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Resilient supplier selection in a supply chain by a new interval-valued fuzzy group decision model based on possibilistic statistical concepts

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Abstract

Supplier selection is one the main concern in the context of supply chain networks by considering their global and competitive features. Resilient supplier selection as generally new idea has not been addressed properly in the literature under uncertain conditions. Therefore, in this paper, a new multi-criteria group decision-making (MCGDM) model is introduced with interval-valued fuzzy sets (IVFSs) and fuzzy possibilistic statistical concepts. Then, a new weighting method for the supply chain experts or decision makers (DMs) is presented under uncertainty in supply chain networks. Additionally, a modified version of an entropy method is extended for computing the weight of each assessment criterion. Possibilistic mean, standard deviation, and the cube-root of skewness are proposed within the MCGDM. In addition, a new fuzzy ranking method based on relative-closeness coefficients are proposed to rank the resilient supplier candidates. Finally, a resilient supplier selection problem is solved by the proposed group decision model to demonstrate its validity and is compared with a recent study.

Keywords: Resilient supplier selection, Interval-valued fuzzy sets, Possibilistic statistics, Supply chain Management, Multi-criteria group decision making

1- INTRODUCTION

Supply chain resilience is a generally new idea that can be characterized as "*the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function*'' (Ponomarov and Holcomb, 2009).

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Organizations can build up the resiliency in three general ways: (1) making redundancies within a supply chain, (2) expanding the supply chain flexibility, and (3) changing the corporate culture (Sheffi, 2005). Christopher and Peck (2004) considered various noticeable general rule that support resilience in supply chains. They presumed that resilience infers flexibility and agility, and its suggestions reach out past procedure redesign to main decisions on sourcing and the foundation of more community oriented supply chain relationships in light of far more prominent straightforwardness of information. Notwithstanding the high level of understanding in what supply chain resilience is by definition, the recent literature is given very disparity on the main characteristics (Ponis and Koronis, 2012). Christopher and Peck (2005) developed knowledge of five rules that took resilience, including i) considering a comprehension of agile supply chain networks capable of responding rapidly to changing conditions, ii) employing a collaborative supplier base strategy with information sharing, iii) making and keeping up agile supply chain networks with ability to rapidly respond to altering conditions, and iv) presenting a supply chain risk management culture. In addition, attributes, including agility, availability, efficiency, flexibility, redundancy, velocity and visibility, in the underlying methodology were dealt with as other characteristics (Petitt et al., 2010).

New supply chains are not straightforward chains or arrangement of procedures, but rather are complex networks where disruptions can happen whenever. This increases the risk connected with supply chains (Meindl and Chopra, 2003). Supplier selection performed by providing more prominent needs to risk related issues lessens vulnerability of a supply chain largely. Real time risk management process ought to include the following phases, including risk identification, risk analysis, risk mitigation and risk monitoring (Matook et al., 2009). Resilience regarded as the capacity of the system to come back to its unique state or a superior one in the wake of being disturbed, expect awesome significance in this context (Christopher and Peck, 2004). The capacity of suppliers to manage risks (i.e., being preferable situated over competitors to manage disruptions) is the embodiment of supplier resilience (Sheffi, 2005).

Jain et al. (2016) managed a supplier selection problem in an Indian automobile company by applying combined fuzzy multi-criteria decision-making approaches (i.e., analytical hierarchy process (AHP) and technique for order of preference by similarity to ideal solution (TOPSIS). Fazlollahtabar (2016) presented a combined decision approach based on fuzzy preference ranking organization method for enrichment evaluation (PROMETHEE) and fuzzy linear programming. Rajesh and Ravi (2015) focused on a resilient supply chain, in which grey possibility values for supplier selection were computed for the ranking. Memon et al. (2015) extended a mix of grey system theory and uncertainty theory, which needs neither any probability distribution nor fuzzy membership function for decreasing the purchasing risks associated with suppliers.

Igoulalene et al. (2015) regarded the strategic supplier selection problem under fuzzy uncertainty to taken the imprecision of supply chain partners in figuring the preferences values of various assessment factors. Junior et al. (2014) exhibited a comparative analysis of these two methods concerning supplier selection decision-making, including fuzzy AHP and fuzzy TOPSIS. Deng et al. (2014) developed a D-AHP method for the supplier selection problem, which regarded the traditional systematic AHP method. Dursun and Karsak (2013) proposed a fuzzy multi-criteria group decision model for the supplier selection problem by the idea of quality function deployment (QFD).

Jüttner and Maklan (2011) regarded supply chain resilience and examined its association with the related supply chain vulnerability (SCV) and supply chain risk management (SCRM). From a survey of the literature, the area of the SCRES was characterized and the proposed associations with the SCRM and SCV were determined. Then, information from a case study by taking three supply chains were introduced to investigate the relationship between the ideas concerning the global financial crisis. Ponis and Koronis (2012) gave experiences into the conceptualization and research methodological foundation of the SCM field. A basic examination of existing theoretical structures for comprehension the relationships between the SCRes idea and its distinguished developmental components, was occurring. Mensah and Merkuryev (2014) focused on the supply chain and risks, examined the resiliency of the supply chain, and provided fitting procedures that would help maintain a strategic distance from these risks, and subsequently, an organization would have the capacity to ricochet back after any twisting along its supply chain.

Zheng et al. (2014) provided a combinatorial advancement for the resilient supply chain. Utilizing genetic algorithms with the 0-1 and floating-point coding, the solution approach was extended. Mari et al. (2015) considered a resilient supply chain network from the viewpoint of a complex network. Different resilience metrics for the supply chains were produced in light of a complex network theory, and then a method for the resilient supply chain was additionally created for outlining a resilient supply chain network. Purvis et al. (2016) developed a structure for the improvement and usage of a resilient supply chain strategy, which represented the significance of different administration standards, including robustness, agility, leanness and flexibility, in expanding an organization's capacity to manage unsettling influences rising up out of its network. Lee and Rha (2016) used two fundamental theoretical frames from the system literature, dynamic capabilities and organizational ambidexterity, to the SCM to inspect alleviation procedures for supply chain interruptions.

The above-related literature on the resilient supplier selection problem denotes that an assessment of selection problem is a multi-criteria group decision-making (MCGDM) framework for the supply chain networks, and is regarded as a new research area. In practice, several evaluation factors or criteria can influence this selection issue under uncertain conditions.

The main contributions of this paper, in contrast to the previous studies for the resilient supplier selection in supply chain networks, are as follows:

- A new MCGDM model is proposed under an interval-valued fuzzy environment based on three possibilistic mean, standard deviation and the cube-root of skewness matrices.
- New relations are presented for obtaining positive and negative ideal solutions with possibilistic mean, possibilistic standard deviation, and the possibilistic cube-root of skewness with interval-valued fuzzy sets.
- A possibilistic interval mean entropy method is extended for the weight of each resilient evaluation criterion with possibilistic statistical concepts.
- A new weighting method of the experts within the group decision-making process is proposed based on interval-valued fuzzy sets and possibilistic statistical concepts.
- A new ranking process based on relative-closeness coefficients is presented to rank all resilient supplier candidates under the interval-valued fuzzy uncertainty.

Finally, this paper presents an illustrative example in supply chain networks from the recent literature to assess the resilient supplier candidates versus different evaluation criteria by the proposed model along with comparison to a recent decision method.

as follows. Section 2 presents some necessary definitions The remainder of this paper is organized about interval-valued fuzzy sets and possibilistic statistical concepts. Section 3 and relations the resilient supplier problem. In Section 4 of this paper, the describes the proposed model for solving conclusions and sensitivity model is discussed with an illustrative example. Finally, presented analysis are given in Section 5.

