



# Establishing an interval-valued fuzzy decision-making method for sustainable selection of healthcare waste treatment technologies in the emerging economies

Hao Li<sup>1</sup> · Jinlin Li<sup>1</sup> · Zengbo Zhang<sup>1</sup> · Xueli Cao<sup>1</sup> · Jingrong Zhu<sup>1</sup> · Wenjia Chen<sup>1</sup>

Received: 4 June 2019 / Accepted: 7 November 2019 / Published online: 16 November 2019  
© Springer Japan KK, part of Springer Nature 2019

## Abstract

Healthcare services provided by hospitals and clinics inevitably produce waste that may be hazardous to the environment and society. However, there is a lack of an effective and comprehensive evaluation framework that takes uncertainty and fuzziness into account to assess healthcare waste treatment technologies in the emerging economies. The objective of this paper is to present a new integrated multi-criteria decision-making method based on interval-valued fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory) and interval-valued fuzzy TOPSIS for evaluating healthcare waste treatment technologies in the emerging economies from a sustainability perspective. In this study, the decision makers are allowed to determine the weights of the evaluation criteria and prioritize the alternatives using linguistic variables. The weights of the evaluation criteria are determined by the interval-valued fuzzy DEMATEL method, and the prioritization of the alternatives is determined by the interval-valued fuzzy TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) method. Four alternatives for healthcare waste treatment technologies including incineration, steam sterilization, microwave and landfill are studied, and the results show that our established method is effective to help the decision-makers to determine the prioritization of the alternatives for healthcare waste treatment technologies.

**Keywords** Healthcare waste treatment technology · Multi-criteria decision-making · Interval-valued fuzzy DEMATEL · Interval-valued fuzzy TOPSIS · Sustainability

## Introduction

Due to the rapid increase of the number of the aging population and the demand for healthcare services in the emerging economies, the amount of healthcare wastes is rising quickly in the past few decades [1, 2]. As a result, healthcare waste management has become a complex and challenging problem in the emerging economies. In fact, providing an eco-friendly and trustworthy healthcare waste management system is one of the key issues for healthcare institutions and communities [3]. However, healthcare waste has not received sufficient attention in the emerging economies, and it is still handled and disposed of together with the domestic waste [4, 5]. In contrast, healthcare waste is classified and

managed scientifically in developed countries. Consequently, it poses a great risk to the environment and the public [6, 7].

The World Health Organization defines healthcare waste as those waste generated from hospitals, medical centres, healthcare establishments and research facilities in diagnosis, treatment, immunization and associated research [8, 9]. Healthcare waste can be infectious, toxic and even lethal because of its potential for the transmission of disease [10]. If not adequately treated, poor healthcare waste management results in adverse effects on the ecological environment and public health [11]. Proper healthcare waste management involves a number of activities, but healthcare waste treatment plays a key role in healthcare waste management. Hence, we focus on the sustainable selection of healthcare waste treatment technologies in this paper. It is of great importance to select the most sustainable healthcare waste treatment technology in the emerging economies by establishing a systematic and effective evaluation method.

To select the most sustainable healthcare waste treatment technology in the emerging economies, the

✉ Jinlin Li  
lijinlin\_bit@126.com

<sup>1</sup> School of Management and Economics, Beijing Institute of Technology, Beijing 100081, People's Republic of China

decision-makers have to consider various criteria simultaneously. In the actual conditions, the evaluation criteria are often interdependent [12, 13], there are also uncertain and ambiguous information existing in the process of decision-making. Moreover, this process involves multiple stakeholders including researchers, administrators, engineers and so on. There is no healthcare waste treatment technology that can satisfy all evaluation criteria simultaneously, so the sustainable selection of healthcare waste treatment technologies requires the participation of multiple stakeholders for a trade-off evaluation.

Plenty of mathematical methods have been applied to study the selection problem for healthcare waste treatment technologies arising from different regions around the world. These mathematical methods include Analytical Hierarchy Process, Analytic Network Process, Data Envelopment Analysis, fuzzy multi-criteria decision-making method, fuzzy decision-making method with data mining and so on [14–18]. However, to our knowledge, the existing mathematical methods do not consider the independent relationships among the evaluation criteria or the uncertainties in the determination of the decision-making matrix simultaneously. In many cases, due to the vagueness of the judgments, it is difficult for decision-makers to express their opinions with an exact numerical value. In other words, it is more reasonable and scientific for multiple stakeholders to use the linguistic variables rather than exact numerical values. This paper aims to establish an interval-valued fuzzy multi-criteria decision making method based on interval-valued fuzzy DEMATEL (Decision-Making Trial and Evaluation Laboratory) and interval-valued fuzzy TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) for sustainable selection of healthcare waste treatment technologies in the emerging economies, which can overcome the limitations of the existing mathematical methods. Specially, a case study in Beijing, the capital of China, is used to explain the computational process and potential benefits of the proposed mathematical method.

Besides the introduction, the rest of this study is organized as follows: The mathematical model established in this study is given in the “[Methods](#)” section. An illustrative case is discussed in the “[Case study](#)” section. The discussions of this study are developed in the “[Discussions](#)” section. Finally, the conclusions and the future research directions are provided in “[Conclusions](#)” section.

Next, we review previous research with respect to the healthcare waste treatment evaluation and related methods in the sustainability performance of waste treatment technology. We also summarize the primary characteristics and the research gaps of sustainable selection of healthcare waste treatment technologies.

## Literature review of selection problems of waste treatment

In this section, we first summarize the existing literature focusing on waste disposal technologies selection and sustainability performance assessment, which is helpful to study sustainable section of healthcare waste treatment technologies in the emerging economies.

For the selection problems of waste treatment, the multi-criteria decision-making method is widely applied to the selection of waste disposal technologies [19–27]. Kharat et al. [28] presented a systematic three-stage evaluation framework to select an appropriate solid waste technology, and the framework is based on the fuzzy Delphi method, fuzzy Analytic Hierarchy Process and the fuzzy TOPSIS technique, which can make the uncertain decision-making process more objective and analytical. Crisóstobal et al. [29] developed a 3-stage methodology which capitalizes on Data Envelopment Analysis (DEA), Life Cycle Assessment (LCA) and the mathematical programming. The developed methodology is applied to the assessment and retrofit of a number of technological options for food waste management. Vučijak et al. [30] presented a multi-criteria decision-making tool for the purpose of selecting the best municipal solid waste management scenario among six different alternatives. Arikan et al. [31] and Wang et al. [32] presented a new fuzzy multi-criteria decision-making method to select the best waste disposal technology.

Over the past decade, sustainability and environment issue of waste management have aroused wide concern around the world. We should put much attention on sustainability and environment performances when selecting an appropriate waste treatment technology. Life Cycle Assessment (LCA) is the most common method that is applied to evaluate sustainability and environment performance of waste management [33]. Lijó et al. [34] compared the environmental performance and sustainability of different management options for livestock waste using Analytic Hierarchy Process (AHP) and Life Cycle Assessment (LCA). Havukainen et al. [35] and Liu et al. [36] studied environmental performance evaluation of different Chinese waste management scenarios using LCA method. Sustainability performance of waste treatment technologies using LCA method is elaborated in Zhou et al. [37] and Chen et al. [38].

## Literature review of healthcare waste management

Due to the fuzziness and ambiguity of the evaluation criteria, the majority of the existing literature adopts the fuzzy

method to study the selection of healthcare waste treatment technologies. Dursun et al. [39] presented a multi-criteria decision-making technique for evaluating healthcare waste treatment alternatives based on multi-level hierarchical structure and fuzzy logic. Karsak et al. [40] established a fuzzy multi-criteria group decision-making framework based on the principles of fuzzy measure and fuzzy integral for evaluating healthcare waste treatment alternatives for Istanbul. Liu et al. [41] developed a new MCDM technique based on fuzzy set theory and VIKOR method for evaluating HCW disposal methods. Shan et al. [42] proposed an interval 2-tuple linguistic MULTIMOORA method for selecting healthcare waste treatment technologies. Especially, both subjective and objective importance coefficients of the evaluation criteria are analyzed in the developed method. You et al. [43] proposed a novel hybrid multi-criteria decision-making model by integrating the 2-tuple DEMATEL technique and fuzzy MULTIMOORA method for selection of HCW treatment alternatives. Shi et al. [44] developed an integrated decision-making framework based on cloud model and MABAC method for selecting the best HCW treatment technology from a multiple stakeholder perspective.

With the development of information technology and the increase of data amount, some new methods based on data mining are gradually being applied to the field of healthcare waste management. To generate predictions and classify previously unseen data, Csorba and Crăciun [45] applied the decision tree algorithm in a sustainable medical waste management process. Baghapour et al. [46] presented a quantitative software-based index to assess the healthcare waste process performance by integrating ontology-based multi-criteria group decision-making technique and data mining. Xiao [47] proposed a novel decision-making model based on D numbers to assess health-care waste treatment technologies.

As it is known to all, sustainability of the healthcare waste treatment technology is fundamental to the environment and society, but it did not get much attention. Up to now, there is little literature studying on sustainability of healthcare waste treatment technology. Hong et al. [48] used a cost-coupled life cycle assessment to quantify the environmental and economic impacts of three medical waste disposal scenarios. Cesaro and Belgiorio [49] studied the sustainability of medical waste management system in different sized healthcare facilities by establishing hospital operational parameters and discussing medical waste pollution data.

