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A multi-distance interval-valued neutrosophic approach for social failure detection in sustainable municipal waste management

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ABSTRACT

Developing sustainable municipal waste management systems requires an in-depth analysis and synthesis of economic, environmental, and social sustainable development indicators. However, despite its profound impact on organizational performance, social sustainability has received little attention in previous studies compared to economic and environmental sustainability. Although a few studies have been conducted to analyze and measure the impact of social sustainability indicators, most of these endeavors fail to consider many indicators that must be evaluated under uncertain and incomplete information. This study proposes a new decision model that implements Interval-Valued Neutrosophic Sets (IVNS) within a multi-distance measure defined with respect to an ideal reference solution. IVNS allows decision-makers to reliably express their opinions using truth, indeterminacy, and falsity membership functions. A linguistic framework is developed to categorize indicators based on their performance and suggest potential solutions when detecting indicators with relatively weak performances. Social sustainability failures in the municipal waste management system of Istanbul are investigated to show the applicability and efficacy of the proposed approach. We identify salary satisfaction and health insurance as the most significant social indicators determining the success of the system, while freedom of association and citizen participation are categorized as the worst-performing ones. The stability of the proposed methodology is illustrated by performing a comparative analysis with Single-Valued Neutrosophic Sets and Interval-Valued Fuzzy Pythagorean Sets.

1. Introduction

Sustainable development has become one of the essential and crucial organizational concepts practiced in different fields to maximize the sustainability of materials and processes for future generations (Adeniran et al., 2017; Rathore and Sarmah, 2020). In essence, sustainable development is focused on structured practices within economic, environmental, and societal pillars (Hosseini and Kaneko, 2012; Mensah and Casadevall, 2019). As cities transform their infrastructures via transportation and waste management systems, most governmental and non-governmental organizations focus on projects that contribute to the economic and environmental aspects but ignore the social ones. However, recent developments have shown the existence of a high demand to address social issues within urban systems, namely, socially sustainable development could greatly contribute to maximize welfare and health statuses in urban communities. Therefore, socially sustainable development requires a higher level of research and investment to achieve its core goals.

Municipal waste management (MWM) systems are critical urban systems with direct relationships to many economic, environmental, and social indicators (Rigamonti et al., 2016). Due to the high rates of population growth and urbanization and the increased demand for organic materials and medical plastics, municipalities and administrative authorities have started to define and apply sustainability guidelines for a few decades now (Kumar et al., 2017). Most practices aimed at developing a sustainable MWM for big cities are impacted by economic

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and environmental indicators. For this purpose, municipalities make serious efforts to establish a sustainable MWM system by improving waste collection and treatment processes such as sanitary landfilling or thermochemical waste-to-energy technologies with a focus on maximizing economic profits and minimizing environmental emissions and costs (de Souza Melaré et al., 2017; Tomić and Schneider, 2020). Although many academic studies have addressed the sustainable development of MWM in big cities, most of them were concentrated on economic and environmental sustainable development indicators (Margallo et al., 2019; Tomić and Schneider, 2020).

There is a mandatory obligation to integrate social sustainability guidelines into MWM systems, considering social sustainability goals and their direct effects on air quality, the health status of urban citizens, and job creation (Ambati, 2019; Ibáñez-Forés et al., 2019). In recent years, significant attention has been given to the implementation of sustainable practices within MWM systems by defining the corresponding indicators within life cycle assessments (Khandelwal et al., 2019; Mayer et al., 2019), optimization models (Darmian et al., 2020; Rabbani et al., 2020; Rathore and Sarmah, 2020), triple bottom line frameworks (Ghannadpour et al., 2021; Manupati et al., 2021), and decision-making models (Yazdani et al., 2020). Once again, most studies focused on assessing the sustainability of MWM systems by identifying environmental and economic failures, leaving the social aspects aside. Undoubtedly, developing a sustainable MWM system requires a comprehensive mechanism encompassing all the pillars of sustainable development.