2- Basic concepts and definitions

2-1-Interval-valued fuzzy sets

The interval-valued fuzzy numbers have considered a special form of generalized fuzzy numbers. These fuzzy numbers can contain interval-valued trapezoidal fuzzy numbers, triangular shape, and fuzzy numbers. Guijun and Xiaoping (1998) described interval-valued triangular valued-interval fuzzy numbers and interval-distribution numbers, and their developed operations alongside their applications. Cornelis et al. (2006) concentrated on the arithmetical portrayal of logical operations in the interval-valued fuzzy logic. Deschrijver (2007) created arithmetic operators in an interval-valued fuzzy sets theory. Wei and Chen (2009) gave a strategy to fuzzy risk evaluation according to similarity measures between interval-valued fuzzy numbers. Chen et al. (2014) amplified ideas of an interval-valued triangular fuzzy soft set, and then a dynamic decision algorithm was given an interval-valued triangular fuzzy soft set.

According to Yao and Lin (2002), an interval-valued triangular fuzzy number are represented by:

$$\tilde{A} = \left[\underline{\tilde{A}}, \overline{\tilde{\tilde{A}}}\right] = \left[\left(\underline{a}_1, \underline{a}_2, \underline{a}_3; \hat{\underline{h}}_{\tilde{A}}\right), \left(\overline{a}_1, \overline{a}_2, \overline{a}_3; \hat{\overline{h}}_{\tilde{A}}\right)\right] \tag{1}$$

Suppose $\underline{\tilde{A}}$ and $\overline{\tilde{\tilde{A}}}$ be two generalized triangular fuzzy numbers (GTFN); hence, $\hat{\underline{h}}_{\tilde{A}}$ and $\hat{\overline{h}}_{\tilde{A}}$ define the denoted in the universe heights of $\underline{\tilde{A}}$ and $\overline{\tilde{\tilde{A}}}$, and $\underline{a}_1, \underline{a}_2, \underline{a}_3$, $\overline{a}_1, \overline{a}_2, \overline{a}_3$ define the real values. $GTFN\ \tilde{A}$ of discourse X is described by: $0 \leq \underline{a}_1 \leq \underline{a}_2 \leq \underline{a}_3 \leq 1$, $0 \leq \overline{a}_1 \leq \overline{a}_2 \leq \overline{a}_3 \leq 1$, $\overline{a}_1 \leq \underline{a}_1$ and $\underline{a}_3 \leq \overline{a}_3$. In addition, $\underline{\tilde{A}} = \left(\underline{a}_1, \underline{a}_2, \underline{a}_3; \hat{\underline{h}}_{\tilde{A}}\right)$, $\overline{\tilde{\tilde{A}}} = \left(\overline{a}_1, \overline{a}_2, \overline{a}_3; \hat{\overline{h}}_{\tilde{A}}\right)$ and $\underline{\tilde{A}} \subset \overline{\tilde{\tilde{A}}}$ are regarded.

2-2- Possibility theory

In this sub-section, some fundamental ideas and definitions about possibility theory are presented. First, a fuzzy number $\tilde{A}$ will be a fuzzy arrangement of the real line x with a normal, fuzzy convex and continuous membership function of limited support (Zhang et al., 2007; Ye and Lin, 2013; Deng and Li, 2014; Li et al., 2010).

Definition 1. A triangular fuzzy variable A is demonstrated by the triplet $(a-\tau, a, a+\sigma)$ crisp numbers with $a-\tau < a < a+\sigma$ and its membership function is provided as below (Kamdem et al., 2012):

$$= \begin{cases} \big(x-(a-\tau)\big)/\big(a-(a-\tau)\big), & if\ a-\tau \leq x \leq a \\ \big(x-(a+\sigma)\big)/\big(a-(a+\sigma)\big), & if\ a \leq x \leq a+\sigma \\ 0 & , otherwise. \end{cases} \tag{2}$$

In what follows, this study denotes $A = (a-\tau, a, a+\sigma)$. Its mean is $E[A] = \frac{\big((a-\tau)+2(a)+(a+\sigma)\big)}{4}$ and its variance is $V[A] = \frac{(33\alpha^3+21\alpha^2\beta+11\alpha\beta^2-\beta^3)}{(384\alpha)}$ where $\alpha = \max\{\big((a)-(a-\tau)\big), \big((a+\sigma)-(a)\big)\}$ and $\beta = \min\{\big((a)-(a-\tau)\big), \big((a+\sigma)-(a)\big)\}$. In particular, if $\big((a)-(a-\tau)\big) = \big((a+\sigma)-(a)\big)$, then we have $E[A] = a$ and $V[A] = \frac{\big((a+\sigma)-(a-\tau)^2\big)}{24}$.

Definition 2. Skewness of triangular fuzzy variable $A = (a-\tau, a, a+\sigma)$ is provided as (Kamdem et al., 2012):

$$S[A] = E[(A-E[A])^3] \tag{3}$$

Then, we have:

$$S[A] = \frac{\big((a+\sigma)-(a-\tau)\big)^2}{32}\left[\big((a+\sigma)-(a)\big)-\big((a)-(a-\tau)\big)\right]. \tag{4}$$

which implies that if $\big((a+\sigma)-(a)\big) \geq \big((a)-(a-\tau)\big)$, then $S[A] \geq 0$ and if $\big((a+\sigma)-(a)\big) \leq \big((a)-(a-\tau)\big)$, then $S[A] \leq 0$. Also, if A can be symmetric, then we have $\big((a)-(a-\tau)\big) = \big((a+\sigma)-(a)\big)$ and $S[A] = 0$. In addition, for fixed $a-\tau$ and $a+\sigma$, if $a = a-\tau$, then $S[A]$ can take its maximum value $\frac{\big((a+\sigma)-(a-\tau)\big)^3}{32}$; and if $a = a+\sigma$, then $S[A]$ can take its minimum value $\frac{-\Big(\big((a+\sigma)-(a-\tau)\big)^3\Big)}{32}$.

Figure 1 depicts a membership function of several interval-valued fuzzy numbers by regarding the optimistic and pessimistic preferences.

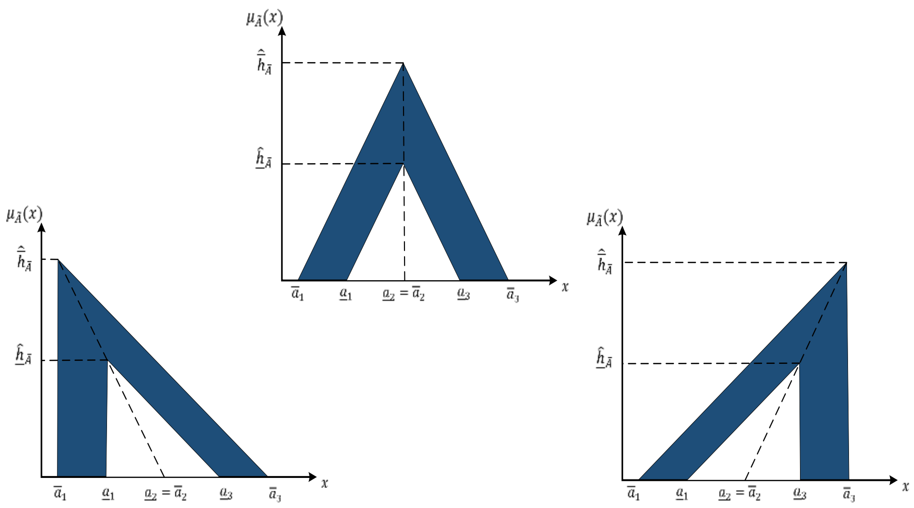

Fig. 1 Membership function of several interval-valued fuzzy numbers by considering the optimistic and pessimistic preferences

3- Proposed decision approach

In this section, a new interval-valued fuzzy group approach for the evaluation of a resilient supplier is presented in the SCM based on possibility theory and statistical concepts. First, it is assumed that:

