An interval type-2 fuzzy sets based Delphi approach to evaluate site selection indicators of sustainable vehicle shredding facilities

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Abstract

This study aims to rank indicators affecting site selection of vehicle shredding facilities using an interval type-2 fuzzy sets based Delphi approach. The introduced methodology consists of four consecutive stages as follows: indicator identification, questionnaire (survey), decision-making analysis, and statistical analysis and indicator classification. In the first stage, the literature searches are performed on vehicle shredding facility location and forty-eight relevant indicators are determined. In the second stage, a questionnaire has been conducted to collect the preferences of relevant international experts from different countries regarding the indicators. Then, the importance of site selection indicators is obtained to define critical, medium, and uncritical indicators. In the last stage, the analysis are carried out to make a distinction between groups of participants

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who respond similarly and discover viewpoints from the industry and academia. The research findings show that the most important indicator for locating vehicle shredding facilities is a financial benefit. Critical indicators, which should be taken into account when locating vehicle shredding facilities, are acquisition cost, affected population, demand fluctuations, end-of-life vehicle policy, financial benefit, land availability, operational costs, recycling system, resource accessibility, and safety management.
Keywords: Vehicle shredding facility, facility location selection, indicators, interval type-2 fuzzy sets, Multi-Criteria Decision Making.

1. Introduction

End-of-life vehicles (ELVs) have crucial importance among the environmental topics in terms of yearly generated volumes, growth rates, material content, and illegal waste flows [1]. Their sustainable management is a complex problem for researchers, industry practitioners, and policymakers. ELV management process consists of the management of material, capital, and information flows between the last owners of the vehicles, collection/dismantling/shredding (VSFs)/re-manufacturing and recycling facilities, second-hand markets, and industrial landfilling sites [2].

VSFs are major participants of the vehicle recycling industry worldwide [3]. They shred vehicle hulks, sort material fractions, transport sorted waste flows to waste entities, and sell isolated metals on the secondary metal market [4]. Locations of VSFs play a key role in sustainable ELV management [5]. Unfortunately, no earlier work has identified and categorized site selection indicators of VSFs. Besides, there is no decision-making framework for evaluating VSF location selection indicators that can reflect the uncertainty of inaccurate and vague information. As a result, the key questions are: *(i)* What are the most important (i.e., critical) VSF site selection indicators? *(ii)* How to evaluate them in an uncertain environment?

Bearing in mind the issues above, this study focuses on evaluating site selection indicators of VSFs. The evaluation process consists of four stages as follows: *(1)* indicator identification through a literature review, *(2)* data collection via online questionnaires, *(3)* decision-making analysis, *(4)* classification and statistical analysis.

The introduced decision-making approach classifies relevant VSF site selection indicators by using a group decision-making approach including entropy and Delphi method based on interval type-2 fuzzy sets (IT2FSs). IT2FSs procure more degree of freedom in the decision-making process compared to type-1 fuzzy sets. Besides, they can reflect the uncertainty and vagueness issues of available information. Finally, a questionnaire is conducted to evaluate the site selection indicators of VSFs.

The aims of this study are: *(i)* to identify relevant indicators for sustainable VSF site selection through a literature review, *(ii)* to conduct a questionnaire for the assessment of indicator importance by the international experts participating from different countries, *(iii)* to build IT2FS-based decision-making approach for evaluating facility location indicators, *(iv)* to make a distinction between groups of participants who respond similarly, *(v)* to discover viewpoints from the industry and academia, *(vi)* to identify critical VSF location selection indicators.

The rest of the paper is structured as follows: Section 2 presents preliminary indicators in the literature for siting VSFs and overviews relevant state-of-the-art studies. Section 3 presents the developed decision-making approach to evaluate site selection indicators of VSFs. Section 4 presents the performed online survey. The results and discussion are provided in Section 5. Section 6 gives the conclusions of the study.

2. Literature Review

In this section, the literature review is provided in three sub-sections. The purpose of dealing with the literature review in three sub-sections is to provide insights to indicate the contributions of this study. The first sub-section presents indicators for locating VSFs from the literature. The second sub-section overviews existing decision-making approaches for ELV management. The third sub-section provides a review of state-of-the-art decision-making approaches for facility location selection.

2.1. Location Selection Indicators

A systematic approach is provided to identify relevant indicators for locating VSFs from the published literature. Only peer-reviewed journal papers were reviewed. Seven electronic databases were selected to find papers published over the last 11 years (2010–2020). These databases are Web of Science, Scopus, Elsevier Science Direct, Taylor and Francis Online, Springer Link, Wiley Online Library, and Google Scholar. The following search strings were used: "end-of-life vehicle" AND MCDM. Titles, abstracts, and full text of 122 articles were screened. Irrelevant papers were eliminated, and therefore 16 eligible state-of-the-art papers remained.

Table 1 presents 48 identified VSF location selection indicators. The comprehensive literature review revealed 13 economic, 8 environmental, 11 social, and 16 technical indicators. Each identified indicator is defined in Table 1. Indicators that are not location-related were not taken into account.

Table 1: Site selection indicators of vehicle shredding facilities identified from the relevant literature.

Indicator	Type	Definition	Reference(s)
Economic cluster			
Acquisition cost	Min	Purchase fee for buying a depolluted and dismantled ELV	Ahmed et al. [6], Tian and Chen [7], Zhou et al. [8], Yang et al. [9]
Competition	Min	Competition environment and the presence of competitors	Karagoz et al. [10]
Distance to authorized dismantling facilities	Min	Authorized dismantling facilities disassemble reusable parts and depollute ELVs through the removal of fluids and other noxious substances	Karagoz et al. [10]
Distance to collection centers	Min	Scrap yards, vehicle dealers, and repair shops that have a valid license	Karagoz et al. [10]
Distances to other network entities	Min	Distances to secondary markets, industrial landfills, battery recycling facilities, etc.	Kannan et al. (2016), Tian et al. [11]
Financial benefit	Max	Direct and indirect financial benefits from opening an additional vehicle shredding facility	Abdulrahman et al. [12], Ahmed et al. [6], Tian and Chen [7], Karagoz et al. [10]
Incentive for vehicle owners	Max	Incentive mechanism based on an old-to-new replacement to encourage vehicle owners to voluntarily deliver ELVs	Gan and Luo [13], Raja Mamat et al. [14], Karagoz et al. [10]
Indirect costs	Min	Land rent, managerial pay, fixed asset depreciation, maintenance, and additional fees (e.g. cleaning, quality, and marketing costs)	Tian and Chen [7]
Initial setup cost	Min	Initial setup costs for new facilities, equipment, and recruitment cost	Abdulrahman et al. [12], Ahmed et al. [6], Schmid et al. [15], Zhang and Chen [16], Tian et al. [17], Yang et al. [9], Karagoz et al. [10]
Operational costs	Min	Labour, material, energy, processing, and landfilling costs	Ahmed et al. [6], Desnica et al. [18], Schmid et al. [15], Tian and Chen [7], Zhou et al. [8], Tian et al. [11], Zhang and Chen [16], Tian et al. [17], Yang et al. [9]
Penalty	Max	Punishment of illegal recycling enterprises	Raja Mamat et al. [19]
Return on investment	Min	Period after which the invested funds start to bring benefits	Tian et al. [17])
Subsidy	Max	Financial support for recycling enterprises	Abdulrahman et al. [12], Gan and Luo [13], Karagoz et al. [10]
Environmental cluster			
Ecotoxicity	Min	Polychlorinated dibenzo(p)dioxin and furan (PCDD/F) and Polychlorinated Biphenyl (PCB) in gases from shredders	Schmid et al. [15]
ELV policy	Min	Environmental and take-back regulations	Abdulrahman et al. [12], Ahmed et al. [6], Kannan et al. [20], Raja Mamat et al. [14], Tian et al. [17], Yang et al. [9], Karagoz et al. [10]

Table 1: Continued.

Indicator	Type	Definition	Reference(s)
Environment management system	Max	Degree that it caters to the ISO 14001 and whether the organization has its environmental issues controlled	Ahmed et al. [6], Zhou et al. [8], Yang et al. [9]
Environmental equipment and facilities	Max	Equipment and facilities for the green activities	Zhou et al. [8]
Global warming	Min	Greenhouse gas emission	Ahmed et al. [6], Schmid et al. [15]
Noise pollution	Min	Shredding activities' negative impact both on the natural ecosystem and urban population	Karagoz et al. [10]
Resource consumption	Min	Resource consumption in terms of raw material, energy, and water during processing	Zhou et al. [8]
Waste material releases	Min	Average volume of wastewater, solid wastes, and harmful material releases during processing	Ahmed et al. [6], Zhou et al. [8]
Social cluster			
Affected population	Min	Ratio of the affected population around a location	Karagoz et al. [10]
Brand image	Max	Corporate reputation and public acceptability	Ahmed et al. [6], Yang et al. [9]
Customer satisfaction	Max	Cognitive and perceived conformance	Zhou et al. [8], Yang et al. [9]
Job opportunities	Max	The number and quality of jobs created due to the opening of a vehicle shredding facility	Ahmed et al. [6], Schmid et al. [15], Karagoz et al. [10]
Employee turnover rate	Max	The working condition and wage levels relative to competitors	Ahmed et al. [6], Zhou et al. [8], Raja Mamat et al. [14], Yang et al. [9]
Local communities influence	Max	Service infrastructure, public services, and community projects	Zhou et al. [8], Karagoz et al. [10]
Occupational hazards	Min	Employee occupational injury and illness	Ahmed et al. [6], Schmid et al. [15], Yang et al. [9]
Public awareness level	Max	Level of knowledge and awareness on the ELV processes and their importance	Gan and Luo [13], Raja Mamat et al. [14], Karagoz et al. [10]
Safety management	Max	Health and safety practices	Desnica et al. [18], Zhou et al. [8]
Skilled workforce	Max	Availability of recycling industry professionals	Abdulrahman et al. [12], Xia et al. [21], Karagoz et al. [10]
Supplier commitment and awareness	Max	Supplier commitment and awareness toward environmental measures through supplier education and audit	Raja Mamat et al. [14]
Technical cluster			
Availability of a baling machine	Max	Heavy-duty baling machine uses strong hydraulic pressure to flatten ELVs	Karagoz et al. [10]
Demand fluctuations	Min	There is no proper demand and-of the demand has fluctuations which make the business slowdown	Abdulrahman et al. [12], Kannan et al. [20]
Flexibility	Max	Ability to react on turbulences on the secondary market	Karagoz et al. [10]
Information management	Max	Online monitoring system to supervise recovery processes	Tian et al. [22], Xia et al. [21], Gan and Luo [13]

Table 1: Continued.