## Summary

At present, people are becoming aware of the importance of sustainable municipal solid waste, electronic waste, food waste and wastewater treatment technologies, but little

attention has been paid to the sustainability of healthcare waste treatment technologies in emerging economies in the existing literature. In this paper, we aim to study sustainable selection of healthcare waste treatment technologies in the emerging economies by establishing a mathematical method. Furthermore, to our knowledge, the existing mathematical methods do not consider the independent relationships among the evaluation criteria or the uncertainties in the determination of the decision-making matrix simultaneously.

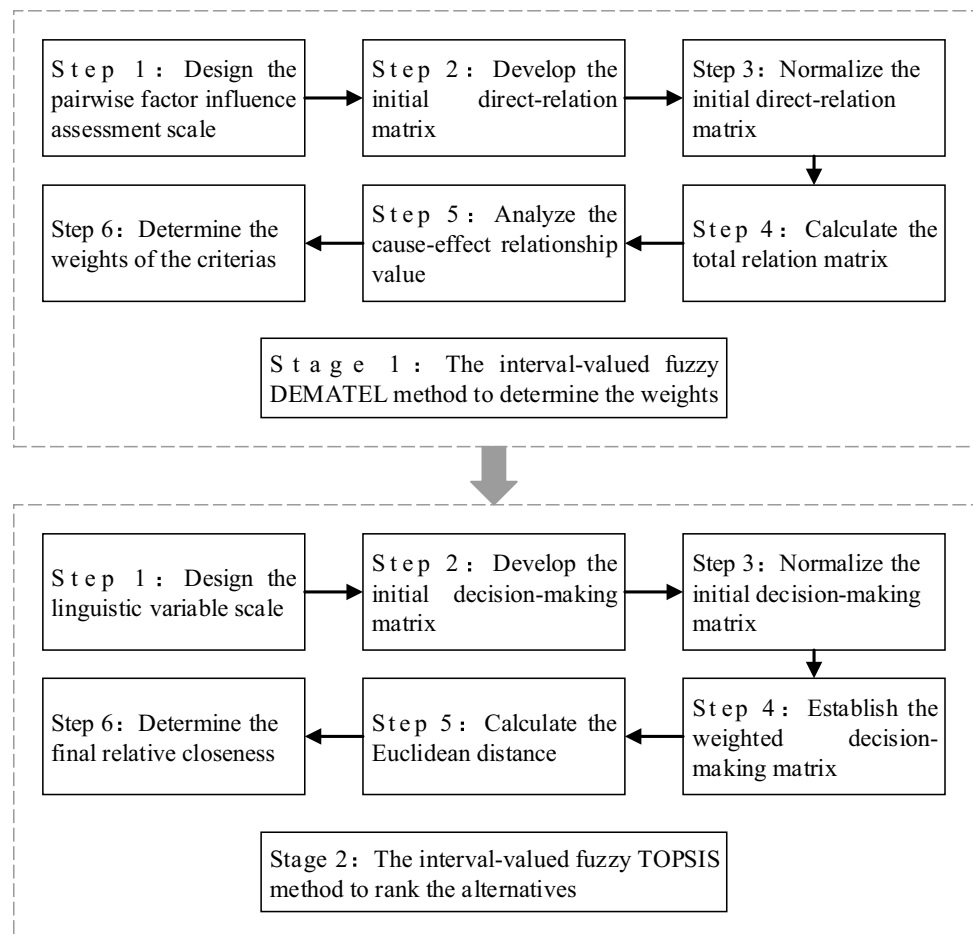
To fill the above-mentioned research gaps, we establish an interval-valued fuzzy decision-making method to study sustainable selection of healthcare waste treatment technologies, and our research has the following three features: (1) there is mounting concern about how to support decision-makers in driving sustainable healthcare waste management, we study selection of healthcare waste treatment technologies from a sustainability perspective; (2) we establish an interval-valued fuzzy DEMATEL method to analyse the independent relationships when determining the weights of the evaluation criteria; (3) we present an interval-valued fuzzy TOPSIS method to address uncertainty and ambiguity in the decision making process, and the preference of multiple stakeholders is taken into account in the method. An explanatory case including four alternatives for healthcare waste treatment technologies is studied by the established method. The results of the case study show that the most sustainable healthcare waste treatment technology among these four alternatives is steam sterilization, followed by microwave, incineration, and landfill in the descending order.

## Methods

The interval-valued fuzzy set theory is widely applied in many fields due to its capability of handling uncertainties [50]. The traditional fuzzy set theory allows the decision-makers to represent the uncertainty using a crisp value [51], while the interval-valued fuzzy set theory allows the decision-makers to represent the uncertainty using an interval number, so the interval-valued fuzzy set theory is superior to the traditional fuzzy set theory in accuracy. The application of the interval-valued fuzzy numbers allows the decision-makers to define the lower and upper bounds values as an interval for matrix's elements and weights of criteria [52]. Therefore, in this paper, we develop a multi-criteria decision-making method based on the interval-valued fuzzy set theory to study sustainable selection of healthcare waste treatment technologies in the emerging economies. The flowchart of the method can be seen in Fig. 1.

We first introduce the basic concept and arithmetic operations of the interval-valued fuzzy set theory. Next, we develop an interval-valued fuzzy DEMATEL method

**Fig. 1** The flowchart of the method



to determine the weights of the evaluation criteria, and the independent relationships among the evaluation criteria are incorporated into the developed method. Finally, we establish an interval-valued fuzzy TOPSIS method to rank the alternatives for healthcare waste treatment technologies.

### The basic introduction of the interval-valued fuzzy set theory

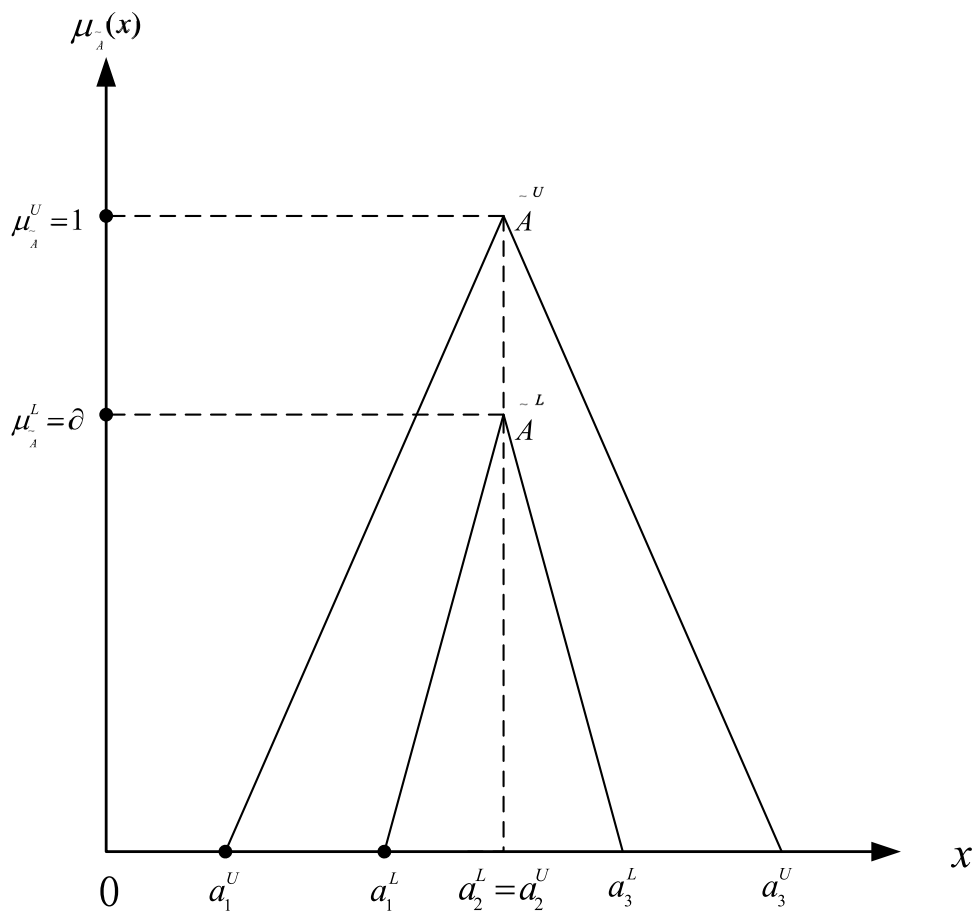
The interval-valued fuzzy set theory was first introduced in the 1980 s, suppose  $\tilde{a} = [(a_1, a'_1); a_2; (a'_3, a_3)]$  and  $\tilde{d} = [(d_1, d'_1); d_2; (d'_3, d_3)]$  are two interval-valued fuzzy numbers (as illustrated in Fig. 2), and  $\beta$  is a positive crisp number. Note that in Fig. 2,  $a_1^U = a_1, a_1^L = a'_1, a_2^L = a_2^U = a_2, a_3^L = a'_3, a_3^U = a_3$ . The definition of the interval-valued fuzzy set and the arithmetic operations of the interval-valued fuzzy numbers are presented in “Appendix”.