$DM = \{DM^k \big| k = 1, \dots, p\}$ as a set of supply chain-decision makers or experts,
$X = \{X_i \big| i = 1, \dots, m\}$ as a finite set of resilient supplier candidates,
$C = \{C_j \big| j = 1, \dots, n\}$ as a finite set of selection criteria for the resilient supplier problem.
Since the information of resilient supplier candidates is uncertain during group decision making in the SCM, the supply chain-decision makers (DMs) or experts can consider an interval-valued fuzzy (IVF) $\tilde{A}_{ij}^k$ to estimate the judgment and opinion on resilient supplier candidate X_i with respect to selection criterionC_i. The MCGDM problem of resilient supplier selection with IVFSs and statistical concepts can be expressed in the following:

$$\tilde{X}_k = \left[\left[\left(\left(x_{ij}^k\right)_1^L, \left(x_{ij}^k\right)_2^L, \left(x_{ij}^k\right)_3^L\right), \left(\left(x_{ij}^k\right)_1^U, \left(x_{ij}^k\right)_2^U, \left(x_{ij}^k\right)_3^U\right)\right]\right]_{m\times n} = \tag{5}$$

$$= \begin{bmatrix} \left[\left(\left(x_{11}^k\right)_1^L, \left(x_{11}^k\right)_2^L, \left(x_{11}^k\right)_3^L\right), \left(\left(x_{11}^k\right)_1^U, \left(x_{11}^k\right)_2^U, \left(x_{11}^k\right)_3^U\right)\right] & \cdots & \left[\left(\left(x_{1n}^k\right)_1^L, \left(x_{1n}^k\right)_2^L, \left(x_{1n}^k\right)_3^L\right), \left(\left(x_{1n}^k\right)_1^U, \left(x_{1n}^k\right)_2^U, \left(x_{1n}^k\right)_3^U\right)\right] \\ \vdots & \ddots & \vdots \\ \left[\left(\left(x_{m1}^k\right)_1^L, \left(x_{m1}^k\right)_2^L, \left(x_{m1}^k\right)_3^L\right), \left(\left(x_{m1}^k\right)_1^U, \left(x_{m1}^k\right)_2^U, \left(x_{m1}^k\right)_3^U\right)\right] & \cdots & [((x_{mn}^k)_1^L, (x_{mn}^k)_2^L, (x_{mn}^k)_3^L), ((x_{mn}^k)_1^U, (x_{mn}^k)_2^U, (x_{mn}^k)_3^U)] \end{bmatrix}$$

According to the above-mentioned descriptions, the steps of the proposed interval-valued fuzzy model based on mean-variance-skewness concepts for the evaluation and selection problem of the resilient supplier are presented as follows:

Step 1. Proper criteria are identified for the selection problem of the resilient supplier.
Step 2. Provide the IVF-decision matrices of resilient supplier candidates for each DMs.
Step 3. Transform the IVF-matrix into the normalized matrix of the resilient supplier candidates. There are two criteria categories for the resilient supplier candidates, namely benefit type and cost type. The higher the benefit type value is, the better it will be. It is opposite for the cost type. To transform different criteria scales into a comparable scale, the linear scale transformation method is used and presented by:

$$\widetilde{H}_k = \left[\left[\left((h_{ij}^k)_1^L, (h_{ij}^k)_2^L, (h_{ij}^k)_3^L\right), \left((h_{ij}^k)_1^U, (h_{ij}^k)_2^U, (h_{ij}^k)_3^U\right)\right]\right]_{m\times n} = \left[\left(\frac{(x_{ij}^k)_1^L}{\left((x_{ij}^k)_3^U\right)^+}, \frac{(x_{ij}^k)_2^L}{\left((x_{ij}^k)_3^U\right)^+}, \frac{(x_{ij}^k)_3^L}{\left((x_{ij}^k)_3^U\right)^+}\right), \left(\frac{(x_{ij}^k)_1^U}{\left((x_{ij}^k)_3^U\right)^+}, \frac{(x_{ij}^k)_2^U}{\left((x_{ij}^k)_3^U\right)^+}, \frac{(x_{ij}^k)_3^U}{\left((x_{ij}^k)_3^U\right)^+}\right)\right], k = 1, \ldots, p \text{ and } j \in \Omega_b \tag{6}$$

$$\left((x_{ij}^k)_3^U\right)^+ = \max_{1\le i\le m} (x_{ij}^k)_3^U$$

and

$$\widetilde{H}_k = \left[\left[\left((h_{ij}^k)_1^L, (h_{ij}^k)_2^L, (h_{ij}^k)_3^L\right), \left((h_{ij}^k)_1^U, (h_{ij}^k)_2^U, (h_{ij}^k)_3^U\right)\right]\right]_{m\times n} = \left[\left(\frac{\left((x_{ij}^k)_1^U\right)^-}{(x_{ij}^k)_3^L}, \frac{\left((x_{ij}^k)_1^U\right)^-}{(x_{ij}^k)_2^L}, \frac{\left((x_{ij}^k)_1^U\right)^-}{(x_{ij}^k)_1^L}\right), \left(\frac{\left((x_{ij}^k)_1^U\right)^-}{(x_{ij}^k)_3^U}, \frac{\left((x_{ij}^k)_1^U\right)^-}{(x_{ij}^k)_2^U}, \frac{\left((x_{ij}^k)_1^U\right)^-}{(x_{ij}^k)_1^U}\right)\right], k = 1, .., p \text{ and } j \in \Omega_c \tag{7}$$

$$\left((x_{ij}^k)_1^U\right)^- = \min_{1\le i\le m} (x_{ij}^k)_1^U$$

where Ω_b and Ω_c are the sets of benefit and cost attribute for the resilient supplier selection problem respectively, the maximum rating of each resilient supplier candidate against each criterion and the minimum rating using the normalization process can be obtained.

Step 4. To determine assessment criteria' weights, construct the possibilistic interval mean matrix for the selection problem of the resilient supplier candidates. The possibilistic interval mean ($\overline{m}_{ij}^k$) of IVF $\widetilde{H}^k$ are defined according to Definition 1:

$$\overline{m}_{ij}^k = \left[m_{ij}^{kL}, m_{ij}^{kU}\right] = \left[\frac{(h_{ij}^k)_1^L + 2\times(h_{ij}^k)_2^L + (h_{ij}^k)_3^L}{4}, \frac{(h_{ij}^k)_1^U + 2\times(h_{ij}^k)_2^U + (h_{ij}^k)_3^U}{4}\right] \tag{8}$$

Then, the possibilistic interval mean matrix is constructed for the selection problem of resilient supplier candidates as follows:

$$\overline{M}_k = \left[\overline{m}_{ij}^k\right]_{m\times n} = \begin{bmatrix} \overline{m}_{11}^k & \overline{m}_{12}^k & \cdots & \overline{m}_{1n}^k \\ \overline{m}_{21}^k & \overline{m}_{22}^k & \cdots & \overline{m}_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \overline{m}_{m1}^k & \overline{m}_{m2}^k & \cdots & \overline{m}_{mn}^k \end{bmatrix}, k = 1, \ldots, p \tag{9}$$

Step 5. Calculate the possibilistic interval mean entropy measure of each assessment criterion.

$$\overline{E}_j^k = \left[E_j^{kL}, E_j^{kU}\right] = \left[-\frac{1}{Ln(m)}\sum_{i=1}^{m} m'^{kL}_{ij} Ln\left(m'^{kL}_{ij}\right), -\frac{1}{Ln(m)}\sum_{i=1}^{m} m'^{kU}_{ij} Ln\left(m'^{kU}_{ij}\right)\right], k = 1, \ldots, p \tag{10}$$

where $\overline{m}'^k_{ij} = \left[m'^{kL}_{ij}, m'^{kU}_{ij}\right] = \left[\frac{m_{ij}^{kL}}{\max_{1\le i\le m} m_{ij}^{kU}}, \frac{m_{ij}^{kU}}{\max_{1\le i\le m} m_{ij}^{kU}}\right]$.

