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Factors Affecting the Use of Blockchain Technology in Humanitarian Supply Chain: A Novel Fuzzy Large-Scale Group-DEMATEL

Lu Chen[1] · **Ayad Hendalianpour**[2] · **Mohammad Reza Feylizadeh**[3] · **Haiyan Xu**[1]

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Abstract

Based on previous evidence, the use of blockchain for improving Supply Chains (SCs) regarding humanitarian projects has received attention over the past five years. The present study is innovative in investigating crucial parameters affecting the using of Blockchain Technology (BT) in Humanitarian Supply Chains (HSCs). More precisely, this study emphasizes parameters that affect blockchain in the HSCs and presents a new fuzzy large-scale group decision-making trial and evaluation laboratory (fuzzy large-scale group-DEMATEL) approach to analyze the interdependence of contributing factors for using BT in HSCs. This method consists of two stages: (1) clustering the large-scale group-experts into small subgroups by their characteristics, and (2) identifying the key factors affecting BT in HSCs with a novel fuzzy large-scale group-DEMATEL approach. According to experts, in this study, among the 25 evaluated factors, disintermediation has been identified as the most important one, followed by anonymity and security. A closer look reveals that 13 and 12 factors have been "cause" and "effect" factors, respectively. Our research can be used to promote the effectiveness of using BT in HSCs, so as to promote the proper distribution of relief materials in practical disasters.

Keywords Blockchain technology · Humanitarian supply chains · Fuzzy sets · Large-scale group-DEMATEL

1 Introduction

Each year, natural disasters such as earthquakes, floods, fires, storms, and droughts affect different parts of the world and are often accompanied by financial and human loss. Further, the severity, dimensions, and factors of these incidents, such

✉ Haiyan Xu
xuhaiyan@nuaa.edu.cn

Extended author information available on the last page of the article

as population growth, changes in weather conditions, the integrity of systems, and the volume of demand for rescue operations, are extremely high. Humanitarian supply chains (HSCs) has been an important research topic as it is critical to alleviating human suffering after a disaster, especially with the outbreak of COVID-19 pandemic, the proper distribution of drugs and medical equipment has become more important than ever (Govindan et al. 2020). It is noted that HSCs have huge chanllenges due to (1) excessive but unclear relief needs, (2) lack of organization, coordination, cooperation and communication, (3) lack of unified and effective information management platform and so on. It is anticipated that the current HSCs will frequently be insufficient to satisfy the demand. As a tool to store information records or facilitate payments by increasing productivity (Angrish et al. 2018; Antonucci et al. 2019), Blockchain Technology (BT) used to improve Supply Chains (SCs) for humanitarian projects has been considered over the past five years (Hendalianpour et al. 2020; Liu et al. 2021). Emergency events, such as COVID-19, tend to be of high complexity. Due to the limitations of human cognition and the incompleteness of information, single or small scale decision makers (DMs) cannot handle such complex decision-making problems. Therefore, a large-scale group-DMs from varying professional backgrounds are required to participate the decision making process.

Large-scale group decision-making (LSGDM) as an important research topic has been widely discussed (Zhang et al. 2021; Tang et al. 2021; Du et al. 2021; Jin et al. 2021; Li et al. 2022a, 2022b), complex decision-making problems can be effectively addressed by aggregating the views of large-scale group-DMs with diverse backgrounds. A widely used method to address the LSGDM problem is used to cluster the large-scale group into small group. For complex decision problems, large-scale group-DMs give the evaluations according to their own status, experience, education and so on, and they may take strongly different preferences on the evaluation objects. Therefore, how to aggregate the opinions of diverse large-scale group-DMs and determine the final decision information becomes an important challenge in LSGDM process. Generally, we can aggregate the large-scale group-DMs by clustering method, which can be divided into hard clustering and fuzzy clustering (Li et al. 2022a, 2022b; Gupta et al. 2022). Hard clustering mainly includes K-means, C-means, etc., and the most popular fuzzy clustering is fuzzy C-means (FCM). Although hard clustering methods have the advantages of fast speed and easy calculation, they often lead to misjudgment. Fuzzy clustering methods can not only avoid the misjudgment problem, but also provide more flexible clustering results. Moreover, clustering methods, such as K-means and kernel K-means, can just deal with the binary data (0 or 1), while FCM can deal with fuzzy numbers ([0,1]). In reality, however, data is often multiple and inconsistent, it is not just a single binary or fuzzy. Therefore, Hendalianpour et al. (2017) proposed a novel clustering algorithm called fuzzy relation clustering (FRC) that can simultaneous processing both crisp, fuzzy quantity and linguistic variables. Table 1 shows the comparisons of the popular clustering algorithms.

BT's capabilities can be used in different parts of the HSCs. The same increase in data management costs, the avoidance of scalability, and centralized models allow data manipulation, limit data reliability, and lead to significant security challenges.

Table 1 Comparisons of the popular clustering algorithms

Clustering methods	Data types	Pros	Cons
Hard clustering			
K-means	Binary	It has fast speed and easy calculation	It needs to preset the number of clusters. Each data is allocated just to one cluster, which may lead to misjudgment
Kernel K-means	Binary	It is possible to improve the clustering effect by mapping all samples to another feature space	
Fuzzy clustering			
Fuzzy C-means	Fuzzy numbers	It can avoid the misjudgment	It can only deal with the fuzzy numbers
Fuzzy relation clustering	Binary, quantitative, linguistic	It can simultaneous processing both crisp and fuzzy quantity variables	–

On the other hand, BT has the potential to overcome these problems. It represents a quantum leap in SCs management because it significantly improves productivity, resource management, product and service security, as well as data transparency (Bai and Sarkis 2020). Communication and collaboration between the various organizations involved in the HSCs are crucial. Some applications of how to use BT to support infrastructure in independent humanitarian actions include: payment management, inefficiency monitoring and modification, implementation, as well as identity encryption security. In HSCs, building trust is important due to different sectors have no acquaintance with each other in many cases. Further, there is an urgent need to respond quickly and create more responsiveness and resilience in HSCs since consumers, investors, governments, and communities may ultimately judge companies on how they react to this disruption. Accordingly, it is essential to identify the pattern of causal relationships between the studied variables, recognize the causal associations while using BT in HSCs, and consider how organizations can respond to these stakeholders in a disaster outbreak using BT in their HSCs.

So far, a large body of research has focused on the impact of BT in the SCs. Saberi et al. (2019) investigated different motivations and barriers to integrating BT in SCs by various industries. In addition, Jayaraman et al. (2019) highlighted key challenges in health care SCs and demonstrated how BTs could play a part in tackling those challenges at that time and shortly. Furthermore, some studies evaluated the impact of BT in the HSCs. Çağlıyangil et al. (2020) suggested an Ethereum blockchain-based framework called ‘KanCoin’, which can deal with and regulate the processes of distribution planning in the blood distribution system more effectively compared to common methods. Although the above studies analyzed the influence and advantages of using BT in SCs, they did not take into account the complexity and interrelated characteristics of factors.

To further promote the HSCs programes and ensure that funds and resources can reach those who need them, improving the efficiency of BT application in HSCs becomes a big chanllenge. Summarizing the existing studies, the use of BT is effected by multiple interrelated factors. Therefore, DMs need to identify the key factors and propose the effective advices (Abosuliman et al. 2020; Khoshaim et al. 2021; Qiyas et al. 2021). Decision-making trial and evaluation laboratory (DEMATEL) method was first proposed by Gabus and Fontela (1972) and has been widely applied in several fields for screening the main factors of complex and interrelated systems and visualizing the results. With the increasing complexity and uncertainty of practical decision-making problems, more and more scholars proposed the fuzzy DEMATEL (FDEMATEL) based on fuzzy theory (Zadeh 1965). Xu et al. (2021a) investigated the barriers of the hydrogen refueling stations' growth in China using a modified FDEMATEL method. Farooque et al. (2020) assessed the blockchain-based life cycle in China by ranking the significant barriers using the FDEMATEL method. Ahmadi et al. (2020) recognized and classified accidents' barriers, starter elements and their risk influence factors based on a conceptual model, and specified the relation between the risk impact factors by utilizing the FDEMATEL method. Although the researches about FDEMATEL have good performance for handling uncertainties, the analysis of the influencing factors requires comprehensive expertise in multiple fields due to the complex and changeable internal and external environment. Besides, the attitudes, beliefs and backgrounds of DMs are limited and difficult to give the accurately evaluation by individual DM. Therefore, some scholars established group-DEMATEL method (Han et al. 2018; Wang et al. 2020; Addae et al. 2021) to solve these problems by organizing group-DMs. For example, Qi et al. (2020) disengaged and determined the relationships between factors and the critical factors, modified a two-step FDEMATEL model for evaluating with group knowledge. But group-DEMATEL method still has limitations in expressing the reliability of DMs' cognitive information and unable to handle the assessment data from large-scale group-DMs. A proper method that cluster the large-scale group-DMs is necessary for reducing the complexity of obtaining evaluation results. At the same time, the uncertain characteristics of DMs and the ambiguity of their evaluation information should also be considered.

BT's influencing factors in the HSCs are complex, diverse and interrelated. It is necessary to analyze the key factors to improve the BT performance by evaluating each factor's importance and level. The DEMATEL method is chosen because of its ability to identify significant barriers and their interdependence. Other decision-oriented methodologies cannot reflect causal relationships and the overall impact of each other's theoretical and empirical analysis factors. In addition, (1) due to the complex and changeable internal and external environment, the influence factor analysis of BT in HSCs requires comprehensive expertise in multiple fields to solve the problem; (2) Personal values, attitudes, beliefs, and backgrounds of DMs are limited, individual DM is unable to solve all kinds of problems well. Therefore, DMs from different fields are required to actively participate in and provide relevant information to understand problems and make decisions from various perspectives.

For above reasons, a new method called 'fuzzy large-scale group-DEMATEL' is designed for identifying critical barriers and interrelated relationships while using BT in HSCs. The proposed method combines the advantages of fuzzy theory, clustering approach, and the DEMATEL technique. Thus, it can efficiently identify the key factors in the use of BT in HSCs. This study is one of the first studies to extensively examine BT and accept barrier-based theoretical frameworks for the use of BT in HSCs and expert perspectives. The whole decision procedure consists of two stages: aggregating large-scale group-DMs (i.e., group-experts), and identifying the key factors affecting BT in HSCs with a novel fuzzy large-scale group-DEMATEL approach. More specifically, in the aggregating large-scale group-experts stage, we cluster the large-scale group-experts by their characteristics, which may contain fuzzy information. Further, FDEMATEL is applied to control and express the uncertainty inherent in human judgments, which helps experts to minimize the vagueness of decision-making. According to the cases mentioned above, the innovations of this research are expressed as follows:

- Clustering the large-scale group-experts through their characteristics (background, age, experience, knowledge, etc.);
- Integrating of FRC method and FDEMATEL method for the use of BT in HSCs;
- Presenting a novel fuzzy large-scale group-DEMATEL method of causal relationships and the overall impact of factors on each other in HSCs;

- Investigating barriers and identifying causal relationships and the overall impact of factors on each other in the BT.

In sum, this paper firstly concentrates on the barrier analysis when using BT in HSCs under emergency (such as COVID-19), innovatively proposes that by considering the characteristic of large-scale group-DMs, we can cluster the large-scale group-DMs into small group to reduce the complexity of decision problems. Then, a FRC algorithm is embedded into FDEMATEL. Thus, DMs can identify the critical barriers and interrelated relationships when using BT in HSCs more efficient than previous studies.

The reminder of the paper is organized as follows. Section 2 reviews the theoretical foundation of fuzzy sets theory, FRC, and FDEMATEL. Our research method, a novel fuzzy large-scale group-DEMATEL, is shown in Sect. 3. Section 4 presents an empirical case to illustrate the procedure of the proposed method. Finally, Sect. 5 deals with the conclusions and future expectations.

