture of objectivity and sensitivity purifies WENSLO particularly appropriate for complex decision-making perspectives concerning multiple interdependent attributes. Further, MPSI method is based on the degree of the oscillation, i.e. variation in the preference value for each criterion. That variation actually presents the distance between normalized value and mean value per criterion and is expressed by using the Euclidean distance. MPSI method is characterized as a very simple and easy to understand approach for defining the objective weights of criteria. In this work, we consider the advantages of both the models by integrating them into a hybrid framework, named as IF-WENSLO-MPSI. In the following, the major contributions of this work in terms of methodology are listed below:

- This study develops an improved score function to distinguish the intuitionistic fuzzy numbers (IFNs), followed by numerical examples involving the comparison with Xu (2007), Xu *et al.* (2015), Zhang *et al.* (2019), Feng *et al.* (2020) and Tripathi *et al.* (2023).
- This paper introduces a new IF-distance formula induced by the proposed score function. Comparison with existing IF-distance formulae (Ngan *et al.*, 2018; Ejegwa and Agbetayo, 2023; Li *et al.*, 2023; Rani and Kumar, 2023; Kumar and Kumar, 2024; Mishra *et al.*, 2025) is presented to exemplify the efficacy of proposed formula.
- In line with the proposed score and distance formulae, an integrated IF-WENSLO-MPSI methodology is proposed to evaluate and prioritize the enablers of SLSS adoption.
- In this method, the experts' weights are determined via a combined IF-score function-based rank reciprocal model.
- A case study of enablers assessment for SLSS adoption within Indian electric manufacturing organizations is presented to illustrate the implementation process of the developed methodology.

Other sections are settled in the following manner. In Section 2, we present the related studies. In Section 3, we firstly present the basic concepts related to this work. Secondly, we propose a modified IF-score formula for ranking intuitionistic fuzzy numbers. Lastly, we develop a new IF-distance formula for estimating the variation degree between IFSs. In Section 4, we present the stepwise procedure of an integrated IF-WENSLO-MPSI method. In Section 5, we implement the proposed IF-WENSLO-MPSI model on a case study of enablers analysis for SLSS adoption, validated through sensitivity and comparative discussions. Section 6 showcases the concluding remarks and suggested some insights for further study.

2. Related Works

Enablers are defined as the critical and fundamental factors that can drive the smooth and efficient implementation of SLSS in business processes (Hussain *et al.*, 2025). Existing literature attests the efforts on the evaluation of enablers for LSS adoption. Pandey *et al.* (2018) utilized Analytic Hierarchy Process (AHP) model for investigating the ranks of enablers influencing green LSS implementation. Kaswan and Rathi (2019) analysed the enablers persuading green LSS adoption in business operations. In addition, they investigated the interactions among these enablers by using an integrated interpretive structural modelling and Impact Matrix Cross-Reference Multiplication Applied to a Classification (MICMAC) based technique. Parmar and Desai (2020) used fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique for evaluating the enablers of SLSS in a manufacturing firm. Swarnakar *et al.* (2020) examined and evaluated the twenty-nine enablers for SLSS adoption using fuzzy MICMAC model within the manufacturing organization. With the use of best worst method, Singh *et al.* (2021) analysed and ordered the enablers of environmental LSS in Indian micro-small and medium organizations. Letchumanan *et al.* (2022) identified the main factors enabling the green LSS adoption and further provided a systematic methodology to conceptualise and set up the green LSS into the Malaysian electronics manufacturing sector. In a study, Singh and Rathi (2022) identified twenty-five enablers influencing LSS operation in Indian micro-small and medium firms, together with their prioritization through AHP model. Perez-Burgoin *et al.* (2024) acknowledged the enablers of green LSS and further investigated the associations between the considered enablers in the execution of green LSS in the Mexican manufacturing organization. As per author's knowledge, there is no such literature available including WENSLO-MPSI in intuitionistic fuzzy environment to evaluate the enablers for SLSS adoption in manufacturing sector. Thus, it motivates us to employ the idea of intuitionistic fuzzy based WENSLO-MPSI in the assessment and prioritization of SLSS adoption enablers.

On the basis of existing studies, we acknowledge some research challenges, given as below:

- Existing works are unable to handle the intuitionistic fuzzy information-based SLSS enablers assessment problem, while IFS, as an extension of FS, is a more powerful tool to manage the uncertainty of a real-life application.
- In the literature, there is no discussion about the experts' weights during the evaluation of enablers influencing SLSS adoption in a business strategy, which may cause information loss in decision results.
- Amalgamation of objective and subjective weighting of enablers overwhelmed the limitations of individual weighting as the objective weighting obtains based on quantitative data, which neglect the preference of experts, whereas the subjective weighting obtains as per the opinions of experts, which may include biasness. However, previous studies ignore the importance of combined objective-subjective assessment degrees of SLSS enablers in the literature.

3. New Intuitionistic Fuzzy Score and Distance Formulae

This section proposes a new IF-score formula together with score-induced IF-distance measure. Before these developments, we present the basic notions related to this study.

3.1. *Basic Concepts*

This subsection contains some basic definitions that form the basis of the work.

Definition 1 (Atanassov, 1986). An IFS 'B' on a fixed universe of discourse $V = \{v_1, v_2, \dots, v_n\}$ is defined as

$$B = \{(v_i, \mu_B(v_i), \nu_B(v_i)) : v_i \in V\}, \tag{1}$$

wherein $\mu_B : V \to [0,1]$ and $\nu_B : V \to [0,1]$ denote the membership and the non-membership degrees of an element v_i to B in V, satisfying $0 \leqslant \mu_B(v_i), \nu_B(v_i) \leqslant 1$ and $0 \leqslant \mu_B(v_i)+\nu_B(v_i) \leqslant 1, \forall v_i \in V$. For each $v_i \in V$, the hesitancy/indeterminacy degree is defined as $\pi_B(v_i) = 1 - \mu_B(v_i) - \nu_B(v_i)$. Atanassov (1986) simply defined the term (μ_B, ν_B) as an intuitionistic fuzzy number (IFN)/intuitionistic fuzzy value (IFV). In this work, we denote it as '$\vartheta = (\mu, \nu)$'.

Definition 2 (Xu, 2007). For two IFNs $\vartheta_1 = (\mu_1, \nu_1)$ and $\vartheta_2 = (\mu_2, \nu_2)$, some operational laws are defined as follows:

(i) $\vartheta_i^c = (\nu_i, \mu_i) \quad (i = 1, 2)$,
(ii) $\vartheta_1 \subseteq \vartheta_2$ if and only if $\mu_1 \leqslant \mu_2$ and $\nu_1 \geqslant \nu_2$,
(iii) $\vartheta_1 = \vartheta_2$ if and only if $\vartheta_1 \subseteq \vartheta_2$ and $\vartheta_1 \supseteq \vartheta_2$,
(iv) $\vartheta_1 \oplus \vartheta_2 = (\mu_1 + \mu_2 - \mu_1\mu_2, \nu_1\nu_2)$,
(v) $\vartheta_1 \otimes \vartheta_2 = (\mu_1\mu_2, \nu_1 + \nu_2 - \nu_1\nu_2)$,
(vi) $\iota\vartheta_i = (1 - (1-\mu_i)^\iota, (\nu_i)^\iota) \quad (\iota > 0, i = 1, 2)$,
(vii) $\vartheta_i^\iota = ((\mu_i)^\iota, 1 - (1-\nu_i)^\iota) \quad (\iota > 0, i = 1, 2)$.

Definition 3 (Xu, 2007). Assume that $\vartheta_i = (\mu_i, \nu_i)$ $(i = 1, 2, \dots, n)$ be a set of IFVs and $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_n)^T$ be the weight vector of ϑ_i $(i = 1, 2, \dots, n)$, with $\alpha_i \in [0,1]$ and $\alpha_1 + \alpha_2 + \cdots + \alpha_n = 1$. To aggregate the IFVs into a single IFV, Xu (2007) presented the ideas of "intuitionistic fuzzy weighted averaging (IFWA)" and "intuitionistic fuzzy weighted geometric (IFWG)" operators, given as

$$IFWA(\vartheta_1, \vartheta_2, \dots, \vartheta_n) = \bigoplus_{i=1}^{n} \alpha_i\vartheta_i = \left[1 - \prod_{i=1}^{n}(1-\mu_i)^{\alpha_i}, \prod_{i=1}^{n} \nu_i^{\alpha_i}\right], \tag{2}$$

$$IFWG(\vartheta_1, \vartheta_2, \dots, \vartheta_n) = \bigotimes_{i=1}^{n} \vartheta_i^{\alpha_i} = \left[\prod_{i=1}^{n} \mu_i^{\alpha_i}, 1 - \prod_{i=1}^{n}(1-\nu_i)^{\alpha_i}\right]. \tag{3}$$

Definition 4 (Xu, 2007). For an IFN $\vartheta = (\mu, \nu)$, Xu (2007) defined the score and accuracy functions, given by Eq. (4) and Eq. (5), respectively.

$$S_X(\vartheta) = \mu - \nu, \quad \text{where } S_X(\vartheta) \in [-1, 1], \tag{4}$$

$$A_X(\vartheta) = \mu + \nu, \quad \text{where } A_X(\vartheta) \in [0, 1]. \tag{5}$$

Definition 5 (Xu and Chen, 2008). Let $B, E \in IFSs(V)$. A distance measure 'd' on $IFS(V)$ is defined as a real-valued function $d : IFSs(V) \times IFSs(V) \to [0,1]$ which satisfies:

(a_1) $0 \leqslant d(B, E) \leqslant 1$,
(a_2) $d(B, E) = 0$ if and only if $B = E$,
(a_3) $d(B, E) = d(E, B)$,
(a_4) If $B \subseteq E \subseteq G$, then $d(B, G) \geqslant d(B, E)$ and $d(B, G) \geqslant d(E, G)$.

3.2. *New Score Function for IFN*

In the setting of IFSs, score function is a key concept to convert an IFN into crisp number. It has been widely used to rank the alternatives in intuitionistic fuzzy decision-making problems. It is defined in such a way that greater the value of it, the more properly the relevant alternative will be able to satisfy the belief of experts. In the literature, several score formulae have been developed for comparing IFNs, however, some of them present unreasonable results in ranking alternatives. For this purpose, this section develops a modified score formula for an IFN 'ϑ'.

Let $\vartheta = (\mu, \nu)$ be an IFN. Then a modified score formula is developed for IFN 'ϑ' and presented by

$$S(\vartheta) = \frac{1}{2}\left[\frac{Y(\vartheta)}{2}\left\{abs(\mu - \nu) + (\mu + \nu)\right\} + 1\right], \tag{6}$$

where $Y(\vartheta) = \operatorname{sgn}(\mu - \nu)$, and sgn(.) and $abs(\cdot)$ represent the sign function and the absolute value function, respectively.

Property 1. For an IFN $\vartheta = (\mu, \nu)$, the function $S(\vartheta)$, given by Eq. (6), is monotonic increasing and decreasing over 'μ' and 'ν', respectively.

Property 2. For an IFN $\vartheta = (\mu, \nu)$, the score function '$S(\vartheta)$' holds the subsequent properties:

(i) $S(\vartheta) = 0$ if and only if $\vartheta = (0, 1)$,
(ii) $S(\vartheta) = 1$ if and only if $\vartheta = (1, 0)$,
(iii) $0 \leqslant S(\vartheta) \leqslant 1$.

In the following, we compare the proposed score function with some of the previously introduced IF-score functions (Xu, 2007; Xu *et al.*, 2015; Zhang *et al.*, 2019; Feng *et al.*, 2020; Tripathi *et al.*, 2023; Kumar and Kumar, 2024; Mishra *et al.*, 2025). Table 1 shows the required comparative results obtained by proposed and existing IF-score functions.

To test the feasibility of the proposed score function $S(\vartheta)$ for comparing IFNs, Table 1 shows the comparison between the results obtained by the proposed score function and the cases of the score functions derived by Xu (2007), Xu *et al.* (2015), Zhang *et al.* (2019), Feng *et al.* (2020), Tripathi *et al.* (2023), Kumar and Kumar (2024) and Mishra *et al.* (2025).