Multicriteria decision-making (MCDM) models are well-known tools designed to address complex problems by outranking, prioritizing, and sorting several alternatives while considering multiple criteria (Hendiani et al., 2021; Torkayesh and Torkayesh, 2021; Yazdani et al., 2021). MCDM models allow decision-makers to express imprecise opinions through different types of uncertainty sets, including fuzzy logic (Mardani et al., 2015; Zadeh, 1988), grey theory (Liu et al., 2012), rough numbers (Pawlak, 1982), and neutrosophic sets (Smarandache, 1999). However, well-known MCDM models such as CoCoSo (Yazdani et al., 2019), TOPSIS (Chi and Liu, 2013), WASPAS (Chakraborty and Zavadskas, 2014), COPRAS (Zavadskas et al., 2007), and CODAS (Keshavarz Ghorabaee et al., 2016) require performing a series of complex soft computing calculations to deal with uncertainty. In this regard, real-life decision-makers who are not familiar with these methods could face problems when expressing their opinions and interpreting the results obtained. Moreover, urban complex systems such as MWM are continuously challenged by different events, implying that there exists incomplete information and vagueness within the system itself, which should encourage decision-makers to adopt reliable uncertain models based on fuzzy logic or neutrosophic sets.

The current paper proposes an uncertain soft computing approach to detect indicators that contribute to social failure when incorporating sustainability objectives into MWM systems. The main contributions of this study are summarized as follows. The sustainable development concept implemented and studied in MWM systems has focused on addressing environmental and economic problems. Less attention has been paid to addressing social issues using soft computing decision support systems. The first contribution of this study consists in detecting and analyzing social indicators that lead to failures in MWM systems. Secondly, unlike the complex uncertainty-based decision models considered in the MCDM literature, decision-makers need a straightforward framework to understand the uncertainty inherent to their opinions and implement the corresponding techniques. Therefore, linguistic terms are used to define interval-valued neutrosophic set (IVNS), allowing decision-makers to express their opinions and evaluate the results within an intuitive soft computing environment.

Finally, a novel method is developed to select the best performing social indicators in sustainable MWM systems under uncertainty and detect those exhibiting weaker performances. The main reason for investigating MWM is related to the high amount of daily waste generated by urban residents, which has increased exponentially in recent years. The high rates of urbanization and consumption together with the population growth, are major causes of the waste increase generated in cities. Moreover, MWM has a more direct relationship with social sustainability indicators than other types of management systems, such as those specialized in medical or industrial waste. Thus, MWM has the potential capacity to incorporate the advantages and positive impacts of social sustainability within its supply chain.

In the proposed approach, the categorization of social indicators is conducted through a performance classification scale based on truth-, indeterminacy-, and falsity-membership parameters. In this regard, IVNS allows decision-makers to express uncertainty and incomplete information more intuitively than fuzzy logic or single-valued neutrosophic sets (SVNS). Using IVNS, decision-makers are able to express their judgments in all membership functions through interval numbers rather than single-valued (crisp) values. In this way, the uncertainty inherent to their judgments can be incorporated within the values of the membership functions. Traditional fuzzy logic and SVNS do not allow decision-makers to express their judgments with such reliability and flexibility.

The proposed approach defines a new mechanism based on a distance-to-ideal-solution combination of Hamming, Euclidean, and two other measures introduced by Ye and Du (2019). The closeness index delivered by the mechanism is used to evaluate the relative performance of the indicators. Euclidean and Hamming measures are well-known and commonly applied in distance-based approaches. The other two distance measures have been selected due to their specific compatibility with IVNS environments. The motivation behind considering a multi-measure framework is to avoid any subjectivity and potential bias inherent to using a single-measure. The integration of different measures according to their relative importance provides a reliable and robust computational framework delivering an overall distance value that can be used to rank the performance of the indicators.