2 Preliminaries

Some basic methods will be shown to accomplish the purpose of this study. This section describes the fuzzy set theory's features, the computational model utilized for the FRC algorithm (Hendalianpour et al. 2017), and FDEMATEL.

2.1 Fuzzy Set Theory

Fuzzy variables (Zadeh 1965) are simply observed to be an effective instrument for offering an approximate and optimal explanation of complex phenomena. The related definitions are shown as below.

Definition 1 (Hendalianpour et al. 2017) (Fuzzy relation) Let X, Y be two universes of discourse, and a fuzzy subset R of $X \times Y = \{(x, y)|x \in X, y \in Y\}$ is called a fuzzy relationship from X to Y:

$$R = \{(x, y), \mu_R(x, y)|(x, y) \in X \times Y\}$$

$$\mu_R : X \times Y \rightarrow [0, 1]$$

where μ_R is the membership function, $R(x, y)$ reflects the degree of R relationship between X and Y

Definition 2 (Hendalianpour et al. 2017) (Max–min composition) Considering $R_1(x, y)$ and $R_2(y, z)$ as two fuzzy relations of $(x, y) \in X \times Y$ and $(y, z) \in Y \times Z$, max–min composition $R_1 \circ R_2$ is defined as follows:

$$R_1 \circ R_2 = \{(x,z), \mathrm{Max}_y\{\mathrm{Min}\{\mu_{R_1}(x,y), \mu_{R_2}(y,z)\}\}|x \in X, y \in Y, z \in Z\}$$

Definition 3 (Hendalianpour et al. 2017) (Fuzzy equivalence relations) The fuzzy relation R on $X \times X$ represents a fuzzy equivalence relation by meeting the following three conditions:

1. *Reflexive* $\mu_R(x,x) = 1, \forall x \in X$.
2. *Symmetric* $R(x,y) = R(y,x), \forall x \in X, y \in Y$.
3. *Transitive* $R \circ R \subseteq R\left(R^2 \subseteq R\right)$.

Definition 4 (Ahmadi et al. 2020; Parmar et al. 2020). (Transitive closure) The transitive closure (R_T), a fuzzy relation R is explained as a transitive relation, which is R-contained and has the lowest possible membership scores. Assume R is a fuzzy reflexive and symmetric relation on a finite universal set X with $|X| = n$, then, the max–min transitive closure of R denotes the relation $R^{(n-1)}$. One may use the following algorithm for achieving the transitive closure $R_T = R^{(n-1)}$.

Algorithm of Transitive Closure

Step 1 Initialize $k = 0$, move to step 2;

Step 2 $k = k + 1$, if $2^k \geq (n-1)$, $R_T = R^{(n-1)}$ and stop. Otherwise, refer to step 3;

Step 3 $R^* = R^{2^{k-1}} \circ R^{2^{k-1}}$, if $R^* \subseteq R^{2^{k-1}}$; Then, $R_T = R^*$ and stop;

Otherwise, return to step 2.

Definition 5 (Zimmermann 2011). (α-cut) The α-cut set of the fuzzy relation (R_α) is:

$$R_\alpha = \{(x,y), \mu_{R_\alpha}(x,y) \big| \mu_R(x,y) \geq \alpha, (x,y) \in X \times Y\}$$

A representative relation of a finite number of elements is further indicated by trees wherein every level represents the n α-cut of the original relation. Researchers use the most popular fuzzy numbers in Multi-Criteria Decision Making (MCDM): Triangular Fuzzy Numbers (TFNs) and Trapezoidal Fuzzy Numbers (TrFNs). The advantage of using TrFNs is that a general case, TrFNs, is usually more useful than a particular case, TFNs (Hiete et al. 2012). We prefer to use TrFNs in this study, the membership function of a TrFN is shown in Fig. 1. Besides, our model is also applicable in the case where it is necessary to use TFNs, because by equating two middle parameters in a TrFN, TFNs can be reached.

Definition 6 (Ye 2011) (The distance of TrFNs) Regarding above algorithm, the distance between the two TrFNs, namely, $A_i = (c_i, a_i, b_i, d_i)$ and $A_j = (c_j, a_j, b_j, d_j)$, is denoted by $D(A_i, A_j)$ as follows:

$$D\left(A_i, A_j\right) = \begin{cases} [0.25\left(\left|c_i - c_j\right|^p + \left|a_i - a_j\right|^p + \left|b_i - b_j\right|^p + \left|d_i - d_j\right|^p\right)]^{\frac{1}{p}}, 1 \leq p < \infty \\ \max\left\{\left|c_i - c_j\right|, \left|a_i - a_j\right|, \left|b_i - b_j\right|, \left|d_i - d_j\right|\right\}, p = \infty \end{cases}$$

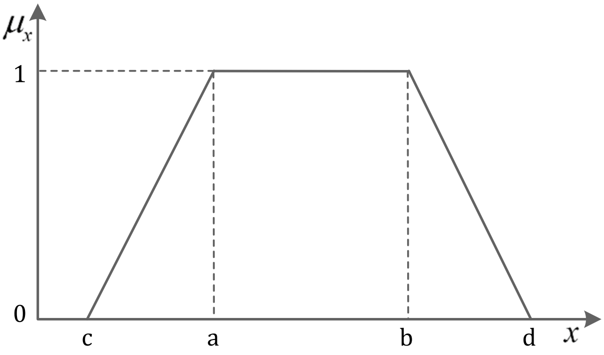

Fig. 1 Membership function of a TrFN

It is worth noting that when $p = 1$, the distance is Manhattan distance; when $p = 2$, it is Euclidean distance; when $p = \infty$, it is Chebyshev distance. We use Euclidean distance to calculate the distance of TrFNs ($p = 2$).

2.2 Fuzzy Relation Clustering (FRC)

For large-scale group-experts, we need to cluster the experts to manage the challenges, such as dimension reduction, weighting and aggregating decision information, behavior management, cost management, knowledge distribution and information increase. Otherwise, a large-scale group-experts will not give us the appropriate results. In practical decision problems, the form of information is not just a single crisp value or fuzzy value, but a variety of forms. The popular clustering algorithms can only deal with single data form, for instance, K-means only copes with the binary data and FCM only copes with fuzzy numbers. While FRC can simultaneous processing both crisp, fuzzy quantity and linguistic variables. Moreover, the research of Hendalianpour et al. (2017) has demonstrated the accuracy and high performance of FRC compared to other clustering methods. Therefore, this paper chooses FRC algorithms to cluster the large-scale group-DMs. Experts' relation information can generally be divided into binary variables (similar to marital status), quantitative variables (similar to age), and linguistic variables (expressed by sentences or words) as following three definitions.

Definition 7 (Hendalianpour et al. 2017) The binary variables are represented by vector X as follows:

$$X_i = \left(x_{i1}, x_{i2}, \ldots, x_{ik}, \ldots, x_{in_1}\right), i = 1, 2, ..., m; \quad k = 1, 2, ..., n_1$$

where m and n_1 indicate the number of experts and the number of binary variables, respectively. The existing relationship between the experts concerning the binary feature is determined as a classical relation with 0 or 1.

Definition 8 (Hendalianpour et al. 2017) The quantitative variables, accept integer or actual values, are represented by vector Y, namely, $Y_i = \left(y_{i1}, y_{i2}, \dots, y_{ik}, \dots, y_{in_2}\right), i = 1, 2, ..., m; k = 1, 2, ..., n_2$, where m and n_2 denote the number of experts and the number of quantitative variables. For the quantitative feature, the relations between the experts rely on the distance between their values. It is noteworthy that reducing the distance will strengthen the experts' relation while the increasing distance will weaken this relation.

Definition 9 (Hendalianpour et al. 2017) Linguistic variables are expressed by sentences or words in an artificial or a natural linguistic setting accepting the values and are demonstrated by fuzzy numbers. Hence, the vector of such linguistic variables is $Z_i = (z_{i1}^{L_1}, z_{i2}^{L_2}, ..., z_{ik}^{L_k}, \dots, z_{in_3}^{L_{n_3}}), i = 1, 2, \dots, m; k = 1, 2, ..., n_3$, where m is the number of experts and n_3 is the number of linguistic variables; $z_{ik}^{L_k}$ represents ith expert's kth linguistic variable value; $\#L_k$ is the number of kth linguistic variable values $\left(L_k = 1, 2, \dots, \#L_k\right)$.

If an expert has multiple linguistic variables, expressed by TrFNs, towards one factor/feature. The fuzzy average (Hiete et al. 2012) of these linguistic variables to fuse experts' opinions is proposed as $\widetilde{A}_i = \left(\frac{\sum_{L_k=1}^{\#L_k} c_i^{L_k}}{\#L_k}, \frac{\sum_{L_k=1}^{\#L_k} a_i^{L_k}}{\#L_k}, \frac{\sum_{L_k=1}^{\#L_k} b_i^{L_k}}{\#L_k}, \frac{\sum_{L_k=1}^{\#L_k} d_i^{L_k}}{\#L_k} \right)$, $i = 1, 2, \dots, m; k = 1, 2, ..., n_3; L_k = 1, 2, \dots, \#L_k$.

According to the above definitions, the steps of experts' segmentation are as follows:

Step 1 Experts' relations.

It is possible to frequently obtain three types of evaluation fuzzy relation matrices, namely, R_X, R_Y, and R_Z from vectors X, Y and Z, respectively.

$$R_X = \begin{array}{c} \\ E_1 \\ E_2 \\ \cdot \\ \cdot \\ \cdot \\ E_m \end{array} \begin{array}{c} \begin{array}{cccccc} E_1 & E_2 & \cdot & \cdot & \cdot & E_m \end{array} \\ \begin{bmatrix} r_{11} & r_{12} & \cdot & \cdot & \cdot & r_{1m} \\ r_{21} & r_{22} & \cdot & \cdot & \cdot & r_{2m} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ r_{m1} & r_{m2} & \cdot & \cdot & \cdot & r_{mm} \end{bmatrix} \end{array}, \quad R_Y = \begin{array}{c} \\ E_1 \\ E_2 \\ \cdot \\ \cdot \\ \cdot \\ E_m \end{array} \begin{array}{c} \begin{array}{cccccc} E_1 & E_2 & \cdot & \cdot & \cdot & E_m \end{array} \\ \begin{bmatrix} r'_{11} & r'_{12} & \cdot & \cdot & \cdot & r'_{1m} \\ r'_{21} & r'_{22} & \cdot & \cdot & \cdot & r'_{2m} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ r'_{m1} & r'_{m2} & \cdot & \cdot & \cdot & r'_{mm} \end{bmatrix} \end{array}, \quad R_Z = \begin{array}{c} \\ E_1 \\ E_2 \\ \cdot \\ \cdot \\ \cdot \\ E_m \end{array} \begin{array}{c} \begin{array}{cccccc} E_1 & E_2 & \cdot & \cdot & \cdot & E_m \end{array} \\ \begin{bmatrix} r''_{11} & r''_{12} & \cdot & \cdot & \cdot & r''_{1m} \\ r''_{21} & r''_{22} & \cdot & \cdot & \cdot & r''_{2m} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ r''_{m1} & r''_{m2} & \cdot & \cdot & \cdot & r''_{mm} \end{bmatrix} \end{array}$$

where E_i represents ith expert ($i = 1, 2, ..., m$) and $0 \le r_{ij}, r'_{ij}, r''_{ij} \le 1$.