Indicator	Type	Definition	Reference(s)
Inventory control	Max	Inventory management system offers cost savings	Tian et al. [17]
Land availability	Max	Availability of enough land is a vital infrastructure prerequisite	Karagoz et al. [10]
Lead time	Min	Due to ELV scarcity lead time moves to a high extent	Kannan et al. [20]
Performance	Max	Global recovery rate	Schmid et al. [15], Zhang and Chen [16]
Process difficulties	Min	Difficulties in layout, sequence, time, and object for high efficiency	Zhang and Chen [16]
Processing convenience	Max	Convenience of sorting and storage	Zhang and Chen [16]
Quality management	Max	Quality of isolated metal flows must meet the industry requirements	Tian et al. [22], Zhou et al. [8], Tian et al. [11]
Recycling system	Max	Proper channel and ELV management system for recycling	Xia et al. [21], Kannan et al. [20]
Resource accessibility	Max	Generated quantity of ELVs in a service zone	Tian et al. [11], Karagoz et al. [10]
Resource utilization	Max	Energy, raw material, manpower, and chemical use	Ahmed et al. [6], Yang et al. [9]
Technology access	Max	Availability of processing technology and the possibility for improving or making existing tools, devices, and equipment more efficient	Tian et al. [22], Xia et al. [21], Desnica et al. [18], Kannan et al. [20], Gan and Luo [13], Tian et al. [11], Zhang and Chen [16], Tian et al. [17], Yang et al. [9]
Traffic congestion	Min	Trip times and vehicular queuing	Karagoz et al. [10]

2.2. Decision-making approaches for ELV management

Previously, many researchers have proposed various decision-making approaches for ELV management.

Pavlovic et al. [23] coupled the fuzzy eigenvector method and ABC analysis for classifying locations for opening an authorized dismantling center into three groups. Wang and Chen [24] utilized the AHP-SWOT approach for determining weights of strengths, weaknesses, opportunities, and threats of the used automotive electronic components recycling industry. Tian et al. [22] used the AHP method for identifying key technology factors influencing the automotive remanufacturing industry. Zhu et al. [25] applied the grey DEMATEL method for examining the cause-effect relationships among implementation barriers for truck engine remanufacturing. Abdulrahman et al. [12] used the AHP method for assessing remanufacturing practices in automotive parts companies.

Ahmed et al. [6] utilized the DEMATEL and the fuzzy AHP methods for prioritizing practices of automobile remanufacturing companies. Desnica et al. [18] employed the AHP method for selecting detoxification equipment. Govindan et al. [26] used the Interpretive structural modeling (ISM) approach and fuzzy ANP method for evaluating barriers of automotive parts remanufacturing. Pourjavad and Mayorga [27] applied the fuzzy AHP-TOPSIS approach for ranking ELV management strategies. Raja Mamat et al. [14] integrated the Exploratory Factor Analysis and Structural Equation Modeling for discovering key success factors of ELV management systems. Schmid et al. [15] utilized the PROMETHEE method for comparing scenarios of dismantling and shredding operations. Tian and Chen [7] used the fuzzy AHP method for appraising manual dismantling cases. Zhou et al. [8] utilized the Shannon entropy and fuzzy VIKOR methods for evaluating ELV recycling service providers.

Ravi and Shankar [28] utilized the ISM approach for analyzing indicators of reverse logistics in the automobile industry. Tian et al. [11] combined the fuzzy AHP, Grey Relational Analysis, and TOPSIS methods for evaluating operation patterns of the automotive industry.

Bacher et al. [29] used the AHP method for prioritizing factors that hinder or limit the transition of the ELV management value chain towards a circular economy. Raja Mamat et al. [14] used the AHP method for identifying the implementation performances of ELV management systems. Zhang and Chen [16] employed the AHP method for ranking sustainable dismantling modes. Zhou et al. [30] coupled the fuzzy DEMATEL, Shannon entropy, and VIKOR methods for choosing the best recycling partner for small-and-medium enterprises.

Chakraborty et al. [31] employed the fuzzy ISM approach for evaluating enablers and barriers of automotive engine remanufacturing. Tian et al. [17] hybridized the grey DEMATEL and fuzzy VIKOR methods for ranking take-back patterns of ELVs. Wang et al. [32] used the DEA-TOPSIS approach for identifying ineffective decision-making units of the ELV reverse logistics industry. Yang et al. [9] coupled the Shannon entropy and TOPSIS methods under the picture hesitant fuzzy environment for prioritizing ELV management alternatives. Zhou et al. [33] utilized the ISM approach for identifying driving and dependence factors for improving performances of ELV management systems.

Recently, Karagoz et al. [10] proposed an intuitionistic fuzzy CODAS method for evaluating locations for an authorized dismantling center. Pavlovic et al. [34] applied the fuzzy TOPSIS for comparing recycling technologies for processing ferromagnetic materials. Zhang et al. [35] coupled the grey correlation and DEMATEL methods for solving the facility layout problem of dismantling centers.

2.3. Decision-making approaches for facility location selection

The facility location selection problem attracted a large interest of researchers in recent years. Many decision-making approaches have been previously developed for solving this strategic MCDM problem.

Cebi and Kahraman [36] reported the hybridization of the Fuzzy axiomatic design and AHP methods for a real estate site evaluation problem. Onüt et al. [37] presented an AHP-TOPSIS approach for investigating potential locations for a new shopping center. Awasthi et al. [38] employed the fuzzy TOPSIS method for evaluating locations for an urban distribution center. Dheena and Mohanraj [39] used the fuzzy TOPSIS method for investigating the distribution center location selection problem. Ertuğrul [40] utilized the fuzzy TOPSIS method for locating a textile company specialized in bed-sets. Mokhtarian and Hadi-Vencheh [41] employed the fuzzy TOPSIS for selecting an industrial zone for constructing a dairy factory. Nazari et al. (2012) [42] applied the fuzzy AHP to identify the best location for municipal solid waste disposal. Ozdagoglu [43] utilized the fuzzy ANP method for solving the facility location selection problem in the food industry. Devi and Yadav [44] employed the intuitionistic fuzzy ELECTRE for selecting an appropriate industrial plant location. Roh et al. [45] used the AHP method to suggest critical evaluation criteria for sitting humanitarian relief warehouses. Zolfani et al. [46] developed a SWARA-WASPAS approach for evaluating shopping mall sites. Ardeshir et al. [47] used the fuzzy AHP method in the GIS environment for ranking sites for the construction of a river bridge. Mokhtarian et al. [48] exploited the interval-valued fuzzy TOPSIS method for determining a suitable location for a municipal wet waste landfill. Cebi and Otay [49] applied the IT2F TOPSIS method for sitting a cement factory. Onden and Eldemir [50] used the fuzzy AHP method and GIS-based spatial analysis for selecting a proper site for a new textile manufacturing facility. Roh et al. [51] employed the fuzzy AHP-TOPSIS approach for positioning warehouses for humanitarian relief organizations. Turskis et al. [52] defined a hybrid model including fuzzy AHP and WASPAS for construction site selection problem. Bolturk et al. [53] presented a hesitant fuzzy AHP method for evaluating humanitarian warehouse locations. Govindan et al. [20] used the AHP-TOPSIS approach for assisting manufacturing companies to identify a preferred facility location. Trivedi and Singh [54] utilized the fuzzy AHP-TOPSIS approach for prioritizing emergency shelter areas. Wang et al. [55] applied the fuzzy ANP method for locating manufacturing plants in the high-technology industry. Barauskas et al. [56]ranked the conceptual locations for a park- and-ride parking lot using EDAS approach. Bolturk and Kahraman [57] presented an interval-valued intuitionistic fuzzy CODAS method for finding a location with the largest wave energy potential. Deveci et al. [58] proposed a GIS-based interval type-2 hesitant fuzzy COPRAS approach for locating a public bread factory. Sennaroglu and Celebi [59] integrated the AHP, PROMETHEE, and VIKOR methods for evaluating military airport locations. Stevic et al. [60] assessed alternative locations for roundabout construction using Rough BWM and Rough WASPAS approaches. Karasan and Kahraman [61] introduced an intuitionistic fuzzy DEMATEL-ANP-TOPSIS approach for selecting the best location for a freight village. Kheybari et al. [62] applied the Best-worst method (BWM) to weight the criteria and rank locations for a bioethanol facility. Mousavi et al. [63] proposed a new decision model based on interval-valued intuitionistic fuzzy for cross-docking center location problem. Song et al. [64] formulated a rough QUALIFLEX method for solving the shelter site selection problem for humanitarian relief operations. Zolfani et al. [65] used the BWM-WASPAS approach for investigating locations for a hotel. Recently, Ayyildiz and Gumus [66] formulated a spherical fuzzy AHP-WASPAS approach for ranking petrol stations.