All in all, the current study aims to address several research questions, namely, (i) identifying the importance of social indicators for the sustainability of MWM systems, as well as (ii) the most important indicators to measure social sustainability failures in MWM systems, (iii) determining the performance of an MWM system over social sustainability indicators, as well as (iv) the most efficient way to detect social sustainability failures, and (v) empowering real-life decision-makers and experts to express their judgments on system performance under uncertain circumstances.

The remainder of the paper is organized as follows. Section 2 presents a comprehensive literature review on socially sustainable waste management systems and the applications of uncertain models to waste management. Section 3 describes the basics of IVNN and the related requirements and operations. The proposed approach is presented in Section 4. A case study based on the MWM system of Istanbul is investigated in Section 5 to show the capacity of the proposed method to deal with real-life problems. Section 6 discusses important managerial insights related to socially sustainable development in MWM systems. Section 7 concludes and suggests potential extensions.

2. Literature review

This section presents an overview of recently published studies in sustainable waste management systems and the application of uncertain models, specifically neutrosophic sets, to address sustainable waste management problems.

2.1. Applications of MCDM to WM

Since the introduction of concepts such as sustainable development and circular economy, cities implementing sustainable practices have found out that MWM problems cannot be exclusively addressed through technical indicators. The implementation of sustainability pillars within

MWM systems has allowed identifying several areas that must be managed to achieve the corresponding sustainability goals. These areas focus on evaluating waste treatment options, developing research on waste-to-energy technologies, risk management of MWM systems, and the location selection process for sustainable disposal options. Sustainability concerns have triggered great interest in developing MWM based on cleaner disposal technologies and minimizing environmental and economic problems. Most of the studies addressing the sustainable development of MWM systems usually provide an assessment framework including all pillars; however, such frameworks mostly deal with economic and environmental aspects.

As discussed earlier, the social aspect of MWM systems has not been investigated enough compared to the environmental and economic ones. Recently, a few studies have tried to attract interest in addressing the social qualities of MWM systems. Ak and Braida (2015) applied the analytical hierarchy process (AHP) from a life cycle perspective to determine the sustainability index of the MWM system in Istanbul based on all three pillars. Fragkou et al. (2014) used an interview-based procedure to analyze socio-economic conditions in Barcelona. Ibáñez-Forés et al. (2019) developed a questionnaire-based comprehensive framework to identify social sustainability indicators for MWM systems in developing countries. Chifari et al. (2018) utilized a multi-scale integrated analysis of societal and ecosystem metabolism approaches to analyze the socio-ecological and socio-economic performance of the MWM system of Naples, Italy. Harijani et al. (2017) integrated an optimization model with a social life cycle assessment framework to incorporate the social impacts of MWM on the urban recycling network.

MCDM methods are also frequently applied to address various types of sustainable or waste-related problems for MWM systems. A brief review of recently published studies in this field of research is presented in Table 1.

Table 1
Summary of studies in the field of waste management.

Reference	Social indicators	Methodology	Uncertainty type
Büyüközkan and Gocer (2017)	Hygiene and safety, taking care of human health	TOPSIS	Intuitionistic fuzzy set
Feyzi et al. (2019)	Distance from urban centers, distance from tourist attraction sites	ANP	Triangular fuzzy set
Karagoz et al. (2020)	Local communities influence, public awareness level, affected population, job opportunities	CODAS	Intuitionistic fuzzy set
Yazdani et al. (2020)	Availability of workforce, regulations, satisfaction level of the affected population	BWM	Rough numbers
Mishra et al. (2020)	Waste disposal technology acceptance, the acceptance level of costs	CoCoSo	Pythagorean fuzzy sets
Torkayesh et al. (2021a)	Employment potential, social acceptance	BWM	Stratification concept
Manupati et al. (2021)	Public acceptability, operational safety	VIKOR	Fuzzy logic
Pamučar et al. (2021)	Safety, acceptability, training, health level	BWM, MABAC	D numbers
Zhang et al. (2021)	Impact on surrounding residents	IOWLAD	Pythagorean fuzzy set
Fetanat et al. (2021)	Job creation, public acceptance, safe working environment	ANP, DEMATEL, MULTIMORRA	Fuzzy logic
Puška et al. (2021)	Community acceptance, system security, need for employees	FUCOM, CRADIS	–
Torkayesh and Simic (2021)	Social acceptance, job creation, affected population	Stratified BWM, Constrained WASPAS-CoCoSo	–