- To compare any two IFNs $\vartheta_1 = (0.5, 0.3)$ and $\vartheta_2 = (0.6, 0.4)$, we can observe the limitations of IF-score functions by Xu (2007), Xu *et al.* (2015) and Tripathi *et al.* (2023) as we are getting $S_1(\vartheta_1) = 0.2 = S_2(\vartheta_2)$, $S_2(\vartheta_1) = 0.6 = S_2(\vartheta_2)$ and $S_5(\vartheta_1) = 0.6 = S_5(\vartheta_2)$.
- For comparing any two IFNs $\vartheta_3 = (0.51, 0.3)$ and $\vartheta_4 = (0.45, 0.26)$, we analyse the counter-intuitive case of Feng *et al.*'s IF-score function $S_4(.)$ due to the acquired result as $S_4(\vartheta_3) = 0.375 = S_4(\vartheta_4)$ (for $p = 2$).

Table 1
Computational results acquired by the developed and extant IF-score functions.

Score functions	$\vartheta_1 = (0.5, 0.3)$, $\vartheta_2 = (0.6, 0.4)$	$\vartheta_3 = (0.51, 0.30)$, $\vartheta_4 = (0.45, 0.26)$	$\vartheta_5 = (0.35, 0.5)$, $\vartheta_6 = (0.312, 0.398)$	$\vartheta_7 = (0, 0)$, $\vartheta_8 = (0, 1)$
Xu (2007) $S_1(\vartheta_i) = (\mu_i - \nu_i)$	$S_1(\vartheta_1) = 0.2$, $S_1(\vartheta_2) = 0.2$	$S_1(\vartheta_3) = 0.21$, $S_1(\vartheta_4) = 0.190$	$S_1(\vartheta_5) = -0.15$, $S_1(\vartheta_6) = -0.086$	$S_1(\vartheta_7) = 0.0$, $S_1(\vartheta_8) = -1.0$
Xu *et al.* (2015) $S_2(\vartheta_i) = 0.5((\mu_i - \nu_i) + 1)$	$S_2(\vartheta_1) = 0.6$, $S_2(\vartheta_2) = 0.6$	$S_2(\vartheta_3) = 0.605$, $S_2(\vartheta_4) = 0.595$	$S_2(\vartheta_5) = 0.425$, $S_2(\vartheta_6) = 0.457$	$S_2(\vartheta_7) = 0.5$, $S_2(\vartheta_8) = 0.0$
Zhang *et al.* (2019) $S_3(\vartheta_i) = \frac{\mu_i}{\mu_i + \nu_i}$	$S_3(\vartheta_1) = 0.625$, $S_3(\vartheta_2) = 0.6$	$S_3(\vartheta_3) = 0.63$, $S_3(\vartheta_4) = 0.634$	$S_3(\vartheta_5) = 0.412$, $S_3(\vartheta_6) = 0.439$	$S_3(\vartheta_7) = NaN$, $S_3(\vartheta_8) = 0.0$
Feng *et al.* (2020) $S_4(\vartheta_i) = (\frac{\mu_i^p + (1-\nu_i)^p}{2})^{1/p}$, where $p \in \mathbb{R}$	$S_4(\vartheta_1) = 0.37$, $S_4(\vartheta_2) = 0.36$	$S_4(\vartheta_3) = 0.375$, $S_4(\vartheta_4) = 0.375$	$S_4(\vartheta_5) = 0.186$, $S_4(\vartheta_6) = 0.23$	$S_4(\vartheta_7) = 0.5$, $S_4(\vartheta_8) = 0.0$
Tripathi *et al.* (2023) $S_5(\theta_i) = \mu_i(1 + (\varepsilon_1 + \varepsilon_2)(1 - \mu_i - \nu_i))$, where $\varepsilon_1 + \varepsilon_2 = 1$	$S_5(\vartheta_1) = 0.6$, $S_5(\vartheta_2) = 0.6$	$S_5(\vartheta_3) = 0.607$, $S_5(\vartheta_4) = 0.581$	$S_5(\vartheta_5) = 0.402$, $S_5(\vartheta_6) = 0.402$	$S_5(\vartheta_7) = 0.0$, $S_5(\vartheta_8) = 0.0$
Kumar and Kumar (2024) $S_6(\vartheta_i) = \frac{1}{2}((\mu_i - \nu_i - \ln(1 + \pi_i)) + 1)$	$S_6(\vartheta_1) = 0.509$, $S_6(\vartheta_2) = 0.6$	$S_6(\vartheta_3) = 0.518$, $S_6(\vartheta_4) = 0.468$	$S_6(\vartheta_5) = 0.355$, $S_6(\vartheta_6) = 0.33$	$S_6(\vartheta_7) = 0.153$, $S_6(\vartheta_8) = 0.0$
Mishra *et al.* (2025) $S_5(\vartheta_i) = \frac{1}{2(e+1)}\left(\sqrt{\mu_i} e^{(\sqrt{\mu_i})} + \sqrt{1-\nu_i} e^{(\sqrt{1-\nu_i})} + (\sqrt{\mu_i} + \sqrt{1-\nu_i})\sqrt{\frac{1+\mu_i-\nu_i}{2}}\right)$	$S_7(\vartheta_1) = 0.568$, $S_7(\vartheta_2) = 0.569$	$S_7(\vartheta_3) = 0.573$, $S_7(\vartheta_4) = 0.563$	$S_7(\vartheta_5) = 0.413$, $S_7(\vartheta_6) = 0.439$	$S_7(\vartheta_7) = 0.402$, $S_7(\vartheta_8) = 0.0$
Proposed IF-score function $S(\vartheta_i) = \frac{1}{2}\left[\frac{Y(\vartheta_i)}{2} \cdot \{abs(\mu_i - \nu_i) + (\mu_i + \nu_i)\} + 1\right]$	$S(\vartheta_1) = 0.75$, $S(\vartheta_2) = 0.800$	$S(\vartheta_3) = 0.755$, $S(\vartheta_4) = 0.725$	$S(\vartheta_5) = 0.25$, $S(\vartheta_6) = 0.301$	$S(\vartheta_7) = 0.5$, $S(\vartheta_8) = 0.000$

*Bold denotes unreasonable results. NaN means “not a number”.

- To compare the IFNs $\vartheta_5 = (0.35, 0.5)$, $\vartheta_6 = (0.312, 0.398)$, Tripathi *et al.*'s score function (Tripathi *et al.*, 2023) provide an unreasonable result as $S_5(\vartheta_5) = 0.402 = S_5(\vartheta_6)$.
- To deal with the case when $\vartheta_7 = (0, 0)$ and $\vartheta_8 = (0, 1)$, Zhang *et al.*'s score function (Zhang *et al.*, 2019) present counter-intuitive results. Additionally, Tripathi *et al.*'s score function (Tripathi *et al.*, 2023) is unable to distinguish these two different IFNs $\vartheta_7 = (0, 0)$ and $\vartheta_8 = (0, 1)$.
- From Table 1, we can find that the proposed score function $S(\vartheta_i)$ can efficiently rank the given IFNs in all the four cases, which showcases its effectiveness.

3.3. *Score-Based Distance Formula for IFSs*

The conception of distance measure is used to investigate the dissimilarity degree between elements/entities (Shyur and Shih, 2024). In the context of IFS, several efforts have made to propose new distance measures for IFSs, however, some of the well-known distance formulae failed to discriminate two different IFSs in many cases. To overcome the limitations of existing measures, this subsection develops a generalized score-induced distance measure for IFSs.

Theorem 1. *Let $B, E \in IFSs(V)$, where $B = \{(v_i, \mu_B(v_i), \nu_B(v_i)) : v_i \in V\}$ and $E = \{(v_i, \mu_E(v_i), \nu_E(v_i)) : v_i \in V\}$. A score-induced function given by Eq.* (7)

$$d(B, E) = \frac{\max\{S(B), S(E)\} - \min\{S(B), S(E)\}}{\max\{S(B), S(E)\}}, \tag{7}$$

is a distance measure for IFSs. In Eq. (7)*, $S(.)$ denotes the score function, given by Eq.* (6)*.*

Proof. To prove this theorem, we need to prove the axioms (a_1)–(a_4) of Definition 5.

(a_1). For any two IFSs B and E, we have $0 \leqslant \mu_B \leqslant 1$, $0 \leqslant \mu_E \leqslant 1$, $0 \leqslant \nu_B \leqslant 1$ and $0 \leqslant \nu_E \leqslant 1$. Since $S(.)$ denotes the score function as given in Eq. (6) and here, $0 \leqslant S(.) \leqslant 1$, therefore, $0 \leqslant \max\{S(B), S(E)\} \leqslant 1$, $0 \leqslant \min\{S(B), S(E)\} \leqslant 1$ and $0 \leqslant \max\{S(B), S(E)\} - \min\{S(B), S(E)\} \leqslant 1$. Thus, we can observe that $0 \leqslant d(B, E) \leqslant 1$.

(a_2). Assume that $d(B, E) = 0$, then from Eq. (7), we get

$$\frac{\max\{S(B), S(E)\} - \min\{S(B), S(E)\}}{\max\{S(B), S(E)\}} = 0,$$

it implies that $\max\{S(B), S(E)\} = \min\{S(B), S(E)\}$, thus, the only possibility is $S(B) = S(E) \Rightarrow \mu_B = \mu_E$ and $\nu_B = \nu_E$. Hence, $B = E$. On the other hand, if we assume $B = E$, then $\mu_B = \mu_E$ and $\nu_B = \nu_E$. Then, from Eq. (7), we get $d(B, E) = 0$.

(a_3). It is obvious from Eq. (7), so we have omitted the proof.

(a_4). For any three IVPFSs B, E and G, let $B \subseteq E \subseteq G$, we have $\mu_B \leqslant \mu_E \leqslant \mu_G$ and $\nu_G \leqslant \nu_E \leqslant \nu_B$. Then, $S(B) \leqslant S(E) \leqslant S(G)$. Therefore, we have $\max\{S(B), S(E)\} \leqslant \max\{S(B), S(G)\}$ and $\min\{S(B), S(E)\} = \min\{S(B), S(G)\}$. Hence, $\max\{S(B), S(G)\} \min\{S(B), S(E)\} \geqslant \max\{S(B), S(E)\} \min\{S(B), S(G)\}$.

Now,

$$
\begin{aligned}
& d(B,G)-d(B,E)\\
&\quad=\frac{\max\{S(B),S(G)\}-\min\{S(B),S(G)\}}{\max\{S(B),S(G)\}}-\frac{\max\{S(B),S(E)\}-\min\{S(B),S(E)\}}{\max\{S(B),S(E)\}}\\
&\quad=\frac{\max\{S(B),S(G)\}\min\{S(B),S(E)\}-\max\{S(B),S(E)\}\min\{S(B),S(G)\}}{\max\{S(B),S(G)\}\max\{S(B),S(E)\}}\geqslant 0.
\end{aligned}
$$

Thus, we get $d(B,G)\geqslant d(B,E)$. Similarly, we can prove that $d(B,G)\geqslant d(E,G)$. Hence the proof. $\square$

Next, we perform the comparison of developed and extant IF-distance measures to check the rationality of the proposed one. In this way, we first review different extant measures by Ngan *et al.* (2018), Ejegwa and Agbetayo (2023), Li *et al.* (2023), Rani and Kumar (2023), Kumar and Kumar (2024) and Mishra *et al.* (2025) in Table 2, and further, employ them to find the discrimination degree on some pairs of IFSs.