Step 6. Calculate modified entropy weight based on the possibilistic interval mean.

$$W_{kj} = [W_j^{kL}, W_j^{kU}] = \left[1 - E_j^{kL}, 1 - E_j^{kU}\right], k = 1, \ldots, p \tag{11}$$

Step 7. To determine the weights of supply chain-DMs or experts, for the possibilistic interval mean matrix $\overline{M}$ of the k-th by considering the different important of each assessment criterion based on Eq. (11), we can construct the weighted normalized interval decision matrix as:

$$v_{ij}^k = \left[v_{ij}^{kL}, v_{ij}^{kU}\right] = \left[W_j^{kL} m_{ij}^{kL}, W_j^{kU} m_{ij}^{kU}\right]$$

$$V_k = \left[v_{ij}^k\right]_{m\times n} = \begin{bmatrix} v_{11}^k & v_{12}^k & \cdots & v_{1n}^k \\ v_{21}^k & v_{22}^k & \cdots & v_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1}^k & v_{m2}^k & \cdots & v_{mn}^k \end{bmatrix}, k = 1, \ldots, p \tag{12}$$

Step 8. As describe in the literature review (Yue, 2011), in mean sense, the best decision result of group should be the average of a group decision matrix:

$$V^* = \left[v_{ij}^*\right]_{m\times n} = \begin{bmatrix} v_{11}^* & v_{12}^* & \cdots & v_{1n}^* \\ v_{21}^* & v_{22}^* & \cdots & v_{2n}^* \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1}^* & v_{m2}^* & \cdots & v_{mn}^* \end{bmatrix} \tag{13}$$

where $v_{ij}^* = \left[v_{ij}^{*L}, v_{ij}^{*U}\right] = \left[\frac{1}{p}\sum_{k=1}^{p} v_{ij}^{kL}, \frac{1}{p}\sum_{k=1}^{p} v_{ij}^{kU}\right]$. So, we define $V^* = \left(\left[v_{ij}^{*L}, v_{ij}^{*U}\right]\right)_{m\times n}$ as the PIS of all individual decisions.

Step 9. The worst result of group decision making should be the result of maximum separation from the PIS.

$$V^- = \left[v_{ij}^-\right]_{m\times n} = \begin{bmatrix} v_{11}^- & v_{12}^- & \cdots & v_{1n}^- \\ v_{21}^- & v_{22}^- & \cdots & v_{2n}^- \\ \vdots & \vdots & \ddots & \vdots \\ v_{m1}^- & v_{m2}^- & \cdots & v_{mn}^- \end{bmatrix} \tag{14}$$

where $v_{ij}^- = \left[v_{ij}^{-L}, v_{ij}^{-U}\right] = \left[\min_{1\le k\le p}\left\{v_{ij}^{kL}\right\}, \max_{1\le k\le p}\left\{v_{ij}^{L}\right\}\right]$. So, we define $V^- = \left(\left[v_{ij}^{-L}, v_{ij}^{-U}\right]\right)_{m\times n}$ as the NIS of all individual decisions.

Step 10. The separation of each individual decision from the PIS, using the *n*-dimensional Euclidean distance, can be currently calculated by:

$$S_k^+ = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\left(v_{ij}^{kL} - v_{ij}^{*L}\right)^2 + \left(v_{ij}^{kU} - v_{ij}^{*U}\right)^2\right)}, k = 1, \ldots, p \tag{15}$$

Similarity, the separation from the NIS is given as

$$S_k^- = \sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\left(v_{ij}^{kL} - v_{ij}^{-L}\right)^2 + \left(v_{ij}^{kU} - v_{ij}^{-U}\right)^2\right)}, k = 1, \ldots, p \tag{16}$$

Step 11. A relative closeness is defined to determine the ranking order of all DMs once the S_k^+ and S_k^- of each individual decision has been calculated. The relative closeness of each individual decision with respect to V^+ is defined by:

$$\eta_k = \frac{S_k^-}{S_k^+ + S_k^-}, \forall k \tag{17}$$

Since $S_k^- \geq 0$ and $S_k^+ \geq 0$, then, clearly, $\eta_k \in [0,1]$ for all k.

Step 12. Obviously, a decision matrix V_k is closer to V^+ and farther from V^- as η_k approaches to 1. Therefore, according to the relative closeness, we can determine the ranking order of all DMs and select the best one from among a set of DMs. If there is p DMs, then the score given by the k-th DM is closer to the average of p scores given by the DMs, the better decision of the *k*-th DM. So, we can define by:

$$\vartheta_k = \frac{\eta_k}{\sum_{k=1}^{p} \eta_k} \ , \forall k \tag{18}$$

as weight of kth ($k \in T$) DM, such that $\vartheta_k \geq 0; \sum_{k=1}^{p} \vartheta_k = 1$.

Step 13. For the supply chain DMs' weight vector $\vartheta = (\vartheta_1, \vartheta_2, \ldots, \vartheta_k)^T$ given in Eq. (18), we can aggregate all the group decision matrices $\widetilde{H}_k$ $(k = 1, \ldots, p)$ into a collective matrix $\tilde{A}$ by:

$$\tilde{A} = \tilde{a}_{ij} = \left[\left[\left((a_{ij})_1^L, (a_{ij})_2^L, (a_{ij})_3^L\right), \left((a_{ij})_1^U, (a_{ij})_2^U, (a_{ij})_3^U\right)\right]\right]_{m\times n} = \left[\left[\left(\frac{1}{p}\sum_{k=1}^{p} \vartheta_k \times (h_{ij}^k)_1^L, \frac{1}{p}\sum_{k=1}^{p} \vartheta_k \times (h_{ij}^k)_2^L, \frac{1}{p}\sum_{k=1}^{p} \vartheta_k \times (h_{ij}^k)_3^L\right), \left(\frac{1}{p}\sum_{k=1}^{p} \vartheta_k \times (h_{ij}^k)_1^U, \frac{1}{p}\sum_{k=1}^{p} \vartheta_k \times (h_{ij}^k)_2^U, \frac{1}{p}\sum_{k=1}^{p} \vartheta_k \times (h_{ij}^k)_3^U\right)\right]\right]_{m\times n} \tag{19}$$

Step 14. To rank the resilient supplier candidates, construct the possibilistic interval mean matrix for the selection problem of the resilient supplier candidates. The possibilistic interval mean ($\overline{m}_{ij}$) of IVF $\left[\left((a_{ij})_1^L, (a_{ij})_2^L, (a_{ij})_3^L\right), \left((a_{ij})_1^U, (a_{ij})_2^U, (a_{ij})_3^U\right)\right]$ are defined according to Definition 1:

$$\overline{m}_{ij} = \left[m_{ij}^L, m_{ij}^U\right] = \left[\frac{(a_{ij})_1^L + 2\times(a_{ij})_2^L + (a_{ij})_3^L}{4}, \frac{(a_{ij})_1^U + 2\times(a_{ij})_2^U + (a_{ij})_3^U}{4}\right] \tag{20}$$

Then, the possibilistic interval mean matrix is constructed for the selection problem of resilient supplier candidates as follows:

$$\overline{M} = \left[\overline{m}_{ij}\right]_{m\times n} = \begin{bmatrix} \overline{m}_{11} & \overline{m}_{12} & \cdots & \overline{m}_{1n} \\ \overline{m}_{21} & \overline{m}_{22} & \cdots & \overline{m}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \overline{m}_{m1} & \overline{m}_{m2} & \cdots & \overline{m}_{mn} \end{bmatrix} \tag{21}$$