In fuzzy relation matrices R_X, R_Y, R_Z, relation quantities $r_{ij}, r'_{ij}, r''_{ij}$ between experts i and j are defined by Eqs. (1–6) as follows, in which $\widetilde{A}_i = \left(\frac{\sum_{L_k=1}^{\#L_k} c_i^{L_k}}{\#L_k}, \frac{\sum_{L_k=1}^{\#L_k} a_i^{L_k}}{\#L_k}, \frac{\sum_{L_k=1}^{\#L_k} b_i^{L_k}}{\#L_k}, \frac{\sum_{L_k=1}^{\#L_k} d_i^{L_k}}{\#L_k} \right)$ is the average TrFN evaluation value of expert i:

$$r_{ij} = \frac{1}{\sum_{k=1}^{n_1} W_k^X} \sum_{k=1}^{n_1} W_k^X \left(1 - \left|x_{ik} - x_{jk}\right|\right), k = 1, 2, \dots, n_1 \tag{1}$$

$$r'_{ij} = \frac{1}{\sum_{k=1}^{n_2} W_k^Y} \sum_{k=1}^{n_2} W_k^Y \left(1 - \frac{\lfloor y_{ik} - y_{jk} \rfloor}{D(y_{ik}, y_{jk})}\right) \tag{2}$$

$$D(y_{ik}, y_{jk}) = \max\{\left|y_{ik} - y_{jk}\right| \mid i,j = 1,2,\dots,m\}, k = 1,2,\dots,n_2 \tag{3}$$

$$r''_{ij} = \frac{1}{\sum_{k=1}^{n_3} W_k^Z} \sum_{k=1}^{n_3} W_k^Z \left(1 - \frac{D\left(z_{ik}^{L_k}, z_{jk}^{L_k}\right)}{D'\left(z_{ik}^{L_k}, z_{jk}^{L_k}\right)}\right) \tag{4}$$

$$\begin{aligned} D\left(z_{ik}^{L_k}, z_{jk}^{L_k}\right) = \Bigg[0.25\Bigg(&\left|\frac{\sum_{L_k=1}^{\#L_k} c_i^{L_k}}{\#L_k} - \frac{\sum_{L_k=1}^{\#L_k} c_j^{L_k}}{\#L_k}\right|^2 + \left|\frac{\sum_{L_k=1}^{\#L_k} a_i^{L_k}}{\#L_k} - \frac{\sum_{L_k=1}^{\#L_k} a_j^{L_k}}{\#L_k}\right|^2 \\ &+ \left|\frac{\sum_{L_k=1}^{\#L_k} b_i^{L_k}}{\#L_k} - \frac{\sum_{L_k=1}^{\#L_k} b_j^{L_k}}{\#L_k}\right|^2 + \left|\frac{\sum_{L_k=1}^{\#L_k} d_i^{L_k}}{\#L_k} - \frac{\sum_{L_k=1}^{\#L_k} d_j^{L_k}}{\#L_k}\right|^2\Bigg)\Bigg]^{\frac{1}{2}} \\ &i,j = 1,2,\dots,m; k = 1,2,\dots,n_3 \end{aligned} \tag{5}$$

$$D'\left(z_{ik}^{L_k}, z_{jk}^{L_k}\right) = \max_{i,j=1}^{m}\{D\left(z_{ik}^{L_k}, z_{jk}^{L_k}\right)\}, k = 1,2,\dots,n_3 \tag{6}$$

where $W_k^X (k = 1,2,\dots,n_1)$ is the weight of the kth variable in vector X. Furthermore, $W_k^Y (k = 1,2,...,n_2)$ and $W_k^Z (k = 1,2,...,n_3)$ denote the weights of the kth variable in vectors Y and Z respectively.

Thus, the final fuzzy relation matrix R can be established by these three types of matrices as follows:

$$R = W_X \cdot R_X + W_Y \cdot R_Y + W_Z \cdot R_Z \tag{7}$$

$$W_X + W_Y + W_Z = 1, \left(W_X, W_Y, W_Z \geq 0\right) \tag{8}$$

where W_X, W_Y, W_Z are the weights of R_X, R_Y, and R_Z, respectively.

Example 1 Assuming that we need to cluster 3 experts, six features of experts are shown in Table 2. It is clear that marital status and gender are binary variables, age and income are quantitative variables, while experience and education are linguistic variables.

Take the binary features of expert 1 and expert 2 for example, $r_{12} = r_{21} = \frac{1}{\sum_{k=1}^{n_1} W_k^X} \sum_{k=1}^{n_1} W_k^X (1 - |x_{1k} - x_{2k}|) = \frac{1}{0.2+0.8}(0.2(1 - |1 - 0|) + 0.8(1 - |1 - 1|)) = 0.75.$

Table 2 Experts' feature information

Experts	Marital status	Gender	Age	Income	Experience	Education
Expert 1	1	1	20	20	Rich (3) General (2)	Medium (1)
Expert 2	0	1	30	18	General (2)	High (2)
Expert 3	0	0	25	30	Very rich (4)	Medium (1)
Value type	Binary	Binary	Quantitative	Quantitative	Linguistic	Linguistic
Weights	0.2	0.8	0.5	0.5	0.6	0.3

Then we can get the binary matrix $R_X = \begin{bmatrix} 1 & 0.75 & 0 \\ 0.75 & 1 & 0.25 \\ 0 & 0.25 & 1 \end{bmatrix}$.

Similarly, quantitative matrix $R_Y = \begin{bmatrix} 1 & 0.42 & 0.33 \\ 0.42 & 1 & 0.25 \\ 0.33 & 0.25 & 1 \end{bmatrix}$.

For linguistic variables, assuming the linguistic scale of experience is $\{0, 1, 2, 3, 4\}$, and education is $\{0, 1, 2\}$. Table 3 shows the corresponding TrFNs.

Let $p = 2$, the distance of TrFNs can be calculated as follows:

For the experience feature,

$$D\left(z_{11}^2, z_{21}^1\right) = 0.25 \times \left(\left| \frac{0.5 + 0.3}{2} - 0.3 \right|^2 + \left| \frac{0.6 + 0.4}{2} - 0.4 \right|^2 \right.$$
$$\left. + \left| \frac{0.7 + 0.5}{2} - 0.5 \right|^2 + \left| \frac{0.8 + 0.6}{2} - 0.6 \right|^2 \right)^{1/2} = 0.05$$

Table 3 Linguistic scale and equivalent TrFNs

Impact score	Description of the linguistic variable	Equivalent TrFNs
Experience		
0	Very poor	$(0, 0, 0.1, 0.2)$
1	Poor	$(0.1, 0.2, 0.3, 0.4)$
2	General	$(0.3, 0.4, 0.5, 0.6)$
3	Rich	$(0.5, 0.6, 0.7, 0.8)$
4	Very rich	$(0.7, 0.8, 0.9, 1)$
Education		
0	Low	$(0, 0.25, 0.35, 0.6)$
1	Medium	$(0.2, 0.45, 0.55, 0.8)$
2	High	$(0.4, 0.65, 0.75, 1)$

$$D\left(z_{11}^{2}, z_{31}^{1}\right) = 0.25 \times \left(\left|\frac{0.5+0.3}{2} - 0.7\right|^2 + \left|\frac{0.6+0.4}{2} - 0.8\right|^2 + \left|\frac{0.7+0.5}{2} - 0.9\right|^2 + \left|\frac{0.8+0.6}{2} - 1\right|^2\right)^{1/2} = 0.15$$

$$D\left(z_{21}^{1}, z_{31}^{1}\right) = 0.25 \times \left(|0.3-0.7|^2 + |0.4-0.8|^2 + |0.5-0.9|^2 + |0.6-1|^2\right)^{1/2} = 0.2$$

$$D'\left(z_{i1}^{L_1}, z_{j1}^{L_1}\right) = \max_{i,j=1}^{3}\{D\left(z_{i1}^{L_1}, z_{j1}^{L_1}\right)\} = \max_{i,j=1}^{3}\{0.05, 0.15, 0.2\} = 0.2.$$

For the education feature,

$$\left(z_{12}^{1}, z_{22}^{1}\right) = 0.25 \times \left(|0.2-0.4|^2 + |0.45-0.65|^2 + |0.55-0.75|^2 + |0.8-1|^2\right)^{1/2} = 0.1$$

$$D\left(z_{12}^{1}, z_{32}^{1}\right) = 0.25 \times \left(|0.2-0.2|^2 + |0.45-0.45|^2 + |0.55-0.55|^2 + |0.8-0.8|^2\right)^{1/2} = 0$$

$$D\left(z_{22}^{1}, z_{32}^{1}\right) = 0.25 \times \left(|0.4-0.2|^2 + |0.65-0.45|^2 + |0.75-0.55|^2 + |1-0.6|^2\right)^{1/2} = 0.1$$

$$D'\left(z_{i2}^{L_2}, z_{j2}^{L_2}\right) = \max_{i,j=1}^{3}\{D\left(z_{i2}^{L_2}, z_{j2}^{L_2}\right)\} = \max_{i,j=1}^{3}\{0.1, 0, 0.1\} = 0.1.$$

Therefore, $r''_{12} = r''_{21} = \frac{1}{\sum_{k=1}^{n_3} W_k^Z} \sum_{k=1}^{n_3} W_k^Z \left(1 - \frac{D\left(z_{1k}^{L_k}, z_{2k}^{L_k}\right)}{D'\left(z_{ik}^{L_k}, z_{jk}^{L_k}\right)}\right) = \frac{1}{0.6+0.3}\left(0.6 \times \left(1 - \frac{0.05}{0.2}\right)\right.$ $\left. +0.3 \times \left(1 - \frac{0.1}{0.1}\right)\right) = 0.5.$

Then we can get the corresponding linguistic matrix $R_Z = \begin{bmatrix} 1 & 0.5 & 0.67 \\ 0.5 & 1 & 0 \\ 0.67 & 0 & 1 \end{bmatrix}$.

Let the weights of R_X, R_Y, R_Z be $W_X = 0.2, W_Y = 0.3, W_Z = 0.5$, respectively; thus, the final fuzzy relation matrix is $R = \begin{bmatrix} 1 & 0.526 & 0.434 \\ 0.526 & 1 & 0.125 \\ 0.434 & 0.125 & 1 \end{bmatrix}$.

Step 2 Experts' segmentation.

Fuzzy relation matrices (i.e., R_X, R_Y, R_Z) are reflexive and symmetric because

$$r_{ii} = r'_{ii} = r''_{ii} = 1 \tag{9}$$

$$r_{ij} = r_{ji}, r'_{ij} = r'_{ji} \text{ and } r''_{ij} = r''_{ji} \tag{10}$$

Moreover, a fuzzy equilibrium relation is obtained by converting fuzzy relation to a transitive closure relation if the real problem does not have the transfer characteristic (by definition 4 in subSect. 2.1). Then, the set of objects can be categorized into groups based on the degree of similarity at α-cut levels using the principles of the fuzzy equilibrium classification (definition 3). The α-cut level is computed based on the v value, which is determined by an expert. The calculation is terminated if the number of categories equals the selected v. Otherwise, a value is added to α, and the α-cut level is recalculated accordingly. It should be noted that the value which is added to α is about 0.02 since the α value is in the interval of (0, 1).

After classifying the sample data by the proposed method, if there is a need to assign a new object to one of the existing groups, the degree of its fuzzy relation to other objects is calculated using Eqs. (1–6). Eventually, the new object is placed in one of the groups according to the classification principle of fuzzy relations at different α-cut levels on the sample data.

2.3 FDEMATEL

DEMATEL method conduces to discovering the ideal solution to solve complex system problems. While experts' judgments are based on their capabilities and experiences, they are mostly made in generally uttered vague linguistic terms instead of crisp values (Mohammadfam et al. 2019; Amirghodsi et al. 2020, 2021). In these circumstances, it is impossible to use the DEMATEL method to seek the long-term evaluation of factors on BT in HSCs. Therefore, modifying the DEMATEL method using fuzzy set theory is necessary. In this regard, the FDEMATEL method, introduced by Wu et al. (2007) and Hiete et al. (2012), is briefly discussed in this section. The implementation algorithm of FDEMATEL is divided into several steps as follows:

Step 1 Experts determine the degree of a direct relationship between the factors.