On the basis of Table 2, we extract the following points:

- For the Case-1: $\{B_1=(v_1,0.8,0.2), E_1=(v_1,0,0)\}$ and Case-2: $\{B_2=(v_1,0.4,0.6), E_2=(v_1,0,0)\}$, the IF-distances by Ejegwa and Agbetayo (2023) and Li *et al.* (2023) failed to measure the dissimilarity between two different sets of IFSs.
- In Case-3: $\{B_3=(v_1,0.41,0.2), E_3=(v_1,0.22,0.28)\}$ and Case-6: $\{B_6=(v_1,0.31,0.41), E_6=(v_1,0.51,0.338)\}$, Kumar and Kumar (2024) and Mishra *et al.* (2025) are unable to distinguish the given IFSs as $d_6(B_3,E_3)=0.14=d_6(B_6,E_6)$ and $d_7(B_3,E_3)=0.016=d_7(B_6,E_6)$.
- Since $B_5=(1,0)$ and $E_5=(0,1)$ are the maximum and the minimum IFNs, therefore, it is expected that the discrimination between B_5 and E_5 is the maximum distance, arriving to '1', while in Case-5, Ngan *et al.*'s IF-distance formulae (Ngan *et al.*, 2018) obtain the results '$d_1(B_5,E_5)=0.333$' and '$d_2(B_5,E_5)=0.5$'.
- From Table 2, we can observe that the proposed IF-distance formula provides reasonable results for all the cases, which confirms its consistency and efficiency over the existing ones.

4. A Hybrid IF-WENSLO-MPSI Model for MCDM Problems

The present section introduces a hybrid framework combining the DEs' weighting model, IF-aggregation operators, and integrated criteria weight-estimating model on IFSs. In the model, we present score function-based structure to obtain the weights of DEs and further aggregate an individual decision opinion of DE into an aggregated decision-matrix. Later, we integrate weight-estimating approach of attributes with WENSLO and MPSI methods on IFSs and obtain an integrated weight of each criterion. For this aim, let us consider an IF-information-based MCDM problem assuming a set of options $M=\{M_1,M_2,\ldots,M_r\}$, which has to be evaluated over criteria set $F=\{F_1,F_2,\ldots,F_s\}$. To choose an optimal alternative, a committee of 'n' DEs $L=\{L_1,L_2,\ldots,L_n\}$ is created

Table 2
Comparative results of developed and existing IF-distance measures.

IF-distance formulae	Case-1	Case-2	Case-3	Case-4	Case-5	Case-6
	$B_1 = \{(v_1, 0.8, 0.2)\}$	$B_2 = \{(v_1, 0.4, 0.6)\}$	$B_3 = \{(v_1, 0.41, 0.2)\}$	$B_4 = \{(v_1, 0.5, 0.45)\}$	$B_5 = \{(v_1, 1, 0)\}$	$B_6 = \{(v_1, 0.31, 0.41)\}$
	$E_1 = \{(v_1, 0, 0)\}$	$E_2 = \{(v_1, 0, 0)\}$	$E_3 = \{(v_1, 0.22, 0.28)\}$	$E_4 = \{(v_1, 0.55, 0.4)\}$	$E_5 = \{(v_1, 0, 1)\}$	$E_6 = \{(v_1, 0.51, 0.338)\}$
Ngan *et al.* (2018): $d_1(B,E) = \frac{1}{3}(\lvert\mu_1-\mu_2\rvert + \lvert\nu_1-\nu_2\rvert + \lvert\max\{\mu_1,\nu_2\} - \max\{\mu_2,\nu_1\}\rvert)$	0.533	0.4	0.1	0.05	**0.333**	0.148
$d_2(B,E) = (\frac{\lvert\mu_1-\mu_2\rvert+\lvert\nu_1-\nu_2\rvert}{4} + \frac{\lvert\max\{\mu_1,\nu_2\}-\max\{\mu_2,\nu_1\}\rvert}{2})$	0.55	0.35	0.125	0.05	**0.5**	0.154
Ejegwa and Agbetayo (2023): $d_3(B,E) = 1 - (\sqrt{\mu_1\mu_2} + \sqrt{\nu_1\nu_2} + \sqrt{\pi_1\pi_2})$	**1**	**1**	0.022	0.001	1	0.024
Li *et al.* (2023): $d_4(B,E) = \frac{1}{\sqrt{2}}\sqrt{(\sqrt{\mu_1}-\sqrt{\mu_2})^2 + (\sqrt{\nu_1}-\sqrt{\nu_2})^2 + (\sqrt{\pi_1}-\sqrt{\pi_2})^2}$	**1**	**1**	**0.15**	0.036	1	**0.15**
Rani and Kumar (2023): $d_5(B,E) = \tan(\frac{\pi}{4}\max\{\lvert\mu_1-\mu_2\rvert, \lvert(1-\nu_1)-(1-\nu_2)\rvert\})$	0.727	0.51	0.154	0.039	1	0.158
Kumar and Kumar (2024): $d_6(B,E) = \frac{1}{5}\begin{pmatrix} \lvert\mu_1-\mu_2\rvert + \lvert\nu_1-\nu_2\rvert \\ + \lvert\frac{\mu_1+1-\nu_1}{2} - \frac{\mu_2+1-\nu_2}{2}\rvert \\ + \lvert\max\{\mu_1,\nu_2\} - \max\{\nu_1,\mu_2\}\rvert \\ + \lvert\min\{\mu_1,\nu_2\} - \min\{\nu_1,\mu_2\}\rvert \end{pmatrix}$	0.38	0.26	**0.14**	0.05	1	**0.14**
Mishra *et al.* (2025): $d_7(B,E) = \frac{1}{2(e-1)}\begin{pmatrix} \frac{\mu_1+1-\nu_1}{2}e^{(\frac{\mu_1+1-\nu_1}{2}-\frac{\mu_2+1-\nu_2}{2})} \\ + \frac{\nu_1+1-\mu_1}{2}e^{(\frac{\nu_1+1-\mu_1}{2}-\frac{\nu_2+1-\mu_2}{2})} \\ + \frac{\mu_2+1-\nu_2}{2}e^{(\frac{\mu_2+1-\nu_2}{2}-\frac{\mu_1+1-\nu_1}{2})} \\ + \frac{\nu_2+1-\mu_2}{2}e^{(\frac{\nu_2+1-\mu_2}{2}-\frac{\nu_1+1-\mu_1}{2})} - 2 \end{pmatrix}$	0.08	0.009	**0.016**	0.002	1	**0.016**
d (Proposed)	0.444	0.6	0.491	0.032	1	0.609

*Bold denotes counter-intuitive results.

Table 3
Linguistic ratings with their corresponding IFNs.

LVs	IFNs
Absolutely high/good (AH/AG)	(0.95, 0.05)
Very very high/good (VVH/VVG)	(0.85, 0.10)
Very high/good (VH/VG)	(0.80, 0.15)
High/Good (H/G)	(0.70, 0.20)
Fairly high/Good (FH/FG)	(0.60, 0.30)
Average (A)	(0.50, 0.40)
Moderately low/bad (ML/MB)	(0.40, 0.50)
Low/Bad (L/B)	(0.30, 0.60)
Very low/ bad (VL/VB)	(0.20, 0.70)
Very very low/bad (VVL/VVB)	(0.10, 0.80)
Extremely low/bad (EL/EB)	(0.05, 0.95)

and asked them to use linguistic value (LV) for rating the performance of alternatives and criteria. Table 3 presents the LVs and their corresponding IFNs, adopted from Mishra *et al.* (2025).

Step 1: Derive the weights of experts.

In this step, we introduce a procedure to determine weights of DEs. First, consider that $\vartheta_i = (\mu_i, \nu_i)$, $i = 1, 2, \dots, n$ be an IFV associated to the LV defined as rating of significance of ith expert. Considering the following Eqs. (8)–(10), the numeric weight of ith DE is determined, where $i = 1, 2, \dots, n$.

Substep 1.1: Taking into account the proposed IF-score function in Eq. (6), the normalized assessment rating of ith DE is calculated, where $i = 1, 2, \dots, n$.

$$\varpi_i^o = \frac{(Y(\vartheta_i) \cdot \{abs(\mu - \nu) + (\mu + \nu)\} + 1)}{\sum_{i=1}^{n}(Y(\vartheta_i) \cdot \{abs(\mu - \nu) + (\mu + \nu)\} + 1)}, \quad i = 1, 2, \dots, n, \tag{8}$$

where $Y(\vartheta_i) = \operatorname{sgn}(\mu_i - \nu_i)$, $\operatorname{sgn}(.)$ and $abs(\cdot)$ represent the sign function and the absolute value function, respectively.

Substep 1.2: In virtue of Eq. (8), acquire the rank (ra_i) of ith expert. Next, compute performance score of ith experts by means of the rank reciprocal formula (9).

$$\varpi_i^s = \frac{1/ra_i}{\sum_{i=1}^{n}(1/ra_i)}, \quad i = 1, 2, \dots, n. \tag{9}$$

Substep 1.3: With the combination of Eqs. (8) and (9), compute the collective significance degree/weight of ith expert, given by Eq. (10).

$$\varpi_i = \alpha\big(\varpi_i^o\big) + (1 - \alpha)\big(\varpi_i^s\big), \quad i = 1, 2, \dots, n, \tag{10}$$

wherein $\alpha \in [0, 1]$ signifies the strategic parameter to derive the numeric weight of ith expert. Moreover, $\varpi = (\varpi_1, \varpi_2, \dots, \varpi_n)^T$ represents the weight vector of DEs with $\varpi_i \in [0, 1]$ and $\sum_{i=1}^{n} \varpi_i = 1$.

Step 2: Create the linguistic performance matrix (LPM).

In this step, a LPM $Z = (z_{jk}^{(i)})$ is created on the basis of experts' linguistic opinions, in which each element $z_{ik}^{(i)}$ denotes LV of an alternative M_j over diverse criterion F_k presented by ith DE.

Step 3: Aggregate the experts' opinions.

To make a group decision, we require to combine diverse opinions of DEs related to each option over each criterion. To this aim, an IFWA operator (Xu, 2007) is applied to construct an intuitionistic fuzzy aggregated decision-matrix (IFADM) $\bar{Z} = (\bar{z}_{jk})_{r\times s}$, where

$$\begin{aligned}\bar{z}_{jk} &= (\bar{\mu}_{jk}, \bar{\nu}_{jk}) = IFWA_{\varpi_i}\big(z_{jk}^{(1)}, z_{jk}^{(2)}, \dots, z_{jk}^{(n)}\big)\\ &= \left(1 - \prod_{i=1}^{n}\big(1-\mu_{jk}^{(i)}\big)^{\varpi_i}, \prod_{i=1}^{n}\big(\nu_{jk}^{(i)}\big)^{\varpi_i}\right).\end{aligned} \tag{11}$$

Step 4: Determine the objective weights by IF-WENSLO model.

Substep 4.1: Normalize the input information.

Construct the normalized decision-matrix $\widehat{Z} = (\widehat{z}_{jk})_{r\times s}$, where

$$\widehat{z}_{jk} = \frac{S(\bar{z}_{jk})}{\sum_{j=1}^{r} S(\bar{z}_{jk})}, \tag{12}$$

and $S(\bar{z}_{jk})$ $(j = 1, 2, \dots, r, k = 1, 2, \dots, s)$ can be calculated through Eq. (6).

Substep 4.2: Compute the criterion class interval.

Taking into account Sturges' rule, find the criterion class interval $(\Delta\widehat{z}_k)$ using Eq. (13).

$$\Delta\tilde{z}_k = \frac{\max_{j=1,2,\dots,r}\widehat{z}_{jk} - \min_{j=1,2,\dots,r}\widehat{z}_{jk}}{1 + 3.332\log(r)}. \tag{13}$$

Substep 4.3: Compute the slope of criterion.

Considering the criterion class interval, the slope of each criterion is computed through Eq. (14).

$$\tan\theta_k = \frac{\sum_{j=1}^{r}\widehat{z}_{jk}}{(r-1)\Delta\widehat{z}_k}, \quad k = 1, 2, \dots, s. \tag{14}$$

Substep 4.4: Derive the envelope of criterion.

On the basis of criterion class interval, the envelope of each criterion is computed by Eq. (15).

$$\rho_k = \sum_{j=1}^{r-1}\sqrt{(\widehat{z}_{(j+1)k} - \widehat{z}_{jk})^2 + (\Delta\widehat{z}_{jk})^2}, \quad k = 1, 2, \dots, s. \tag{15}$$

Substep 4.5: Determine the envelope-slope ratio.

In accordance with previous steps, the ratio of envelope-slope of kth criterion is estimated using Eq. (16).

$$\alpha_k = \frac{\rho_k}{\tan\theta_k}, \quad k = 1, 2, \dots, s. \tag{16}$$

Substep 4.6: Derive the objective weight of criterion.