Step 15. Construct the possibilistic interval standard deviation matrix for the selection problem of resilient supplier candidates. The interval possibilistic standard deviation ($\overline{Sd}_{ij}$) of IVF $\left[\left((a_{ij})_1^L, (a_{ij})_2^L, (a_{ij})_3^L\right), \left((a_{ij})_1^U, (a_{ij})_2^U, (a_{ij})_3^U\right)\right]$ are determined according to Definition 1:

$$\overline{SD}_{ij}=[\overline{SD}_{ij}^{L},\overline{SD}_{ij}^{U}]=\left[\sqrt{\frac{\left(33\left(\alpha_{ij}^{L}\right)^{3}+21\left(\alpha_{ij}{}^{L}\right)^{2}\left(\beta_{ij}^{L}\right)+11\left(\alpha_{ij}^{L}\right)\left(\beta_{ij}^{L}\right)^{2}-\left(\beta_{ij}^{L}\right)^{3}\right)}{\left(384\left(\alpha_{ij}^{L}\right)\right)}},\right.$$
$$\left.\sqrt{\frac{\left(33\left(\alpha_{ij}^{U}\right)^{3}+21\left(\alpha_{ij}^{U}\right)^{2}\left(\beta_{ij}^{U}\right)+11\left(\alpha_{ij}^{U}\right)\left(\beta_{ij}^{U}\right)^{2}-\left(\beta_{ij}^{U}\right)^{3}\right)}{\left(384\left(\alpha_{ij}^{U}\right)\right)}}\right] \tag{22}$$

where $\alpha_{ij}^{U}=\left(a_{ij}\right)_{2}^{U}-\left(a_{ij}\right)_{1}^{U}$, $\alpha_{ij}^{L}=\left(a_{ij}\right)_{2}^{L}-\left(a_{ij}\right)_{1}^{L}$, $\beta_{ij}^{U}=\left(a_{ij}\right)_{3}^{U}-\left(a_{ij}\right)_{1}^{U}$ and $\beta_{ij}^{L}=\left(a_{ij}\right)_{3}^{L}-\left(a_{ij}\right)_{1}^{L}$.

Then, the possibilistic interval standard deviation matrix is constructed for the selection problem of the resilient supplier as follows:

$$\overline{Sd}=\left[\overline{Sd}_{ij}\right]_{m\times n}=\begin{bmatrix}\overline{Sd}_{11} & \overline{Sd}_{12} & \dots & \overline{Sd}_{1n}\\ \overline{Sd}_{21} & \overline{Sd}_{22} & \dots & \overline{Sd}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \overline{Sd}_{m1} & \overline{Sd}_{m2} & \dots & \overline{Sd}_{mn}\end{bmatrix} \tag{23}$$

Step 16. Construct the possibilistic interval cube-root of skewness matrix of the selection problem of a resilient supplier. The possibilistic interval cube-root of skewness ($\overline{Crs}_{ij}$), $\left[\left(\left(a_{ij}\right)_{1}^{L},\left(a_{ij}\right)_{2}^{L},\left(a_{ij}\right)_{3}^{L}\right),\left(\left(a_{ij}\right)_{1}^{U},\left(a_{ij}\right)_{2}^{U},\left(a_{ij}\right)_{3}^{U}\right)\right]$, are determined according to Definition 2:

$$\begin{aligned}\overline{Crs}_{ij}&=[\overline{Crs}_{ij}^{L},\overline{Crs}_{ij}^{U}]\\&=\left[\sqrt[3]{\left(\frac{\left(\left(a_{ij}\right)_{3}^{L}-\left(a_{ij}\right)_{1}^{L}\right)^{2}}{32}\right)\left(\left(a_{ij}\right)_{3}^{L}+\left(a_{ij}\right)_{1}^{L}-2\times\left(a_{ij}\right)_{2}^{L}\right)},\right.\\&\left.\sqrt[3]{\left(\frac{\left(\left(a_{ij}\right)_{3}^{U}-\left(a_{ij}\right)_{1}^{U}\right)^{2}}{32}\right)\left(\left(a_{ij}\right)_{3}^{U}+\left(a_{ij}\right)_{1}^{U}-2\times\left(a_{ij}\right)_{2}^{U}\right)}\right].\end{aligned} \tag{24}$$

Then, the possibilistic interval cube-root of skewness matrix is constructed for the selection problem of the resilient supplier as follows:

$$\overline{Crs}=\left[\overline{Crs}_{ij}\right]_{m\times n}=\begin{bmatrix}\overline{Crs}_{11} & \overline{Crs}_{12} & \dots & \overline{Crs}_{1n}\\ \overline{Crs}_{21} & \overline{Crs}_{22} & \dots & \overline{Crs}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \overline{Crs}_{m1} & \overline{Crs}_{m2} & \dots & \overline{Crs}_{mn}\end{bmatrix} \tag{25}$$

Step 17. Define positive-ideal and negative-ideal vectors (PIV and NIV) of possibilistic interval mean for the selection problem of a resilient supplier. The PIV ($\overline{M}^{*}$) and NIV ($\overline{M}^{-}$) are calculated by:

$$\overline{M}^{*}=\left[\left(m_{j}^{*}\right)^{L},\left(m_{j}^{*}\right)^{U}\right]=\left\{\overline{M}_{1}^{*},\overline{M}_{2}^{*},\dots,\overline{M}_{n}^{*}\right\}=\left\{\max_{i}\overline{m}_{ij}\middle| i=1,2,\dots,m\right\} \tag{26}$$

$$\overline{M}^{-}=\left[\left(m_j^{-}\right)^L,\left(m_j^{-}\right)^U\right]=\left\{\overline{M}_1^{-},\overline{M}_2^{-},\ldots,\overline{M}_n^{-}\right\}=\left\{\min_i \overline{m}_{ij}\middle| i=1,2,\ldots,m\right\} \tag{27}$$

Step 18. Define positive-ideal and negative-ideal vector (PIV and NIV) of possibilistic interval standard deviation. The PIV ($\overline{Sd}^{*}$) and NIV ($\overline{Sd}^{-}$) are determined by:

$$\overline{Sd}^{*}=\left[\left(Sd_j^{*}\right)^L,\left(Sd_j^{*}\right)^U\right]=\left\{\overline{Sd}_1^{*},\overline{Sd}_2^{*},\ldots,\overline{Sd}_n^{*}\right\}=\left\{\min_i \overline{Sd}_{ij}\middle| i=1,2,\ldots,m\right\} \tag{28}$$

and

$$\overline{Sd}^{-}=\left[\left(Sd_j^{-}\right)^L,\left(Sd_j^{-}\right)^U\right]=\left\{\overline{Sd}_1^{-},\overline{Sd}_2^{-},\ldots,\overline{Sd}_n^{-}\right\}=\left\{\max_i \overline{Sd}_{ij}\middle| i=1,2,\ldots,m\right\} \tag{29}$$

Step 19. Define positive-ideal and negative-ideal vector (PIV and NIV) of possibilistic interval cube-root of skewness. The PIV ($\overline{Crs}^{*}$) and NIV ($\overline{Crs}^{-}$) are determined by:

$$\overline{Crs}^{*}=\left[\left(Crs_j^{*}\right)^L,\left(Crs_j^{*}\right)^U\right]=\left\{\overline{Crs}_1^{*},\overline{Crs}_2^{*},\ldots,\overline{Crs}_n^{*}\right\}=\left\{\min_i \overline{Crs}_{ij}\middle| i=1,2,\ldots,m\right\} \tag{30}$$

and

$$\overline{Crs}^{-}=\left[\left(Crs_j^{-}\right)^L,\left(Crs_j^{-}\right)^U\right]=\left\{\overline{Crs}_1^{-},\overline{Crs}_2^{-},\ldots,\overline{Crs}_n^{-}\right\}=\left\{\max_i \overline{Crs}_{ij}\middle| i=1,2,\ldots,m\right\} \tag{31}$$

Step 20. Calculate the separation measures of each resilient supplier candidate's possibilistic interval mean, standard deviation and cube-root of skewness from the PIV ($\overline{M}^{*}$, $\overline{Sd}^{*}$ and $\overline{Crs}^{*}$), respectively. The separation vectors of possibilistic interval mean, standard deviation and cube-root of skewness from the PIV are obtained for the selection problem of the resilient supplier as follows:

$$D_i\left(\overline{m}_{ij},\overline{M}_j^{*}\right)=\sqrt{\sum_{j=1}^{n}\left(\left(\left(m_j^{*}\right)^L-m_{ij}^L\right)^2+\left(\left(m_j^{*}\right)^U-m_{ij}^U\right)^2\right)} \tag{32}$$

$$D_i\left(\overline{Sd}_{ij},\overline{Sd}_j^{*}\right)=\sqrt{\sum_{j=1}^{n}\left(\left(\left(Sd_j^{*}\right)^L-Sd_{ij}^L\right)^2+\left(\left(Sd_j^{*}\right)^U-Sd_{ij}^U\right)^2\right)} \tag{33}$$

and,

$$D_i\left(\overline{Crs}_{ij},\overline{Crs}_j^{*}\right)=\sqrt{\sum_{j=1}^{n}\left(\left(\left(Crs_j^{*}\right)^L-Crs_{ij}^L\right)^2+\left(\left(Crs_j^{*}\right)^U-Crs_{ij}^U\right)^2\right)} \tag{34}$$