This step deals with designing a suitable fuzzy linguistic scale and the corresponding fuzzy numbers to obtain experts' collective perspectives regarding the intended objective. These opinions are collected and registered as fuzzy numbers. The fuzzy average to fuse experts' opinions has been mentioned above, as shown in subSect. 2.2.

Step 2 This step focuses on the extraction of the fuzzy direct relation matrix.

The fuzzy direct relation matrix $\widetilde{U}$ is an $n \times n$ matrix for influential factors $F_1, F_2, \ldots, F_n$ as follows:

$$\tilde{U} = \left[\tilde{u}_{ij}\right]_{n\times n}(i,j = 1,2,\ldots,n)$$

where TrFN $\widetilde{u}_{ij} = \left(c_{ij}, a_{ij}, b_{ij}, d_{ij}\right)$ represents the direct relation between factors F_i and F_j.

Step 3 The fuzzy direct relation matrix is normalized in this step.

The normalized fuzzy direct relation matrix $\widetilde{N}$, relative to the fuzzy direct relation matrix $\widetilde{U} = \left[\widetilde{u}_{ij}\right]_{n\times n}(i,j = 1,2,\ldots,n)$, can be denoted as follows:

$$\tilde{N} = \left[\tilde{n}_{ij}\right]_{n\times n}(i,j = 1, 2, \ldots, n), \quad \tilde{n}_{ij} = \frac{\left(\tilde{u}_{ij} - \underset{1 \le i \le n}{\min} c^t_{ij}\right)}{\max^n_{i=1} d^t_{ij} - \min^n_{i=1} c^t_{ij}}$$

where $\min c^t_{ij}$ and $\max d^t_{ij}$ are the lowest lower and the highest upper bounds in every column of matrix $\widetilde{U}$.

Step 4 This step aims to defuzzify the normalized fuzzy direct relation matrix.

The Converted Fuzzy data into Crisp Scores (CFCS) was used by Opricovic et al. (2003) in order to convert fuzzy numbers into relevant crisp values. It was argued that CFCS is better than previous conventional methods such as the center of the area and the center of gravity, since it can identify different versions of fuzzy equivalents for two similar crisp values. The implementation stages of the CFCS technique are elucidated as follows (Mahmoudi et al. 2019).

Calculation of the Left and Right Bounds of Normal Values

Definition 10 Assume that $\widetilde{N} = \left[\widetilde{n}_{ij}\right]_{n\times n}(i,j = 1, 2, 3, \ldots, n)$ is the normalized fuzzy direct relation matrix and $\widetilde{n}_{ij} = \left(c_{ij}, a_{ij}, b_{ij}, d_{ij}\right)$ denotes a TrFN relating to the matrix, then the left and right bounds of normal values can be computed by Eqs. (11) and (12):

$$c^s_{ij} = \frac{\left(a^x_{ij} + b^x_{ij}\right)/2}{\left(1 + \frac{\left(a^x_{ij}+b^x_{ij}\right)}{2} - c^s_{ij}\right)} \tag{11}$$

$$d^s_{ij} = \frac{d^x_{ij}}{\left(1 + d^x_{ij} - \frac{\left(a^x_{ij}+b^x_{ij}\right)}{2}\right)} \tag{12}$$

where c^s_{ij} and d^s_{ij} indicate the left and right bounds of normal values, respectively.

Calculation of Crisp Normalized Values

The crisp normalized values concerning the right and left bounds of normal values are represented by Eq. (13):

$$P_{ij} = \frac{c^s_{ij}\left(1 - c^s_{ij}\right) + (d^s_{ij})^2}{\left(1 - c^s_{ij}\right) + d^s_{ij}} \tag{13}$$

Computation of Final Crisp Values

The final crisp direct relation matrix is calculated in the final phase of the CFCS algorithm by Eq. (14):

$$Q_{ij} = \left(P_{ij} \times \left(\max d^t_{ij} - \min c^t_{ij}\right)\right) + \underset{1 \le i \le n}{\min} c^t_{ij} \tag{14}$$

Step 5 The crisp total relation matrix is calculated in this step.

The crisp total relation matrix $T = \left[t_{ij}\right]_{n\times n}(i,j = 1,2,\ldots,n)$ can be computed by Eq. (15):

$$T = \lim_{k\to\infty}\left(Q + Q^2 + \ldots + Q^k\right) = Q(I - Q)^{-1} \tag{15}$$

where I indicates the identity matrix.

Step 6 The results of FDEMATEL are computed.

In this step, the sum of the rows V and columns K of matrix T is demonstrated as follows:

$$T = \left[T_{ij}\right]_{n\times n}(i,j = 1,2,\ldots,n) \tag{16}$$

$$V = \left[\sum_{j=1}^{n} T_{ij}\right]_{n\times 1} = \left[v_j\right]_{n\times 1} \tag{17}$$

$$K = \left[\sum_{i=1}^{n} T_{ij}\right]_{1\times n} = \left[k_i\right]_{1\times n} \tag{18}$$

where vectors V and K indicate the sum of rows and columns related to the crisp values of matrix Q, respectively. $(V + K)$ is the prominence of a barrier, indicating its total effects in terms of influenced and influential power. $(V - K)$ explains the causal-effect relationship between the barriers. In terms of the $(V - K)$ index, the relation map is plotted as the cause and effect category. The positivity of the index value of a factor implies that this factor has influenced other factors. On the other hand, a negative value demonstrates that other factors affect that factor.

3 Research Method: A Novel Fuzzy Large-Scale Group-DEMATEL

To sustainable evaluate the factors affecting BT in HSCs, this assessment should be made through a large-scale group decision-making process, since various experts can provide various suggestions from varying backgrounds in the evaluation process, and the accurate comprehensive evaluation information is obtained only after considering the evaluation information of each expert in large-scale group-experts. As the number of experts is a large-scale group, it is necessary to aggregate the large-scale group-experts' score to avoid the leverage effect caused by the deliberate praise and belittlement in the evaluating process. A lot of studies in the field of psychology have proved that DMs' features, such as gender, age, education level, etc., will obviously affect their decision preference (Chang 2011; Al-Afifi et al. 2019; Arachchi et al. 2021). That is to say, DMs with the same or similar features tend to give similar decision preferences. Thus, clustering the large-scale group-DMs with their characteristics can effectively deal with the complex decision-making problems. However, the previous clustering studies ignore the diverse characteristics of DMs.

Accordingly, this section presents a novel fuzzy large-scale group-DEMATEL approach to assess the interdependence of factors affecting BT in HSCs. More specifically, the proposed method consists of two stages: (1) aggregating large-scale group-experts relation matrices according to experts' characteristics, and (2) identifying the crucial factors affecting BT in HSCs with the FDEMATEL method. Based on these definitions and the above algorithm, a procedure of the novel fuzzy large-scale group-DEMATEL method is presented as follows.

3.1 Stage 1 Clustering Large-Scale Group-Experts into Small Subgroups by Using FRC

Step 1 Obtaining three types (binary, quantitative and linguistic variables) features of experts to construct fuzzy relation matrices between diverse large-scale group-experts by Eqs. (1-6).

Step 2 Establishing the final fuzzy relation matrix R by relation quantities through Eqs. (7, 8).

Step 3 Categorizing the large-scale group-experts into small subgroups based on the degree of similarity at α-cut levels by using the principles of the fuzzy equilibrium classification.

3.2 Stage 2 Analyzing the Interaction of BT Influencing Factors in HSCs with the Fuzzy Large-Scale Group-DEMATEL Method

Step 4 Designing a suitable fuzzy linguistic scale, which can express the fuzzy characteristic of experts' thinking pattern. Then, obtaining the pair-wise comparisons between BT's key factors in HSCs by small subgroup-experts, and using the fuzzy average of several TrFNs to fuse experts' opinions.

The fuzzy linguistic scale is designed according to the number of the linguistic variables. For example, if there are 3 linguistic variables (bad, medium, good) for evaluating the object, we can averagely divide $[0, 1]$ into 3 TrFNs, namely, $(0, 0.25, 0.35, 0.6)$, $(0.2, 0.45, 0.55, 0.8)$ and $(0.4, 0.65, 0.75, 1)$ (see Fig. 2).

Step 5 Conducting the aggregated fuzzy evaluation in S_l by Eq. (19).

Different experts with varying opinions are engaged in the decision-making procedure, so large-scale group-experts' evaluation information needs to be aggregated. Let m and n represent the number of experts and opinions in the clusters, respectively. Assume that 't' clusters $S_1, S_2, \ldots, S_l, \ldots, S_t$ are formed, and the number of opinions in the lth cluster (i.e., S_l) is n_l in such a way that $\sum_{l=1}^{t} n_l = m, (m = n)$ and $S_l \cap S_{l'} = \varnothing, \forall l, l' = 1, 2, \ldots, t; l \neq l'$. The aggregated fuzzy evaluation in S_l is conducted by

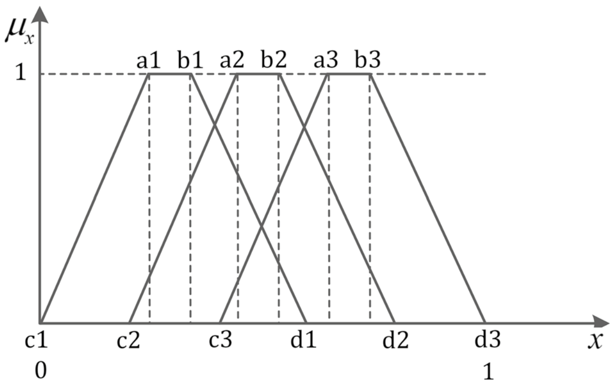

Fig. 2 An example of designing fuzzy linguistic scale

$$\tilde{R}^l = \frac{1}{n_l} \oplus_{i=1}^{m} R_i \tag{19}$$

where $\oplus$ is the fuzzy bounded sum, R_i is the final fuzzy relation matrix R for expert i.

Step 6 Aggregating small subgroup-experts' evaluation information to determine fuzzy direct relation matrix through Eq. (20).

Next, $w_l = \#S_l/m$ is used to compute the weight of the cluster $S_l(l = 1, 2, \dots, t)$, where $\#S_l$ is the number of cluster members. Hence, the aggregated fuzzy score is obtained as follows:

$$\tilde{R} = \frac{\oplus_{l=1}^{t} w_l \times \tilde{R}^l}{\sum_{l=1}^{t} w_l} \tag{20}$$

In the decision making process, large-scale group-experts will provide the fuzzy evaluation values for BT's key factors in HSCs. After clustering the large-scale group-experts into small subgroups according to their features, the opinion of each small subgroup can be elicitated by Eq. (19). Then, the comprehensive evaluation information can be aggregated with the weights and opinons of each small subgroup through Eq. (20). Due to the scale of experts is very large and evaluation factors are many, opinions from experts with similar characteristics are often equally important. In the whole information elicitation step: (1) All the opinions in the small subgroup and the weight of each small subgroup are considered; (2) We always use fuzzy information without changing the form of the evaluation values, which maintain the consistency of the data; (3) Giving the same weight to the experts in the same small subgroup, avoiding the subjectivity in the aggregation process; (4) At the same time, weighted averaging operator is applied for calculating the comprehensive information, the weight is determined by the number of members in each cluster, which is objective and considers the diverse importance of clusters (Harsanyi 1955; Ribeiro et al. 2003; Xu et al. 2021b; Li et al. 2022a, 2022b). Therefore, the above measures can efficiently reduce the biases of information aggregation process.

Step 7 Defuzzifying the fuzzy influence matrix through the CFCS technique (Step 4 in subsection 2.3).

Step 8 Computing the total relation matrix by Eqs. (15).