### The interval-valued fuzzy DEMATEL method to determine the weights

We establish an interval-valued fuzzy DEMATEL method to determine the weights of the evaluation criteria for sustainable selection of healthcare waste treatment technologies in the emerging economies. The Decision-Making Trial and Evaluation Laboratory (DEMATEL) was first introduced in 1987 [54]. The DEMATEL method is used to analyze and visualize the structure of complex systems, and the proposed method combines DEMATEL with the interval-valued fuzzy set theory, which has the ability to deal with interdependence among the evaluation criteria and offer a better representation of uncertainty. The steps of the interval-valued fuzzy DEMATEL method are described as follows:

*Step 1* Design the pairwise factor influence assessment scale. The proposed pairwise influence assessment scale (Table 1) include six levels: “No influence”, “Very low

**Fig. 2** An interval-valued fuzzy number



**Table 1** Linguistic terms for the pairwise factor influence assessment [32]

Linguistic terms	Interval-valued fuzzy numbers
No influence (N)	[(0, 0); 0; (0, 0)]
Very low influence (VL)	[(1.0, 1.5); 2.0; (2.5, 3.0)]
Low influence (L)	[(2.0, 2.5); 3.0; (3.5, 4.0)]
Medium influence (M)	[(3.0, 3.5); 4.0; (4.5, 5.0)]
High influence (H)	[(4.0, 4.5); 5.0; (5.5, 6.0)]
Very high influence (VH)	[(5.0, 5.5); 6.0; (6.5, 7.0)]

influence”, “Low influence”, “Medium influence”, “High influence”, “Very High influence”, respectively. Each

interval-valued fuzzy number corresponds to a linguistic term. For example, if the decision-maker think the relative influence level between a pair of factors is “High influence”, then denoted by [(4.0, 4.5);5.0;(5.5, 6.0)].

*Step 2* Develop the initial direct-relation matrix  $\tilde{Q}$ . We suppose that there are  $n$  criteria to be taken into account in the system. The decision makers are asked to assess the direct influence level between each pair of facors using an interval-valued fuzzy number.  $\tilde{q}_{ij}$  is an interval-valued fuzzy number, which refers to the influence of the  $i$ -th criteria on the  $j$ -th criteria determined by the decision-maker. The initial direct-relation matrix  $\tilde{Q}$  can form a  $n \times n$  matrix, as showed in Eq. (1).

$$\tilde{Q} = \begin{bmatrix} \tilde{q}_{11} & \tilde{q}_{12} & \cdots & \tilde{q}_{1n} \\ \tilde{q}_{21} & \tilde{q}_{22} & \cdots & \tilde{q}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{q}_{n1} & \tilde{q}_{n1} & \cdots & \tilde{q}_{nn} \end{bmatrix} \tag{1}$$

$$= \begin{bmatrix} (0, 0);0;(0, 0) & (q_{12}^1, q_{12}^1);q_{12}^2;(q_{12}^3, q_{12}^3) & \cdots & (q_{1n}^1, q_{1n}^1);q_{1n}^2;(q_{1n}^3, q_{1n}^3) \\ (q_{21}^1, q_{21}^1);q_{21}^2;(q_{21}^3, q_{21}^3) & (q_{22}^1, q_{22}^1);q_{22}^2;(q_{22}^3, q_{22}^3) & \cdots & (q_{2n}^1, q_{2n}^1);q_{2n}^2;(q_{2n}^3, q_{2n}^3) \\ \vdots & \vdots & \ddots & \vdots \\ (q_{n1}^1, q_{n1}^1);q_{n1}^2;(q_{n1}^3, q_{n1}^3) & (q_{n2}^1, q_{n2}^1);q_{n2}^2;(q_{n2}^3, q_{n2}^3) & \cdots & (q_{nn}^1, q_{nn}^1);q_{nn}^2;(q_{nn}^3, q_{nn}^3) \end{bmatrix}$$

*Step 3* Normalize the initial direct-relation matrix. Let  $\tilde{P}$  be the normalized direct-relation matrix, which could be obtained by Eqs. (2)–(4).

$$\tilde{P} = [\tilde{P}_{ij}]_{n \times n} = \left[ (p_{ij}^1, p_{ij}^1); p_{ij}^2; (p_{ij}^3, p_{ij}^3) \right]_{n \times n} \tag{2}$$

$$\tilde{P}_{ij} = \lambda \tilde{q}_{ij} = \lambda \left[ (q_{ij}^1, q_{ij}^1); q_{ij}^2; (q_{ij}^3, q_{ij}^3) \right] = \left[ (\lambda q_{ij}^1, \lambda q_{ij}^1); \lambda q_{ij}^2; (\lambda q_{ij}^3, \lambda q_{ij}^3) \right] \tag{3}$$

$$\lambda = \frac{1}{\max_{1 \leq i \leq n} \sum_{j=1}^n q_{ij}^3} \tag{4}$$

*Step 4* Calculate the total relation matrix. Let  $\tilde{T} = [\tilde{T}_{ij}]_{n \times n}$  be the total relation matrix that expresses both direct and indirect effects. With the increase of the powers of the total relation matrix  $\tilde{T}$ , the indirect effects will continuously decrease, and  $\tilde{T}_\infty$  approaches to zero, which guarantees convergent solutions to the matrix inversion [32], the total relation matrix  $\tilde{T}$  could be expressed as follows:

$$\tilde{T} = [\tilde{T}_{ij}]_{n \times n} = \lim_{m \rightarrow \infty} (\tilde{P}^1 + \tilde{P}^2 + \dots + \tilde{P}^m) = \tilde{P}(I - \tilde{P})^{-1} \tag{5}$$

where  $I$  refers to the identity matrix.

$$\tilde{T}_{ij} = [(t_{ij}^1, t_{ij}^1); t_{ij}^2; (t_{ij}^3, t_{ij}^3)] \tag{6}$$

$t_{ij}^1, t_{ij}^1, t_{ij}^2, t_{ij}^3$  and  $t_{ij}^3$  could be obtained by Eqs. (7)–(16).

$$P_1 = [p_{ij}^1]_{n \times n} \tag{7}$$

$$P'_1 = [p_{ij}^1]_{n \times n} \tag{8}$$

$$P_2 = [p_{ij}^2]_{n \times n} \tag{9}$$

$$P'_3 = [p_{ij}^3]_{n \times n} \tag{10}$$

$$P_3 = [p_{ij}^3]_{n \times n} \tag{11}$$

$$T^1 = [t_{ij}^1]_{n \times n} = P_1(I - P_1)^{-1} \tag{12}$$

$$T'^1 = [t_{ij}^1]_{n \times n} = P'_1(I - P'_1)^{-1} \tag{13}$$

$$T^2 = [t_{ij}^2]_{n \times n} = P_2(I - P_2)^{-1} \tag{14}$$

$$T'^3 = [t_{ij}^3]_{n \times n} = P'_3(I - P'_3)^{-1} \tag{15}$$

$$T^3 = [t_{ij}^3]_{n \times n} = P_3(I - P_3)^{-1} \tag{16}$$

*Step 5* Analyze the cause-effect relationship value.  $\tilde{r}_i$  refers to the total influence that the  $i$ -th criteria exerts to the rest of the criteria, while  $\tilde{c}_j$  refers to the total influence that the  $j$ -th criteria affected by the rest of the criteria.

$$\tilde{r}_i = \sum_{j=1}^n \tilde{t}_{ij} = [(r_i^1, r_i^1); r_i^2; (r_i^3, r_i^3)] \tag{17}$$

$$\tilde{c}_j = \sum_{i=1}^n \tilde{t}_{ij} = [(c_j^1, c_j^1); c_j^2; (c_j^3, c_j^3)] \tag{18}$$

If  $i=j$ ,  $\tilde{r}_j + \tilde{c}_j$  refers to the prominence value, which represents the relative importance of the  $j$ th criteria, while  $\tilde{r}_j - \tilde{c}_j$  refers to the reason value, which represents the net effect of the  $j$ th criteria.

$$\tilde{r}_j + \tilde{c}_j = [(r_j^1 + c_j^1, r_j^1 + c_j^1); r_j^2 + c_j^2; (r_j^3 + c_j^3, r_j^3 + c_j^3)] \tag{19}$$

$$\tilde{r}_j - \tilde{c}_j = [(r_j^1 - c_j^3, r_j^1 - c_j^3); r_j^2 - c_j^2; (r_j^3 - c_j^1, r_j^3 - c_j^1)] \tag{20}$$

The defuzzified form of  $\tilde{r}_j + \tilde{c}_j$  and  $\tilde{r}_j - \tilde{c}_j$  can be determined by Eqs. (21) and (22).

$$r_j + c_j = \frac{(r_j^1 + c_j^1 + r_j^1 + c_j^1) + 2(r_j^2 + c_j^2) + (r_j^3 + c_j^3; r_j^3 + c_j^3)}{6} \tag{21}$$

$$r_j - c_j = \frac{[(r_j^1 - c_j^3) + (r_j^1 - c_j^3)] + 2(r_j^2 - c_j^2) + [(r_j^3 - c_j^1) + (r_j^3 - c_j^1)]}{6} \tag{22}$$

*Step 6* Determine the weights of the criteria. The cause-effect relationship value can be used to determine the weights of the criteria. The normalized weights represent the relative importance of these criteria, then the weights can be determined.

$$\bar{w}_j = \sqrt{(r_j + c_j)^2 + (r_j - c_j)^2} \tag{23}$$

$$w_j = \bar{w}_j / \sum_{j=1}^n \bar{w}_j \tag{24}$$

### The interval-valued fuzzy TOPSIS method to rank the alternatives

We establish an interval-valued fuzzy TOPSIS method to rate the alternatives for sustainable selection of healthcare waste treatment technologies in the emerging economies. Assuming that there are  $m$  ( $i=1, 2, \dots, m$ ) alternatives of healthcare waste treatment technologies to be assessed by

**Table 2** Linguistic variables for prioritizing the alternatives [55]

Linguistic variables	Interval-valued fuzzy numbers
Very poor (VP)	[(0, 0); 0; (1.0, 1.5)]
Poor (P)	[(0, 0.5); 1.0; (2.5, 3.5)]
Moderately poor (MP)	[(0, 1.5); 3.0; (4.5, 5.5)]
Fair (F)	[(2.5, 3.5); 5.0; (6.5, 7.5)]
Moderately good (MG)	[(4.5, 5.5); 7.0; (8.0, 9.5)]
Good (G)	[(5.5, 7.5); 9.0; (9.5, 10.0)]
Very good (VG)	[(8.5, 9.5); 10.0; (10.0, 10.0)]

$n$  ( $j = 1, 2, \dots, n$ ) metrics. The steps of the interval-valued fuzzy TOPSIS method are described as follows:

*Step 1* Design the linguistic variable scale that is used to prioritize the alternatives of healthcare waste treatment technologies with respect to the evaluation criteria. The scale (Table 2) include seven levels: “Very poor”, “Poor”, “Moderately poor”, “Fair”, “Moderately good”, “Good”, “Very good”, respectively. Each interval-valued fuzzy number corresponds to a linguistic term. For example, if the decision maker think the linguistic variable is “Good”, then denoted by [(5.5, 7.5);9.0;(9.5, 10.0)].