Considering the envelope-slope ratio of each criterion, the objective assessment degree 'w_k^o' of kth criterion is determined via Eq. (17).

$$w_k^o = \frac{\alpha_k}{\sum_{k=1}^{s} \alpha_k}, \quad k = 1, 2, \dots, s. \tag{17}$$

Step 5: Derive the subjective weights by IF-MPSI model.

Substep 5.1: In this step, each expert gives the linguistic assessment rating of each criterion using Table 3. Then, find the IF-score of each IF-assessment rating of criterion by means of Eq. (6) and build the IF-score matrix $A = (A_{ik})_{n\times s}$. Here, A_{ik} signifies the attained IF-score value of each entry of IFADM, wherein $i = 1, 2, \dots, n$ and $k = 1, 2, \dots, s$.

Substep 5.2: Normalize the IF-score decision-matrix $A = (A_{ik})_{n\times s}$ and construct the normalized IFADM $\bar{A} = (\bar{A}_{ik})_{n\times s}$, where $\bar{A}_{ik} = \frac{A_{ik}}{A_k^{\max}}$ and $A_k^{\max}$ is the maximum value for each criterion.

Substep 5.3: Compute the average score through Eq. (18).

$$A_k = \frac{1}{n}\sum_{i=1}^{n} \bar{A}_{ik}. \tag{18}$$

Substep 5.4: Calculate the degree of preference variation taking into account the proposed IF-distance measure using Eq. (19).

$$\varphi_k = \frac{1}{n}\sum_{i=1}^{n} D(\bar{A}_{ik}, A_k) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\max\{S(\bar{A}_{ik}), S(A_k)\} - \min\{S(\bar{A}_{ik}), S(A_k)\}}{\max\{S(\bar{A}_{ik}), S(A_k)\}}\right). \tag{19}$$

Substep 5.5: Compute the subjective weight of kth criterion through Eq. (20).

$$w_k^s = \frac{\varphi_k}{\sum_{k=1}^{s} \varphi_k}, \quad k = 1, 2, \dots, s. \tag{20}$$

Step 6: Determine the assessment degree of criterion.

With the amalgamation of objective and subjective assessment degrees by IF-WENSLO and IF-MPSI methods, respectively, a collective assessment degree of each criterion is computed using Eq. (21).

$$w_k = \zeta w_k^o + (1 - \zeta) w_k^s, \quad k = 1, 2, \dots, s, \tag{21}$$

where $\zeta \in [0, 1]$ signifies the decision precision factor. Generally, we take $\zeta = 0.5$. If $\zeta = 0$, then Eq. (21) considers only subjective assessment degree via IF-MPSI model, while if $\zeta = 1$, then Eq. (21) only computes the objective assessment degree through IF-WENSLO model. On the other hand, if $\zeta = 0.5$, then the combined weight is obtained as an average of objective and subjective weights of criteria.

Step 7: Rank the criteria as per the descending values of assessment degrees.

Based on the assessment degrees, SLSS adoption enablers are ranked in descending order. It must be pointed that the SLSS adoption enablers with maximum degree signifies the most significant enabler among the other SLSS adoption enablers in Indian electric manufacturing organizations. The systematic steps of the proposed method are given by Algorithm 1.

Algorithm 1 Proposed IF-WENSLO-MPSI methodology for assessing the SLSS adoption enablers

1. Compute the experts' weights using Eqs. (8)–(10).
2. Construct the LPM.
3. Using Eq. (11), create an IFADM.
4. Derive the objective assessment degrees of enablers by IF-WENSLO method, given by Eqs. (12)–(17).
5. Compute the subjective assessment degrees of enablers through IF-MPSI model, given by Eqs. (18)–(20).
6. Determine the assessment degree of criterion using IF-WENSLO-MPSI method by Eq. (21).
7. Rank the criteria.

5. Results and Discussion

In this section, we present an application of enablers assessment for SLSS adoption in Indian electric manufacturing organizations. Next, sensitivity and comparative discussions are provided to confirm the validity of obtained outcomes.

5.1. *Case Study: SLSS Enablers Assessment for Electric Manufacturing Companies*

For this case study, we selected five electric manufacturing companies of Lucknow, Uttar Pradesh. These companies produce high-quality electrical components to meet the demanding needs of various industries. We adopted five electric manufacturing companies and named as Company-1 (M_1), Company-2 (M_2), Company-3 (M_3), Company-4 (M_4) and Company-5 (M_5) to ensure confidentiality. To identify the SLSS enablers, an inclusive literature review was conducted by identifying the key terms "Sustainable Lean Six Sigma", "Lean Six Sigma", "Manufacturing" and "Enablers". Later, an experts' committee is formed with four experts to participate in the assessment of considered SLSS adoption enablers. Table 4 presents the list of identified enablers for SLSS adoption, together with their sources.

Table 4
Enablers for SLSS adoption with their sources.

Enablers	Description	Source
Organizational culture (F_1)	It can be defined as how workers communicate at work. It encourages the workers to form positive relationships at work.	Knapp, 2015; Parmar and Desai, 2020; Naveed *et al.*, 2022
Quality characteristics of raw materials (F_2)	It can affect the safety, potency, purity, quality, and efficacy of a product.	Pandey *et al.*, 2018; Parmar and Desai, 2020; Utama and Abirfatin, 2023
Effective scheduling (F_3)	Proper scheduling can help ensure the effective use of equipment. It also reduces lead time, improving productivity, performance, and cost.	Cherrafi *et al.*, 2016; Hossain *et al.*, 2023; Tuominen *et al.*, 2023; Utama and Abirfatin, 2023
Remain competitive in the global market (F_4)	To stay in the market, organisations should stay ahead of consumer trends. They can remain on top by regularly analysing customer, business, marketing, and organisational data.	Cherrafi *et al.*, 2016; Pandey *et al.*, 2018; Parmar and Desai, 2020; Utama and Abirfatin, 2023
Enhance customer satisfaction (F_5)	Reducing lead time and increasing product quality and reliability can improve customer satisfaction.	Hossain *et al.*, 2023; Tuominen *et al.*, 2023; Utama and Abirfatin, 2023
Effective communication and updated data information (F_6)	It refers to creating an effective and positive environment in a company.	Cherrafi *et al.*, 2016; Pandey *et al.*, 2018; Parmar and Desai, 2020
Quality control management (F_7)	It plays a vital role in detecting, averting, and correcting product defects, while meeting customer requirements.	Cherrafi *et al.*, 2016; Pandey *et al.*, 2018; Parmar and Desai, 2020
Green design principles (F_8)	It aims to minimize adverse environmental impacts of a product.	Cherrafi *et al.*, 2016; Pandey *et al.*, 2018; Parmar and Desai, 2020
Linking SLSS to business strategies (F_9)	It considers efficiency and precision to optimize processes within a company while embedding sustainability at the core of quality and continuous improvement.	Cherrafi *et al.*, 2016; Pandey *et al.*, 2018; Parmar and Desai, 2020
Initiative to use environmentally friendly packaging of products (F_{10})	The organization should focus on bio-degradable or recyclable packaging materials. This initiative builds a positive image of the organization as a green product in the market.	Parmar and Desai, 2020; Hossain *et al.*, 2023; Utama and Abirfatin, 2023
Employee involvement and motivation (F_{11})	It refers to maintaining a supportive environment for the cooperative development of a company.	Pandey *et al.*, 2018; Parmar and Desai, 2020; De Medeiros *et al.*, 2025
Environmental management system (F_{12})	It is a mechanism to improve and standardize environmental standard practices around the globe.	Pandey *et al.*, 2018; Parmar and Desai, 2020; Singh *et al.*, 2021
Government policies (F_{13})	It refers to the rules and regulations enforced by the government authorities to change and control the behaviour of an organization.	Pandey *et al.*, 2018; Parmar and Desai, 2020; Singh *et al.*, 2021

Here, we present the execution steps of proposed IF-WENSLO-MPSI methodology for assessing and prioritizing the SLSS adoption enablers at the five electric companies of Lucknow.

Table 5
The DE's weight for assessing the SLSS enablers in manufacturing sector.

DEs	L_1	L_2	L_3	L_4
LVs	VG	G	VVG	AG
Score degrees	0.770	0.840	0.8925	0.950
ϖ_i^o	0.816	0.796	0.826	0.845
ra_i	0.249	0.242	0.252	0.257
$1/\ ra_i$	0.25	1	0.5	0.333
ϖ_i^s	0.12	0.48	0.24	0.16
ϖ_i	0.184	0.361	0.246	0.209

Table 6
An LPM for assessing the SLSS enablers in manufacturing sector.

	M_1	M_2	M_3	M_4	M_5
F_1	(FH, ML, H, A)	(A, A, ML, FH)	(A, VH, ML, H)	(VVH, ML, FH, L)	(H, A, ML, VH)
F_2	(ML, H, L, FH)	(FH, VVH, ML, A)	(VVH, FH, ML, A)	(FH, L, H, L)	(H, FH, L, ML)
F_3	(A, L, A, H)	(H, ML, VH, H)	(H, FH, L, ML)	(VH, H, A, ML)	(VH, H, A, FH)
F_4	(A, FH, H, A)	(VH, A, H, A)	(ML, ML, FH, H)	(ML, FH, A, ML)	(H, ML, VL, A)
F_5	(FH, FH, H, A)	(ML, H, H, FH)	(FH, ML, A, H)	(ML, A, VH, H)	(VVH, H, VH, A)
F_6	(VH, FH, A, FH)	(A, VH, ML, A)	(VH, H, A, FH)	(H, A, FH, ML)	(H, FH, ML, FH)
F_7	(A, FH, L, A)	(H, ML, VH, A)	(ML, FH, A, A)	(FH, A, ML, H)	(H, VH, ML, A)
F_8	(FH, VH, VH, A)	(A, H, H,A)	(ML, A, FH, ML)	(A, FH, ML, FH)	(H,L, VL, FH)
F_9	(FH, FH, H, A)	(A, VH, H, FH)	(A, ML, H, ML)	(ML, VH, FH, A)	(VVH, H, FH, A)
F_{10}	(A, VH, H, FH)	(L, FH, H, A)	(A, FH, ML, H)	(FH, ML, FH, H)	(VH, A, VL, A)
F_{11}	(FH, ML, H, A)	(FH, FH, VH, ML)	(FH, VH, A, FH)	(H, A, FH, H)	(FH, FH, A, A)
F_{12}	(H, FH, ML, A)	(ML, FH, ML, A)	(H, VH, A, FH)	(VH, A, FH, A)	(H, A, FH, H)
F_{13}	(FH, A, H, FH)	(A, FH, H, FH)	(A, FH, ML, A)	(FH, ML, A, FH)	(H, A, VL, ML)

Step 1: Considering the LVs, we provide the linguistic significance of each expert by means of their knowledge, expertise and skills. Consequently, the weight of each expert is derived through Eqs. (8)–(10), and given in Table 5.

Step 2: Next, a LPM is created with the use of DEs' opinion to evaluate the SLSS adoption enablers in Indian electric manufacturing organizations with respect to each enabler, given in Table 6.

Step 3: By the use of DEs' weights in Eq. (11) and Table 6, an IFADM is formed to aggregate the individual opinions of experts into a group decision. Table 7 presents the required result of IFADM for assessing the SLSS enablers in manufacturing sector.

Step 4: In this step, we determine the objective weight/assessment degree of enablers through IF-WENSLO approach. The first step of this approach is to compute the score degree of each entry of IFADM and then by means of Eq. (12), the normalized decision-matrix is created and mentioned in Table 8.

The stepwise procedure of IF-WENSLO method is computed through Eqs. (12)–(17) and presented in Table 9, which consists of class interval, slope, envelope, ratio of envelope-slope and objective weights of enablers.

Table 7
An IFADM for assessing the SLSS enablers in manufacturing sector.