Karasan et al. [67] proposed an interval-valued intuitionistic fuzzy DEMATEL-AHP-TOPSIS approach for assessing locations for a charging station of electric vehicles. Kaya et al. [68] used the Pythagorean fuzzy AHP method for sitting waste electric and electronic equipment (WEEE) recycling facility. Kumar et al. [69] applied the BWM-VIKOR approach for ranking sustainable locations for a WEEE recycling facility. Karagoz et al. [70] improved an interval type-2 fuzzy sets based ARAS method for recycling facility location problems.

In addition, fuzzy Delphi method studies have been used for identifying and assessing the criteria [71], prioritizing failures [72], and identify critical sustainable transportation indicators [73]. Also, IT2FSs have been applied to various decision-making problems such as electric vehicle charging station allocation [74], selection of a car sharing station [75], and the assessment of smart city projects [76].

According to the literature review, the research gaps are:

(i) The indicators of sustainable VSF location selection have not been identified and categorized before;

(ii) None of the available studies for ELV management has integrated entropy and Delphi method into a unique decision-making framework;

(iii) No IT2FS-based decision-making approach for ELV management has been applied before;

(iv) There is no decision-making framework to evaluate indicators for facility location selection that can reflect the uncertainty of inaccurate and vague information.

3. Preliminaries

3.1. Interval Type-2 Fuzzy Set

The concept of the type-2 fuzzy sets was firstly proposed by Zadeh [77] as an extension of the concept of type-1 fuzzy sets [78]. While the type-1 fuzzy sets are characterized in two-dimensional membership functions (MFs), the type-2 fuzzy sets are characterized by three-dimensional MFs. Because of this extended structure, type-2 fuzzy sets often have a better potential than type-1 sets to capture uncertainty [79, 80]. Interval type-2 fuzzy sets based decision making models have been successfully applied various problems such as: Zhong and Yao [81], Montazeri-Gh and Yazdani [82], Qin et al. [83], Pan and Wang [84], Wu and Liu (2020) [85], Wu et al. (2021) [86], Wu et al. [87] and so on.

Based on the ideas of Zadeh, the mathematical definition of the type-2 fuzzy set is presented in 1976, Mizumoto and Tanaka [88]. Since then, these sets have been studied by various researchers. The definitions of interval type-2 fuzzy sets (IT2Fs) are given by Mendel et al. [80] as follows.

Definition 1: A type-2 fuzzy set (T2FS) is denoted with $\tilde{A}$. For $\tilde{A}$, a membership function (the degree of membership) denoted as $\mu_{\tilde{A}}(x,u)$ characterize a fuzzy set shown as $\tilde{A}$ where $x \in X$ in $\tilde{A}$ and $u \in J_x \subseteq [0,1]$ [89]. It is also shown as:

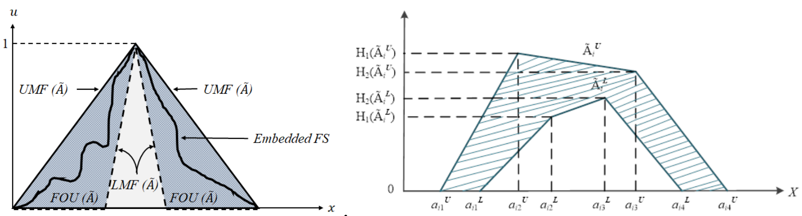
$$\tilde{A} = \{(x,u), \mu_{\tilde{A}}(x,u))|\ \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \tag{1}$$

where $0 \leq \mu_{\tilde{A}}(x,u) \leq 1$ and an $\tilde{A}$ fuzzy set can also be defined with type-2 membership function as follows:

$$\tilde{A} = \int_{x\in X} \int_{u\in J_x} \mu_{\tilde{A}}(x,u)/(x,u) \tag{2}$$

Here, x denotes the primary variable in domain X and u denotes the secondary variable for each $x \in X$ in interval ${}_x[0,1]$. J_x is defined as the primary membership of variable x and $\mu_{\tilde{A}}(x,u)$ shows the secondary membership values of set $\tilde{A}$. The expression $\int\int$ shows over all acceptable x and u.

Definition 2: The upper membership function (UMF) and lower membership function (LMF) of $\tilde{A}$ are two type-1 membership functions that bound the footprint of uncertainty (FOU). An example of an IT2FS is shown in Fig. 1a [80].



(a) FOU, LMF, UMF and FS. (b) LMF and UMF

Figure 1: Interval type-2 fuzzy sets.

Definition 3: When all $\mu_{\tilde{A}}(x,u) = 1$ for $\forall x \in X$ and $u \in J_x \subseteq [0,1]$, then $\tilde{A}$ is named as an interval type-2 fuzzy set (IT2Fs) [80].

Although the third dimension of the general T2FS is redundant, because it does not convey new information about IT2FS, this special case of the general T2FS can be expressed as follows:

$$\tilde{A} = \int_{x\in X}\int_{u\in J_x} 1/(x,u)\ \ J_x \subseteq [0,1] \tag{3}$$

Although, there are different types of membership functions in the literature (e.g. triangular, trapezoidal, Gaussian, etc.), a trapezoidal interval type-2 fuzzy sets (IT2FSs), $\tilde{A}_i$ is used in this study and some definitions are given as follows [90, 80]:

$$\begin{aligned}\tilde{A}_i = (\tilde{A}_i^U, \tilde{A}_i^L) =& ((a_{i1}^u, a_{i2}^u, a_{i3}^u, a_{i4}^u; h_1(\tilde{A}_i^U), h_2(\tilde{A}_i^U)),\\ &(a_{i1}^l, a_{i2}^l, a_{i3}^l, a_{i4}^l; h_1(\tilde{A}_i^L), h_2(\tilde{A}_i^L))\end{aligned} \tag{4}$$

where $a^u_{i1}, a^u_{i2}, a^u_{i3}, a^u_{i4}; a^l_{i1}, a^l_{i2}, a^l_{i3}$ and a^l_{i4} are the reference points of the interval type-2 fuzzy set $\tilde{A}_i$, $H_j(\tilde{A}^U_i)$ denotes the membership value of the element $a^U_{i(j+1)}$ in the upper trapezoidal membership function $\tilde{A}^u_i$, $1 \leq \jmath \leq 2$, $H_j(\tilde{A}^L_i)$ denotes the membership value of the element $a^L_{i(j+1)}$ in the lower trapezoidal membership function $\tilde{A}^L_i$, $1 \leq \jmath \leq 2$.

In addition, algebraic operations used in this work are addition and multiplication. In the following, they are given as an example for the trapezoidal interval type-2 fuzzy sets $\tilde{A}_1$ and $\tilde{A}_2$;

The addition between trapezoidal interval type-2 fuzzy sets are shown as in the following:

$$\begin{aligned}\tilde{A}_1 \oplus \tilde{A}_2 &= (\tilde{A}^U_1, \tilde{A}^L_1) \oplus (\tilde{A}^U_2, \tilde{A}^L_2)\\ &= ((a^u_{11} + a^u_{21}, a^u_{12} + a^u_{22}, a^u_{13} + a^u_{23}, a^u_{14} + a^u_{24};\\ &min(h_1(\tilde{A}^U_1), h_1(\tilde{A}^U_2)), min(h_2(\tilde{A}^U_1), h_2(\tilde{A}^U_1))),\\ &(a^l_{11} + a^l_{21}, a^l_{12} + a^l_{22}, a^l_{13} + a^l_{23}, a^l_{14} + a^l_{24};\\ &min(h_1(\tilde{A}^L_1), h_1(\tilde{A}^L_2)), (h_2(\tilde{A}^L_1), h_2(\tilde{A}^L_2)))\end{aligned} \tag{5}$$

The subtraction between trapezoidal interval type-2 fuzzy sets are shown as in the following:

$$\begin{aligned}\tilde{A}_1 \ominus \tilde{A}_2 &= (\tilde{A}^U_1, \tilde{A}^L_1) \ominus (\tilde{A}^U_2, \tilde{A}^L_2)\\ &= ((a^u_{11} - a^u_{24}, a^u_{12} - a^u_{23}, a^u_{13} - a^u_{22}, a^u_{14} - a^u_{21};\\ &min(h_1(\tilde{A}^U_1), h_1(\tilde{A}^U_2)), min(h_2(\tilde{A}^U_1), h_2(\tilde{A}^U_1))),\\ &(a^l_{11} - a^l_{24}, a^l_{12} - a^l_{23}, a^l_{13} - a^l_{22}, a^l_{14} - a^l_{21};\\ &min(h_1(\tilde{A}^L_1), h_1(\tilde{A}^L_2)), (h_2(\tilde{A}^L_1), h_2(\tilde{A}^L_2)))\end{aligned} \tag{6}$$

The multiplication between trapezoidal interval type-2 fuzzy sets are shown as in the following:

$$\begin{aligned}\tilde{A}_1 \otimes \tilde{A}_2 =& (\tilde{A}_1^U, \tilde{A}_1^L) \otimes (\tilde{A}_2^U, \tilde{A}_2^L) \\ &= ((a_{11}^u \times a_{21}^u, a_{12}^u \times a_{22}^u, a_{13}^u \times a_{23}^u, a_{14}^u \times a_{24}^u; \\ & min(h_1(\tilde{A}_1^U), h_1(\tilde{A}_2^U)), min(h_2(\tilde{A}_1^U), h_2(\tilde{A}_2^U))), \\ & (a_{11}^l \times a_{21}^l, a_{12}^l \times a_{22}^l, a_{13}^l \times a_{23}^l, a_{14}^l \times a_{24}^l; \\ & min(h_1(\tilde{A}_1^L), h_1(\tilde{A}_2^L)), (h_2(\tilde{A}_1^L), h_2(\tilde{A}_2^L))).\end{aligned} \tag{7}$$