Step 21. Compute the separation measures of each resilient supplier candidates' possibilistic interval mean, standard deviation and cube-root of skewness from the NIV ($\overline{M}^{-}$, $\overline{Sd}^{-}$ and $\overline{Crs}^{-}$), respectively. The separation vectors of possibilistic interval mean, standard deviation and cube-root of skewness from the NIV is obtained for the selection problem of the resilient supplier as follows:

$$D_i\left(\overline{m}_{ij}, \overline{M}_j^-\right) = \sqrt{\sum_{j=1}^{n}\left(\left(\left(m_j^-\right)^L - m_{ij}^L\right)^2 + \left(\left(m_j^-\right)^U - m_{ij}^U\right)^2\right)} \tag{35}$$

$$D_i\left(\overline{Sd}_{ij}, \overline{Sd}_j^-\right) = \sqrt{\sum_{j=1}^{n}\left(\left(\left(Sd_j^-\right)^L - Sd_{ij}^L\right)^2 + \left(\left(Sd_j^-\right)^U - Sd_{ij}^U\right)^2\right)} \tag{36}$$

and

$$D_i\left(\overline{Crs}_{ij}, \overline{Crs}_j^-\right) = \sqrt{\sum_{j=1}^{n}\left(\left(\left(Crs_j^-\right)^L - Crs_{ij}^L\right)^2 + \left(\left(Crs_j^-\right)^U - Crs_{ij}^U\right)^2\right)} \tag{37}$$

Step 22. Construct the distance vectors for the selection problem of a resilient supplier. The distance vectors are constructed as follows:

$$D_i = \left\{D_i^1, D_i^2, D_i^3, D_i^4, D_i^5, D_i^6\right\} = \left\{D_i\left(\overline{m}_{ij}, \overline{M}_j^*\right), D_i\left(\overline{Sd}_{ij}, \overline{Sd}_j^*\right), D_i\left(\overline{Crs}_{ij}, \overline{Crs}_j^*\right),\right.$$
$$\left. D_i\left(\overline{m}_{ij}, \overline{M}_j^-\right), D_i\left(\overline{Sd}_{ij}, \overline{Sd}_j^-\right), D_i\left(\overline{Crs}_{ij}, \overline{Crs}_j^-\right)\right\} \tag{38}$$

Step 23. Determine the positive ideal and negative ideal solutions from the distance vectors for the selection problem of a resilient supplier.
The positive ideal solution C^* and negative ideal solution C^- from the distance vectors are calculated by:

$$C_i^* = \{C_1^*, C_2^*, C_3^*, C_4^*, C_5^*, C_6^*\} = \left\{\min_i D_i\left(\overline{m}_{ij}, \overline{M}_j^*\right), \min_i D_i\left(\overline{Sd}_{ij}, \overline{Sd}_j^*\right), \min_i D_i\left(\overline{Crs}_{ij}, \overline{Crs}_j^*\right),\right.$$
$$\left.\max_i D_i\left(\overline{m}_{ij}, \overline{M}_j^-\right), \max_i D_i\left(\overline{Sd}_{ij}, \overline{Sd}_j^-\right), \max_i D_i\left(\overline{Crs}_{ij}, \overline{Crs}_j^-\right)\right\} \tag{39}$$

and

$$C_i^- = \{C_1^-, C_2^-, C_3^-, C_4^-, C_5^-, C_6^-\} = \left\{\max_i D_i\left(\overline{m}_{ij}, \overline{M}_j^*\right), \max_i D_i\left(\overline{Sd}_{ij}, \overline{Sd}_j^*\right), \max_i D_i\left(\overline{Crs}_{ij}, \overline{Crs}_j^*\right),\right.$$
$$\left.\min_i D_i\left(\overline{m}_{ij}, \overline{M}_j^-\right), \min_i D_i\left(\overline{Sd}_{ij}, \overline{Sd}_j^-\right), \min_i D_i\left(\overline{Crs}_{ij}, \overline{Crs}_j^-\right)\right\} \tag{40}$$

Step 24. Define novel separation measures using the Euclidean distance for the selection problem of the resilient supplier. The separations of each resilient supplier candidate from the positive and negative ideal solutions are determined by:

$$\Lambda^* = [\delta_i^*] = \sqrt{\left[D_i^1 - C_1^*\right]^2 + \left[D_i^2 - C_2^*\right]^2 + \cdots + \left[D_i^6 - C_6^*\right]^2} \tag{41}$$

and

$$\Lambda^- = [\delta_i^-] = \sqrt{\left[D_i^1 - C_1^-\right]^2 + \left[D_i^2 - C_2^-\right]^2 + \cdots + \left[D_i^6 - C_6^-\right]^2} \tag{42}$$

Step 25. Rank the preference order of resilient supplier candidates. For ranking using Λ_i, it can be ranked by K_i in ascending order.

$$K_i = \sqrt{[\Lambda_i^* - min(\Lambda_i^*)]^2 + [\Lambda_i^- - max(\Lambda_i^-)]^2} \quad (43)$$

The proposed new interval-valued fuzzy group decision model based on possibilistic statistical concepts in the supply chain for the resilient supplier selection is shown in Fig. 2. In fact, for equations (41) to (43), we have a distance-vector in Step 22, which is defined between each of the statistical concepts, including mean, standard deviation and skewness, and then their ideal positive and negative solutions are constructed. Finally, in Step 24 based on Relations (41) and (42), the Euclidean distance is achieved between negative and positive solutions (the ideal vector) for integrating the positive and negative aspects related to the six aspects. In relation (43), a new ranking is also offered based on the positive and negative solutions with interval computations.

4- Illustrative example

In this section, an illustrative example is provided from the recent literature for the resilient supplier selection problem (Sahu et al., 2016). It has been assumed that a company wishes to take a proactive resiliency strategy into account to rank potential suppliers as its commitment to the global marketplace. A finite number of candidate resilient suppliers have been identified for the further analysis. From different functional areas, five DMs (experts) participated towards evaluating the suppliers. In this regard, DM_1 and DM_2 are optimistic; DM_3, DM_4 and DM_5 are neutral.