	M_1	M_2	M_3	M_4	M_5
F_1	(0.548, 0.347)	(0.501, 0.398)	(0.662, 0.257)	(0.566, 0.341)	(0.607, 0.303)
F_2	(0.554, 0.338)	(0.675, 0.243)	(0.614, 0.295)	(0.544, 0.403)	(0.526, 0.367)
F_3	(0.492, 0.401)	(0.651, 0.259)	(0.526, 0.367)	(0.635, 0.272)	(0.665, 0.245)
F_4	(0.593, 0.304)	(0.628, 0.282)	(0.530, 0.364)	(0.504, 0.394)	(0.454, 0.438)
F_5	(0.610, 0.288)	(0.638, 0.258)	(0.539, 0.356)	(0.629, 0.283)	(0.734, 0.190)
F_6	(0.628, 0.283)	(0.624, 0.296)	(0.665, 0.245)	(0.553, 0.344)	(0.581, 0.316)
F_7	(0.499, 0.398)	(0.612, 0.300)	(0.523, 0.376)	(0.549, 0.347)	(0.658, 0.261)
F_8	(0.725, 0.209)	(0.633, 0.263)	(0.492, 0.407)	(0.540, 0.359)	(0.449, 0.440)
F_9	(0.610, 0.288)	(0.698, 0.223)	(0.511, 0.383)	(0.648, 0.272)	(0.685, 0.225)
F_{10}	(0.698, 0.223)	(0.567, 0.328)	(0.566, 0.330)	(0.564, 0.332)	(0.526, 0.383)
F_{11}	(0.548, 0.347)	(0.633, 0.281)	(0.671, 0.251)	(0.613, 0.284)	(0.557, 0.342)
F_{12}	(0.561, 0.335)	(0.501, 0.397)	(0.688, 0.233)	(0.600, 0.311)	(0.613, 0.284)
F_{13}	(0.596, 0.301)	(0.612, 0.286)	(0.518, 0.381)	(0.511, 0.387)	(0.469, 0.423)

Table 8
IF-score and normalized decision-matrix for evaluating the SLSS enablers.

	M_1	M_2	M_3	M_4	M_5	M_1	M_2	M_3	M_4	M_5
F_1	0.762	0.75	0.788	0.766	0.775	0.198	0.195	0.205	0.199	0.202
F_2	0.763	0.791	0.777	0.761	0.756	0.198	0.205	0.202	0.198	0.197
F_3	0.748	0.785	0.756	0.782	0.788	0.194	0.203	0.196	0.203	0.204
F_4	0.772	0.78	0.757	0.751	0.738	0.203	0.205	0.199	0.198	0.194
F_5	0.776	0.782	0.76	0.78	0.803	0.199	0.201	0.195	0.2	0.206
F_6	0.78	0.779	0.788	0.763	0.769	0.201	0.201	0.203	0.197	0.198
F_7	0.75	0.777	0.756	0.762	0.787	0.196	0.203	0.197	0.199	0.205
F_8	0.801	0.781	0.748	0.76	0.737	0.209	0.204	0.195	0.199	0.193
F_9	0.776	0.795	0.753	0.785	0.793	0.199	0.204	0.193	0.201	0.203
F_{10}	0.795	0.766	0.766	0.765	0.756	0.207	0.199	0.199	0.199	0.196
F_{11}	0.762	0.781	0.79	0.777	0.764	0.197	0.202	0.204	0.201	0.197
F_{12}	0.765	0.75	0.793	0.774	0.777	0.198	0.194	0.206	0.201	0.201
F_{13}	0.773	0.777	0.754	0.753	0.742	0.203	0.204	0.199	0.198	0.195

Table 9
Class interval, slope values, envelop, ratio of envelope-slope and objective weight of SLSS enablers.

	Class interval	Slope	Envelope	Ratio of envelope-slope	Objective weight
F_1	0.0015	162.79	0.0121	0.0001	0.0839
F_2	0.0014	179.94	0.0091	0.0001	0.0576
F_3	0.0016	152.86	0.014	0.0001	0.1041
F_4	0.0017	144.78	0.0075	0.0001	0.059
F_5	0.0017	143.34	0.0101	0.0001	0.0796
F_6	0.001	242.27	0.0072	0.00003	0.0339
F_7	0.0015	164.27	0.0112	0.0001	0.0775
F_8	0.0026	95.13	0.0124	0.0001	0.1481
F_9	0.0017	145.51	0.0148	0.0001	0.1151
F_{10}	0.0016	157.42	0.0081	0.0001	0.0581
F_{11}	0.0011	220.79	0.0073	0.00003	0.0375
F_{12}	0.0018	142.78	0.0129	0.0001	0.1026
F_{13}	0.0014	176.26	0.0067	0.00004	0.043

Table 10
Significance degree of enablers for assessing the SLSS enablers in manufacturing sector.

	L_1	L_2	L_3	L_4	L_1	L_2	L_3	L_4
F_1	H	H	A	L	0.796	0.796	0.75	0.226
F_2	A	FH	A	FH	0.75	0.774	0.75	0.774
F_3	A	ML	L	H	0.75	0.25	0.226	0.796
F_4	H	L	A	A	0.796	0.226	0.75	0.75
F_5	L	FH	H	ML	0.226	0.774	0.796	0.25
F_6	A	H	FH	A	0.75	0.796	0.774	0.75
F_7	ML	A	H	L	0.25	0.75	0.796	0.226
F_8	FH	A	L	FH	0.774	0.75	0.226	0.774
F_9	ML	A	FH	ML	0.25	0.75	0.774	0.25
F_{10}	H	FH	ML	FH	0.796	0.75	0.25	0.774
F_{11}	A	ML	A	H	0.226	0.204	0.774	0.25
F_{12}	ML	A	FH	L	0.25	0.75	0.774	0.226
F_{13}	H	ML	L	FH	0.796	0.25	0.226	0.774

Table 11
Subjective weight of enablers using IF-MPSI method for assessing the SLSS enablers in manufacturing sector.

	Normalized IF-score values				A_k	φ_k	w_k^s
	L_1	L_2	L_3	L_4			
F_1	1	1	0.942	0.284	0.807	0.204	0.0499
F_2	0.969	1	0.969	1	0.985	0.226	0.0553
F_3	0.942	0.314	0.284	1	0.635	0.401	0.0981
F_4	1	0.284	0.942	0.942	0.792	0.206	0.0505
F_5	0.284	0.972	1	0.314	0.643	0.405	0.0991
F_6	0.942	1	0.972	0.942	0.964	0.152	0.0372
F_7	0.314	0.942	1	0.284	0.635	0.401	0.0981
F_8	1	0.969	0.292	1	0.815	0.226	0.0553
F_9	0.323	0.969	1	0.323	0.654	0.38	0.0928
F_{10}	1	0.942	0.314	0.972	0.807	0.204	0.0499
F_{11}	0.292	0.264	1	0.323	0.47	0.486	0.1189
F_{12}	0.323	0.969	1	0.292	0.646	0.392	0.0958
F_{13}	1	0.314	0.284	0.972	0.643	0.405	0.0991

Step 5: To compute the assessment degree of SLSS enablers using IF-MPSI model, each expert provides the linguistic assessment rating to the performance of each enabler and further converts into IFNs through Table 3. Next, find the score degree of individual performance value of enabler given by DEs using the proposed IF-score formula and consequently, IF-score matrix is formed in Table 10. Afterward, the IF-score matrix is normalized and presented in Table 11. In line with normalized values, the average normalized IF-score rating of enablers is computed by Eq. (18). Applying Eq. (19), the degree of preference variation of enablers for SLSS enablers is determined based on the proposed IF-distance formula, and finally, the subjective weight of enablers for SLSS adoption is calculated by utilizing Eq. (20) and displayed in Table 11.

Steps 6–7: By virtue of Eq. (21), the collective assessment degrees of enablers are computed for $\zeta = 0.5$ and given as $w_k = (0.0669, 0.0565, 0.1011, 0.0547, 0.0894, 0.0355,$

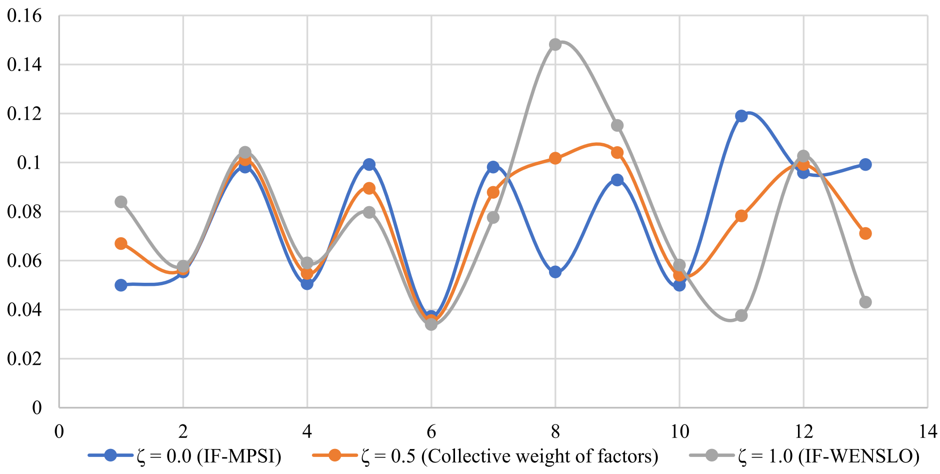

Fig. 1. Representation of obtained assessment degrees by IF-WENSLO, IF-MPSI and IF-WENSLO-MPSI models.

0.0878, 0.1017, 0.104, 0.054, 0.0782, 0.0992, 0.071). After calculating the assessment degrees through Step 6, the ranking order of considered sustainable lean six sigma enablers is obtained as per their decreasing assessment degrees. Thus, the enabler "Linking SLSS to business strategies (F_9)" has maximum weight in implementing SLSS principles in manufacturing sector, following "Green design principles (F_8)", "Effective scheduling (F_3)", "Environmental management system (F_{12})", "Enhance customer satisfaction (F_5)", "Quality control management (F_7)", "Employee involvement and motivation (F_{11})", "Government policies (F_{13})", "Organizational culture (F_1)", "Quality characteristics of raw materials (F_2)", "Remain competitive in the global market (F_4)", "Initiative to use environmentally friendly packaging of products (F_{10})" and "Effective communication and updated data information (F_6)". Figure 1 shows the assessment degrees of enablers for SLSS adoption in manufacturing sector.

5.2. *Sensitivity Analysis*

In the part, we emphasize the importance of conducting sensitivity analysis with respect to strategic parameter 'α' and decision precision factor 'ζ' while ranking SLSS enablers in the manufacturing sector. In the following two phases, we analyse the impact of sensitivity analysis on the acquired outcomes.

Phase 1 (*Sensitivity analysis over strategic parameter* 'α'): In IF-WENSLO-MPSI model, experts' weights are computed through an integrated weighting model, consisting of a strategic parameter 'α', where $\alpha \in [0, 1]$. In this phase, we consider some different values of 'α' and, accordingly, compute the assessment degrees of SLSS enablers. Thus, a set of scenarios is obtained and the effect of variations on the final result is examined in Table 12. Figure 2 presents the pictorial representation of sensitivity analysis with respect to strategy coefficient ($0 \leqslant \alpha \leqslant 1$). As per an observation on Table 12, it seems that IF-

Table 12
Influences of the changing strategic parameter (α) on the enablers' assessment degrees.