*Step 2* Develop the initial decision-making matrix  $\tilde{X}$ . The element of initial interval-valued fuzzy decision-making matrix  $\tilde{X}$  is determined by the decision-maker. According to the evaluation criteria, the decision-maker express his opinion on the alternatives of healthcare waste treatment technologies using the linguistic variables. Then the sustainability performance of the alternatives can be determined. The initial decision-making matrix  $\tilde{X}$  can form a  $m \times n$  matrix, as showed in Eq. (25).

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m1} & \dots & \tilde{x}_{mn} \end{bmatrix} = \begin{bmatrix} (x_{11}^1, x_{11}^1); x_{11}^2; (x_{11}^3, x_{11}^3) & (x_{12}^1, x_{12}^1); x_{12}^2; (x_{12}^3, x_{12}^3) & \dots & (x_{1n}^1, x_{1n}^1); x_{1n}^2; (x_{1n}^3, x_{1n}^3) \\ (x_{21}^1, x_{21}^1); x_{21}^2; (x_{21}^3, x_{21}^3) & (x_{22}^1, x_{22}^1); x_{22}^2; (x_{22}^3, x_{22}^3) & \dots & (x_{2n}^1, x_{2n}^1); x_{2n}^2; (x_{2n}^3, x_{2n}^3) \\ \vdots & \vdots & \ddots & \vdots \\ (x_{m1}^1, x_{m1}^1); x_{m1}^2; (x_{m1}^3, x_{m1}^3) & (x_{m2}^1, x_{m2}^1); x_{m2}^2; (x_{m2}^3, x_{m2}^3) & \dots & (x_{mn}^1, x_{mn}^1); x_{mn}^2; (x_{mn}^3, x_{mn}^3) \end{bmatrix} \tag{25}$$

*Step 3* Normalize the initial decision-making matrix. The elements in the interval-valued fuzzy decision-making matrix  $\tilde{X}$  are used to rank the alternatives of healthcare waste treatment technologies, and the normalized interval-valued fuzzy decision-making matrix  $\tilde{G}$  can be obtained by Eqs. (26) and (27).

$$\tilde{G} = \begin{bmatrix} \tilde{g}_{11} & \tilde{g}_{12} & \dots & \tilde{g}_{1n} \\ \tilde{g}_{21} & \tilde{g}_{22} & \dots & \tilde{g}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{g}_{m1} & \tilde{g}_{m1} & \dots & \tilde{g}_{mn} \end{bmatrix} \tag{26}$$

$$\tilde{g}_{ij} = \left[ \left( \frac{x_{ij}^1}{\max_i \{x_{ij}^3\}}, \frac{x_{ij}^1}{\max_i \{x_{ij}^3\}} \right); \frac{x_{ij}^2}{\max_i \{x_{ij}^3\}}; \left( \frac{x_{ij}^3}{\max_i \{x_{ij}^3\}}, \frac{x_{ij}^3}{\max_i \{x_{ij}^3\}} \right) \right] \tag{27}$$

*Step 4* Establish the weighted decision-making matrix  $\tilde{V}$ . By considering the corresponding weights of each evaluation criteria, the weighted interval-valued fuzzy decision-making matrix  $\tilde{V}$  can be determined.

$$\tilde{v}_{ij} = \left[ (v_{ij}^1, v_{ij}^1); v_{ij}^2; (v_{ij}^3, v_{ij}^3) \right] = w_j \tilde{g}_{ij} = w_j \left[ (g_{ij}^1, g_{ij}^1); g_{ij}^2; (g_{ij}^3, g_{ij}^3) \right] = \left[ (w_j g_{ij}^1, w_j g_{ij}^1); w_j g_{ij}^2; (w_j g_{ij}^3, w_j g_{ij}^3) \right] \tag{28}$$

Then, the ideal solution  $A^+$  can be defined as:

$$A^+ = [(1, 1); 1; (1, 1)] \tag{29}$$

The negative ideal solution  $A^-$  can be defined as:

$$A^- = [(0, 0); 0; (0, 0)] \tag{30}$$

*Step 5* Calculate the Euclidean distance. The Euclidean distance of each alternative from the ideal alternative in the form of interval-valued fuzzy set can be expressed by Eqs. (31) and (32).

$$D_{i1}^+ = \sum_{j=1}^n \sqrt{\frac{1}{3} \left[ (v_{ij}^1 - 1)^2 + (v_{ij}^2 - 1)^2 + (v_{ij}^3 - 1)^2 \right]} \tag{31}$$

$$D_{i2}^+ = \sum_{j=1}^n \sqrt{\frac{1}{3} \left[ (v_{ij}^1 - 1)^2 + (v_{ij}^2 - 1)^2 + (v_{ij}^3 - 1)^2 \right]} \tag{32}$$

The Euclidean distance of each alternative from the negative ideal alternative in the form of interval-valued fuzzy set can be expressed by Eqs. (33) and (34).

$$D_{i1}^- = \sum_{j=1}^n \sqrt{\frac{1}{3} \left[ (v_{ij}^1 - 0)^2 + (v_{ij}^2 - 0)^2 + (v_{ij}^3 - 0)^2 \right]} \tag{33}$$

$$D_{i2}^- = \sum_{j=1}^n \sqrt{\frac{1}{3} \left[ \left( v_{ij}^1 - 0 \right)^2 + \left( v_{ij}^2 - 0 \right)^2 + \left( v_{ij}^3 - 0 \right)^2 \right]} \quad (34)$$

Step 6 Determine the final relative closeness. The initial relative closeness can be determined as follows:

$$RC_{i1} = \frac{D_{i1}^-}{D_{i1}^+ + D_{i1}^-}, RC_{i2} = \frac{D_{i2}^-}{D_{i2}^+ + D_{i2}^-}, \quad i = 1, 2, \dots, m, \quad 0 < RC_i \leq 1 \quad (35)$$

The final relative closeness  $RC_i^*$  to the ideal alternative can be defined as follows:

$$RC_i^* = RC_{i1} + RC_{i2}, \quad i = 1, 2, \dots, m \quad (36)$$

### Case study

In this section, we conduct an empirical case study in Beijing. Beijing is a representative city in the emerging economies, with a population of over 21 million dispersed in 16 different districts. The purpose of the case study is to illustrate the developed interval-valued fuzzy decision-making method for sustainable selection of healthcare waste treatment technologies in the emerging economies. Through literature review and expert interview in Beijing, we discussed the problem of sustainable selection encountered in healthcare waste management. Then four representative alternatives for healthcare waste treatment technologies are studied, and they are incineration ( $A_1$ ), steam sterilization ( $A_2$ ), landfill ( $A_3$ ) and microwave ( $A_4$ ).

For incineration ( $A_1$ ), the bottom ash is clean and the heat from combustion can be used to generate electricity [6], but it also consumes plenty of resources. For steam sterilization ( $A_2$ ), many researchers in the healthcare waste treatment industry think that it is a promising and environmentally friendly technology. For landfill ( $A_3$ ), it is an economic alternative but has adverse effect on environmental sustainability and public health. For microwave ( $A_4$ ), it has better performance in heating speed, automatic control and energy saving.

The sustainable selection of healthcare waste treatment technologies in the emerging economies is a complex multi-criteria decision-making problem. In this paper, five criteria including economic sustainability ( $C_1$ ), environmental sustainability ( $C_2$ ), social sustainability ( $C_3$ ), technical sustainability ( $C_4$ ) and resource sustainability ( $C_5$ ) are used to evaluate the alternatives. The data of the initial direct-influenced matrix (Table 3) and the initial decision-making matrix (Table 5) are determined by the expert team using Delphi method. The Beijing municipal government began to pay attention to healthcare waste management from 2018. To promote the sustainable selection of healthcare

**Table 3** The initial direct-influenced matrix determined by the decision-maker using Delphi method

Evaluation criterias	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
Economic sustainability ( $C_1$ )	N	N	M	N	N
Environmental sustainability ( $C_2$ )	VL	N	H	N	VL
Social sustainability ( $C_3$ )	N	N	N	N	M
Technical sustainability ( $C_4$ )	H	VH	M	N	L
Resource sustainability ( $C_5$ )	N	N	M	N	N

**Table 4** The cause-effect relationship value and the criteria weights

	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
$r_j + c_j$	2.191	3.338	7.451	6.803	6.314
$r_j - c_j$	0.197	1.984	- 5.061	6.803	- 3.924
Type	Cause	Cause	Effect	Cause	Effect
$w_j$	0.068	0.121	0.281	0.299	0.231

waste treatment technologies, an academic committee was established in Beijing. The academic committee is made up of five authoritative experts focusing on healthcare waste management and healthcare waste treatment technology, and data in this study was obtained from five experts of the academic committee. The expert team consist of two researchers, one administrator and two engineers in Beijing. The two researchers have been studying healthcare waste management for 10 years, the one administrator has been working on policy making of healthcare waste treatment for the last 7 years, and the two engineers have been engaged in technology development of healthcare waste treatment for 12 years. The experts are allowed to use the interval-valued fuzzy numbers to express their opinions on the dependent relationship between each pair of criteria and the prioritization with respect to each criteria. First, each expert gives his opinion using the interval-valued fuzzy numbers separately, then the expert team meets to make a final decision. Finally, the consistent opinions on the relationship between each pair of criteria and the prioritization with respect to each criteria among the experts can be obtained and listed in Tables 3 and 5.