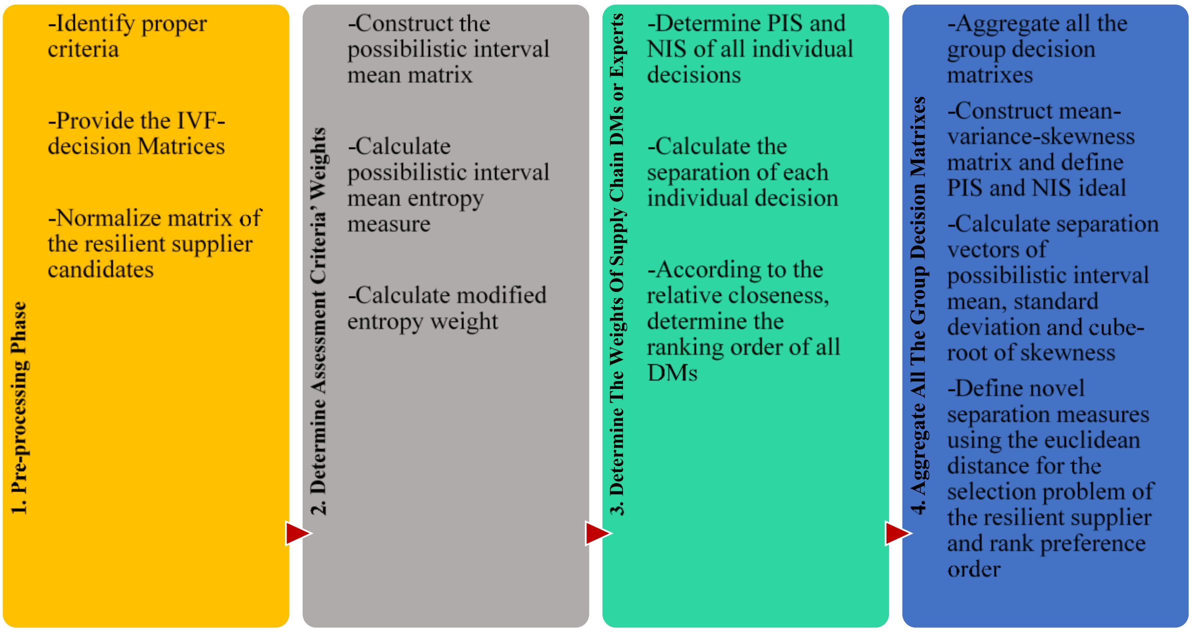

Fig. 2 Main steps of the proposed group decision approach

4-1- Computational results

In this step, the supplier alternatives under a resiliency strategy are taken into account. A disrupted supply chain network needs a dynamic assessment of strategic planning. Three strategic planning factors have been reported in developing resiliency to the SCM, namely, R_1, R_2 and R_3, as provided in table 1.

Table 1. Definition and identification factors (Haldar et al., 2014)

(R_1)	(R_2)	(R_3)
Investment in capacity buffers	Responsiveness	Capacity for holding strategic inventory stocks for crises
The factor regards ability of individual organization to investment the money for reserve the excess product as a safeguard against unforeseen shortages or demands	The factor is related to the willingness to respond to customer requires the help of several medium, i.e., answering their phone or e-mail requests quickly, by acknowledging them quickly	The factor is regarded as a capacity of firm to holding a large stock of key materials and goods to withstand a long period of scarcity caused by a natural disaster, war or strike action

The priority weight described by linguistic terms of each of the three-resiliency factors or criteria provided by the individual supply chain-DMs are provided in table 2. Each DM rates a resilient supplier candidate with respect to each assessment criterion, and the data are reported in Table 3. Because the supply chain experts' judgments partially depend on the personal preference, the DMs' opinions are provided by linguistic terminologies, which are further converted into appropriate interval-valued fuzzy numbers.

Table 2. Linguistic variables for the values of resilient supplier candidates

Linguistic variables	Interval-valued fuzzy numbers
Very Poor (VP)	[(0.00,0.00,1.00), (0.00,0.00,1.50)]
Poor (P)	[(0.50,1.00,2.50), (0.00,1.00,3.50)]
Moderately Poor (MP)	[(1.50,3.00,4.50), (0.00,3.00,5.50)]
Fair (F)	[(3.50,5.00,6.50), (2.50,5.00,7.50)]
Moderately Good (MG)	[(5.50,7.00,8.00), (4.50,7.00,9.50)]
Good (G)	[(7.50,9.00,9.50), (5.50,9.00,10.00)]
Very Good (VG)	[(9.50,10.00,10.00), (8.50,10.00,10.00)]

To determine assessment criteria' weights, the possibilistic interval mean matrix is established for the selection problem of the resilient supplier candidates. Then, a proposed modified entropy weight based on the possibilistic interval mean is computed as given in Table 4 by equation (11).

Table 3. Performance rating of the supplier candidates by linguistic variables for the resilient supplier selection

Criteria	Supplier	Decision makers				
		DM_1	DM_2	DM_3	DM_4	DM_5
R_1	S_1	MG	VG	MG	MG	G
	S_2	G	G	MG	MG	G
	S_3	MG	F	MP	F	F
	S_4	MP	MP	G	G	F
	S_5	VG	G	G	MG	MG
R_2	S_1	MG	MG	MG	MG	MG
	S_2	G	VG	G	G	G
	S_3	MG	VG	VG	MG	G
	S_4	G	MG	G	G	G
	S_5	G	MG	MG	F	F
R_3	S_1	VG	VG	G	F	F
	S_2	VG	G	MG	VG	VG
	S_3	MG	MG	MG	MP	MP
	S_4	G	VG	G	VG	MG
	S_5	VG	G	VG	VG	VG

The weights of the supply chain DMs or experts are obtained. The possibilistic interval mean matrix by considering the different important of each assessment criterion is established. Then, a relative closeness is defined and computed to determine the ranking order of all five DMs. Finally, the DMs' weight vector is as below:

$\vartheta = (\vartheta_1, \vartheta_2, \vartheta_3, \vartheta_4, \vartheta_5)^T = (0.1703, 0.1951, 0.2226, 0.2116, 0.2005)$

Table 4. Assessment criteria' weights by the proposed modified entropy weight based on the possibilistic interval mean

	R_1	R_2	R_3
DM_1	[0.425,0.534]	[0.772,0.901]	[0.758,0.854]
DM_2	[0.441,0.488]	[0.563,0.720]	[0.714,0.802]
DM_3	[0.485,0.550]	[0.498,0.564]	[0.498,0.564]
DM_4	[0.422,0.469]	[0.514,0.579]	[0.516,0.561]
DM_5	[0.433,0.492]	[0.605,0.690]	[0.375,0.409]

The aggregated weight normalized decision matrix is provided in table 5 for the resilient supplier selection. To rank the resilient supplier candidates, the possibilistic interval mean matrix is established. Then, possibilistic interval mean matrix, the possibilistic interval standard deviation matrix and possibilistic interval cube-root of skewness matrix are constructed for the resilient supplier selection problem.

The weighted separation measures of each resilient supplier candidate's possibilistic interval mean, standard deviation and cube-root of skewness are computed from the PIV and NIV. Then, the distance vectors are constructed for the selection problem of a resilient supplier as reported in Table 6. Finally, the preference order of resilient supplier candidates is provided as given in Table 7. In addition, the computational results have been compared with the method proposed by Sahu et al. (2016) regarded as the recent literature and reported in this table. Both fuzzy decision methods propose S_2 and S_5 as the first rank and second rank for the resilient supplier selection problem.

The proposed decision model, compared with the study taken by Sahu et al. (2016), has the following main features:

- Sahu et al. (2016) used triangular fuzzy numbers while the proposed method considered interval-valued fuzzy numbers to handle uncertainty in the selection of resilient suppliers.
- The proposed model regarded asymmetric data in terms of the weighting and assessment computation, in such a way that each of experts with optimistic, pessimistic and neutral attitudes can provide their judgments in the decision matrix, unlike the previous studies.
- In Sahu et al. (2016), the criteria weights were described by linguistic variables; however, in the proposed model, we extend the concept of entropy method with the possibilistic statistical concept.
- In Sahu et al. (2016), weights of the decision-makers were not considered in the calculations; however, the proposed approach presented a new weighting method of the experts within the group decision process based on interval-valued fuzzy sets and possibilistic statistical concepts.

Moreover, in the proposed model, new relations are introduced for getting positive and negative ideal solutions with possibilistic mean, possibilistic standard deviation, and the possibilistic cube-root of skewness with interval-valued fuzzy sets. Then, a new ranking process based on relative-closeness coefficients is presented to rank all resilient supplier candidates under the interval-valued fuzzy uncertainty, unlike the previous studies.