	$\alpha=0.0$	$\alpha=0.1$	$\alpha=0.2$	$\alpha=0.3$	$\alpha=0.4$	$\alpha=0.5$	$\alpha=0.6$	$\alpha=0.7$	$\alpha=0.8$	$\alpha=0.9$	$\alpha=1.0$
F_1	0.0268	0.0267	0.0265	0.0264	0.0275	0.0669	0.0651	0.0631	0.0607	0.0582	0.056
F_2	0.029	0.0289	0.0287	0.0286	0.0294	0.0565	0.0553	0.0542	0.0528	0.0514	0.0502
F_3	0.0507	0.0507	0.0507	0.0507	0.052	0.1011	0.1023	0.1033	0.1044	0.1062	0.1071
F_4	0.2597	0.2606	0.2615	0.2623	0.0269	0.0547	0.0561	0.0578	0.0598	0.062	0.0644
F_5	0.0512	0.0511	0.051	0.0509	0.0519	0.0894	0.0884	0.0873	0.0858	0.0842	0.0821
F_6	0.0192	0.0191	0.0191	0.0191	0.0195	0.0355	0.0365	0.0377	0.039	0.0404	0.0417
F_7	0.0501	0.0501	0.0501	0.0502	0.0512	0.0878	0.0907	0.0938	0.0968	0.0997	0.1032
F_8	0.2785	0.2783	0.2782	0.2779	0.5029	0.1017	0.0991	0.0963	0.0929	0.0893	0.0879
F_9	0.0487	0.0486	0.0485	0.0483	0.0498	0.104	0.1024	0.1009	0.1006	0.1	0.0986
F_{10}	0.0261	0.0261	0.026	0.0259	0.0267	0.054	0.0533	0.0524	0.0512	0.0498	0.0488
F_{11}	0.0604	0.0603	0.0602	0.0601	0.0606	0.0782	0.0769	0.0756	0.075	0.0745	0.0739
F_{12}	0.0494	0.0494	0.0494	0.0494	0.0507	0.0992	0.1018	0.1045	0.1068	0.109	0.1102
F_{13}	0.0502	0.0502	0.0502	0.0502	0.0507	0.071	0.0721	0.0732	0.0742	0.0751	0.0758

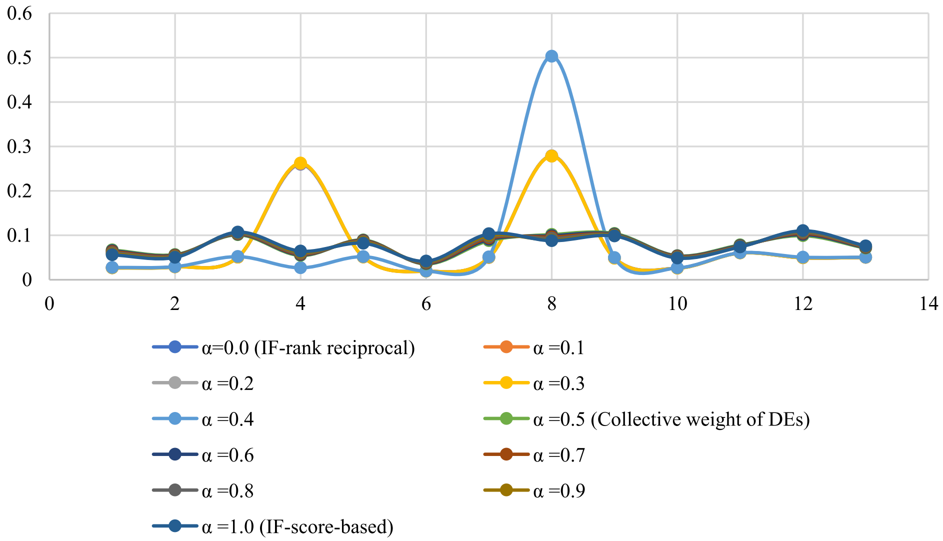

Fig. 2. Results of the sensitivity analysis over strategic parameter (α).

WENSLO-MPSI model has a reasonable sensitivity to changes in the experts' strategic parameter.

Phase 2 (*Sensitivity analysis over decision precision factor* 'ζ'): Employing the IF-WENSLO-MPSI model, the objective and subjective weights of enablers are incorporated by means of a decision precision factor 'ζ', where $\zeta \in [0, 1]$. To see the impact of this factor, we consider some different values of 'ζ' and, correspondingly, determine the assessment degrees of SLSS enablers. Therefore, a set of scenarios is obtained in Table 13. Figure 3 presents the pictorial representation of sensitivity analysis with respect to decision precision factor. As per an observation on Table 13, it seems that IF-WENSLO-MPSI model has a reasonable sensitivity to changes in the enablers' weighting coefficient.

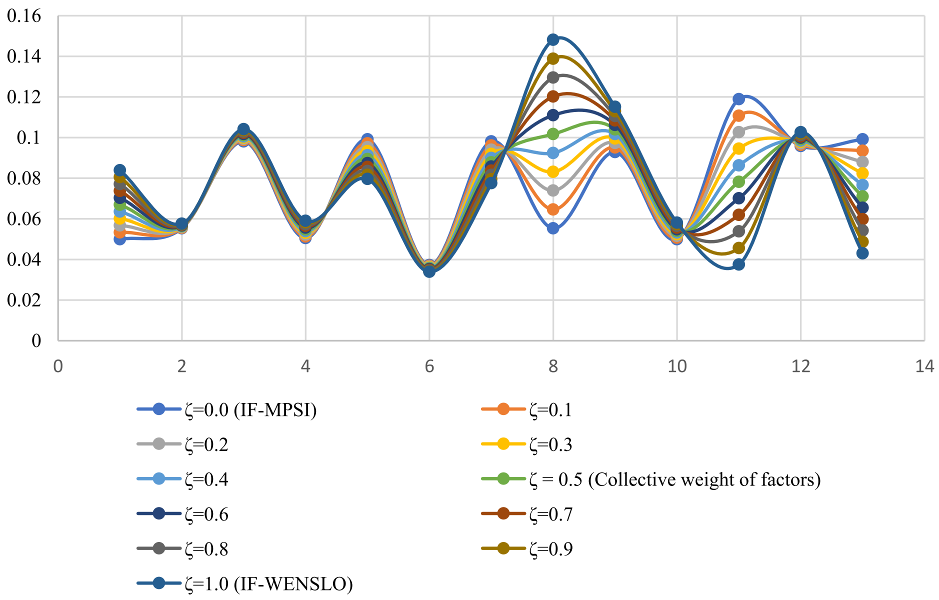

Fig. 3. Results of the sensitivity analysis over decision precision factor (ζ).

Table 13
Influences of the changing decision precision factor (ζ) on the enablers' assessment degrees.

	$\zeta=0.0$	$\zeta=0.1$	$\zeta=0.2$	$\zeta=0.3$	$\zeta=0.4$	$\zeta=0.5$	$\zeta=0.6$	$\zeta=0.7$	$\zeta=0.8$	$\zeta=0.9$	$\zeta=1.0$
F_1	0.0499	0.0533	0.0567	0.0601	0.0635	0.0669	0.0703	0.0737	0.0771	0.0805	0.0839
F_2	0.0553	0.0555	0.0558	0.056	0.0562	0.0565	0.0567	0.0569	0.0571	0.0574	0.0576
F_3	0.0981	0.0987	0.0993	0.0999	0.1005	0.1011	0.1017	0.1023	0.1029	0.1035	0.1041
F_4	0.0505	0.0513	0.0522	0.053	0.0539	0.0547	0.0556	0.0565	0.0573	0.0582	0.059
F_5	0.0991	0.0971	0.0952	0.0933	0.0913	0.0894	0.0874	0.0855	0.0835	0.0816	0.0796
F_6	0.0372	0.0368	0.0365	0.0362	0.0358	0.0355	0.0352	0.0349	0.0345	0.0342	0.0339
F_7	0.0981	0.0961	0.094	0.0919	0.0899	0.0878	0.0857	0.0837	0.0816	0.0795	0.0775
F_8	0.0553	0.0646	0.0739	0.0831	0.0924	0.1017	0.111	0.1202	0.1295	0.1388	0.1481
F_9	0.0928	0.0951	0.0973	0.0995	0.1017	0.104	0.1062	0.1084	0.1106	0.1129	0.1151
F_{10}	0.0499	0.0507	0.0516	0.0524	0.0532	0.054	0.0548	0.0556	0.0565	0.0573	0.0581
F_{11}	0.1189	0.1107	0.1026	0.0945	0.0863	0.0782	0.0701	0.0619	0.0538	0.0456	0.0375
F_{12}	0.0958	0.0964	0.0971	0.0978	0.0985	0.0992	0.0999	0.1005	0.1012	0.1019	0.1026
F_{13}	0.0991	0.0935	0.0879	0.0823	0.0766	0.071	0.0654	0.0598	0.0542	0.0486	0.043

5.3. *Comparison with Existing Approaches*

In this part, the proposed IF-WENSLO-MPSI methodology is compared with the IF-MEREC-RS method (Rani *et al.*, 2025), IF-SWARA (Ziquan *et al.*, 2025), IF-SPC-RS (Hezam *et al.*, 2023) and IF-entropy-SWARA (Li *et al.*, 2023) for the aforementioned case study of SLSS enablers in the manufacturing sector. Figure 4 displays the ranking results of SLSS adoption enablers by different methods.

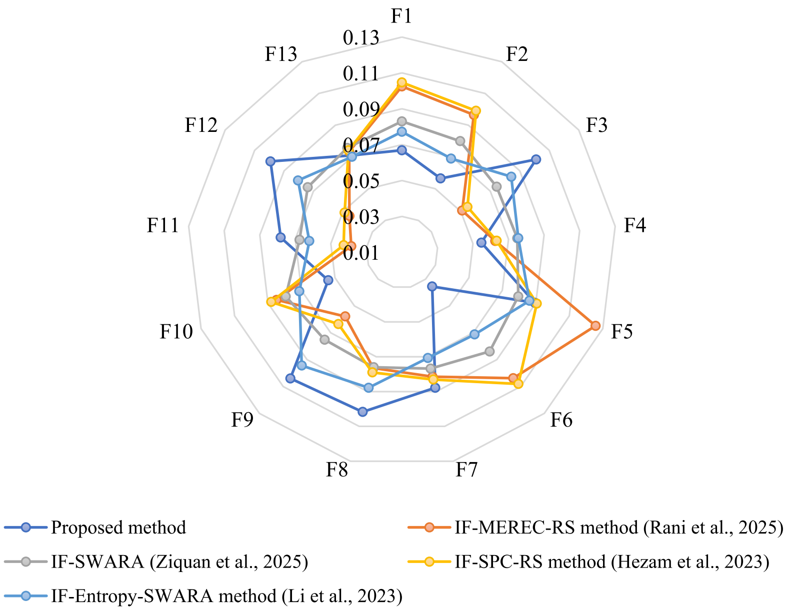

Fig. 4. Ranking results by the proposed and existent methods.

5.3.1. *IF-MEREC-RS Method*

After applying the IF-MEREC-RS method (as given by Algorithm 2) on the aforesaid case study, we need to normalize the IFADM. However, all the enablers are of the same nature, so there is no need to use Eq. (22). Next, we get the overall performance degree of each company using Eq. (23) $O_1 = 0.374$, $O_2 = 0.35$, $O_3 = 0.388$, $O_4 = 0.392$ and $O_5 = 0.389$. The subsequent steps of IF-MEREC model are presented in Table 14, followed by the performance value of each option by removing each enabler through Eq. (24), summing the absolute difference of O_{jk}^{P} and O_k via Eq. (25) and the objective weight of each enabler with Eq. (26).

To measure the subjective assessment degree of SLSS adoption enablers, the DEs are asked to evaluate the enablers using LVs, see Table 15. Next, individual linguistic ratings are combined through IFWA operator. Consequently, the score values of aggregated elements are calculated and shown in Table 15. Next, the enablers are ranked as per the descending values of score degrees and lastly, the subjective assessment degrees of enablers are computed via Eq. (28), mentioned in Table 15.

Combining the results of IF-MEREC and IF-RS methods, an integrated assessment degree of each enabler for SLSS adoption is computed as $w_k = (0.1025, 0.0965, 0.0509, 0.0625, 0.1257, 0.1038, 0.0815, 0.0765, 0.0578, 0.0849, 0.0385, 0.0456, 0.0734)$. In line with the acquired result, the enabler "Enhance customer satisfaction (F_5)" has maximum preference among the others in successful implementation of SLSS.