In this paper, we develop an interval-valued fuzzy decision-making method to study the sustainable selection of healthcare waste treatment technologies in the emerging economies. The interval-valued fuzzy DEMATEL method is first used to analyze the independent relationships among the five evaluation criteria and determine the weights. First, the initial direct-relation matrix for the five evaluation criteria is shown in Table 3. Accordingly, the form of the interval-valued fuzzy numbers of the initial direct-influenced matrix  $\tilde{Q} = [\tilde{q}_{ij}]_{5 \times 5}$  is shown in Table 7. Next, the form of the interval-valued fuzzy numbers



**Table 5** The initial decision-making matrix determined by the decision-maker using Delphi method

	$C_1$ (economic sustainability)	$C_2$ (environmental sustainability)	$C_3$ (social sustainability)	$C_4$ (technical sustainability)	$C_5$ (resource sustainability)
$A_1$ (incineration)	MP	VP	F	VG	P
$A_2$ (steam sterilization)	G	F	VG	G	VG
$A_3$ (landfill)	P	MG	P	F	MG
$A_4$ (microwave)	MG	G	G	P	F

**Table 6** The Euclidean distance and the final relative closeness

	$D_{i1}^+$	$D_{i2}^+$	$D_{i1}^-$	$D_{i2}^-$	$RC_i^*$
$A_1$ (incineration)	4.491	4.538	0.861	0.488	0.231
$A_2$ (steam sterilization)	4.110	4.199	0.896	0.849	0.347
$A_3$ (landfill)	4.503	4.574	0.692	0.453	0.224
$A_4$ (microwave)	4.420	4.494	0.614	0.545	0.269

of the normalized direct-relation matrix  $\tilde{P} = [\tilde{p}_{ij}]_{5 \times 5}$  is obtained by Eqs. (2)–(4) and shown in Table 8. Third, the total relation matrix  $\tilde{T} = [\tilde{t}_{ij}]_{5 \times 5}$  for the five evaluation criteria is calculated by Eqs. (3)–(16) and presented in Table 9. Then, the cause-effect relationship value can be obtained by Eqs. (17)–(22) and shown in Table 4. Finally, using Eqs. (23) and (24), we can determine the weights of the five evaluation criteria, and the result of the weights is presented in Table 4. The weights of the five evaluation criteria are 0.068, 0.121, 0.281, 0.299, and 0.231, respectively.

After calculating the weights for the five evaluation criteria using the interval-valued fuzzy DEMATEL method, we further establish an interval-valued fuzzy TOPSIS method to determine the prioritization of the alternatives for the healthcare waste treatment technologies. Firstly, the initial decision-making matrix for the alternatives is shown in Table 5. Accordingly, the form of the interval-valued fuzzy numbers of the initial decision-making matrix  $\tilde{X} = [\tilde{x}_{ij}]_{4 \times 5}$  is shown in Table 11. Next, the form of the interval-valued fuzzy numbers of the normalized decision-making matrix  $\tilde{G} = [\tilde{g}_{ij}]_{4 \times 5}$  is obtained by Eqs. (26) and (27) and shown in Table 12. Third, the form of the interval-valued fuzzy numbers of the weighted decision-making matrix  $\tilde{V} = [\tilde{v}_{ij}]_{4 \times 5}$  is obtained by Eqs. (28)–(30) and shown in Table 13. Fourth, the Euclidean distance can be calculated by Eqs. (31)–(34) and shown in Table 6. Finally, the final relative closeness can be determined by Eqs. (35) and (36) and shown in Table 6. Note that the greater the value of the final relative closeness, the better the corresponding alternative will be. Therefore, the descending order of the alternatives is steam sterilization ( $A_2$ ), microwave ( $A_4$ ), incineration ( $A_1$ ) and landfill ( $A_3$ ).

## Discussions

First, the results of the the interval-valued fuzzy DEMATEL (see Table 4) show that technical sustainability ( $C_4$ ) is the most important criteria with the weight of 0.299, social sustainability ( $C_3$ ) is the second with the weight of 0.281, while economic sustainability ( $C_1$ ) is the least important criteria with the weight of 0.068. These findings reveal that the dimension of technical sustainability ( $C_4$ ) and social sustainability ( $C_3$ ) should be given much attention when selecting the most sustainable healthcare waste treatment technology. Further, the interval-valued fuzzy DEMATEL method can also be used to analyze the independent relationships among the five evaluation criteria. It shows that technical sustainability ( $C_4$ ) and environmental sustainability ( $C_2$ ) have more influence over the other factors, which means that they can be regarded as the critical factors for assessing and improving the alternatives.

Next, steam sterilization ( $A_2$ ) is regarded as the best healthcare waste treatment technology among the four alternatives from a sustainability perspective, followed by microwave ( $A_4$ ), incineration ( $A_1$ ), and landfill ( $A_3$ ) in the descending order. Among the four alternatives, steam sterilization ( $A_2$ ) has the best social sustainability, the greatest resource sustainability and high economic sustainability, environmental sustainability and technical sustainability based on the opinion of the experts. The managerial implications of steam sterilization are presented as follows: (1) steam sterilization has better performance on environmental sustainability, social sustainability and resource sustainability with lower operation cost. The emerging economies is comprised of different developing countries, so steam sterilization is a better alternative in the emerging economies. (2) Steam sterilization can beautify the environment and improve the air quality, because it can not only dispose healthcare waste thoroughly but also only create a minor negative environment impact. (3) China has mature technology and rich experience on steam sterilization, then China could provide the support of the development and promotion of steam sterilization to the other developing countries in the emerging economies.

The results of the developed interval-valued fuzzy decision-making method is comparable to the research of Dursun et al. [40]. Both of the two studies analyze the selection

of healthcare waste treatment technologies, but traditional fuzzy set theory was applied to describe the opinion of the decision-maker using a crisp fuzzy number in the work of Dursun et al. [40], while we use the interval-valued fuzzy number to describe the opinion of the decision-maker in this paper. The traditional fuzzy set theory allows the decision-makers to represent the uncertainty using a crisp value, while the interval-valued fuzzy set theory allows the decision-makers to represent the uncertainty using an interval number. The application of the interval-valued fuzzy numbers allows the decision-makers to define the lower and upper bounds values as an interval for matrix's elements, so the interval-valued fuzzy set theory is superior to the traditional fuzzy set theory in accuracy. The developed interval-valued fuzzy decision-making method not only analyzes the independent relationships among the evaluation criteria but also takes into account the uncertainty and fuzziness in the process of the sustainable selection of healthcare waste treatment technologies in the emerging economies.

## Conclusions

Due to the rapid increase in the number of the aging population and the demand for healthcare services in the emerging economies, healthcare waste management is becoming a complex problem. In this paper, we establish an interval-valued fuzzy decision-making method to study the sustainable selection of healthcare waste treatment technologies in the emerging economies. The decision-maker is allowed to describe his opinions using the interval-valued fuzzy numbers, the interval-valued fuzzy DEMATEL method is used to deal with independent relationships among the evaluation criteria when determining the weights, and interval-valued fuzzy TOPSIS method is used to rank the alternatives for the healthcare waste treatment technologies in the emerging economies taking into account the uncertainty and fuzziness in the process of decision making.

A case study conducted in Beijing, China is used to illustrate the application of the developed interval-valued fuzzy decision-making method. Steam sterilization ( $A_2$ ) is regarded as the best healthcare waste treatment technology among the four alternatives from a sustainability perspective, followed by microwave ( $A_4$ ), incineration ( $A_1$ ), and landfill ( $A_3$ ) in the descending order. The priority order of the four healthcare waste treatment technologies agrees almost completely with that determined by some of the previous research works. It is proved that the developed interval-valued fuzzy decision-making method is effective to select the best alternative for healthcare waste treatment technologies in the emerging economies from a sustainability perspective.

In future research, the following directions are suggested. First, an integrated model based on fuzzy multi-criteria

decision-making method, partially observable Markov decision process and life cycle assessment method should be developed to study selection of the healthcare waste treatment technologies from a dynamic and whole cycle perspective. Next, due to the rapid development of information technology, Artificial Intelligence (AI) could be applied to the selection of healthcare waste treatment technologies, which can facilitate the man–machine interaction and help the decision-maker to evaluate the healthcare waste treatment technology dynamically.