The arithmetic operations between trapezoidal interval type-2 fuzzy sets and scalar s are shown as in the following:

$$\begin{aligned}s\tilde{A}_1 =& ((s \times a_{11}^u, s \times a_{12}^u, s \times a_{13}^u, s \times a_{14}^u \times a_{24}^u; h_1(\tilde{A}_i^U), h_2(\tilde{A}_i^U)), \\ & (s \times a_{11}^l, s \times a_{12}^l, s \times a_{13}^l, s \times a_{14}^l; h_1(\tilde{A}_i^L), h_2(\tilde{A}_i^L))).\end{aligned} \tag{8}$$

3.2. Proposed Methodology

In this study, interval type-2 fuzzy sets, entropy and Delphi methods are combined to highlight the vagueness and uncertainty in the group decision-making process. The schematic diagram of the proposed methodology is shown in Fig. 2. In the first stage, unique indicators of sustainable VSFs are identified and grouped into four clusters through a literature review. In the second stage, the online questionnaire approach is employed to collect evaluations of the clusters and initial indicators as well as suggestions on additional indicators from invited experts. In the last stage, the importance of site selection indicators of sustainable VSFs is obtained to define critical, medium, and uncritical indicators.

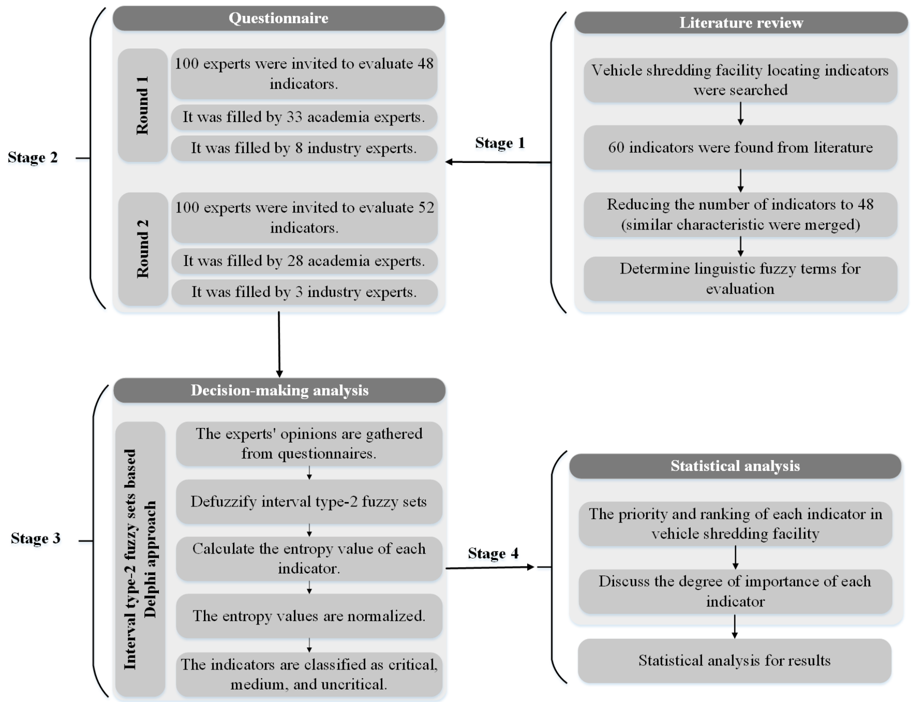


Figure 2: The schematic diagram of the overall framework.

The steps of the proposed IT2FS-based Delphi approach are given as follows:

Step 1: The experts' evaluations are gathered via questionnaires for each indicator. The average fuzzy value of each indicator i, denoted as $\tilde{w_i}$ is calculated based on Eq. (5) using the following equation.

$$\tilde{w_i} = \frac{1}{E} \sum_{\forall e} \tilde{A}_{ie} \tag{9}$$

where $\tilde{A}_{ie}$ $(i = 1, 2, ..., n)$ denotes the importance of each indicator i for each expert e, n and E denoting the total number of indicators and experts, respectively.

Step 2: Defuzzify $\tilde{w_i}$ using score function (S_i) of Chen et al. [91] for IT2FSs as in following:

$$d(S_i) = \sum_{\tilde{w} \in \tilde{h}} score \left[\frac{a_1^u + a_4^u}{2} + \frac{H_1(\tilde{a}_1^U) + H_1(\tilde{a}_1^U) + H_2(\tilde{a}_1^L) + H_2(\tilde{a}_1^L)}{4} \right] \times \frac{a_1^u + a_2^u + a_3^u + a_4^u + a_1^l + a_2^l + a_3^l + a_4^l}{8} \tag{10}$$

where $d(S_i)$ is a crisp score which denotes the aggregate importance of each VSF locating indicator.

Step 3: Finally, the entropy values are normalized by using following equation:

$$\delta_i = \frac{S_i}{Max\{S_i\}} \tag{11}$$

where δ_i is a normalized value.

Step 4: The VRF site selection indicators can be classified by δ_i as *critical*, *medium*, and *uncritical*. These categories are defined in the Table 2.

Table 2: The categories indicators affecting site selection of VRFs.

Degrees	Interval
Uncritical	$0.00 \leq \delta_i < 0.619$
Medium	$0.619 \leq \delta_i < 0.850$
Critical	$0.850 \leq \delta_i \leq 1.00$

4. Survey

4.1. Problem Description

As it is stated in the Introduction, one of the main motivations of this study is to identify importance of the VSF locating selection indicator via the collaboration of participants from both academia and industry. As a result of the literature review, 48 indicators, grouped into 4 clusters, are identified (see Table 1). An online questionnaire is conducted and is sent to international participants for the assessment of these indicators. Detailed steps of the survey are represented in the following sub-sections.

4.2. Data Collection

As the first step of the data collection process, online questionnaire forms for the Delphi method is created via Google Forms and it is sent to experts via email. In the first part of the questionnaire forms, the participants are asked to enter their name, gender, occupation, department, total years of experience and country information. In the second part of the questionnaire, the participants are asked to rank the indicator clusters (i.e., economic, environmental, social, and technical) and their self expertise. Also, the participants are asked whether they suggest any other indicator to be added to the list of the questionnaire in the next round.

The online questionnaire forms are evaluated by the participants in two rounds (Round 1 and Round 2). Table 3 represents the main characteristics and statistical distribution of the experts.

Table 3: The main characteristics of the experts.

Main characteristics	***Round 1***	***Round 2***
	N	***N***
Number of participants	41	31
Countries		
Albania	1	0
Australia	3	0
Belgium	0	1
Brazil	0	1
Bulgaria	0	1
Canada	1	0
Chile	1	0
China	5	1
France	2	0
Germany	3	1
Greece	1	1
Italy	9	2
Japan	0	3
Malaysia	5	5
Poland	1	2
Romania	1	0
Serbia	4	5
Sweden	1	0
Taiwan	0	1
Turkey	3	4
United Kingdom	0	1
United States	0	2
Occupation	***N (%)***	***N (%)***
Academia	33 (80.5%)	28 (90.3%)
Industrial experts	8 (19.5%)	3 (9.7%)

4.3. Round 1

Table 3 depicts that the questionnaire is filled out by 41 international experts from 15 countries in Round 1. As can be seen from this table, 80.5% of the participants are officials from academia and 19.5% of the participants are industrial experts. Most of the invited academic experts have a strong industrial background. They regularly serve as external consultants or directly took part in project consortia for the recycling industry. Some of the invited experts from academia also serve as policymakers on national, European, and international dimensions. In Round 1, the participants are asked to evaluate 48 location selection indicators identified from the literature. Besides, they are requested to suggest any other potential indicator to be added to the list. As a result, four new indicators are suggested by the participants and added to the indicator list for Round 2. More detailed, one social and three technical indicators are proposed. They are (i) Political situation - Security for foreign investments in recycling enterprises and interrelations with government layers; (ii) Logistics convenience - Feasibility and accessibility of a location according to transportation and logistics activities for the recycling process; (iii) Design-for-recycling - A systematic approach allowing the design of more environmentally-friendly vehicles; and (iv) Industry 4.0 implementation - End-to-end integration of crowdsourcing, personalization, servitization, and Internet of Things in recycling enterprises. Finally, "Political situation" is added to the Social cluster, while "Logistics convenience", "Design-for-recycling", and "Industry 4.0 implementation" are added to the Technical cluster.

4.4. Round 2

In the second round, the questionnaire is filled out by 31 international experts from 15 countries (see Table 3). Fifty-two location selection indicators are evaluated by the participants. There were no new suggestions on missing indicators. About 90.3% of the participants are experts from academia, whereas 9.7% of them are industry experts. Fig. 3, 4, and 5 underline a more detailed statistical distribution of the participants.

In Round 1, 54% of the experts are male, 44% of them are female and 2% of the experts prefer not to say their gender. In round 2, 61% of the participants are male and 39% of them are female. This distribution underlines that although rate of the genders is slightly close, the majority of the participants have male gender in both rounds.

In Round 1, 33 out of 41 participants are from academia whereas only 8 out of 41 participants are from industry. Similarly, 28 out of 31 participants are officials from academia whereas only 3 out of 31 participants are industry experts in Round 2. The results of the distributions represent that evaluation results of the questionnaires tend to be biased to the academy rather than the industry.