5.3.2. *IF-SWARA Model*

Applying IF-SWARA (as given by Algorithm 3) on the aforesaid case study, the score values of enablers are obtained as per the aggregated ratings in Table 15 and, sub-

Algorithm 2 IF-MEREC-RS methodology (Rani *et al.*, 2025)

1. Steps 1–3 are similar to the proposed IF-WENSLO-MPSI model.
2. Determination of objective weight of enablers through IF-MEREC model, given by Eqs. (22)–(26).
   - Create the normalized IFADM $T=(\omega_{jk})_{r\times s}$, where

$$\omega_{jk}=\begin{cases}\bar{z}_{jk}=(\mu_{jk},\nu_{jk}), & j\in F_b,\\ (\bar{z}_{jk})^c=(\nu_{jk},\mu_{jk}), & j\in F_n.\end{cases} \tag{22}$$

   - Construct the IF-score matrix $\tilde{T}=(\tilde{\omega}_{jk})_{r\times s}$, where $\tilde{\omega}_{jk}$ denotes the score function of Xu *et al.* (2015).
   - Find the overall performance degree of options via Eq. (23).

$$O_j=\ln\left(1+\left(\frac{1}{s}\sum_j\left|ln(\tilde{\omega}_{jk})\right|\right)\right). \tag{23}$$

   - Find the performance value of each option by removing each criterion through Eq. (24).

$$O_{jk}^P=\ln\left(1+\left(\frac{1}{s}\sum_{v,v\neq k}\left|\ln(\tilde{\omega}_{jv})\right|\right)\right). \tag{24}$$

   - Sum the absolute difference of O_{jk}^P and O_k by means of Eq. (25).

$$D_k=\sum_j\left|O_{jk}^P-O_j\right|. \tag{25}$$

   - Derive the objective weight using Eq. (26).

$$w_k^o=\frac{D_k}{\sum_{k=1}^s D_k},\quad k=1,2,\dots,s. \tag{26}$$

3. Determine the subjective weight of criteria through IF-RS model, given by Eq. (27).
   - Ask the experts to provide the linguistic assessment rating to each enabler.
   - Aggregate the individual performance rating into combined rating for each enabler using IFWA operator (Xu, 2007).
   - Compute the score degree of each aggregated rating using Xu *et al.*'s score function (Xu *et al.*, 2015).
   - Rank the enabler as per the descending values of score degrees.
   - Find the subjective weight via Eq. (28).

$$w_k^s=\frac{s-\varepsilon_k+1}{\sum_{k=1}^s(s-\varepsilon_k+1)},\quad \forall k. \tag{27}$$

   Here, 'ε_k' denotes the enabler's rank.
4. Determine the assessment degree of criterion using IF-MEREC-RS method by Eq. (28).

$$w_k=\zeta w_k^o+(1-\zeta)w_k^s,\quad k=1,2,\dots,s. \tag{28}$$

5. Rank the enabler.

Table 14
Objective assessment degree of each enabler for SLSS adoption using IF-MEREC model.

	Performance degrees					D_k	w_k^o
	M_1	M_2	M_3	M_4	M_5		
F_1	0.346	0.317	0.37	0.366	0.366	0.127	0.0732
F_2	0.347	0.332	0.366	0.363	0.36	0.125	0.0722
F_3	0.341	0.33	0.359	0.372	0.371	0.119	0.0688
F_4	0.35	0.328	0.36	0.361	0.353	0.141	0.081
F_5	0.352	0.33	0.219	0.371	0.375	0.246	0.1415
F_6	0.353	0.328	0.37	0.366	0.365	0.112	0.0647
F_7	0.342	0.327	0.359	0.365	0.37	0.13	0.075
F_8	0.359	0.329	0.356	0.364	0.353	0.132	0.076
F_9	0.352	0.333	0.358	0.372	0.372	0.105	0.0607
F_{10}	0.357	0.324	0.363	0.367	0.359	0.123	0.0708
F_{11}	0.346	0.329	0.37	0.371	0.363	0.115	0.066
F_{12}	0.347	0.317	0.372	0.369	0.367	0.12	0.0693
F_{13}	0.35	0.327	0.358	0.362	0.355	0.141	0.0809

Table 15
Subjective assessment degrees of enablers through IF-RS method.

	L_1	L_2	L_3	L_4	Aggregated IFNs	Crisp values	Rank	Weight
F_1	H	H	A	L	(0.594, 0.298)	0.648	2	0.1319
F_2	A	FH	A	FH	(0.560, 0.340)	0.61	3	0.1209
F_3	A	ML	L	H	(0.479, 0.415)	0.532	11	0.033
F_4	H	L	A	A	(0.486, 0.408)	0.539	10	0.044
F_5	L	FH	H	ML	(0.550, 0.343)	0.604	4	0.1099
F_6	A	H	FH	A	(0.606, 0.290)	0.658	1	0.1429
F_7	ML	A	H	L	(0.511, 0.383)	0.564	6	0.0879
F_8	FH	A	L	FH	(0.502, 0.395)	0.554	7	0.0769
F_9	ML	A	FH	ML	(0.492, 0.407)	0.542	9	0.0549
F_{10}	H	FH	ML	FH	(0.546, 0.350)	0.598	5	0.0989
F_{11}	A	ML	A	H	(0.380, 0.515)	0.433	13	0.011
F_{12}	ML	A	FH	L	(0.475, 0.423)	0.526	12	0.022
F_{13}	H	ML	L	FH	(0.496, 0.397)	0.55	8	0.0659

sequently, ranked. Next, we find the average rating of relative importance, degree of coefficient, initial weight and normalized weight through Eqs. (29)–(31), as presented in Table 16. Thus, the assessment degree of SLSS adoption enabler is $w_k = (0.083,$ $0.08, 0.0743, 0.0749, 0.0795, 0.0839, 0.0768, 0.076, 0.0751, 0.0794, 0.0676, 0.0739,$ $0.0757)$. Hence, the SLSS enabler "Effective communication and updated data information (F_6)" is ranked first among the others as per the given data.

5.3.3. *IF-SPC-RS method (Hezam* et al.*, 2023)*

Applying the IF-SPC-RS model (as given by Algorithm 4) on the aforesaid case study, we need to normalize the IFADM. However, all the enablers are of the same nature, so there is no need to normalize IFADM. Next, the score values of IFADM are computed through Xu *et al.*'s score function (Xu *et al.*, 2015) and then, symmetry value of each enabler is derived via Eq. (32). Table 17 presents the score values of IFADM along with the symmetry value of each enabler.

Algorithm 3 IF-SWARA methodology (Ziquan *et al.*, 2025)

1. Steps 1–3 are similar to the proposed IF-WENSLO-MPSI model.
2. Determine the weight of enablers through IF-SWARA model, given by Eqs. (29)–(31).
   – Ask the experts to provide the linguistic assessment rating to each enabler.
   – Aggregate the individual performance rating into combined rating for each enabler using IFWA operator (Xu, 2007).
   – Compute the score degree of each aggregated rating using Xu *et al.*'s score formula (Xu *et al.*, 2015).
   – Arrange the positions of enablers as per the descending values of score degrees.
   – Estimate the average rating (a_k) of relative importance that represents how the enabler at the kth place is more significant than the enabler at the $(k+1)$th place.
   – Find the degree of coefficient via Eq. (29).

$$\iota_k = \begin{cases} 1, & k = 1, \\ a_k + 1, & k > 1. \end{cases} \tag{29}$$

   – Determine the initial weight by Eq. (30).

$$\upsilon_k = \begin{cases} 1, & k = 1, \\ \frac{\upsilon_{k-1}}{\iota_k}, & k > 1. \end{cases} \tag{30}$$

   – Find the weight via Eq. (31).

$$w_k = \frac{\upsilon_k}{\sum_{k=1}^{s} \upsilon_k}, \quad k = 1, 2, \dots, s. \tag{31}$$

Table 16
Weight of enablers using IF-SWARA model for SLSS enablers in manufacturing sector.

	Score values	Average rating of relative importance	Degree of coefficient	Initial weights	Subjective weights
F_6	0.658	–	1.00	1.00	0.0839
F_1	0.648	0.010	1.010	0.9901	0.083
F_2	0.61	0.038	1.038	0.9539	0.08
F_5	0.604	0.006	1.006	0.9482	0.0795
F_{10}	0.598	0.002	1.002	0.9463	0.0794
F_7	0.564	0.034	1.034	0.9152	0.0768
F_8	0.554	0.010	1.010	0.9061	0.076
F_{13}	0.55	0.004	1.004	0.9025	0.0757
F_9	0.542	0.008	1.008	0.8953	0.0751
F_4	0.539	0.003	1.003	0.8926	0.0749
F	0.532	0.007	1.007	0.8864	0.0743
F_{12}	0.526	0.006	1.006	0.8811	0.0739
F_{11}	0.433	0.093	1.093	0.8061	0.0676

The subsequent steps consist of, respectively, calculating the matrix of absolute deviations (Eq. (33)), calculating the matrix of moduli of symmetry (Eq. (34)), calculating the modulus of symmetry of enabler (Eq. (35)), and finally determining the objective weight of each enabler through Eq. (36). Table 18 presents the matrix of absolute deviations ob-

Algorithm 4 IF-SPC-RS methodology (Hezam *et al.*, 2023)

1. Steps 1–3 are similar to the proposed IF-WENSLO-MPSI model.
2. Determination of objective weight of enablers through IF-SPC model, given by Eqs. (32)–(36).
   – Create the normalized IFADM $T = (\omega_{jk})_{r\times s}$, as per Algorithm 2.
   – Calculate the score degree (α_{jk}) of each element of normalized matrix, where $j = 1, 2, \dots, r$ and $k = 1, 2, \dots, s$.
   - Find the symmetry value of each enabler via Eq. (32).

$$\beta_k = \frac{\min\{\alpha_{jk}\} + \max\{\alpha_{jk}\}}{2}, \quad j = 1, 2, \dots, r, k = 1, 2, \dots, s. \tag{32}$$

   - Create the matrix of absolute deviations $D = (|d_{jk}|)_{r\times s}$ where d_{jk} is given by Eq. (33).

$$D = \big(|d_{jk}|\big)_{r\times s} = |\alpha_{jk} - \beta_k|, \quad j = 1, 2, \dots, r, \ k = 1, 2, \dots, s. \tag{33}$$

   – Construct the matrix of moduli of symmetry as

$$M = \big(|\bar{m}_{jk}|\big)_{r\times s} = \begin{pmatrix} \frac{\sum_{j=1}^{r} d_{i1}}{r.\alpha_{11}} & \frac{\sum_{j=1}^{r} d_{i2}}{s.\alpha_{12}} & \dots & \frac{\sum_{j=1}^{r} d_{is}}{r.\alpha_{1s}} \\ \frac{\sum_{j=1}^{r} d_{i1}}{r.\alpha_{21}} & \frac{\sum_{j=1}^{r} d_{i2}}{r.\alpha_{22}} & \dots & \frac{\sum_{j=1}^{r} d_{is}}{r.\alpha_{2s}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\sum_{j=1}^{r} d_{i1}}{r.\alpha_{r1}} & \frac{\sum_{j=1}^{r} d_{i2}}{r.\alpha_{r2}} & \dots & \frac{\sum_{j=1}^{r} d_{is}}{r.\alpha_{rs}} \end{pmatrix}_{r\times s}. \tag{34}$$

   – Compute the modulus of symmetry of enabler as

$$Q = (q_k) = \left(\frac{\sum_{j=1}^{r} \bar{m}_{j1}}{r} \frac{\sum_{j=1}^{r} \bar{m}_{j2}}{r} \dots \frac{\sum_{j=1}^{r} \bar{m}_{js}}{r}\right), \quad k = 1, 2, \dots, s. \tag{35}$$

   – Derive the objective weight using Eq. (36).

$$w_k^o = \frac{q_k}{\sum_{k=1}^{s} q_k}, \quad k = 1, 2, \dots, s. \tag{36}$$

3. Determine the subjective weight (w_k^s) of criteria through IF-RS model, given by IF-MEREC-RS model.
4. Determine the assessment degree of criterion using IF-SPC-RS method by Eq. (37).

$$w_k = \zeta w_k^o + (1 - \zeta) w_k^s, \quad k = 1, 2, \dots, s. \tag{37}$$

5. Rank the enabler.

tained through Eq. (33). Table 19 consists of results of matrix of moduli of symmetry, modulus of symmetry of enabler and objective weight of each enabler.

Next, with the use of IF-RS model, the subjective weight of enabler is obtained as $w_k^s = (0.1319, 0.1209, 0.033, 0.044, 0.1099, 0.1429, 0.0879, 0.0769, 0.0549, 0.0989, 0.011, 0.022, 0.0659)$. Combining the results of IF-MEREC and IF-RS methods through Eq. (37), an integrated weight for SLSS enablers is computed and given as $w_k =$

Table 17
IF-score matrix and symmetric point of each enabler for SLSS enablers in manufacturing sector.