**Acknowledgements** The authors are very grateful to the editor and anonymous referees for their valuable comments and suggestions that contributed significantly to improve the quality of this paper. This work was supported by the Key Program of National Natural Science Foundation of China (No. 71432002) and Chinese Government Scholarship of China Scholarship Committee (No. 201906030126).

## Appendix

The definition of the interval-valued fuzzy set are as follows [53]:

$$\tilde{A} = \left\{ x, \left[ \mu_{\tilde{A}}^L(x), \mu_{\tilde{A}}^U(x) \right] \right\}, x \in (-\infty, +\infty),$$

$$\mu_{\tilde{A}}^L(x), \mu_{\tilde{A}}^U(x) : (-\infty, +\infty) \rightarrow [0, 1] \quad (37)$$

$$\mu_{\tilde{A}}(x) = \left[ \mu_{\tilde{A}}^L(x), \mu_{\tilde{A}}^U(x) \right], \mu_{\tilde{A}}^L(x) \leq \mu_{\tilde{A}}^U(x), \quad \forall x \in (-\infty, +\infty) \quad (38)$$

where  $\mu_{\tilde{A}}^L$  refers to the lower limit of the membership degree,  $\mu_{\tilde{A}}^U$  refers to the upper limit of the membership degree, and  $\tilde{A}$  is the interval-valued fuzzy number.

The arithmetic operations of the interval-valued fuzzy numbers are as follows:

(1) Addition of two interval-valued fuzzy numbers:

$$\tilde{a} + \tilde{d} = [(a_1, a'_1); a_2; (a'_3, a_3)] \times [(d_1, d'_1); d_2; (d'_3, d_3)]$$

$$= [(a_1 + d_1, a'_1 + d'_1); a_2 + d_2; (a'_3 + d'_3, a_3 + d_3)] \quad (39)$$

(2) Subtraction of two interval-valued fuzzy numbers:

$$\tilde{a} - \tilde{d} = [(a_1, a'_1); a_2; (a'_3, a_3)] - [(d_1, d'_1); d_2; (d'_3, d_3)]$$

$$= [(a_1 - d_3, a'_1 - d'_3); a_2 - d_2; (a'_3 - d'_1, a_3 - d_1)] \quad (40)$$

(3) Multiplication of two interval-valued fuzzy numbers:

$$\tilde{a} \times \tilde{d} = [(a_1, a'_1); a_2; (a'_3, a_3)] \times [(d_1, d'_1); d_2; (d'_3, d_3)]$$

$$= [(a_1 d_1, a'_1 d'_1); a_2 d_2; (a'_3 d'_3, a_3 d_3)] \quad (41)$$

(4) Multiplication between a positive crisp number and an interval-valued fuzzy number:

$$\beta \cdot \tilde{a} = \beta \times [(a_1, a'_1); a_2; (a'_3, a_3)] = [(\beta a_1, \beta a'_1); \beta a_2; (\beta a'_3, \beta a_3)] \tag{42}$$

(5) Division of two interval-valued fuzzy numbers:

$$\tilde{a} \div \tilde{d} = [(a_1, a'_1); a_2; (a'_3, a_3)] \div [(d_1, d'_1); d_2; (d'_3, d_3)] = [(a_1/d_3, a'_1/d'_3); a_2/d_2; (a'_3/d'_1, a_3/d_1)] \tag{43}$$

(6) Reciprocal of two interval-valued fuzzy numbers [12]:

$$(\tilde{a})^{-1} = [(a_1, a'_1); a_2; (a'_3, a_3)]^{-1} = [(1/a_3, 1/a'_3); 1/a_2; (1/a'_1, 1/a_1)] \tag{44}$$

(7) Exponentiation of two interval-valued fuzzy numbers [12]:

$$(\tilde{a})^n = [(a_1, a'_1); a_2; (a'_3, a_3)]^n = [((a_1)^n, (a'_1)^n); (a_2)^n; ((a'_3)^n, (a_3)^n)] \tag{45}$$

(8) Defuzzification of the interval-valued fuzzy number [32]:

$$f(\tilde{a}) = \frac{a_1 + a'_1 + 2a_2 + a'_3 + a_3}{6} \tag{46}$$

See Tables 7, 8, 9, 10, 11, 12 and 13.

**Table 7** The form of the interval-valued fuzzy numbers of the initial direct-influenced matrix

	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
$C_1$	[(0, 0); 0; (0, 0)]	[(0, 0); 0; (0, 0)]	[(3.0, 3.5); 4.0; (4.5, 5.0)]	[(0, 0); 0; (0, 0)]	[(0, 0); 0; (0, 0)]
$C_2$	[(1.0, 1.5); 2.0; (2.5, 3.0)]	[(0, 0); 0; (0, 0)]	[(4.0, 4.5); 5.0; (5.5, 6.0)]	[(0, 0); 0; (0, 0)]	[(1.0, 1.5); 2.0; (2.5, 3.0)]
$C_3$	[(0, 0); 0; (0, 0)]	[(0, 0); 0; (0, 0)]	[(0, 0); 0; (0, 0)]	[(0, 0); 0; (0, 0)]	[(3.0, 3.5); 4.0; (4.5, 5.0)]
$C_4$	[(4.0, 4.5); 5.0; (5.5, 6.0)]	[(5.0, 5.5); 6.0; (6.5, 7.0)]	[(3.0, 3.5); 4.0; (4.5, 5.0)]	[(0, 0); 0; (0, 0)]	[(2.0, 2.5); 3.0; (3.5, 4.0)]
$C_5$	[(0, 0); 0; (0, 0)]	[(0, 0); 0; (0, 0)]	[(3.0, 3.5); 4.0; (4.5, 5.0)]	[(0, 0); 0; (0, 0)]	[(0, 0); 0; (0, 0)]

**Table 8** The form of the interval-valued fuzzy numbers of the normalized direct-influenced matrix

	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
$C_1$	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.413, 0.482); 0.551; (0.620, 0.689)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]
$C_2$	[(0.138, 0.207); 0.275; (0.344, 0.413)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.551, 0.620); 0.689; (0.758, 0.826)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.138, 2.207); 0.275; (0.344, 0.413)]
$C_3$	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.413, 0.482); 0.551; (0.620, 0.689)]
$C_4$	[(0.551, 0.620); 0.689; (0.758, 0.826)]	[(0.689, 0.758); 0.826; (0.895, 0.964)]	[(0.413, 0.482); 0.551; (0.620, 0.689)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.275, 0.344); 0.413; (0.482, 0.551)]
$C_5$	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.413, 0.482); 0.551; (0.620, 0.689)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]

**Table 9** The form of the interval-valued fuzzy numbers of the total relation matrix

	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
$C_1$	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.498, 0.628); 0.791; (0.380, 1.312)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.206, 0.303); 0.436; (0.484, 0.904)]
$C_2$	[(0.138, 0.207); 0.275; (0.000, 0.413)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.802, 1.068); 1.424; (0.830, 2.656)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.469, 0.722); 1.060; (0.899, 2.243)]
$C_3$	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.206, 0.303); 0.436; (0.484, 0.904)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.498, 0.628); 0.791; (0.380, 1.312)]
$C_4$	[(0.646, 0.777); 0.916; (0.189, 1.224)]	[(0.689, 0.758); 0.826; (0.000, 0.964)]	[(1.462, 2.042); 2.840; (2.900, 5.679)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.974, 1.485); 2.205; (2.593, 4.862)]
$C_5$	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.498, 0.628); 0.791; (0.380, 1.312)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(0.206, 0.303); 0.436; (0.484, 0.904)]

**Table 10** The form of the interval-valued fuzzy numbers of the cause-effect relationship

$\tilde{r}_i$	$\tilde{c}_j$	$\tilde{r}_j + \tilde{c}_j$	$\tilde{r}_j - \tilde{c}_j$
$C_1$ [(0.704, 0.931); 1.227; (0.864, 2.216)]	[(0.784, 0.984); 1.191; (0.189, 1.637)]	[(1.488, 1.915); 2.418; (1.053, 3.853)]	[- 0.933, 0.742); 0.030; (- 0.120, 1.432)]
$C_2$ [(1.409, 1.997); 2.759; (1.729, 5.312)]	[(0.689, 0.758); 0.826; (0.000, 0.964)]	[(2.098, 2.755); 3.585; (1.729, 6.276)]	[(0.445, 1.997); 1.933; (0.971, 4.623)]
$C_3$ [(0.704, 0.931); 1.227; (0.864, 2.216)]	[(3.466, 4.669); 6.282; (4.974, 11.863)]	[(4.170, 5.600); 7.509; (5.838, 14.079)]	[(− 11.159, − 4.043); − 5.055; (− 3.805, − 1.250)]
$C_4$ [(3.771, 5.062); 6.787; (5.682, 12.729)]	[(0.000, 0.000); 0.000; (0.000, 0.000)]	[(3.771, 5.062); 6.787; (5.682, 12.729)]	[(3.771, 5.062); 6.787; (5.682, 12.729)]
$C_5$ [(0.704, 0.931); 1.227; (0.964, 2.216)]	[(2.353, 3.441); 4.928; (4.840, 10.225)]	[(3.057, 4.372); 6.155; (5.704, 12.441)]	[(− 9.521, − 3.909); − 3.701; (− 2.577, − 0.137)]