Fig. 3 represents that the majority of the participants have more than 4 years and very few of the participants have more than 30 years of work experience in Round 1. However, the majority of the participants have more than 5 years and the minority of the participants have more than 40 years of experience in Round 2.

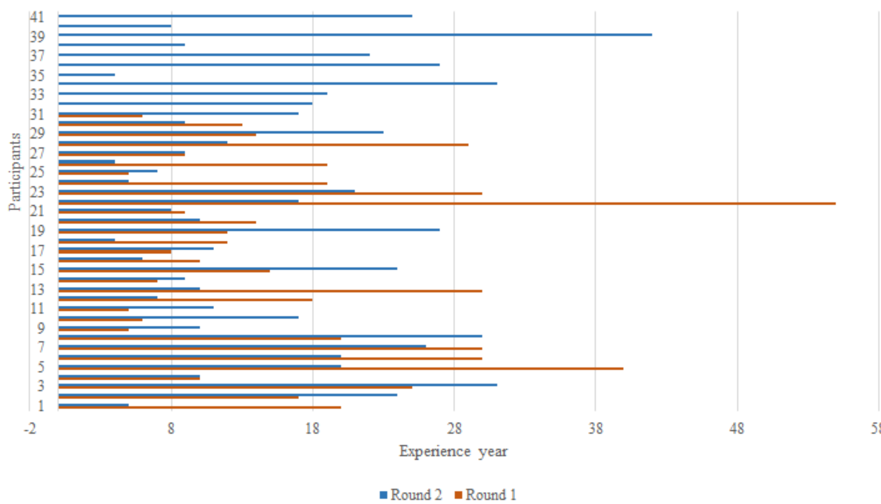


Figure 3: Total years of work experience of the experts for Round 1 and Round 2.

Fig. 4 highlights that the average number of work experience years are 15.83 and 17.48 for Round 1 and Round 2, respectively. Furthermore, most of the participants have 12 years and 14 years of work experience for Round 1 and Round 2 respectively.

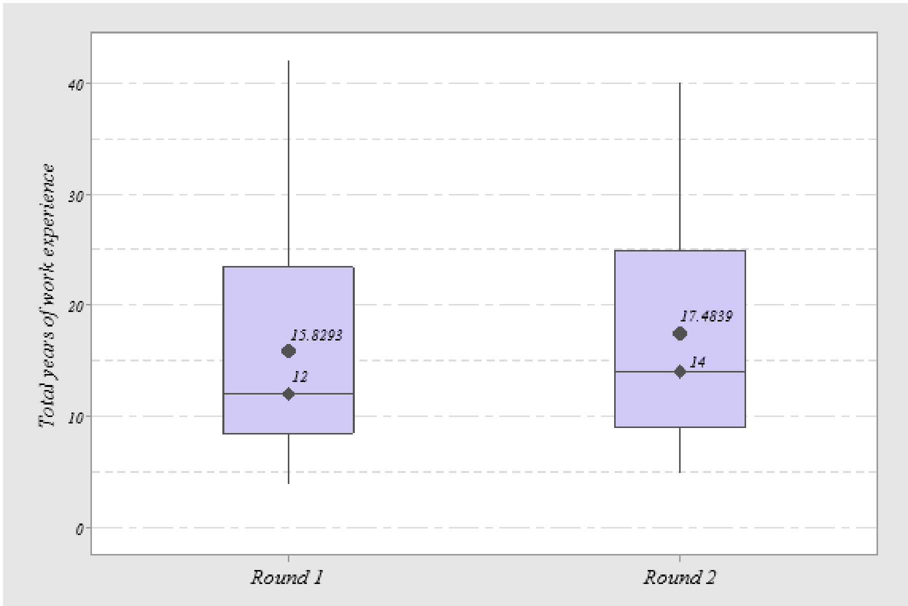
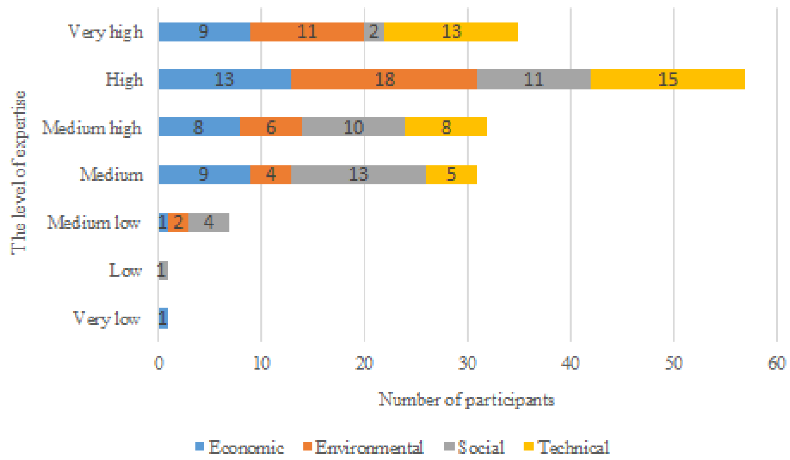
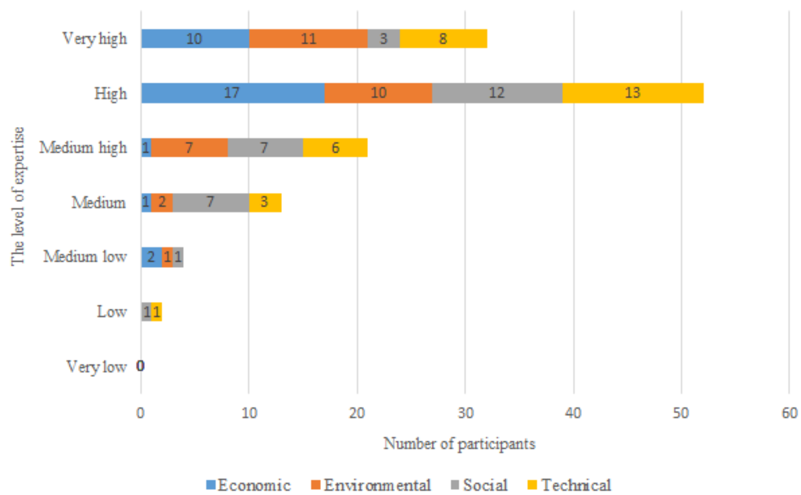


Figure 4: Box plot diagram for the total years of work experiences of the participants.

Fig. 5 represents the self-rate evaluation of the experts regarding four indicator clusters. In Round 1, the average values for the economic, environmental, social, and technical indicator clusters are medium high, high, medium high, and high, respectively. For instance, the first histogram chart highlights that 73.17% of the participants have a high level of expertise (medium high, high, or very high), 21.95% of the participants have a low level of expertise (i.e., medium low, low, or very low), and 4.88% of the participants have a medium level of expertise in the economic indicator cluster. In Round 2, the average values for the economic, environmental, social, and technical indicator clusters are high, high, medium high, and high, respectively.



(a) Round 1



(b) Round 2

Figure 5: Self-rated expertise.

4.5. Linguistic Terms

To determine the importance degrees of the VSF site selection indicators, a seven-point linguistic rating scale is used in the questionnaire. The linguistic terms "Very low" (VL), "Low" (L), "Medium low" (ML), "Medium" (M), "Medium high" (MH), "High" (H), "Very high" (VH) and their corresponding

IT2FSs are presented in Table 4, respectively.

Table 4: Linguistic variables for importance evaluation [92].

Linguistic terms	$\tilde{A}_i^U$						$\tilde{A}_i^L$					
	a_{i1}^u	a_{i2}^u	a_{i3}^u	a_{i4}^u	$h_1(\tilde{A}_i^U)$	$h_2(\tilde{A}_i^U)$	a_{i1}^l	a_{i2}^l	a_{i3}^l	a_{i4}^l	$h_1(\tilde{A}_i^L)$	$h_2(\tilde{A}_i^L)$
Very low (VL)	0.00	0.00	0.00	0.10	1.00	1.00	0.00	0.00	0.00	0.05	0.90	0.90
Low (L)	0.00	0.10	0.10	0.30	1.00	1.00	0.05	0.10	0.10	0.20	0.90	0.90
Medium low (ML)	0.10	0.30	0.30	0.50	1.00	1.00	0.20	0.30	0.30	0.40	0.90	0.90
Medium (M)	0.30	0.50	0.50	0.70	1.00	1.00	0.40	0.50	0.50	0.60	0.90	0.90
Medium high (MH)	0.50	0.70	0.70	0.90	1.00	1.00	0.60	0.70	0.70	0.80	0.90	0.90
High (H)	0.70	0.90	0.90	1.00	1.00	1.00	0.80	0.90	0.90	0.95	0.90	0.90
Very high (VH)	0.90	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.00	0.90	0.90

5. Results and Discussions

5.1. Comparison Results

Firstly, the stability of the data by using normality is tested. Histograms and probability plots for each group (all participants, academia and industry) are shown in Fig. 6. When we check these plots, the groups are normally distributed.