Step 9 Calculating the sum of rows (V) and columns (K) by Eqs. (17, 18), and computing $V+K$ (prominence) and $V-K$ (relationship). If $V-K>0$, the factor is "Cause", otherwise it is "Effect". The value of $V+K$ of the factor is larger, the system's role in the system is greater.

Step 10 Drawing a cause and effect graph by mapping the dataset of $(V+K, V-K)$.

In sum, the features of experts are considered for clustering the large-scale group-experts by FRC algorithm. Then, the aggregation measures are proposed to fuse the large fuzzy evaluation information, which can efficiently reduce the biases of information aggregation process. Finally, after combining the FRC algorithm and DEMATEL method, we proposed a novel fuzzy large-scale group-DEMATEL method to analyze the interaction of BT influencing factors in HSCs.

Finally, the whole procedure of using fuzzy large-scale group-DEMATEL to investigate factors affecting BT in HSCs are shown in Fig. 3.

4 Application

4.1 Identify the Key Factors Using BT in HSCs

BT increases in popularity largely due to the transparency and security potential offered by the design of this technology (Albanese et al. 2020; Rathee et al. 2021). It is essentially a digitization technology that establishes a trusted data ecosystem by the exchange and sharing of data among many organizations following the key

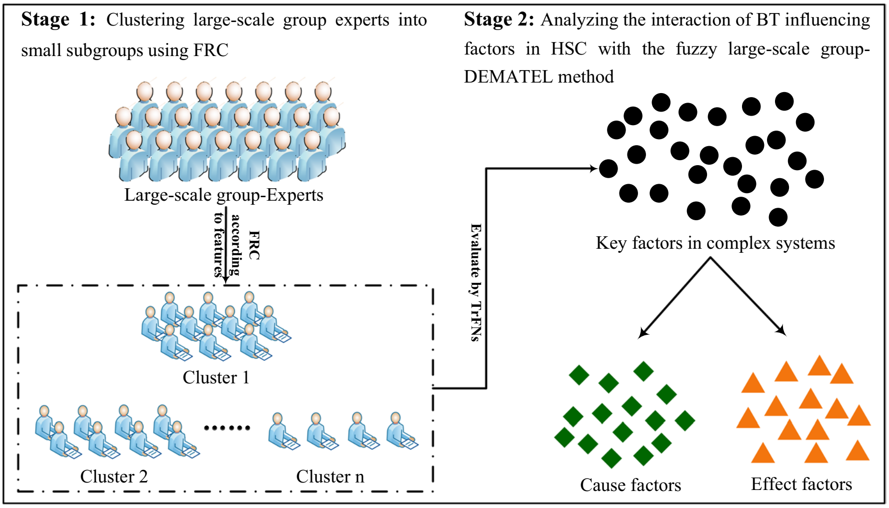

Fig. 3 The procedure of using fuzzy large-scale group-DEMATEL

principles, such as transparency, security, immutability, decentralized database, sharing database, and smart contracts in order to achieve a higher level of privacy and security. It also improves the communication and collaboration between the various organizations involved in the HSCs, and plays a key role in optimizing the coordination of logistics flows while integrating different SCs.

BT can help HSCs to respond the urgent needs in a shorter time during the disaster period, and speed up the delivery of emergency supplies to disaster-stricken areas. The excess capacities of one organization can be utilized by BT's digitization technology to support distribution and transportation, as exemplified by the need to shift emergency sources and delivery. The blockchain application in the crisis also leads to electronic schemata and designs for printing new parts in an additive manufacturing setting in the HSCs. Based on the context of HSCs and BT's characteristics and principles, and the literature review in the introduction, we design the following factors (Table 4) and apply them to the constructed fuzzy large-scale group-DEMATEL model to explore the impact and the influence degree of factors of BT.

4.2 Processes

Facing such huge key factors, single or small scale experts may not give accurate evaluation values about the relationships between huge key factors. Moreover, due to the limitations of experts' cognitive ability and the incompleteness of information, experts are often unable to provide accurate preferences, but can only give fuzzy preferences. Therefore, we invite large-scale group-experts to evaluate the relationship between the key factors when using BT in HSCs, and the preferences are expressed in fuzzy linguistic.

The data in this case was gathered from 22 DMs. These DMs comprise of 10 academic people and 12 experts from different companies who are familiar with BT. Among the academic experts of universities, 7 experts are Ph.D., 3 of them are master's degrees. Also, among the experts from different companies, the experience of 8 people is more than 15 years, and the experience of 4 persons is between 10 to 15 years (Table 5).

The weights of R_X, R_Y, and R_Z are $W_X = 0.2, W_Y = 0.3, W_Z = 0.5$ respectively. Table 6 presents the fuzzy linguistic scales of academic degrees, experience and experts' evaluation.

Tables 7, 8 present the obtained values based on the Eqs. (1–10) and the clustering method's implementation steps in the first stage. More specifically, Table 7 provides the R total relation between 22 experts obtained from Eqs. (7, 8), and Table 8 shows the fuzzy equivalence matrix of R total relation through transitive closure algorithm (Definition 4). Furthermore, we illustrate the effect of diverse α in α-cut on the clustering results, as shown in Fig. 4. In order to get a better evaluation result, experts are partitioned in three clusters by $\alpha = 0.78$, and the weights of three clusters are obtained through $w_l = \#S_l/22(l = 1, 2, 3)$, the results are shown in Table 9.

Table 4 Descriptions of factors

Index	Factors	Definition
F_1	Disintermediation	Disintermediation can make HSCs more efficient (e.g., the growth of online shopping)
F_2	Transparency with pseudonymity	Transparency with pseudonymity causes high visibility in a network and reduces the intermediaries
F_3	Security	Security is considered by the private key while using blockchain
F_4	Anonymity	Blockchain observes frameworks to ensure information security by considering anonymity
F_5	Privacy	BT considers data security without endangering the privacy of stakeholders
F_6	Distributed and sustainable	BT presents resolutions that look suitable and sustainable
F_7	Indelible	Indelible information in a blockchain is rich-documented and accountability-minded
F_8	Transparency	Transparency leads to clarity for all persons in a network, which decreases the requirement of a reliable mediator
F_9	Consensus-based and transaction	In HSCs, a transaction is a relationship between the supplier and the buyer
F_{10}	Orchestrated and flexible	The orchestrated HSCs includes multi-enterprise HSCs networks, end-to-end HSCs visibility, and the like
		A flexible HSCs helps organizations handle their resources and costs
F_{11}	Auditability	Auditability is an outstanding feature of BT, and an appropriate database makes a flawless blockchain while helping keep track of the audits
F_{12}	Decentralized database	A decentralized database improves confidence among the shareholders in a blockchain
F_{13}	Immutability	Immutability includes events that do not change or are not changeable
F_{14}	Improved risk management	Preventing a delay in ineffective asset management practices, threats, and payment data is an important point of improved risk management
F_{15}	Reduced transaction costs	Reduced transaction costs can be used for developing the base of multi-suppliers
F_{16}	Reduced settlement lead times	BT can help reduce the settlement lead time by strengthening and removing the unessential steps in the settlement process
F_{17}	Shared database	BT employs a shared database to secure the database for empowering the learning organizations
F_{18}	Smart contracts	BT enables smart contracts to make them safe from accidents and attacks
F_{19}	Trust	Trust in the HSCs helps corporations to collaborate and affect their performance
F_{20}	Context	The context of HSCs helps managers to remain competitive in purchasing and operation
F_{21}	Performance	Performance in HSCs improves the strategic goals and outcomes of its achievements

Table 4 (continued)

Index	Factors	Definition
F_{22}	Consensus	Consensus helps the experts of HSCs to identify its HSCope
F_{23}	Market competition and uncertainty	The market competition in uncertain conditions is considered an important factor for organizations to succeed in their processes
F_{24}	Monitoring	Monitoring in HSCs helps evaluate the system's efficacy and track the products of the logistics process
F_{25}	Permanent availability	Permanent availability in HSCs needs an integrated approach in its planning

Table 5 Personal information of experts

Experts	Gender	Participate in HSCs projects	Age	Academic degrees	Experience in companies
E1	F	Y	27	Ph.D	Pre-experience
E2	M	N	27	Ph.D	Pre-experience
E3	F	Y	28	Ph.D	Pre-experience
E4	M	Y	28	Ph.D	Pre-experience
E5	M	N	28	Ph.D	Pre-experience
E6	F	Y	29	Ph.D	Pre-experience
E7	M	Y	30	Ph.D	Pre-experience
E8	F	N	24	Master	Pre-experience
E9	M	N	24	Master	Pre-experience
E10	M	N	25	Master	Pre-experience
E11	F	Y	34	Bachelor	More than 15 years
E12	F	N	35	Bachelor	More than 15 years
E13	F	N	37	Bachelor	More than 15 years
E14	M	N	37	Bachelor	More than 15 years
E15	M	Y	38	Bachelor	More than 15 years
E16	M	Y	38	Bachelor	More than 15 years
E17	F	Y	39	Other	More than 15 years
E18	F	Y	40	Other	More than 15 years
E19	F	N	28	Bachelor	Between 10 to 15 years
E20	M	N	30	Bachelor	Between 10 to 15 years
E21	M	Y	31	Other	Between 10 to 15 years
E22	F	Y	33	Bachelor	Between 10 to 15 years
Value Type	Binary	Binary	Quantitative	Linguistic	Linguistic
Weight	0.2	0.5	1	0.5	0.8

Consequently, the aggregated score for each cluster and final assessments for all items are obtained by Eq. (20), and the defuzzification result is shown in Table 10. Further, Table 11 shows the total relation matrix. Furthermore, by calculating the sum of rows (V) and columns (K) through Eqs. (17, 18) and the results of fuzzy large-scale group-DEMATEL are presented in Table 12. Figure 5 reveals that 13 and 12 cases were "Cause" and "Effect" factors in this study, respectively, indicating the homogeneity of the definition of variables in this research and the reliability of the results.

4.3 Discussions

4.3.1 Cause Factors

It should be noted that a system cannot have proper acceptance among the users without market competition and uncertainty (F23) compared to other systems on the

Table 6 Fuzzy linguistic scale

Academic degrees		
Impact score	Description of linguistic variable	Equivalent TrFNs
0	Other	(0, 0.1, 0.2, 0.4)
1	Bachelor	(0.1, 0.3, 0.4, 0.6)
2	Master	(0.3, 0.5, 0.6, 0.8)
3	Ph.D	(0.5, 0.7, 0.8, 1)
Experience in companies		
Impact score	Description of linguistic variable	Equivalent TrFNs
0	Pre-experience	(0, 0.25, 0.35, 0.6)
1	Between 10 to 15 years	(0.2, 0.45, 0.55, 0.8)
2	More than 15 years	(0.4, 0.65, 0.75, 1)
Influence degrees between factors		
Impact score	Description of linguistic variable	Equivalent TrFNs (Hiete et al. 2012)
0	No influence (No)	(0, 0, 0.1, 0.2)
1	Very low influence (VL)	(0.1, 0.2, 0.3, 0.4)
2	Low influence (L)	(0.3, 0.4, 0.5, 0.6)
3	High influence (H)	(0.5, 0.6, 0.7, 0.8)
4	Very High influence (HL)	(0.7, 0.8, 0.9, 1)

market, even by observing other effective points and characteristics. Therefore, F23 has the second rank among all Cause factors after disintermediation (F1). Based on Fig. 5, orchestrated and flexibility (F10) ranks third in this respect. Considering that one of the main goals of creating a blockchain is transparency while not knowing users' real identities in other users' sights, the result demonstrates that experts are careful in paying attention to this important attribute.

Figure 5 further confirms that 13 factors, including transparency with pseudonymity (F2), permanent availability (F25), immutability (F13), reduced settlement lead times (F16), and others, are all recognized as the main influential factors of the system. Based on the findings of our study because they can affect other factors such as improved risk management (F14), distributed and sustainable (F6), and most importantly, performance (F21), which are the requirements of an HSCs system in an emergency.