Büyüközkan and Gocer (2017) suggested a TOPSIS-based framework with intuitionistic fuzzy sets to analyze hazardous waste management. Using the same type of uncertainty sets, Kahraman et al. (2017) extended the Evaluation based on Distance from Average Solution (EDAS) method to locate a disposal technology for the MWM system of Istanbul. Coban et al. (2018) developed a consolidated MCDM model using TOPSIS and PROMETHEE I & II to select the most suitable waste disposal alternative for Istanbul from a sustainability perspective. Abdullah et al. (2019) proposed an interval-valued intuitionistic fuzzy DEcision-MAking Trial and Evaluation Laboratory (DEMATEL) method and Choquet integral to analyze effective and sustainable waste management system indicators. They found that collaboration and synergy are the most crucial indicators for an MWM system. Alao et al. (2020) integrated Shannon's Entropy and TOPSIS to evaluate waste-to-energy technologies as sustainable options for modern MWM systems in Nigeria, where incineration was selected as the most appropriate option.

To incorporate vagueness and incomplete information into the analysis, Pamučar et al. (2021) suggested a hybrid model based on D numbers and consisting of the Best-Worst Method (BWM) and MABAC to evaluate different strategies in the procurement section of an upgraded healthcare waste management department. Torkayesh et al. (2021b) developed a two-stage uncertain decision model based on grey interval numbers to locate a sanitary landfill for healthcare waste during the COVID-19 pandemic considering sustainability indicators along with geological conditions. Although traditional fuzzy sets and their extensions suffice to incorporate information uncertainty, the higher malleability and efficiency of neutrosophic sets when addressing incomplete information scenarios has led to their application in several waste management studies. Kazimieras Zavadskas et al. (2015) suggested a WASPAS method based on a single-valued neutrosophic set (SVNS) to locate an incineration plant while considering a given set of sustainability factors. Karasan and Bolturk (2019) used the CoCoSo method with IVNS to select the most suitable location for a disposal facility in Istanbul. Rani and Mishra (2020) integrated CoCoSo with similarity measures in the form of SVNS to address electrical waste and the selection of electronic equipment recycling partners under sustainable development conditions in India.

As can be observed, most studies addressing socially sustainable waste management systems have considered life cycle assessment or descriptive techniques. MCDM methods, including uncertain-based versions, also addressed sustainable waste management systems while favoring economic and environmental aspects. Few efforts have been applied to analyze the social sustainability of MWM systems and detect barriers within the system using soft computing approaches. In addition, most studies address uncertain aspects of sustainable MWM through fuzzy techniques that are less reliable and precise than neutrosophic sets. On the other hand, decision models using neutrosophic sets within MCDM methods require complicated calculations far from being straightforward for decision-makers in real-life systems. These shortcomings motivate the introduction of an intuitive soft computing quantitative method designed to detect potential weaknesses in MWSM systems regarding sustainable social development.

2.2. Applications of IVNS to MCDM

Due to the high dynamicity and vagueness in the expressions of decision-makers and experts, uncertainty models built on neutrosophic sets have been consistently integrated with MCDM methods. The wide applicability of neutrosophic set-based MCDM methods has attracted researchers from different academic fields.