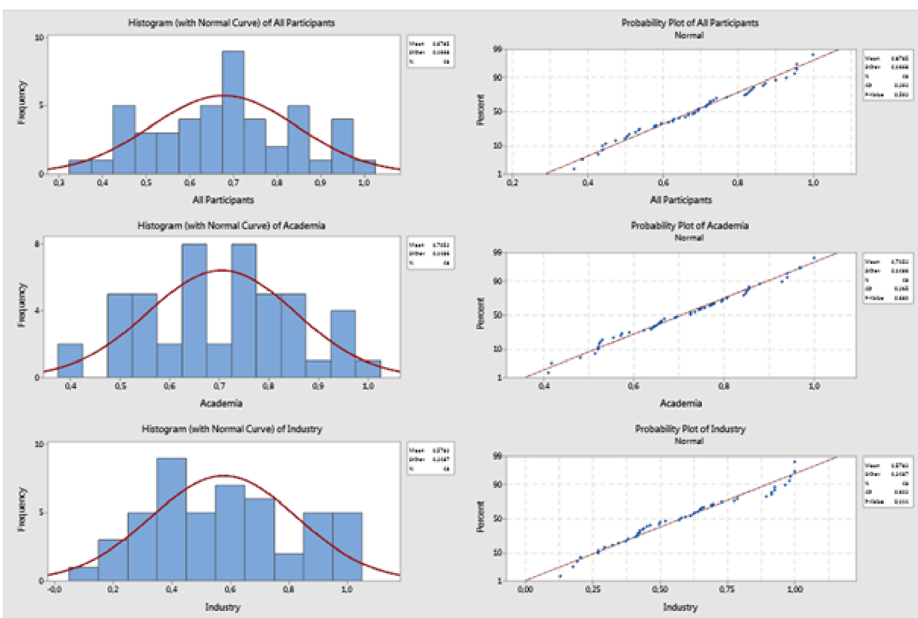


Figure 6: The histograms and probability for round 1 (all participants, academia and industry experts).

A hierarchical clustering approach is carried out to highlight the similarities among the participants. The hierarchical relationship among the participants is illustrated by the dendrogram in Fig. 7. According to the dendrogram, [1, 6, 7], [32, 37], [21, 28], [5, 41], [16, 23], and [3, 14] are the most similar clusters. Fig. 7. represents that most of the clusters contain experts from the same occupational field. However, there are a few clusters that have high similarity and mixed occupational fields; e.g., [3, 14] and [16, 23].

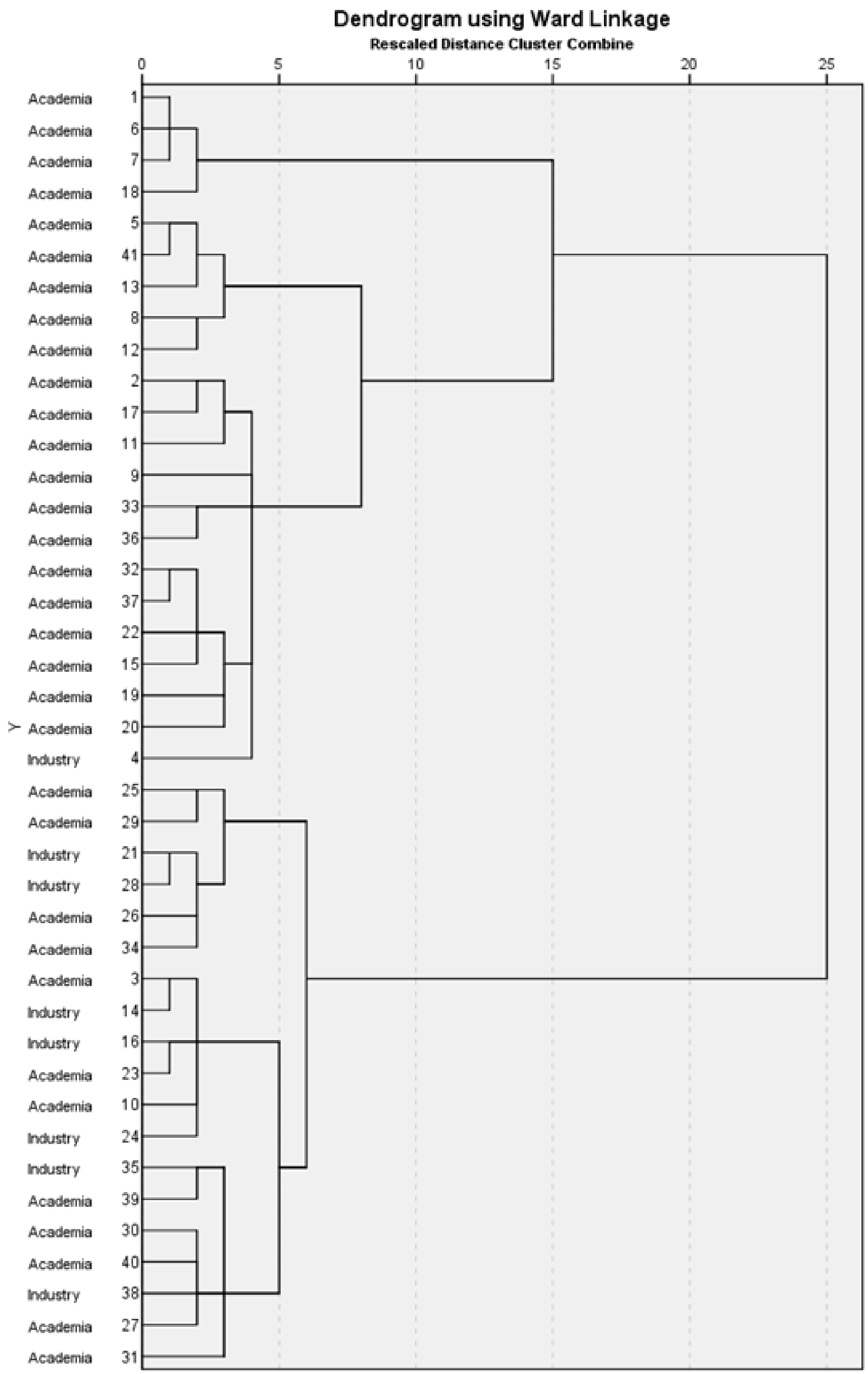


Figure 7: The hierarchical relationship of responses for Round 1.

Fig. 8 represents the ranking results of the main indicator cluster in terms of Round 1 and Round 2. Ranking results for Round 1 highlight that "the Environmental" cluster has the highest priority for both academic and industrial experts. However, "the Economic" cluster is the most important for both academic and industrial experts in Round 2. In both rounds, "the Social" cluster is the least important. Results for all participants in both rounds show the trend of academic experts.

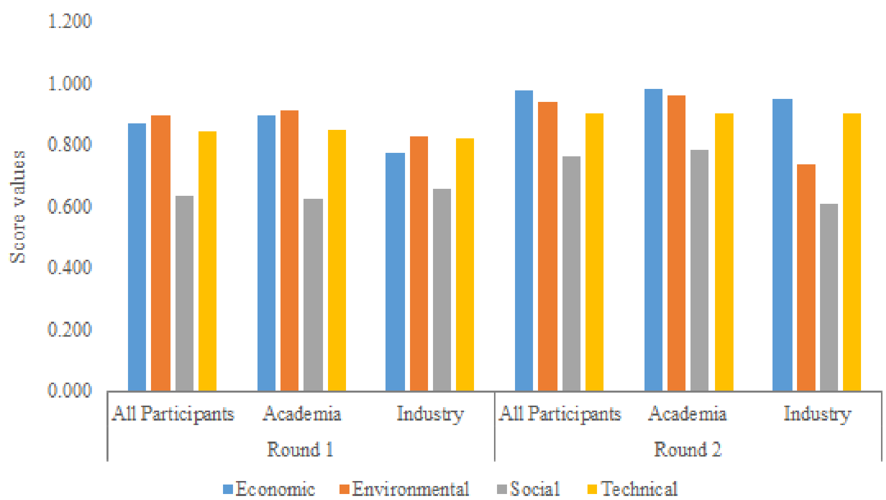


Figure 8: Ranking of indicator clusters in terms of Round 1 and Round 2.

Table 5 represents the sample size, median and mode values of the indicator clusters for Round 2. It shows that the Economic cluster has the highest mean and fuzzy weight of the median value on the linguistic scale of *H*. However, the Environmental cluster has the highest value of mode on the linguistic scale of *VH*.

Table 5: Median and mod of indicator cluster for Round 2.

Cluster	Economic	Environmental	Social	Technical
N Valid	31	31	31	31
Mean	0.835	0.801	0.663	0.775
Median (fuzzy weights)	0.851	0.851	0.620	0.851
Median (scale)	H	H	MH	H
Mode (fuzzy weights)	0.851	1.000	0.851	0.851
Mode (scale)	H	VH	H	H

Table 6 represents the sample size, median and mode values of fifty-two VFR location selection indicators for Round 2. Indicator C_6 (financial benefit) has the highest mean, while C_{26} (employee turnover rate) has the smallest mean in the indicator list. Seven indicators (i.e., C_6, C_{15}, C_{21}, C_{25}, C_{39}, C_{45} and C_{46}) have the highest fuzzy weight of mode in the linguistic scale of VH.

Table 6: Median and mode of VRF location selection indicators for Round 2.