Furthermore, it is noteworthy that a shared database undoubtedly is one of the most influential factors in an HSCs system. This issue allows everyone to identify and access priorities, areas in need of faster and more attention, the historical performance of operations, and the like. Accuracy in Fig. 5 shows that the shared database (F17) in this study has been correctly identified as a highly effective criterion.

4.3.2 Effect Factors

A system will become very fragile and easily affected by other systems on the market without security (F3), which ranks first among all effect factors indicating that

Table 7 R total relation of large-scale group-experts

Experts	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11
E1	1.000	0.800	0.921	0.881	0.781	0.903	0.844	0.734	0.694	0.713	0.353
E2	0.800	1.000	0.781	0.821	0.921	0.763	0.784	0.794	0.834	0.853	0.213
E3	0.921	0.781	1.000	0.900	0.800	0.921	0.863	0.715	0.675	0.694	0.371
E4	0.881	0.821	0.900	1.000	0.840	0.881	0.903	0.675	0.715	0.734	0.331
E5	0.781	0.921	0.800	0.840	1.000	0.781	0.803	0.775	0.815	0.834	0.231
E6	0.903	0.763	0.921	0.881	0.781	1.000	0.881	0.697	0.657	0.675	0.390
E7	0.844	0.784	0.863	0.903	0.803	0.881	1.000	0.638	0.678	0.697	0.369
E8	0.734	0.794	0.715	0.675	0.775	0.697	0.638	1.000	0.900	0.881	0.246
E9	0.694	0.834	0.675	0.715	0.815	0.657	0.678	0.900	1.000	0.921	0.206
E10	0.713	0.853	0.694	0.734	0.834	0.675	0.697	0.881	0.921	1.000	0.225
E11	0.353	0.213	0.371	0.331	0.231	0.390	0.369	0.246	0.206	0.225	1.000
E12	0.234	0.294	0.253	0.213	0.313	0.271	0.250	0.327	0.287	0.306	0.821
E13	0.196	0.256	0.215	0.175	0.275	0.234	0.213	0.290	0.250	0.268	0.784
E14	0.156	0.296	0.175	0.215	0.315	0.194	0.253	0.250	0.290	0.308	0.744
E15	0.238	0.178	0.256	0.296	0.196	0.275	0.334	0.131	0.171	0.190	0.825
E16	0.238	0.178	0.256	0.296	0.196	0.275	0.334	0.131	0.171	0.190	0.825
E17	0.215	0.075	0.234	0.194	0.094	0.253	0.231	0.108	0.068	0.087	0.802
E18	0.196	0.056	0.215	0.175	0.075	0.234	0.213	0.089	0.049	0.068	0.783
E19	0.544	0.604	0.562	0.522	0.622	0.544	0.485	0.637	0.597	0.616	0.549
E20	0.466	0.606	0.485	0.525	0.625	0.504	0.562	0.559	0.599	0.618	0.546
E21	0.504	0.444	0.522	0.562	0.462	0.541	0.600	0.397	0.437	0.455	0.621
E22	0.550	0.410	0.569	0.529	0.429	0.587	0.566	0.443	0.403	0.422	0.743

Experts	E12	E13	E14	E15	E16	E17	E18	E19	E20	E21	E22
E1	0.234	0.196	0.156	0.238	0.238	0.215	0.196	0.544	0.466	0.504	0.550
E2	0.294	0.256	0.296	0.178	0.178	0.075	0.056	0.604	0.606	0.444	0.410
E3	0.253	0.215	0.175	0.256	0.256	0.234	0.215	0.562	0.485	0.522	0.569
E4	0.213	0.175	0.215	0.296	0.296	0.194	0.175	0.522	0.525	0.562	0.529
E5	0.313	0.275	0.315	0.196	0.196	0.094	0.075	0.622	0.625	0.462	0.429
E6	0.271	0.234	0.194	0.275	0.275	0.253	0.234	0.544	0.504	0.541	0.587
E7	0.250	0.213	0.253	0.334	0.334	0.231	0.213	0.485	0.562	0.600	0.566
E8	0.327	0.290	0.250	0.131	0.131	0.108	0.089	0.637	0.559	0.397	0.443
E9	0.287	0.250	0.290	0.171	0.171	0.068	0.049	0.597	0.599	0.437	0.403
E10	0.306	0.268	0.308	0.190	0.190	0.087	0.068	0.616	0.618	0.455	0.422
E11	0.821	0.784	0.744	0.825	0.825	0.802	0.783	0.549	0.546	0.621	0.743
E12	1.000	0.903	0.863	0.744	0.744	0.720	0.702	0.630	0.628	0.502	0.624
E13	0.903	1.000	0.900	0.781	0.781	0.758	0.739	0.593	0.590	0.464	0.586
E14	0.863	0.900	1.000	0.821	0.821	0.718	0.699	0.553	0.630	0.504	0.546
E15	0.744	0.781	0.821	1.000	0.940	0.837	0.818	0.434	0.511	0.586	0.628
E16	0.744	0.781	0.821	0.940	1.000	0.837	0.818	0.434	0.511	0.586	0.628
E17	0.720	0.758	0.718	0.837	0.837	1.000	0.921	0.411	0.408	0.571	0.604
E18	0.702	0.739	0.699	0.818	0.818	0.921	1.000	0.392	0.389	0.553	0.586
E19	0.630	0.593	0.553	0.434	0.434	0.411	0.392	1.000	0.863	0.699	0.746

Table 7 (continued)

Experts	E12	E13	E14	E15	E16	E17	E18	E19	E20	E21	E22
E20	0.628	0.590	0.630	0.511	0.511	0.408	0.389	0.863	1.000	0.777	0.744
E21	0.502	0.464	0.504	0.586	0.586	0.571	0.553	0.699	0.777	1.000	0.818
E22	0.624	0.586	0.546	0.628	0.628	0.604	0.586	0.746	0.744	0.818	1.000

they are also relatively least likely to be affected by causal factors among outcome factors. Based on Fig. 5, consensus (F22) and anonymity (F4) have the second and third rank in effect factors. Although BT provides innovative possibilities for decentralized solutions, in countries where personal privacy is more important, more control based on security and anonymity is needed. Therefore, experts' evaluation of this indicator are very cautious. In HSCs systems, factors such as monitoring (F24), performance (F21), improved risk management (F14), and distributed and sustainable (F6), in addition to having a highly decisive role in achieving the defined goals, are influenced by the other internal and external factors of the system.

Additionally, Fig. 5 further confirms that 12 factors, including indelible (F7), auditability (F11), trust (F19), decentralized database (F12), and others, are all recognized as the main affected factors of the system. Based on the findings of the present study, they can be influenced by other factors such as transparent (F8), shared database (F17), consensus-based and transactional (F9), and context (F20).

In contrast, the factors of "distributed and sustainable" (F6), "decentralized database" (F12), and "reduced transaction costs" (F15) are influenced by disintermediation (F1), "market competition and uncertainty" (F23), "transparency with pseudonymity" (F2), and other causal factors. So policymakers should pay more attention to them in the decision-making process.

4.3.3 Impact of the Factors

Among the 25 studied factors in this study, disintermediation (F1) has been identified as the most important one with a considerable distance, as illustrated in Fig. 5. Without the disintermediation of a system, factors such as system anonymity (F4), system security (F3), consensus-based and transactional (F9), no need for a centralized database, stability, and like. After disintermediation (F1), anonymity (F4) and security (F3) rank second and third, respectively. Considering that these two factors are also the main objectives for defining BT, the results are entirely justifiable. On the other hand, improved risk management (F14), transaction costs (F15) and decentralized databases (F12) have been recognized as the least important factors because factors are automatically in the optimal state if they are provided optimally (which are the main objectives of defining BT).

Table 8 Fuzzy equivalence matrix of R total relation

Experts	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11
E1	1.000	0.840	0.921	0.900	0.840	0.921	0.900	0.840	0.840	0.840	0.637
E2	0.840	1.000	0.840	0.840	0.921	0.840	0.840	0.853	0.853	0.853	0.637
E3	0.921	0.840	1.000	0.900	0.840	0.921	0.900	0.840	0.840	0.840	0.637
E4	0.900	0.840	0.900	1.000	0.840	0.900	0.903	0.840	0.840	0.840	0.637
E5	0.840	0.921	0.840	0.840	1.000	0.840	0.840	0.853	0.853	0.853	0.637
E6	0.921	0.840	0.921	0.900	0.840	1.000	0.900	0.840	0.840	0.840	0.637
E7	0.900	0.840	0.900	0.903	0.840	0.900	1.000	0.840	0.840	0.840	0.637
E8	0.840	0.853	0.840	0.840	0.853	0.840	0.840	1.000	0.900	0.900	0.637
E9	0.840	0.853	0.840	0.840	0.853	0.840	0.840	0.900	1.000	0.921	0.637
E10	0.840	0.853	0.840	0.840	0.853	0.840	0.840	0.900	0.921	1.000	0.637
E11	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	1.000
E12	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.821
E13	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.821
E14	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.821
E15	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.825
E16	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.825
E17	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.825
E18	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.825
E19	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.743
E20	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.743
E21	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.743
E22	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.743

Experts	E12	E13	E14	E15	E16	E17	E18	E19	E20	E21	E22
E1	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E2	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E3	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E4	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E5	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E6	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E7	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E8	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E9	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E10	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637	0.637
E11	0.821	0.821	0.821	0.825	0.825	0.825	0.825	0.743	0.743	0.743	0.743
E12	1.000	0.903	0.900	0.821	0.821	0.821	0.821	0.743	0.743	0.743	0.743
E13	0.903	1.000	0.900	0.821	0.821	0.821	0.821	0.743	0.743	0.743	0.743
E14	0.900	0.900	1.000	0.821	0.821	0.821	0.821	0.743	0.743	0.743	0.743
E15	0.821	0.821	0.821	1.000	0.940	0.837	0.837	0.743	0.743	0.743	0.743
E16	0.821	0.821	0.821	0.940	1.000	0.837	0.837	0.743	0.743	0.743	0.743
E17	0.821	0.821	0.821	0.837	0.837	1.000	0.921	0.743	0.743	0.743	0.743
E18	0.821	0.821	0.821	0.837	0.837	0.921	1.000	0.743	0.743	0.743	0.743
E19	0.743	0.743	0.743	0.743	0.743	0.743	0.743	1.000	0.863	0.777	0.777

Table 8 (continued)

Experts	E12	E13	E14	E15	E16	E17	E18	E19	E20	E21	E22
E20	0.743	0.743	0.743	0.743	0.743	0.743	0.743	0.863	1.000	0.777	0.777
E21	0.743	0.743	0.743	0.743	0.743	0.743	0.743	0.777	0.777	1.000	0.818
E22	0.743	0.743	0.743	0.743	0.743	0.743	0.743	0.777	0.777	0.818	1.000

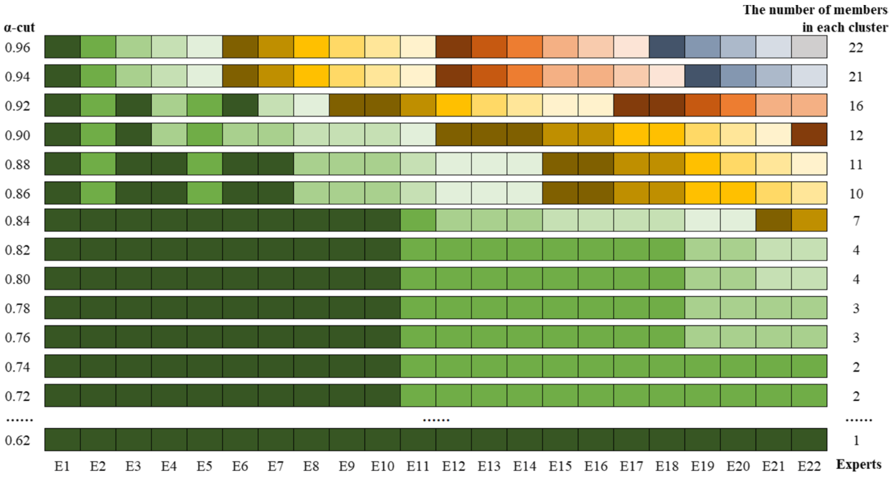

Fig. 4 Clustering results by diverse α

Table 9 Clustering Members

Clusters	Number	Members	Weights
Cluster 1	10	E1, E2, E3, E4, E5, E6, E7, E8, E9, E10	0.454
Cluster 2	8	E11, E12, E13, E14, E15, E16, E17, E18	0.364
Cluster 3	4	E19, E20, E21, E22	0.182

4.4 Comparative Analysis

Another comparative analysis is presented to illustrate the validity and reliability of our proposed fuzzy large-scale group-DEMATEL method. We use two classical methods, (1) individual DEMATEL decision method, and (2) cluster the experts only by their evaluation information, to calculate the case in this paper.