**Table 11** The form of the interval-valued fuzzy numbers of the initial decision-making matrix

	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
$A_1$	[(0, 1.5); 3.0; (4.5, 5.5)]	[(0, 0); 0; (1.0, 1.5)]	[(2.5, 3.5); 5.0; (6.5, 7.5)]	[(8.5, 9.5); 10.0; (10.0, 10.0)]	[(0, 0.5); 1.0; (2.5, 3.5)]
$A_2$	[(5.5, 7.5); 9.0; (9.5, 10.0)]	[(2.5, 3.5); 5.0; (6.5, 7.5)]	[(8.5, 9.5); 10.0; (10.0, 10.0)]	[(5.5, 7.5); 9.0; (9.5, 10.0)]	[(8.5, 9.5); 10.0; (10.0, 10.0)]
$A_3$	[(0, 0.5); 1.0; (2.5, 3.5)]	[(4.5, 5.5); 7.0; (8.0, 9.5)]	[(0, 0.5); 1.0; (2.5, 3.5)]	[(2.5, 3.5); 5.0; (6.5, 7.5)]	[(4.5, 5.5); 7.0; (8.0, 9.5)]
$A_4$	[(4.5, 5.5); 7.0; (8.0, 9.5)]	[(5.5, 7.5); 9.0; (9.5, 10.0)]	[(5.5, 7.5); 9.0; (9.5, 10.0)]	[(0, 0.5); 1.0; (2.5, 3.5)]	[(2.5, 3.5); 5.0; (6.5, 7.5)]

**Table 12** The form of the interval-valued fuzzy numbers of the normalized decision-making matrix

	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
$A_1$	[(0.000, 0.150); 0.300; (0.450, 0.550)]	[(0.000, 0.000); 0.000; (0.100, 0.150)]	[(0.250, 0.350); 0.500; (0.650, 0.750)]	[(0.850, 0.950); 1.000; (1.000, 1.000)]	[(0.000, 0.050); 0.100; (0.250, 0.350)]
$A_2$	[(0.550, 0.750); 0.900; (0.950, 1.000)]	[(0.250, 0.350); 0.500; (0.650, 0.750)]	[(0.850, 0.950); 1.000; (1.000, 1.000)]	[(0.550, 0.750); 0.900; (0.950, 1.000)]	[(0.850, 0.950); 1.000; (1.000, 1.000)]
$A_3$	[(0.000, 0.053); 0.105; (0.263, 0.368)]	[(0.474, 0.579); 0.737; (0.842, 1.000)]	[(0.000, 0.053); 0.105; (0.263, 0.368)]	[(0.263, 0.368); 0.526; (0.684, 0.789)]	[(0.474, 0.579); 0.737; (0.842, 1.000)]
$A_4$	[(0.450, 0.550); 0.700; (0.800, 0.950)]	[(0.550, 0.750); 0.900; (0.950, 1.000)]	[(0.550, 0.750); 0.900; (0.950, 1.000)]	[(0.000, 0.050); 0.100; (0.250, 0.350)]	[(0.250, 0.350); 0.500; (0.650, 0.750)]

**Table 13** The form of the interval-valued fuzzy numbers of the weighted decision-making matrix

	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$
$A_1$	[(0.000, 0.010); 0.020; (0.031, 0.037)]	[(0.000, 0.000); 0.000; (0.012, 0.018)]	[(0.070, 0.098); 0.141; (0.183, 0.211)]	[(0.254, 0.284); 0.299; (0.299, 0.299)]	[(0.000, 0.012); 0.023; (0.058, 0.081)]
$A_2$	[(0.037, 0.051); 0.061; (0.065, 0.068)]	[(0.030, 0.042); 0.061; (0.079, 0.091)]	[(0.239, 0.267); 0.281; (0.281, 0.281)]	[(0.164, 0.224); 0.269; (0.284, 0.299)]	[(0.196, 0.219); 0.231; (0.450, 0.231)]
$A_3$	[(0.000, 0.003); 0.007; (0.018, 0.025)]	[(0.057, 0.070); 0.089; (0.102, 0.121)]	[(0.000, 0.150); 0.030; (0.074, 0.103)]	[(0.079, 0.110); 0.157; (0.205, 0.236)]	[(0.109, 0.134); 0.170; (0.195, 0.231)]
$A_4$	[(0.031, 0.037); 0.048; (0.054, 0.065)]	[(0.067, 0.091); 0.109; (0.115, 0.121)]	[(0.155, 0.211); 0.253; (0.267, 0.281)]	[(0.000, 0.015); 0.030; (0.075, 0.105)]	[(0.058, 0.081); 0.116; (0.150, 0.173)]

## References

1. Aghajani Mir M, Taherei Ghazvinei P, Sulaiman NMN, Basri NEA, Saheri S, Mahmood NZ, Jahan A, Begum RA, Aghamohammadi N (2016) Application of TOPSIS and VIKOR improved versions in a multi criteria decision analysis to develop an optimized municipal solid waste management model. *J Environ Manage* 166:109–115. <https://doi.org/10.1016/j.jenvman.2015.09.028>
2. Thakur V, Vikas A (2015) Healthcare waste management research: a structured analysis and review (2005–2014). *Waste Manage Res* 33:855–870. <https://doi.org/10.1177/0734242X15594248>
3. Shwesin AT, Luan S, Xu Q (2019) Application of multi-criteria-decision approach for the analysis of medical waste management systems in Myanmar. *J Clean Prod* 222:733–745. <https://doi.org/10.1016/j.jclepro.2019.03.049>
4. Taghipour H, Mosaferi M (2009) Characterization of medical waste from hospitals in Tabriz. *Iran. Sci Total Environ* 407(5):1527–1535. <https://doi.org/10.1016/j.scitotenv.2008.11.032>
5. Lee S, Vaccari M, Tudor T (2016) Considerations for choosing appropriate healthcare waste management treatment technologies: a case study from an East Midlands NHS Trust, in England. *J Clean Prod* 165:139–147. <https://doi.org/10.1016/j.jclepro.2016.05.166>
6. Manga VE, Forton OT, Mofor LA, Woodard R (2011) Health care waste management in Cameroon: a case study from the South-western Region. *Resour Conserv Recycl* 57:108–116. <https://doi.org/10.1016/j.resconrec.2011.10.002>
7. Mbongwe B, Mmereki BT, Magashula A (2008) Healthcare waste management: current practices in selected healthcare facilities, Botswana. *Waste Manage* 28(1):226–233. <https://doi.org/10.1016/j.wasman.2006.12.019>
8. Windfeld ES, Brooks MS (2015) Medical waste management—a review. *J Environ Manage* 163:98–108. <https://doi.org/10.1016/j.jenvman.2015.08.013>
9. Brent AC, Rogers DEC, Ramabitsa-Siimane TSM, Rohwer MB (2007) Application of the analytical hierarchy process to establish health care waste management systems that minimise infection risks in developing countries. *Eur J Oper Res* 181(1):403–424. <https://doi.org/10.1016/j.ejor.2006.06.015>
10. Su EC, Chen Y (2018) Policy or income to affect the generation of medical wastes: an application of environmental Kuznets curve by using Taiwan as an example. *J Clean Prod* 188:489–496. <https://doi.org/10.1016/j.jclepro.2018.04.011>
11. Ananth AP, Prashanthini V, Visvanathan C (2010) Healthcare waste management in Asia. *Waste Manage* 31(1):154–161. <https://doi.org/10.1016/j.wasman.2009.07.018>
12. Wu W (2012) Segmenting critical factors for successful knowledge management implementation using the fuzzy DEMATEL method. *Appl Soft Comput* 12(1):535–572. <https://doi.org/10.1016/j.asoc.2011.08.008>
13. Streimikiene D, Balezentis T, Krisciukaitienė I, Balezentis A (2012) Prioritizing sustainable electricity production technologies: MCDM approach. *Renew Sustain Energy Rev* 16(5):3302–3311. <https://doi.org/10.1016/j.rser.2012.02.067>
14. Javid AA, Seyedi P, Syam SS (2017) A survey of healthcare facility location. *Comput Oper Res* 79:223–263. <https://doi.org/10.1016/j.cor.2016.05.018>
15. Caniato M, Tudor T, Vaccari M (2015) International governance structures for health-care waste management: a systematic review of scientific literature. *J Environ Manage* 153:93–107. <https://doi.org/10.1016/j.jenvman.2015.01.039>
16. Sharma SK, Gupta S (2017) Healthcare waste management scenario: a case of Himachal Pradesh (India). *Clin Epidemiol Global Health* 5(4):169–172. <https://doi.org/10.1016/j.cegh.2017.07.002>
17. Scavarda A, Daú-Gláucya L, Scavarda LF, Korzenowski AL (2019) A proposed healthcare supply chain management framework in the emerging economies with the sustainable lenses: the theory, the practice, and the policy. *Resour Conserv Recycl* 141:418–430. <https://doi.org/10.1016/j.resconrec.2018.10.027>
18. Tabash MI, Hussein RA, Mahmoud AH, El-Borgy MD, Abu-Hamad BA (2016) Impact of an intervention programme on knowledge, attitude and practice of healthcare staff regarding pharmaceutical waste management, Gaza, Palestine. *Public Health* 138:127–137. <https://doi.org/10.1016/j.puhe.2016.04.001>
19. Okumura S, Tasaki T, Moriguchi Y, Jangprajak W (2017) Economic growth and selection of municipal waste treatment options in Bangkok. *J Mater Cycles Waste* 19(2):718–730. <https://doi.org/10.1007/s10163-016-0473-4>
20. Malekhamadi F, Yunesian M, Yaghmaeian K (2014) Analysis of the healthcare waste management status in Tehran hospitals. *J Environ Health Sci Eng* 12:116–120. <https://doi.org/10.1186/s40201-014-0116-4>
21. Sartaj M, Arabgol R (2015) Assessment of healthcare waste management practices and associated problems in Isfahan Province (Iran). *J Mater Cycles Waste*. 17:99–106. <https://doi.org/10.1007/s10163-014-0230-5>
22. Mmereki D, Baldwin A, Li B, Liu M (2017) Healthcare waste management in Botswana: storage, collection, treatment and disposal system. *J Mater Cycles Waste* 19(1):351–365. <https://doi.org/10.1007/s10163-015-0429-0>
23. Iacovidou E, Voulvoulis N (2018) A multi-criteria sustainability assessment framework: development and application in comparing two food waste management options using a UK region as a case study. *Environ Sci Pollut Res* 25(36):35821–35834. <https://doi.org/10.1007/s11356-018-2479-z>
24. Ali Y, Aslam Z, Dar HS, Mumtaz U (2018) A multi-criteria decision analysis of solid waste treatment options in Pakistan: Lahore city—a case in point. *Environ Syst Decis* 38(4):528–543. <https://doi.org/10.1007/s10669-018-9672-y>
25. Ali M, Kuroiwa C (2009) Status and challenges of hospital solid waste management: case studies from Thailand, Pakistan, and Mongolia. *J Mater Cycles Waste* 11(3):251–257. <https://doi.org/10.1007/s10163-009-0238-4>
26. Cesaro A, Belgiorio V (2017) Sustainability of medical waste management in different sized health care facilities. *Waste Biomass Valoriz* 19:351–365. <https://doi.org/10.1007/s10163-015-0429-0>
27. Çetinkaya AY, Kuzu SL, Demir A (2019) Medical waste management in a mid-populated Turkish city and development of medical waste prediction model. *Dev Sustain, Environ*. <https://doi.org/10.1007/s10668-019-00474-6>
28. Kharat MG, Murthy S, Kamble SJ, Raut RD, Kamble SS, Kharat MG (2018) Fuzzy multi-criteria decision analysis for environmentally conscious solid waste treatment and disposal technology selection. *Technol Soc*. <https://doi.org/10.1016/j.techsoc.2018.12.005>
29. Cristóbal J, Limleamthong P, Manfredi S, Guillén-Gosálbez G (2016) Methodology for combined use of data envelopment analysis and life cycle assessment applied to food waste management. *J Clean Prod* 135:158–168. <https://doi.org/10.1016/j.jclepro.2016.06.085>
30. Vučićak B, Kurtagić SM, Siladžić I (2016) Multicriteria decision making in selecting best solid waste management scenario: a municipal case study from Bosnia and Herzegovina. *J Clean Prod* 130:166–174. <https://doi.org/10.1016/j.jclepro.2015.11.030>
31. Arikani E, Şimşit-Kalender ZT, Vayvay Ö (2017) Solid waste disposal methodology selection using multi-criteria decision making methods and an application in Turkey. *J Clean Prod* 142:403–412. <https://doi.org/10.1016/j.jclepro.2015.10.054>