Table 5. Aggregated weight normalized decision matrix for the resilient supplier selection

Supplier Candidates	(R_1)	(R_2)	(R_3)
S_1	[(0.13,0.16,0.17); (0.11,0.17,0.19)]	[(0.11,0.15,0.16); (0.09,0.16,0.19)]	[(0.13,0.15,0.17); (0.11,0.15,0.18)]
S_2	[(0.13,0.17,0.18); (0.10,0.17,0.20)]	[(0.16,0.19,0.19); (0.12,0.19,0.20)]	[(0.16,0.18,0.19); (0.14,0.19,0.20)]
S_3	[(0.07,0.11,0.13); (0.05,0.12,0.15)]	[(0.15,0.18,0.18); (0.13,0.18,0.20)]	[(0.08,0.11,0.13); (0.05,0.13,0.16)]
S_4	[(0.09,0.13,0.14); (0.06,0.14,0.16)]	[(0.14,0.18,0.18); (0.11,0.19,0.20)]	[(0.16,0.18,0.19); (0.13,0.18,0.20)]
S_5	[(0.14,0.17,0.18); (0.11,0.17,0.20)]	[(0.10,0.14,0.15); (0.08,0.14,0.18)]	[(0.18,0.20,0.20); (0.16,0.20,0.20)]

Table 6. Construct the distance vectors for the selection problem of resilience supplier

Supplier Candidates	D_1	D_2	D_3	D_4	D_5	D_6
S_1	0.0796	0.0018	0.0137	0.1018	0.0017	0.0136
S_2	0.0228	0.0019	0.0280	0.1440	0.0018	0.0147
S_3	0.1442	0.0022	0.0299	0.0578	0.0019	0.0164
S_4	0.0656	0.0017	0.0337	0.1126	0.0019	0.0155
S_5	0.0670	0.0020	0.0248	0.1455	0.0022	0.0148

4-2- Sensitivity Analysis

In this section, a sensitivity analysis is conducted to further study the impact of weights of five supply chain-experts for the evaluation and selection problem on the final ranking. The results of this sensitivity analysis are reported in Tables 8 and 9, respectively, and figure 3. The idea of the evaluation is to exchange each weight of five supply chain-experts with another expert’s weight. In addition, the main condition illustrates the original results of the resilient supplier selection application. It corresponds with what this paper expects, most rankings are remaining with limited changes.

Table 7. Preference order of resilient supplier candidates for the selection problem

Supplier Candidates	Λ^{+}	Λ^{-}	K_i	Ranking based on the proposed approach	OSI_{NRi}	Ranking based on (Sahu et al., 2016)
S_1	0.07176	0.08071	0.08915	4	0.865	4
S_2	0.01453	0.14907	0.00000	1	1	1
S_3	0.15071	0.00471	0.19846	5	0.718	5
S_4	0.05763	0.09586	0.06848	3	0.892	3
S_5	0.04565	0.11724	0.04451	2	0.955	2

Table 8. Changes on weights of five supply chain-experts in the supplier selection problem

Conditions	ϑ_1	ϑ_2	ϑ_3	ϑ_4	ϑ_5
Main	0.1703	0.1951	0.2226	0.2116	0.2005
1	0.1951	0.1703	0.2226	0.2116	0.2005
2	0.2226	0.1951	0.1703	0.2116	0.2005
3	0.2116	0.1951	0.2226	0.1703	0.2005
4	0.2005	0.1951	0.2226	0.2116	0.1703
5	0.1703	0.2226	0.1951	0.2116	0.2005
6	0.1703	0.2116	0.2226	0.1951	0.2005
7	0.1703	0.2005	0.2226	0.2116	0.1951
8	0.1703	0.1951	0.2116	0.2226	0.2005
9	0.1703	0.1951	0.2005	0.2116	0.2226
10	0.1703	0.1951	0.2226	0.2005	0.2116

Table 9. Sensitivity analysis on final ranking for weights of five supply chain-experts in the supplier selection problem

Conditions	S_1	S_2	S_3	S_4	S_5
Main	0.089	0.000	0.198	0.068	0.045
1	0.091	0.000	0.199	0.069	0.042
2	0.094	0.000	0.202	0.084	0.047
3	0.081	0.000	0.192	0.081	0.038
4	0.084	0.000	0.194	0.070	0.038
5	0.090	0.000	0.199	0.076	0.049
6	0.000	0.000	0.000	0.000	0.000
7	0.088	0.000	0.197	0.069	0.044
8	0.092	0.000	0.201	0.068	0.047
9	0.095	0.000	0.203	0.074	0.050
10	0.089	0.000	0.198	0.071	0.045

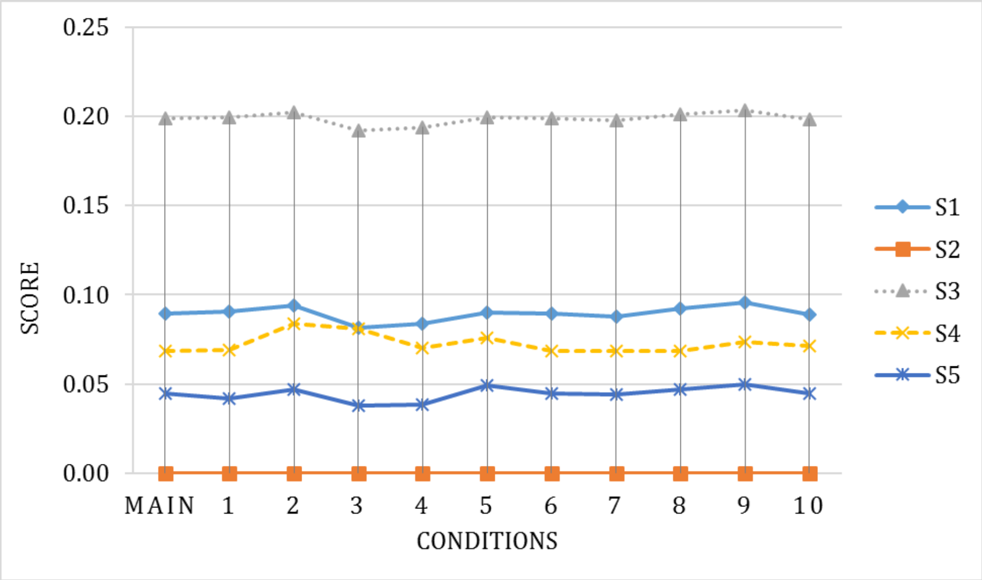

Fig. 3 Sensitivity analysis on the scoring based on weights of the supply chain experts

5- Conclusion

Main objective of the supplier selection is to choose appropriate suppliers by regarding resilient capabilities of the organization's supply chain. Considering the resilient strategy in supply chain networks can decrease their risks and costs. To the best of the authors' knowledge, no research has been observed for assessment of suppliers in terms of a resilient supply chain for group decision-making process based on interval-valued fuzzy sets and possibilistic statistical concepts. This paper introduced a new multi-criteria group decision-making (MCGDM) approach to evaluate the suitable resilient supplier selection under uncertain conditions in supply chain networks. This new MCGDM model was proposed under an interval-valued fuzzy environment based on three possibilistic mean, standard deviation and the cube-root of skewness matrices. New relations were presented for obtaining positive and negative ideal solutions with possibilistic mean, possibilistic standard deviation, and the possibilistic cube-root of skewness with interval-valued fuzzy sets. Also, a possibilistic interval mean entropy method was developed for the weight of each resilient evaluation criterion. In addition, a new weighting method of the experts within the group decision-making process was proposed based on interval-valued fuzzy sets and possibilistic statistical concepts. Finally, a new ranking process based on relative-closeness coefficients was introduced to rank all resilient supplier candidates under the interval-valued fuzzy uncertainty. An illustrative example was provided from the recent literature for the resilient supplier selection problem and then was solved by the proposed approach. Further, a sensitivity analysis was reported regarding the weights' impacts for five supply chain-experts to the further study on the final rankings. Also, a comparative analysis in details was provided with the fuzzy decision method by Sahu et al. (2016) for the resilient supplier evaluation problem. For the further research, the proposed MCGDM approach can be improved by exploring the potential of using of the last aggregation approach and different weights of the supply chain experts. To obtain the criteria weights, an entropy method can be extended with other aspects of possibilistic statistical concepts, such as standard deviation and skewness. Moreover, the group decision approach can be hybridized by an optimization technique with respect to amplifying agreement to decide weights of the resilient supply chain decision makers under uncertainty.

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