The results are shown in Table 13.

According to the procedure of comparative analysis, we can find that: (1) F1, F4, F3 are the most important factors in three methods. (2) For the division of cause factor and result factors, except F3, the evaluation results after clustering are almost the

Table 10 Crisp direct relation matrix

Factors	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
F1	0.001	0.047	0.046	0.040	0.046	0.039	0.041	0.041	0.041	0.046	0.049	0.042
F2	0.027	0.001	0.024	0.034	0.028	0.051	0.026	0.025	0.026	0.023	0.030	0.039
F3	0.027	0.047	0.001	0.025	0.050	0.026	0.026	0.026	0.026	0.039	0.039	0.013
F4	0.026	0.013	0.027	0.001	0.038	0.013	0.038	0.039	0.026	0.039	0.052	0.026
F5	0.044	0.032	0.037	0.047	0.001	0.021	0.013	0.028	0.040	0.031	0.033	0.014
F6	0.030	0.026	0.013	0.026	0.021	0.001	0.026	0.020	0.026	0.013	0.013	0.001
F7	0.048	0.001	0.038	0.039	0.013	0.026	0.001	0.026	0.013	0.027	0.026	0.039
F8	0.048	0.023	0.043	0.029	0.043	0.018	0.038	0.001	0.052	0.013	0.025	0.013
F9	0.047	0.014	0.045	0.046	0.044	0.026	0.039	0.013	0.001	0.029	0.025	0.052
F10	0.037	0.039	0.026	0.027	0.025	0.026	0.026	0.026	0.026	0.001	0.026	0.026
F11	0.028	0.026	0.039	0.024	0.026	0.027	0.026	0.013	0.025	0.025	0.000	0.027
F12	0.012	0.013	0.001	0.013	0.013	0.026	0.014	0.013	0.013	0.013	0.026	0.001
F13	0.027	0.026	0.027	0.027	0.027	0.025	0.024	0.024	0.030	0.026	0.026	0.026
F14	0.026	0.014	0.026	0.026	0.026	0.013	0.025	0.013	0.013	0.013	0.013	0.013
F15	0.013	0.013	0.026	0.014	0.013	0.013	0.013	0.013	0.013	0.001	0.001	0.026
F16	0.040	0.024	0.038	0.029	0.037	0.013	0.038	0.037	0.038	0.013	0.038	0.026
F17	0.039	0.016	0.049	0.039	0.038	0.013	0.039	0.039	0.026	0.013	0.026	0.013
F18	0.048	0.005	0.032	0.041	0.025	0.051	0.029	0.013	0.039	0.013	0.052	0.013
F19	0.029	0.017	0.020	0.026	0.015	0.015	0.029	0.013	0.038	0.015	0.013	0.014
F20	0.036	0.026	0.035	0.028	0.036	0.030	0.025	0.014	0.016	0.015	0.026	0.038
F21	0.031	0.026	0.025	0.027	0.014	0.025	0.040	0.026	0.026	0.027	0.026	0.028
F22	0.030	0.025	0.013	0.035	0.026	0.013	0.026	0.026	0.016	0.030	0.013	0.025
F23	0.045	0.034	0.026	0.042	0.019	0.030	0.023	0.029	0.026	0.020	0.028	0.031
F24	0.014	0.026	0.039	0.013	0.026	0.026	0.052	0.014	0.001	0.013	0.026	0.013
F25	0.017	0.025	0.013	0.050	0.013	0.026	0.030	0.026	0.025	0.013	0.030	0.026

Factors	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25
F1	0.042	0.032	0.041	0.041	0.041	0.050	0.041	0.051	0.030	0.051	0.031	0.042	0.028
F2	0.026	0.026	0.029	0.026	0.024	0.025	0.033	0.026	0.026	0.038	0.038	0.038	0.038
F3	0.026	0.027	0.030	0.015	0.026	0.039	0.025	0.027	0.030	0.026	0.026	0.026	0.026
F4	0.039	0.013	0.013	0.039	0.039	0.038	0.013	0.026	0.013	0.052	0.039	0.014	0.026
F5	0.031	0.021	0.051	0.024	0.014	0.026	0.028	0.039	0.051	0.013	0.032	0.013	0.015
F6	0.001	0.001	0.001	0.003	0.003	0.022	0.039	0.014	0.015	0.015	0.013	0.003	0.001
F7	0.026	0.013	0.039	0.012	0.026	0.013	0.026	0.039	0.038	0.026	0.026	0.025	0.026
F8	0.025	0.013	0.013	0.033	0.051	0.040	0.031	0.026	0.051	0.013	0.006	0.007	0.001
F9	0.025	0.027	0.025	0.027	0.028	0.052	0.013	0.013	0.039	0.026	0.025	0.013	0.013
F10	0.026	0.030	0.026	0.039	0.038	0.026	0.026	0.026	0.025	0.025	0.026	0.026	0.026
F11	0.026	0.013	0.026	0.026	0.013	0.026	0.013	0.013	0.026	0.026	0.016	0.025	0.026
F12	0.013	0.013	0.026	0.013	0.013	0.013	0.013	0.012	0.014	0.014	0.014	0.015	0.001
F13	0.001	0.026	0.026	0.029	0.038	0.040	0.026	0.027	0.026	0.026	0.026	0.026	0.026
F14	0.013	0.001	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013	0.013
F15	0.013	0.013	0.001	0.013	0.013	0.012	0.013	0.013	0.013	0.013	0.013	0.001	0.001
F16	0.027	0.026	0.026	0.001	0.013	0.025	0.029	0.013	0.027	0.013	0.026	0.043	0.013

Table 10 (continued)

Factors	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25
F17	0.026	0.027	0.013	0.030	0.001	0.038	0.013	0.026	0.039	0.012	0.028	0.013	0.038
F18	0.026	0.013	0.025	0.027	0.039	0.001	0.038	0.020	0.039	0.013	0.026	0.026	0.039
F19	0.014	0.013	0.002	0.013	0.001	0.013	0.001	0.013	0.013	0.013	0.012	0.013	0.013
F20	0.016	0.025	0.036	0.026	0.013	0.013	0.026	0.001	0.039	0.026	0.025	0.039	0.025
F21	0.026	0.013	0.026	0.027	0.013	0.026	0.013	0.027	0.001	0.026	0.026	0.026	0.026
F22	0.026	0.025	0.026	0.015	0.029	0.026	0.026	0.026	0.013	0.001	0.013	0.013	0.026
F23	0.029	0.023	0.029	0.027	0.033	0.023	0.029	0.029	0.028	0.038	0.001	0.029	0.042
F24	0.001	0.040	0.026	0.026	0.001	0.001	0.025	0.015	0.036	0.016	0.016	0.001	0.001
F25	0.026	0.013	0.025	0.026	0.041	0.038	0.026	0.025	0.025	0.026	0.026	0.002	0.001

same. The large deviation in the results of individual experts is because the weights of individual experts are the same, and individuals with extreme scores may affect the accuracy of identification of key factors. Besides, the complexity of evaluation process is reduced by clustering experts in large groups. (3) Security (F3) is an important effect factor instead of cause factor in the use of BT in HSCs, therefore, clustering results based on the characteristics of experts before evaluation are more reasonable than clustering results based directly on the evaluation information of factors. These findings indicate the effectiveness and rationality of the proposed method in this paper.

5 Conclusion

In HSCs, the improvement of the efficiency of emergency material delivery is crucial. BT, as a digital technology, can improve communication and collaboration among organizations participating in HSCs, and plays a key role in optimizing the coordination of logistics flow. However, the factors that influence the use of BT in HSCs are too complex and interrelated, and an appropriate approach to identify those most important of all intrinsically interrelated factors can help policymakers better improve the use of BT. As a system analysis method using matrix tools, DEMATEL can be applied to determine the interrelation relationship between factors and the position of each factor in the complex systems. In addition, due to the multiple and complex, factor analysis of such a large system often requires evaluation by large-scale group-experts with diversity backgrounds to accurately identify key factors, but large-scale group-experts usually make it difficult to obtain the appropriate results. Therefore, we can cluster experts with similar features, such as education and expertise, to reduce the decision-making complexity by FRC method. Furthermore, some characteristics of large-scale group-experts are uncertain and their evaluation information is often ambiguous, to better illustrate the uncertain

Table 11 Total relation matrix

Factors	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
F1	0.079	0.102	0.117	0.114	0.112	0.098	0.111	0.096	0.103	0.098	0.115	0.100
F2	0.082	0.042	0.075	0.087	0.075	0.093	0.077	0.066	0.071	0.061	0.078	0.080
F3	0.082	0.086	0.053	0.079	0.096	0.069	0.076	0.066	0.071	0.076	0.086	0.055
F4	0.083	0.055	0.080	0.057	0.087	0.057	0.089	0.080	0.072	0.077	0.100	0.069
F5	0.099	0.073	0.089	0.100	0.051	0.065	0.065	0.069	0.085	0.070	0.082	0.058
F6	0.059	0.046	0.040	0.054	0.046	0.024	0.052	0.041	0.050	0.034	0.039	0.024
F7	0.095	0.039	0.083	0.085	0.056	0.063	0.047	0.062	0.053	0.061	0.069	0.076
F8	0.102	0.062	0.094	0.082	0.091	0.060	0.088	0.042	0.096	0.052	0.074	0.055
F9	0.102	0.055	0.096	0.099	0.092	0.070	0.089	0.055	0.047	0.068	0.076	0.093
F10	0.090	0.077	0.076	0.079	0.072	0.067	0.075	0.065	0.069	0.038	0.073	0.067
F11	0.071	0.058	0.079	0.067	0.064	0.061	0.066	0.046	0.061	0.056	0.040	0.061
F12	0.038	0.031	0.025	0.037	0.035	0.045	0.037	0.031	0.034	0.030	0.047	0.021
F13	0.079	0.063	0.075	0.077	0.072	0.065	0.072	0.062	0.072	0.061	0.071	0.065
F14	0.056	0.037	0.054	0.055	0.052	0.037	0.053	0.036	0.038	0.035	0.040	0.036
F15	0.036	0.030	0.046	0.036	0.033	0.031	0.034	0.030	0.032	0.017	0.022	0.043
F16	0.091	0.062	0.086	0.079	0.082	0.054	0.085	0.074	0.080	0.050	0.083	0.066
F17	0.092	0.055	0.098	0.091	0.084	0.055	0.087	0.078	0.070	0.051	0.074	0.054
F18	0.101	0.046	0.083	0.094	0.073	0.092	0.080	0.054	0.083	0.052	0.099	0.055
F19	0.060	0.039	0.049	0.056	0.042	0.039	0.057	0.036	0.062	0.037	0.041	0.039
F20	0.083	0.062	0.079	0.074	0.077	0.067	0.070	0.050	0.055	0.049	0.068	0.075
F21	0.078	0.060	0.068	0.072	0.055	0.062	0.082	0.060	0.064	0.059	0.067	0.064
F22	0.072	0.056	0.053	0.076	0.063	0.046	0.065	0.057	0.051	0.059	0.051	0.058
F23	0.099	0.074	0.077	0.095	0.068	0.073	0.075	0.070	0.071	0.059	0.077	0.074
F24	0.050	0.052	0.071	0.047	0.056	0.053	0.083	0.040	0.030	0.038	0.056	0.040
F25	0.065	0.058	0.057	0.095	0.054	0.062	0.073	0.061	0.064	0.045	0.071	0.062