32. Wang Z, Ren J, Goodsite ME, Xu G (2018) Waste-to-energy, municipal solid waste treatment, and best available technology: comprehensive evaluation by an interval-valued fuzzy multi-criteria decision making method. *J Clean Prod* 172:887–899. <https://doi.org/10.1016/j.jclepro.2017.10.184>
33. Ibáñez-Forés V, Bovea MD, Coutinho-Nóbrega C, Medeiros HR (2019) Assessing the social performance of municipal solid waste management systems in developing countries: proposal of indicators and a case study. *Ecol Indic* 98:164–178. <https://doi.org/10.1016/j.ecolind.2018.10.031>
34. Lijó L, Frison N, Fatone F, González-García S, Feijoo G, Moreira MT (2018) Environmental and sustainability evaluation of livestock waste management practices in Cyprus. *Sci Total Environ* 634:127–140. <https://doi.org/10.1016/j.scitotenv.2018.03.299>
35. Havukainen J, Zhan M, Dong J, Liikanen M, Deviatkin I, Li X, Horttanainen M (2017) Environmental impact assessment of municipal solid waste management incorporating mechanical treatment of waste and incineration in Hangzhou, China. *J Clean Prod* 141:453–461. <https://doi.org/10.1016/j.jclepro.2016.09.146>
36. Liu Y, Xing P, Liu J (2017) Environmental performance evaluation of different municipal solid waste management scenarios in China. *Resour Conserv Recycl* 125:98–106. <https://doi.org/10.1016/j.resconrec.2017.06.005>
37. Zhou Z, Tang Y, Dong J, Chi Y, Ni M, Li N, Zhang Y (2018) Environmental performance evolution of municipal solid waste management by life cycle assessment in Hangzhou, China. *J Environ Manage* 227:23–33. <https://doi.org/10.1016/j.jenvman.2018.08.083>
38. Chen G, Wang X, Li J, Yan B, Wang Y, Wu X, Velichkova R, Cheng Z, Ma W (2019) Environmental, energy, and economic analysis of integrated treatment of municipal solid waste and sewage sludge: a case study in China. *Sci Total Environ* 647:1433–1443. <https://doi.org/10.1016/j.scitotenv.2018.08.104>
39. Dursun M, Karsak EE, Karadayi MA (2011) Assessment of health-care waste treatment alternatives using fuzzy multi-criteria decision making approaches. *Resour Conserv Recycl* 57:98–107. <https://doi.org/10.1016/j.resconrec.2011.09.012>
40. Dursun M, Karsak EE, Karadayi MA (2011) A fuzzy multi-criteria group decision making framework for evaluating health-care waste disposal alternatives. *Expert Syst Appl* 38(9):11453–11462. <https://doi.org/10.1016/j.eswa.2011.03.019>
41. Liu H, Wu J, Li P (2013) Assessment of health-care waste disposal methods using a VIKOR-based fuzzy multi-criteria decision making method. *Waste Manage* 13(2):2744–2751. <https://doi.org/10.1016/j.wasman.2013.08.006>
42. Liu H, You J, Lu C, Shan M (2014) Application of interval 2-tuple linguistic MULTIMOORA method for health-care waste treatment technology evaluation and selection. *Waste Manage* 34(11):2355–2364. <https://doi.org/10.1016/j.wasman.2014.07.016>
43. Liu H, You J, Lu C, Chen Y (2015) Evaluating health-care waste treatment technologies using a hybrid multi-criteria decision making model. *Renew Sustain Energy Rev* 41:932–942. <https://doi.org/10.1016/j.rser.2014.08.061>
44. Shi H, Liu H, Li P, Xu X (2017) An integrated decision making approach for assessing healthcare waste treatment technologies from a multiple stakeholder. *Waste Manage* 59:508–517. <https://doi.org/10.1016/j.wasman.2016.11.016>
45. Csorba LM, Crăciun M (2018) An application of the multi period decision trees in the sustainable medical waste investments. *Soft Comput Appl* 2:540–5560. [https://doi.org/10.1007/978-3-319-62524-9\\_40](https://doi.org/10.1007/978-3-319-62524-9_40)
46. Baghapour MA, Shoosharian MR, Javaheri MR, Dehghanifard S, Sefidkar R, Nobandegani AF (2018) A computer-based approach for data analyzing in hospital's health-care waste management sector by developing an index using consensus-based fuzzy multi-criteria group decision-making models. *Int J Med Inform* 118:5–15. <https://doi.org/10.1016/j.ijmedinf.2018.07.001>
47. Xiao F (2018) A novel multi-criteria decision making method for assessing health-care waste treatment technologies based on D numbers. *Eng Appl Artif Intel* 71:216–225. <https://doi.org/10.1016/j.engappai.2018.03.002>
48. Hong J, Zhan S, Yu Z, Hong J, Qi C (2018) Life-cycle environmental and economic assessment of medical waste treatment. *J Clean Prod* 174:65–73. <https://doi.org/10.1016/j.jclepro.2017.10.206>
49. Cesaro A, Belgiorio V (2017) Sustainability of medical waste management in different sized health care facilities. *Waste Biomass Valoriz* 8(5):1819–1827. <https://doi.org/10.1007/s12649-016-9730-y>
50. Bouhental M, Ghanai M, Chafaa K (2019) Interval-valued membership function estimation for fuzzy modeling. *Fuzzy Sets Syst* 361:101–113. <https://doi.org/10.1016/j.fss.2018.06.008>
51. Yager RR, Reformat MZ, To ND (2019) Drawing on the iPad to input fuzzy sets with an application to linguistic data science. *Inform. Sciences* 479:277–291. <https://doi.org/10.1016/j.ins.2018.11.048>
52. Ashtiani B, Haghighirad F, Makui A, Montazer GA (2009) Extension of fuzzy TOPSIS method based on interval-valued fuzzy sets. *Appl Soft Comput* 9(2):457–461. <https://doi.org/10.1016/j.asoc.2008.05.005>
53. Gorzalczyński MB (1987) A method of inference in approximate reasoning based on interval-valued fuzzy sets. *Fuzzy Sets Syst* 21(1):1–17. [https://doi.org/10.1016/0165-0114\(87\)90148](https://doi.org/10.1016/0165-0114(87)90148)
54. Hwang CL, Lin MJ (1987) Group decision making under multiple criteria. Springer. <https://doi.org/10.1007/978-3-642-61580-1>
55. Kuo MS (2011) A novel interval-valued fuzzy MCDM method for improving airlines' service quality in Chinese cross-strait airlines. *Transport Res E-Log* 47(6):1177–1193. <https://doi.org/10.1016/j.tre.2011.05.007>

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.