	M_1	M_2	M_3	M_4	M_5	$\min\{\alpha_{jk}\}$	$\max\{\alpha_{jk}\}$	β_k
F_1	0.601	0.551	0.703	0.613	0.652	0.551	0.703	0.627
F_2	0.608	0.716	0.659	0.57	0.58	0.57	0.716	0.643
F_3	0.546	0.696	0.58	0.681	0.71	0.546	0.71	0.628
F_4	0.645	0.673	0.583	0.555	0.508	0.508	0.673	0.591
F_5	0.661	0.69	0.592	0.673	0.772	0.592	0.772	0.682
F_6	0.672	0.664	0.71	0.604	0.633	0.604	0.71	0.657
F_7	0.55	0.656	0.574	0.601	0.699	0.55	0.699	0.624
F_8	0.758	0.685	0.542	0.59	0.505	0.505	0.758	0.631
F_9	0.661	0.737	0.564	0.688	0.73	0.564	0.737	0.651
F_{10}	0.737	0.62	0.618	0.616	0.571	0.571	0.737	0.654
F_{11}	0.601	0.676	0.71	0.664	0.608	0.601	0.71	0.655
F_{12}	0.613	0.552	0.728	0.645	0.664	0.552	0.728	0.64
F_{13}	0.647	0.663	0.568	0.562	0.523	0.523	0.663	0.593

Table 18
Resulting matrix of absolute distances for SLSS enablers in manufacturing sector.

	M_1	M_2	M_3	M_4	M_5
F_1	0.027	0.076	0.076	0.015	0.025
F_2	0.035	0.073	0.016	0.073	0.064
F_3	0.082	0.068	0.048	0.054	0.082
F_4	0.054	0.082	0.008	0.035	0.082
F_5	0.021	0.008	0.09	0.009	0.09
F_6	0.015	0.007	0.053	0.053	0.025
F_7	0.074	0.032	0.051	0.023	0.074
F_8	0.127	0.054	0.089	0.041	0.127
F_9	0.01	0.087	0.087	0.037	0.079
F_{10}	0.083	0.035	0.036	0.038	0.083
F_{11}	0.055	0.02	0.055	0.009	0.048
F_{12}	0.027	0.088	0.088	0.005	0.025
F_{13}	0.054	0.07	0.025	0.031	0.07

Table 19
Matrix of moduli and weight of enabler for SLSS enablers in manufacturing sector.

	M_1	M_2	M_3	M_4	M_5	q_k	w_k^o
F_1	0.221	0.253	0.205	0.138	0.268	0.217	0.0776
F_2	0.218	0.195	0.219	0.148	0.301	0.216	0.0773
F_3	0.243	0.201	0.249	0.124	0.246	0.213	0.0759
F_4	0.206	0.208	0.247	0.152	0.344	0.231	0.0827
F_5	0.201	0.203	0.244	0.126	0.226	0.2	0.0714
F_6	0.198	0.211	0.203	0.14	0.276	0.205	0.0734
F_7	0.241	0.213	0.251	0.141	0.25	0.219	0.0783
F_8	0.175	0.204	0.266	0.143	0.346	0.227	0.0811
F_9	0.201	0.19	0.256	0.123	0.239	0.202	0.0721
F_{10}	0.18	0.226	0.233	0.137	0.306	0.216	0.0773
F_{11}	0.221	0.207	0.203	0.127	0.287	0.209	0.0747
F_{12}	0.217	0.253	0.198	0.131	0.263	0.212	0.0759
F_{13}	0.205	0.211	0.254	0.151	0.334	0.231	0.0825

(0.1047, 0.0991, 0.0545, 0.0633, 0.0906, 0.1081, 0.0831, 0.079, 0.0635, 0.0881, 0.0428, 0.0489, 0.0742). Therefore, the enabler "Effective communication and updated data information (F_6)" has maximum preference among the others in successful implementation of SLSS in manufacturing sector.

5.3.4. *IF-Entropy-SWARA Method (Li* et al.*, 2023)*

Algorithm 5 IF-Entropy-SWARA methodology (Li *et al.*, 2023)

1. Steps 1–3 are similar to the proposed IF-WENSLO-MPSI model.
2. Find the objective assessment degree of enabler using entropy-based formula

$$w_k^o = \frac{\sum_{j=1}^{r}(1 - \bar{E}(\bar{z}_{jk}))}{\sum_{k=1}^{s}(\sum_{j=1}^{r}(1 - \bar{E}(\bar{z}_{jk})))}, \tag{38}$$

   where $\bar{E}(\bar{z}_{jk}) = E(\bar{z}_{jk})/\max_{i=1,\dots,m} E(\bar{z}_{jk})$, $k = 1, 2, \dots, s$, and

$$E(\bar{z}_{jk}) = 1 - \frac{1}{r}\sum_{j=1}^{r}\big[(\mu_{jk} - \nu_{jk})I_{[\mu_{jk} \geqslant \nu_{jk}]} + (\nu_{jk} - \mu_{jk})I_{[\mu_{jk} < \nu_{jk}]}\big].$$

3. Determine the weight of enablers through IF-SWARA model, given by Algorithm 3.
4. Determine the assessment degree of criterion using IF-SPC-RS method by Eq. (39).

$$w_k = \zeta w_k^o + (1 - \zeta)w_k^s, \quad k = 1, 2, \dots, s. \tag{39}$$

5. Estimate the ranking of enablers.

After using the IF-Entropy-SWARA model (as given by Algorithm 5) on the above-mentioned application, we obtain the objective assessment degree of each enabler by means of entropy formula (Eq. (38)), given as w_k^o = (0.0714, 0.058, 0.0941, 0.076, 0.0929, 0.0584, 0.0645, 0.0996, 0.1137, 0.0631, 0.0566, 0.0871, 0.0645). Table 20 presents the required results obtained during the computation of objective weight of enabler.

Next, with the use of IF-SWARA model, the subjective weight of each enabler is obtained as w_k^s = (0.083, 0.08, 0.0743, 0.0749, 0.0795, 0.0839, 0.0768, 0.076, 0.0751, 0.0794, 0.0676, 0.0739, 0.0757). In line with the results of IF-Entropy and IF-SWARA methods through Eq. (39), an integrated weight for each SLSS enabler is computed and given as w_k = (0.0772, 0.0690, 0.0842, 0.0755, 0.0862, 0.0712, 0.0707, 0.0878, 0.0944, 0.0713, 0.0621, 0.0805, 0.0701). Therefore, the enabler "Linking SLSS to business strategies (F_9)" has maximum preference among the others in successful implementation of SLSS in manufacturing sector.

On the basis of comparative results, we extract the following advantages of IF-WENSLO-MPSI methodology, given as below:

– Comparative methods including IF-MEREC-RS model (Rani *et al.*, 2025), IF-SWARA (Ziquan *et al.*, 2025), IF-SPC-RS (Hezam *et al.*, 2023) and IF-Entropy-SWARA (Li *et*

Table 20
IF-entropy and normalized entropy for weight of SLSS enablers in manufacturing sector.

	M_1	M_2	M_3	M_4	M_5	M_1	M_2	M_3	M_4	m_5
	$E(\bar{z}_{jk})$					$\bar{E}(\bar{z}_{jk}) = E(\bar{z}_{jk}) / \max_{i=1,\dots,m} E(\bar{z}_{jk})$				
F_1	0.799	0.897	0.594	0.775	0.696	0.89	1	0.662	0.864	0.776
F_2	0.783	0.568	0.681	0.859	0.841	0.912	0.661	0.793	1	0.979
F_3	0.908	0.608	0.841	0.637	0.58	1	0.67	0.926	0.701	0.638
F_4	0.711	0.654	0.834	0.889	0.983	0.723	0.665	0.848	0.904	1
F_5	0.679	0.62	0.817	0.654	0.455	0.831	0.759	1	0.802	0.558
F_6	0.655	0.672	0.58	0.791	0.735	0.828	0.85	0.733	1	0.929
F_7	0.899	0.688	0.853	0.798	0.603	1	0.765	0.948	0.887	0.67
F_8	0.484	0.629	0.915	0.819	0.991	0.489	0.635	0.924	0.827	1
F_9	0.679	0.525	0.872	0.624	0.54	0.778	0.602	1	0.715	0.619
F_{10}	0.525	0.761	0.763	0.768	0.857	0.613	0.887	0.89	0.896	1
F_{11}	0.799	0.649	0.58	0.671	0.785	1	0.812	0.726	0.84	0.982
F_{12}	0.774	0.896	0.545	0.711	0.671	0.864	1	0.608	0.794	0.749
F_{13}	0.705	0.675	0.863	0.876	0.954	0.739	0.707	0.905	0.919	1

al., 2023) have used the existing score function of Xu *et al.* (2015), while this work proposes a new score function to compute the assessment degree of each expert, which overcomes the limitations of several existing score formulae (Xu, 2007; Xu *et al.*, 2015; Zhang *et al.*, 2019; Feng *et al.*, 2020; Tripathi *et al.*, 2023) and avoids the information loss during group decision-making. This shows the effectiveness of proposed method over the existing ones.

– This method introduces a modified score-induced distance formula for calculating the degree of preference variations in IF-MPSI method, and also avoids the inadequacies of extant IF-distance formulae (Ngan *et al.*, 2018; Ejegwa and Agbetayo, 2023; Li *et al.*, 2023; Kumar and Kumar, 2024; Mishra *et al.*, 2025).

– For the first time, this work combines the IF-WENSLO and IF-MPSI models for computing the integrated objective-subjective weights of enablers in the implementation of SLSS approach in the manufacturing sector. It means that the proposed IF-WENSLO-MPSI method does not only consider the quantitative data for determining the enabler's objective assessment degree with the IF-WENSLO approach but also include the experts' subjective opinions in the calculation of subjective assessment degree of enabler with the IF-MPSI approach.

6. Conclusions

Manufacturing companies are facing pressure to incorporate innovative strategies into their business practices along with the consideration of sustainability aspects. Sustainable Lean Six Sigma (SLSS) entails streamlining processes and procedures to eliminate waste, improve quality, promote sustainability practices and thereby maximize productivity. In this study, thirteen enablers were identified through literature survey and discussion with experts for the successful implementation of SLSS in electric manufacturing companies. To achieve this aim, a set of four experts has been invited to participate in this work. Next, the significance degree of each expert has determined via a combined IF-score function and rank reciprocal-based procedure. To evaluate and prioritize the enablers, a hybrid IF-WENSLO-MPSI methodology has been proposed with the combination of IF-WENSLO model for objective assessment degree and IF-MPSI method for subjective assessment degree under IFSs environment. Corresponding to IF-WENSLO-MPSI methodology, an enabler "Linking SLSS to business strategies (F_9)" with weight '0.104' is the most dominant factor for the successful execution of SLSS. It is followed by the "Green design principles (F_8)" with '0.1017', "Effective scheduling (F_3)" with '0.1011', "Environmental management system (F_{12})" with '0.0992', "Enhance customer satisfaction (F_5)" with '0.0894', "Quality control management (F_7)" with '0.0878', "Employee involvement and motivation (F_{11})" with '0.0782', "Government policies (F_{13})" with '0.071', "Organizational culture (F_1)" with '0.0669', "Quality characteristics of raw materials (F_2)" with '0.0565', "Remain competitive in the global market (F_4)" with '0.0547', "Initiative to use environmentally friendly packaging of products (F_{10})" with '0.054' and "Effective communication and updated data information (F_6)" with '0.0355'. Sensitivity analysis has been conducted with respect to experts and criteria weighting parameters to analyse the impact of these parameters on the final ranking results. Lastly, comparison with existing IF-MEREC-RS, IF-SWARA, IF-SPC-RS and IF-Entropy-SWARA models has been performed to test the validity of proposed results.

However, this work is unable to measure the correlation among the SLSS enablers. Further research can be conducted to overcome the limitations of this work. Additionally, some more dimensions of sustainability can be considered in further work. In future, this work can be combined with machine learning approaches and also can be extended under other generalizations of fuzzy set.

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