For instance, Reddy et al. (2016) integrated AHP and TOPSIS within an IVNS environment to address a supplier selection problem considering lean manufacturing standards. Bolturk and Kahraman (2018) developed an IVNS-AHP model for the selection of energy alternatives

using cosine similarity measures. Karaşan et al. (2019) proposed a new extension of EDAS based on an IVNS environment to evaluate and rank social responsibility projects. Kahraman et al. (2020) extended AHP under SVNS and IVNS to analyze the performance of law firms based on a multicriteria framework. Yazdani et al. (2021) introduced an integrated IVNS-based CRITIC-CoCoSo decision model to address the selection of sustainable suppliers in a dairy company. Deveci and Torkayesh (2021) suggested a novel decision-making model using Shannon's entropy and the Mixed Aggregation by COmprehensive Normalization Technique (MACONT) to select the best charging type for electric buses in Turkey.

2.3. Research gap and contribution

Social sustainability has become one of the most important metrics in waste management systems, particularly in cities with large populations. Thus, an efficient waste management system must incorporate social sustainability problems among its priorities. Even though various studies have been conducted to address similar waste management problems, several important gaps prevail. For instance, most studies dealing with social sustainability challenges in waste management have focused on descriptive techniques and literature reviews to analyze the previous and current situation (Hua et al., 2021; Knickmeyer, 2020). To address this gap, quantitative and qualitative studies have been recently conducted based on MCDM methods such as DEMATEL, BWM, and the Analytical Network Process (ANP) (Alidoosti et al., 2021; Bui et al., 2020; Tsai et al., 2021). Although these studies propose systematic methodologies to maximize the reliability of the results for social sustainability in WM, a couple of drawbacks must be highlighted:

- First, experts and decision-makers in the fields of social sustainability and waste management are not completely familiar with complex MCDM methods such as DEMTAEL or ANP. This leads to very time-consuming and complex implementation processes.
- Second, most of these studies fail to consider the degree of uncertainty inherent to the judgments of decision-makers.

We address these two gaps by developing a soft computing-based approach sufficiently simple to be used by experts from different research areas. We empower experts to express their opinions and judgments using linguistics terms via IVNS, which allows them to account for real-life uncertainty through three different membership functions. This technique can be very useful for experts and decision-makers in the field of waste management due to the qualitative nature of most problems. In this regard, we propose a comprehensive framework based on 17 indicators and identify the role played by each one of them in the adoption and implementation of social sustainability strategies in MWM systems.

3. Preliminaries

This section presents basic requirements and the most common definitions and operations of IVNS. The notation used through this section is standard, with inf and sup referring to the infimum and supremum of a given set, respectively. The remaining notations used to define and operate with IVNS are described below.

Notations	
X	Space of points
$T_A(x)$	Truth-membership function
$T_A^L(x)$	Lower truth-membership function value
$T_A^U(x)$	Upper truth-membership function value
$I_A(x)$	Indeterminacy-membership function
$I_A^L(x)$	Lower indeterminacy-membership function value
$I_A^U(x)$	Upper indeterminacy-membership function value
$F_A(x)$	Falsity-membership function
$F_A^L(x)$	Lower falsity-membership function value
$F_A^U(x)$	Upper falsity-membership function value
α	Constant non-negative value
w_j	Weight of indicator j

Definition 1. (Smarandache, 1999; Zhang et al., 2014). Let X be a space of points (x ∈ X). A neutrosophic set (NS) A in X consists of a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$ and a falsity-membership function $F_A(x)$, where $T_A(x)$, $I_A(x)$ and $F_A(x)$ are subsets of $^-0,\ 1^+[.T_A(x): X\rightarrow]^-0,\ 1^+[, \mathrm{I}_A(x): X\rightarrow]^-0, 1^+[$ *and* $F_A(x): X\rightarrow]^-0, 1^+]$. Since there exists no constraint on the summation of membership functions, $0- \leq supT_A(x) + supI_A(x) + supF_A(x) \leq 3+$.