Characteristics	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
N Valid	31	31	31	31	31	31	31	31	31	31	31	31	31
Mean	0.765	0.582	0.624	0.573	0.469	0.853	0.581	0.547	0.729	0.777	0.476	0.725	0.692
Median (fuzzy weights)	0.851	0.620	0.620	0.620	0.389	0.851	0.620	0.620	0.851	0.851	0.389	0.851	0.851
Median (scale)	H	MH	MH	MH	M	H	MH	MH	H	H	M	H	H
Mode (fuzzy weights)	0.851	0.620	0.851	0.389	0.389	1.000	0.620	0.389	0.851	0.851	0.389	0.851	0.851
Mode (scale)	H	MH	H	M	M	VH	MH	M	H	H	M	H	H

	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26
N Valid	31	31	31	31	31	31	31	31	31	31	31	31	31
Mean	0.643	0.825	0.709	0.608	0.505	0.662	0.545	0.642	0.756	0.427	0.533	0.726	0.417
Median (fuzzy weights)	0.620	0.851	0.851	0.620	0.389	0.620	0.620	0.620	0.851	0.389	0.620	0.851	0.389
Median (scale)	MH	H	H	MH	M	MH	MH	MH	H	M	MH	H	M
Mode (fuzzy weights)	0.389	1.000	0.851	0.389	0.389	0.620	0.620	1.000	0.851	0.389	0.389	1.000	0.389
Mode (scale)	M	VH	H	M	M	MH	MH	VH	H	M	M	VH	M

	C27	C28	C29	C30	C31	C32	C33	C34	C35	C36	C37	C38	C39
N Valid	31	31	31	31	31	31	31	31	31	31	31	31	31
Mean	0.564	0.662	0.535	0.758	0.730	0.531	0.604	0.556	0.788	0.629	0.598	0.506	0.800
Median (fuzzy weights)	0.620	0.620	0.389	0.851	0.851	0.620	0.620	0.620	0.851	0.620	0.620	0.389	0.851
Median (scale)	MH	MH	M	H	H	MH	MH	MH	H	MH	MH	M	H
Mode (fuzzy weights)	0.620	0.620	0.389	0.851	0.851	0.620	0.620	0.620	0.851	0.620	0.389	0.620	1.000
Mode (scale)	MH	MH	M	H	H	MH	MH	MH	H	MH	M	MH	VH

	C40	C41	C42	C43	C44	C45	C46	C47	C48	C49	C50	C51	C52
N Valid	31	31	31	31	31	31	31	31	31	31	31	31	31
Mean	0.483	0.617	0.477	0.569	0.697	0.823	0.794	0.541	0.716	0.421	0.734	0.700	0.593
Median (fuzzy weights)	0.389	0.620	0.389	0.620	0.620	0.851	0.851	0.620	0.620	0.389	0.851	0.620	0.620
Median (scale)	M	MH	M	MH	MH	H	H	MH	MH	M	H	MH	MH
Mode (fuzzy weights)	0.620	0.620	0.620	0.389	0.620	1.000	1.000	0.389	0.620	0.389	0.851	0.620	0.620
Mode (scale)	MH	MH	MH	M	MH	VH	VH	M	MH	M	H	MH	MH

Table 7 represents overall score values for Round 1 and Round 2. Results of the overall scores indicate that C_6 (financial benefit), C_{15} (ELV policy), and C_{44} (recycling system) are the three most important VSF site selection indicators in Round 1. On the other hand. C_{24} (customer satisfaction), C_{48} (traffic congestion), and C_{23} (brand image) have the lowest overall scores.

In Round 2, C_6 (financial benefit), C_{45} (recycling system), and C_{15} (ELV policy) have the largest overall scores. Therefore, the research findings show that they are the most important VSF site selection indicators. On the other hand, C_{23} (brand image), C_{49} (traffic congestion), and C_{26} (employee turnover rate) are the least important indicators.

In the last column of Table 7, the VRF location selection indicators are classified according to the degree of importance to *critical*, *medium*, and *uncritical*. Ten critical indicators are acquisition cost, affected population, demand fluctuations, ELV policy, financial benefit, land availability, operational costs, recycling system, resource accessibility, and safety management. They must be taken into account when locating vehicle shredding facilities.

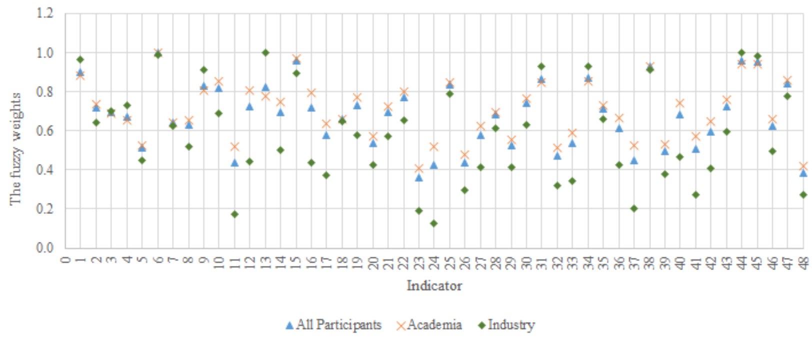
Indicators that have medium importance are availability of a baling machine, competition, design-for-recycling, distance to authorized dismantling facilities, distance to collection centers, ecotoxicity, environment management system, environmental equipment and facilities, flexibility, incentive for vehicle owners, indirect costs, industry 4.0 implementation, information management, initial setup cost, job opportunities, local communities influence, logistics convenience, noise pollution, occupational hazards, performance, political situation, processing convenience, quality management, return on investment, skilled workforce, subsidy, technology access, and waste material releases. It is strongly suggested to also consider these twenty-eight indicators when evaluating potential sites for locating new VSFs.

Other 14 indicators are *uncritical*; i.e., C_5, C_{11}, C_{18}, C_{20}, C_{23}, C_{24}, C_{26}, C_{29}, C_{32}, C_{38}, C_{40}, C_{42}, C_{47}, and C_{49}. They can be omitted when solving location selection problems. However, if the first two or more location alternatives have close utility scores, then waste managers can perform additional analysis based on the uncritical indicators to find a dominant solution.

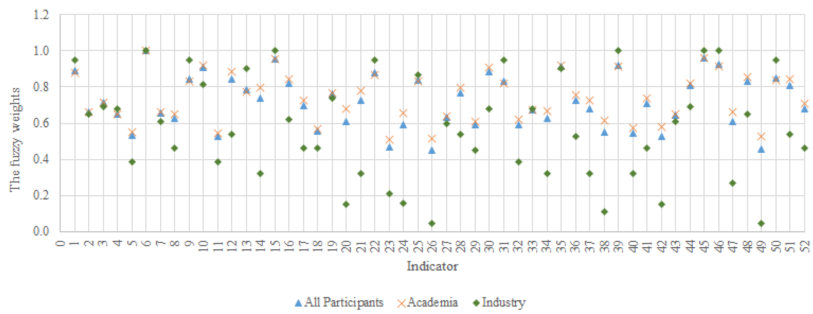
Table 7: Overall score of VRF location selection indicators for Round 1 and Round 2.

No	Indicator	Round 1				No	Indicator	Round 2			
		All Participants	Academia	Industry	Degree			All Participants	Academia	Industry	Degree
C1	Acquisition cost	0.901	0.881	0.966	Critical	C1	Acquisition cost	0.887	0.880	0.949	Critical
C2	Competition	0.719	0.737	0.643	Medium	C2	Competition	0.663	0.664	0.650	Medium
C3	Distance to authorized dismantling facilities	0.695	0.692	0.698	Medium	C3	Distance to authorized dismantling facilities	0.714	0.716	0.693	Medium
C4	Distance to collection centers	0.669	0.652	0.728	Medium	C4	Distance to collection centers	0.651	0.647	0.681	Medium
C5	Distances to other network entities	0.511	0.526	0.451	Uncritical	C5	Distances to other network entities	0.535	0.553	0.389	Uncritical
C6	Financial benefit	1.000	1.000	0.986	Critical	C6	Financial benefit	1.000	1.000	1.000	Critical
C7	Incentive for vehicle owners	0.643	0.645	0.627	Medium	C7	Incentive for vehicle owners	0.654	0.659	0.608	Medium
C8	Indirect costs	0.628	0.656	0.521	Medium	C8	Indirect costs	0.626	0.647	0.461	Medium
C9	Initial setup cost	0.830	0.806	0.914	Medium	C9	Initial setup cost	0.842	0.830	0.949	Medium
C10	Operational costs	0.819	0.852	0.689	Medium	C10	Operational costs	0.911	0.922	0.817	Critical
C11	Penalty	0.439	0.520	0.176	Uncritical	C11	Penalty	0.526	0.544	0.389	Uncritical
C12	Return on investment	0.726	0.806	0.441	Medium	C12	Return on investment	0.845	0.886	0.538	Medium
C13	Subsidy	0.825	0.778	1.000	Medium	C13	Subsidy	0.788	0.775	0.899	Medium
C14	Ecotoxicity	0.696	0.749	0.499	Medium	C14	Ecotoxicity	0.735	0.794	0.322	Medium
C15	ELV policy	0.956	0.969	0.894	Critical	C15	ELV policy	0.957	0.952	1.000	Critical
C16	Environment management system	0.716	0.795	0.437	Medium	C16	Environment management system	0.820	0.846	0.620	Medium
C17	Environmental equipment and facilities	0.580	0.638	0.372	Uncritical	C17	Environmental equipment and facilities	0.698	0.729	0.461	Medium
C18	Global warming	0.660	0.661	0.650	Medium	C18	Global warming	0.557	0.569	0.461	Uncritical
C19	Noise pollution	0.733	0.773	0.578	Medium	C19	Noise pollution	0.762	0.765	0.738	Medium
C20	Resource consumption	0.540	0.570	0.423	Uncritical	C20	Resource consumption	0.609	0.678	0.154	Uncritical
C21	Waste material releases	0.695	0.726	0.571	Medium	C21	Waste material releases	0.723	0.780	0.322	Medium
C22	Affected population	0.769	0.798	0.652	Medium	C22	Affected population	0.877	0.869	0.949	Critical
C23	Brand image	0.362	0.411	0.191	Uncritical	C23	Brand image	0.470	0.507	0.208	Uncritical
C24	Customer satisfaction	0.427	0.522	0.128	Uncritical	C24	Customer satisfaction	0.590	0.654	0.160	Uncritical
C25	Job opportunities	0.835	0.845	0.789	Medium	C25	Job opportunities	0.837	0.833	0.865	Medium
C26	Employee turnover rate	0.440	0.480	0.295	Uncritical	C26	Employee turnover rate	0.454	0.518	0.049	Uncritical
C27	Local communities influence	0.579	0.623	0.416	Uncritical	C27	Local communities influence	0.633	0.637	0.596	Medium
C28	Occupational hazards	0.681	0.696	0.615	Medium	C28	Occupational hazards	0.765	0.794	0.538	Medium
C29	Public awareness level	0.526	0.555	0.416	Uncritical	C29	Public awareness level	0.594	0.612	0.451	Uncritical
C30	Safety management	0.741	0.768	0.631	Medium	C30	Safety management	0.882	0.908	0.681	Critical
C31	Skilled workforce	0.868	0.850	0.927	Critical	C31	Skilled workforce	0.834	0.820	0.949	Medium
C32	Supplier commitment and awareness	0.473	0.515	0.320	Uncritical	C32	Supplier commitment and awareness	0.594	0.621	0.389	Uncritical
C33	Availability of a baling machine	0.536	0.589	0.345	Uncritical	C33	Political situation	0.675	0.675	0.681	Medium
C34	Demand fluctuations	0.873	0.856	0.927	Critical	C34	Availability of a baling machine	0.627	0.669	0.322	Medium
C35	Flexibility	0.715	0.727	0.660	Medium	C35	Demand fluctuations	0.916	0.918	0.899	Critical
C36	Information management	0.614	0.666	0.423	Uncritical	C36	Flexibility	0.728	0.753	0.527	Medium
C37	Inventory control	0.449	0.523	0.202	Uncritical	C37	Information management	0.677	0.727	0.322	Medium
C38	Land availability	0.930	0.931	0.914	Critical	C38	Inventory control	0.550	0.617	0.111	Uncritical
C39	Lead time	0.498	0.530	0.379	Uncritical	C39	Land availability	0.921	0.912	1.000	Critical
C40	Performance	0.684	0.744	0.465	Medium	C40	Lead time	0.543	0.573	0.322	Uncritical
C41	Process difficulties	0.505	0.573	0.271	Uncritical	C41	Performance	0.707	0.739	0.461	Medium
C42	Processing convenience	0.595	0.645	0.409	Uncritical	C42	Process difficulties	0.525	0.580	0.154	Uncritical
C43	Quality management	0.724	0.757	0.594	Medium	C43	Processing convenience	0.644	0.649	0.608	Medium
C44	Recycling system	0.956	0.941	1.000	Critical	C44	Quality management	0.808	0.822	0.693	Medium
C45	Resource accessibility	0.952	0.941	0.980	Critical	C45	Recycling system	0.963	0.958	1.000	Critical
C46	Resource utilization	0.626	0.659	0.495	Medium	C46	Resource accessibility	0.924	0.915	1.000	Critical
C47	Technology access	0.843	0.857	0.776	Medium	C47	Resource utilization	0.611	0.659	0.267	Uncritical
C48	Traffic congestion	0.387	0.418	0.271	Uncritical	C48	Technology access	0.834	0.858	0.650	Medium
						C49	Traffic congestion	0.459	0.525	0.049	Uncritical
						C50	Logistics convenience	0.849	0.837	0.949	Medium
						C51	Design-for-recycling	0.808	0.843	0.538	Medium
						C52	Industry 4.0 implementation	0.681	0.710	0.461	Medium