Factors	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25
F1	0.097	0.080	0.101	0.098	0.097	0.113	0.099	0.107	0.098	0.107	0.086	0.091	0.078
F2	0.066	0.060	0.072	0.067	0.064	0.071	0.075	0.067	0.074	0.079	0.077	0.073	0.073
F3	0.066	0.061	0.073	0.057	0.066	0.084	0.067	0.068	0.078	0.067	0.065	0.061	0.062
F4	0.080	0.049	0.058	0.081	0.081	0.086	0.056	0.068	0.064	0.092	0.078	0.051	0.063
F5	0.072	0.056	0.094	0.067	0.056	0.074	0.070	0.080	0.098	0.056	0.072	0.050	0.052
F6	0.023	0.019	0.024	0.025	0.025	0.046	0.060	0.036	0.040	0.037	0.034	0.022	0.021
F7	0.062	0.044	0.077	0.050	0.062	0.055	0.063	0.075	0.080	0.063	0.061	0.057	0.057
F8	0.066	0.047	0.056	0.074	0.090	0.087	0.071	0.067	0.099	0.054	0.046	0.044	0.038
F9	0.067	0.062	0.070	0.069	0.070	0.098	0.056	0.056	0.087	0.068	0.066	0.050	0.050
F10	0.065	0.063	0.067	0.078	0.077	0.071	0.066	0.065	0.072	0.065	0.064	0.061	0.061
F11	0.058	0.041	0.061	0.059	0.046	0.063	0.047	0.046	0.064	0.059	0.048	0.054	0.054
F12	0.031	0.029	0.045	0.032	0.031	0.034	0.032	0.031	0.036	0.033	0.032	0.031	0.017
F13	0.039	0.058	0.066	0.068	0.076	0.083	0.065	0.065	0.071	0.064	0.063	0.059	0.060
F14	0.036	0.020	0.037	0.036	0.036	0.039	0.036	0.036	0.040	0.036	0.035	0.033	0.033
F15	0.030	0.027	0.019	0.030	0.030	0.032	0.030	0.030	0.033	0.030	0.029	0.016	0.016
F16	0.065	0.059	0.067	0.040	0.051	0.069	0.068	0.052	0.073	0.052	0.063	0.076	0.046

Table 11 (continued)

Factors	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25
F17	0.066	0.060	0.056	0.070	0.042	0.084	0.054	0.066	0.086	0.053	0.066	0.048	0.073
F18	0.066	0.047	0.067	0.068	0.078	0.049	0.079	0.061	0.086	0.055	0.065	0.061	0.074
F19	0.037	0.033	0.027	0.036	0.025	0.040	0.025	0.036	0.040	0.037	0.035	0.033	0.033
F20	0.051	0.056	0.074	0.062	0.048	0.054	0.063	0.038	0.080	0.062	0.060	0.070	0.056
F21	0.060	0.043	0.063	0.062	0.049	0.065	0.049	0.062	0.043	0.061	0.059	0.057	0.056
F22	0.057	0.052	0.059	0.048	0.061	0.062	0.058	0.058	0.051	0.033	0.044	0.041	0.054
F23	0.070	0.058	0.072	0.069	0.074	0.071	0.071	0.070	0.076	0.080	0.042	0.065	0.077
F24	0.027	0.061	0.054	0.051	0.026	0.030	0.052	0.042	0.066	0.042	0.041	0.025	0.024
F25	0.061	0.042	0.061	0.061	0.076	0.078	0.061	0.060	0.066	0.061	0.060	0.033	0.033

Table 12 DEMATEL results

Factors	V	K	$V + K$	$V - K$	Cause/Effect
F1	2.50	1.94	4.44	0.56	Cause
F2	1.80	1.42	3.22	0.38	Cause
F3	1.77	1.80	3.57	−0.03	Effect
F4	1.82	1.89	3.71	−0.07	Effect
F5	1.80	1.69	3.49	0.11	Cause
F6	0.92	1.51	2.43	−0.59	Effect
F7	1.60	1.79	3.39	−0.19	Effect
F8	1.74	1.43	3.17	0.31	Cause
F9	1.81	1.58	3.39	0.23	Cause
F10	1.72	1.33	3.05	0.39	Cause
F11	1.43	1.70	3.13	−0.27	Effect
F12	0.83	1.49	2.32	−0.66	Effect
F13	1.67	1.42	3.09	0.25	Cause
F14	0.98	1.23	2.21	−0.25	Effect
F15	0.74	1.52	2.26	−0.78	Effect
F16	1.67	1.46	3.13	0.21	Cause
F17	1.71	1.44	3.15	0.27	Cause
F18	1.77	1.64	3.41	0.13	Cause
F19	0.99	1.47	2.46	−0.48	Effect
F20	1.58	1.44	3.02	0.14	Cause
F21	1.52	1.70	3.22	−0.18	Effect
F22	1.39	1.45	2.84	−0.06	Effect
F23	1.81	1.39	3.20	0.42	Cause
F24	1.16	1.26	2.42	−0.10	Effect
F25	1.52	1.26	2.78	0.26	Cause

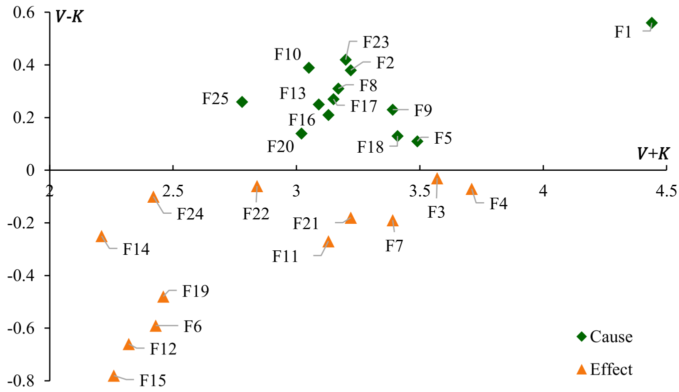

Fig. 5 DEMATEL casual-effect diagram

characteristics and the vagueness evaluation information of experts, TrFN is introduced into FRC and DEMATEL methods to obtain more accurate result of factor analysis.

As a result, this study aims to present a new method called "fuzzy large-scale group-DEMATEL" to identify the interrelated relationships between the studied factors as well as recognize the key factors while using BT in HSCs. It is notable that the proposed method consolidates the fuzzy theory, clustering approach and the DEMATEL technique, thus combing the advantages of all these methods. The research results provide important contributions for identifying the key factors in the use of BT in HSCs. Our findings show that experts can be divided into three clusters based on their characteristics as determined by FRC. Then the FDEMATEL method is applied to identify BT's effect and cause factors in HSCs. Among the 25 factors considered in this study, disintermediation, improved risk management, and security have been identified as the 3 most important, with a considerable distance from others. A closer look reveals that 13 and 12 factors have been identified as "cause" and "effect" factors, respectively. Policymakers need to pay more attention to the improvement of these most important factors, and take some meatures to control those cause factors, such as decentralize the power of organizations in HSCs, so that each participant can conduct peer-to-peer transactions freely. Finally, the effectiveness and rationality of the proposed method are demonstrated by comparing with the existing methods.

The future work can be done on more decision-making situations, and the clustering of large-scale group-DMs should not only considers their characteristics but also the behavior patterns. In addition, a more in depth discussion of BT

Table 13 Comparative analysis with two existing methods

Factors	Individual DEMATEL decision method			Cluster the experts only by their evaluation information			The method proposed in this paper		
	$V+K$	$V-K$	Cause/effect	$V+K$	$V-K$	Cause/effect	$V+K$	$V-K$	Cause/effect
F1	<u>4.60</u>	0.52	Cause	<u>3.00</u>	0.57	Cause	<u>4.44</u>	0.56	Cause
F2	3.22	0.38	Cause	1.66	0.26	Cause	3.22	0.38	Cause
F3	<u>3.54</u>	**0.06**	**Cause**	<u>2.18</u>	0.01	**Cause**	<u>3.57</u>	−0.03	**Effect**
F4	<u>3.56</u>	−0.07	Effect	<u>2.25</u>	−0.02	Effect	<u>3.71</u>	−0.07	Effect
F5	2.49	**−0.21**	**Effect**	1.94	0.01	**Cause**	3.49	0.11	**Cause**
F6	2.43	−0.59	Effect	1.07	−0.40	Effect	2.43	−0.59	Effect
F7	3.39	−0.19	Effect	1.99	−0.07	Effect	3.39	−0.19	Effect
F8	3.17	0.31	Cause	1.71	0.29	Cause	3.17	0.31	Cause
F9	0.39	0.24	Cause	1.98	0.25	Cause	3.39	0.23	Cause
F10	2.05	0.39	Cause	1.66	0.51	Cause	3.05	0.39	Cause
F11	1.13	−0.27	Effect	1.71	−0.28	Effect	3.13	−0.27	Effect
F12	1.32	−0.66	Effect	0.86	−0.62	Effect	2.32	−0.66	Effect
F13	1.59	0.25	Cause	1.67	0.13	Cause	3.09	0.25	Cause
F14	1.27	−0.25	Effect	0.72	−0.30	Effect	2.21	−0.25	Effect
F15	1.20	−0.78	Effect	0.91	−0.75	Effect	2.26	−0.78	Effect
F16	2.18	0.21	Cause	1.70	0.22	Cause	3.13	0.21	Cause
F17	1.25	0.27	Cause	1.75	0.30	Cause	3.15	0.27	Cause
F18	1.53	0.13	Cause	1.95	0.15	Cause	3.41	0.13	Cause
F19	1.45	−0.48	Effect	0.95	−0.48	Effect	2.46	−0.48	Effect
F20	2.20	0.14	Cause	1.60	0.15	Cause	3.02	0.14	Cause
F21	2.67	−0.18	Effect	1.76	−0.17	Effect	3.22	−0.18	Effect
F22	1.84	−0.06	Effect	1.33	−0.07	Effect	2.84	−0.06	Effect
F23	2.20	0.42	Cause	1.59	0.23	Cause	3.20	0.42	Cause
F24	1.52	**0.02**	**Cause**	1.18	−0.06	**Effect**	2.42	−0.10	**Effect**
F25	1.23	0.26	Cause	1.50	0.13	Cause	2.78	0.26	Cause

* The values of V+K with underline indicate these are top 3 factors; The values of V-K and Cause/effect in bold indicate opposite results

and HSCs can be further analyzed. Furthermore, we may consider the real data in HSCs to more effectively solve the distribution of relief materials in practical disasters.

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Authors and Affiliations

Lu Chen[1] · **Ayad Hendalianpour**[2] · **Mohammad Reza Feylizadeh**[3] · **Haiyan Xu**[1]

Lu Chen
chenlu@nuaa.edu.cn

Ayad Hendalianpour
hendalianpour@ut.ac.ir

Mohammad Reza Feylizadeh
feylizadeh_mr@yahoo.com

1 College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, Jiangsu, People's Republic of China

2 Soshianest Enterprise Miner, North Vancouver, BC V7N2J7, Canada

3 Department of Industrial Engineering, Shiraz Branch, Islamic Azad University, Shiraz, Iran