Definition 2. (Smarandache, 1999; Zhang et al., 2014, 2016). An IVNS A over X is an object taking the form $A = \{< x,\ T_A(x),\ I_A(x),\ F_A(x) >: x \in X\}$, where $T_A(x): x\rightarrow[0,1]$, $I_A(x): x\rightarrow[0,1]$ and $F_A(x): x\rightarrow[0,1]$, with $0 \leq supT_A(x) + supI_A(x) + supF_A(x) \leq 3$ for all $x \in X$. In this regard, an IVN number (IVNN) is defined as

$$A=\{<x,[\inf T_A(x),\sup T_A(x)],[\inf I_A(x),\sup I_A(x)],[\inf F_A(x),\sup F_A(x)]>:x\in X\} \tag{1}$$

where $\inf T_A(x)$ and $\sup T_A(x)$ are denoted by $T_A^L(x)$ and $T_A^U(x)$, respectively, $\inf I_A(x)$ and $\sup I_A(x)$ by $I_A^L(x)$ and $I_A^U(x)$, and $\inf F_A(x)$ and $\sup F_A(x)$ by $F_A^L(x)$ and $F_A^U(x)$.

Therefore, an IVNN can be defined via $A = ([T^L, T^U], [I^L, I^U], [F^L, F^U])$.

Definition 3. The main arithmetic operations between two IVNNs $A =< [T_A^L(x), T_A^U(x)], [I_A^L(x),\ I_A^U(x)], [F_A^L(x),\ F_A^U(x)]\rangle$ and $B =< [T_B^L(x), T_B^U(x)],\ [I_B^L(x),\ I_B^U(x)],\ [F_B^L(x),\ F_B^U(x)]\rangle$ can be defined using the following equations (Hussain et al., 2019; Zhang et al., 2016):

$$\alpha A = < \left[1-\left(1-T_A^L(x)\right)^\alpha, 1-\left(1-T_A^U(x)\right)^\alpha\right],\ \left[\left(I_A^L(x)\right)^\alpha, I_A^U(x))^\alpha\right], \left(F_A^L(x)\right)^\alpha, F_A^U(x))^\alpha] > \tag{2}$$

$$A^\alpha = < \left[\left(T_A^L(x)\right)^\alpha, \left(T_A^U(x)\right)^\alpha\right],\ \left[1-\left(1-I_A^L(x)\right)^\alpha, 1-\left(1-I_A^U(x)\right)^\alpha\right],\ \left[1-\left(1-F_A^L(x)\right)^\alpha, 1-\left(1-F_A^U(x)\right)^\alpha\right] > \tag{3}$$

$$A+B = < \left[T_A^L(x)+T_B^L(x)-T_A^L(x).T_B^L(x),\ T_A^U(x)+T_B^U(x)-T_A^U(x).T_B^U(x)\right],\ \left[I_A^L(x).I_B^L(x), I_A^U(x).I_B^U(x)\right],\ \left[F_A^L(x).F_B^L(x), F_A^U(x).F_B^U(x)\right] > \tag{4}$$

$$A-B = < \left[T_A^L(x)-T_B^U(x), T_A^U(x)-T_B^L(x)\right],\ \left[\max\left(I_A^L(x), I_B^L(x)\right), \max\left(I_A^U(x), I_B^U(x)\right)\right],\ \left[F_A^L(x)-F_B^U(x), F_A^U(x)-F_B^L(x)\right] > \tag{5}$$

$$A.B = < \left[T_A^L(x).T_B^L(x), T_A^U(x).T_B^U(x)\right], \left[I_A^L(x)+I_B^L(x)-I_A^L(x).I_B^L(x), I_A^U(x)+I_B^U(x)-I_A^U(x).I_B^U(x)\right], \left[F_A^L(x)+F_B^L(x)-F_A^L(x).F_B^L(x), F_A^U(x)+F_B^U(x)-F_A^U(x).F_B^U(x)\right] > \tag{6}$$