Fig. 9 represents an indicator overlapping chart of data series for three groups regarding the evaluation of the experts. It highlights that experts from academia are more dominant with the determination of the fuzzy weights. In Round 1, about five indicators are completely overlapped for "all Participants", "academia", and "industry". In round 2, about 10 indicators are completely overlapped. VRF location selection indicators C_3 (distance to authorized dismantling facilities), C_6 (financial benefit), and C_{45} (resource accessibility) are overlapped in both rounds.



(a) Round 1



(b) Round 2

Figure 9: Indicator overlapping chart of data series for three groups.

5.2. Comparative Analysis

In this section, we present a comparison analysis of the proposed model with T1FSs based Delphi [93, 94] approach to exhibit the validity of the IT2FSs based Delphi approach. We extend the Delphi and the Entropy methods into the interval type-2 fuzzy environment and compare it with type-1 fuzzy sets (T1FSs) based Delphi [93, 94]. The ranking results of the two methods are shown in Fig. 10. Considering the ranking results of the proposed model, C_6 is the most important indicator, followed by C_{45}, C_{15}, C_{46}, and C_{39}, while C_{26} is least important indicator. If we consider the ranking results of the T1FSs based Delphi [93, 94], C_{15} is the most important, followed by C_{10}, C_9, C_6, and C_{45}, while C_{26} is the least important. The ranking results of the proposed model are more meaningful as expert opinions address a higher degree of uncertainty in the decision-making process.

In order to statistically test the ranking results of our proposed model and type-1 fuzzy sets based Delphi approach from literature, Independent samples t-test was applied. The characteristics of two methods are reported in Table 8 as mean, standard deviation (Std. Deviation) and standard error mean (Std. Error Mean) values. Independent samples t-test was used to compare the equality of variances and means of two independent groups (methods) as given in Table 9. In this statistical analysis, the variances of the two methods are homogeneous as the p value of Levene's test is > 0.05. Nevertheless, the results show that there is a difference between the equality of means of the two methods because the value of Sig. (2-tailed) is < 0.05.

Table 8: Group statistics.

	Methods	N	Mean	Std. Deviation	Std. Error Mean
Score	T2FSs based Delphi	52	0.720865	0.1449042	0.0200946
	T1FSs based Delphi	52	0.594748	0.1518857	0.0210628

N: Number of indicators

Table 9: Independent samples test.

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Score	Equal variances assumed	0.058	0.810	4.332	102	0.000	0.1261173	0.0291107	0.0683764	0.1838583
	Equal variances not assumed			4.332	101.775	0.000	0.1261173	0.0291107	0.0683749	0.1838598

From the ranking results shown in Fig. 10 and given in Table 9, it can be observed that indicators have different ranking results in terms of the two methods. The ranking results and reliability of the proposed model are verified by the experts.

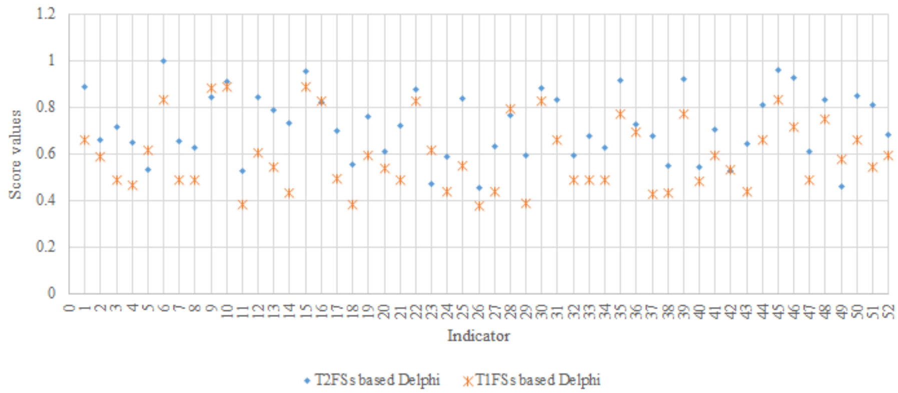


Figure 10: Ranking results of indicator in terms of two methods.

5.3. Limitations of the Study

The data collection process is the most difficult stage of the proposed decision-making approach. In the conducted survey, 41 international experts participated in Round 1, while 31 international experts contributed in Round 2. The number of participants is crucial for an accurate decision support system. Larger participation can improve the confidence level of the results.

As it is presented in Table 3, 80.5% of the participants in Round 1 are academic experts and 19.5% of the participants are industrial experts. Additionally, 90.3% of the participants in Round 2 are academic experts and 9.7% of the participants are industrial experts. The statistical distribution of the participants exhibits that there is a noticeable academic expert dominance in the results. During the data collection process, experts are asked if they suggest any other indicator to be added. As a result, four indicator are suggested by the participants in Round 1. More suggestions from the participants can increase the impacts of the experts on this study.

6. Conclusion

The IT2FS-based Delphi approach is introduced in this study to help waste managers to evaluate the site selection indicators of VSFs in the uncertain environment. The major contributions of this study are: *(i)* For the first time, the comprehensive list of VSF location selection indicators is provided; *(ii)* The novel four-stage IT2FS-based Delphi approach is formulated; *(iii)* The valuable results of the conducted online survey, in which both academia and industry took part, are presented in detail; *(iv)* The clear distinction between groups of participants who respond similarly is made; *(v)* The viewpoints from the industry and academia are discovered; *(vi)* All indicators are categorized to critical, medium, and uncritical to generate guidelines and set rules of thumbs for locating new VSFs.

The research findings show that the most important indicator is a financial benefit; i.e., direct and indirect financial benefits from opening an additional VSF. Critical indicators are (in alphabetical order) acquisition cost, affected population, demand fluctuations, ELV policy, financial benefit, land availability, operational costs, recycling system, resource accessibility, and safety management. These indicators must be taken into account when locating new VSFs. Besides, it is strongly recommended to consider 28 medium importance indicators when evaluating potential sites for locating new VSFs

Limitations of this study can indicate its possible extension areas. The majority of the participants in this study are academic experts. An increase in the number of industry participants can increase the homogeneity of the experts' review. Besides, other fuzzy sets can be used to capture the uncertainty of experts' subjective judgments. Finally, the proposed IT2FS-based Delphi approach can be also applied to evaluate indicators of other location selection problems in an uncertain environment.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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