$$\frac{A}{\alpha} = < \left[min\left(\frac{T_A^L(x)}{\alpha}, 1\right), min\left(\frac{T_A^U(x)}{\alpha}, 1\right)\right], \left[\min\left(\frac{I_A^L(x)}{\alpha}, 1\right), min\left(\frac{I_A^U(x)}{\alpha}, 1\right)\right], \left[\min\left(\frac{F_A^L(x)}{\alpha}, 1\right), min\left(\frac{F_A^U(x)}{\alpha}, 1\right)\right] > \tag{7}$$

$$\begin{aligned}\frac{A}{B} = < &\left[\min\left\{\frac{T_A^L(x)}{T_B^L(x)}, \frac{T_A^L(x)}{T_B^U(x)}, \frac{T_A^U(x)}{T_B^L(x)}, \frac{T_A^U(x)}{T_B^U(x)}\right\}, \max\left\{\frac{T_A^L(x)}{T_B^L(x)}, \frac{T_A^L(x)}{T_B^U(x)}, \frac{T_A^U(x)}{T_B^L(x)}, \frac{T_A^U(x)}{T_B^U(x)}\right\}\right], \left[\min\left\{\frac{I_A^L(x)}{I_B^L(x)}, \frac{I_A^L(x)}{I_B^U(x)}, \frac{I_A^U(x)}{I_B^L(x)}, \frac{I_A^U(x)}{I_B^U(x)}\right\}, \max\left\{\frac{I_A^L(x)}{I_B^L(x)}, \frac{I_A^L(x)}{I_B^U(x)}, \frac{I_A^U(x)}{I_B^L(x)}, \frac{I_A^U(x)}{I_B^U(x)}\right\}\right], \\ &\left[\min\left\{\frac{F_A^L(x)}{F_B^L(x)}, \frac{F_A^L(x)}{F_B^U(x)}, \frac{F_A^U(x)}{F_B^L(x)}, \frac{F_A^U(x)}{F_B^U(x)}\right\}, \max\left\{\frac{F_A^L(x)}{F_B^L(x)}, \frac{F_A^L(x)}{F_B^U(x)}, \frac{F_A^U(x)}{F_B^L(x)}, \frac{F_A^U(x)}{F_B^U(x)}\right\}\right]\end{aligned} \tag{8}$$

$$A^{-1} = < \left[\left(T_A^L(x)\right)^{-1}, \left(T_A^U(x)\right)^{-1}\right], \left[\left(I_A^L(x)\right)^{-1}, \left(I_A^U(x)\right)^{-1}\right], \left[\left(F_A^L(x)\right)^{-1}, \left(F_A^U(x)\right)^{-1}\right] > \tag{9}$$

We now define the interval neutrosophic weighted arithmetic averaging (INWAA) and the interval neutrosophic weighted geometric averaging (INWGA) operators (Zhang et al., 2016). Assume that a_j $(j = 1, 2, \ldots, n)$ is a collection of IVNNs and w_j is the weight assigned to a_j $(j = 1, 2, \ldots, n)$, where $w_j \in [0, 1]$ and $\sum_{j=1}^{n} w_j = 1$. The INWAA operator is defined as follows:

$$(a_1, a_2, \ldots, a_n) = \sum_{j-1}^{n} w_j a_j = < \left[1 - \prod_{j=1}^{n}\left(1 - T_j^L\right)^{w_j}, 1 - \prod_{j=1}^{n}\left(1 - T_j^U\right)^{w_j}\right], \left[\prod_{j=1}^{n}\left(I_j^L\right)^{w_j}, \prod_{j=1}^{n}\left(I_j^U\right)^{w_j}\right], \left[\prod_{j=1}^{n}\left(F_j^L\right)^{w_j}, \prod_{j=1}^{n}\left(F_j^U\right)^{w_j}\right] > \tag{10}$$

while the INWGA operator is given by:

$$\begin{aligned}(a_1, a_2, \ldots, a_n) = \prod_{j=1}^{n} a_j^{w_j} =< &\left[\prod_{j=1}^{n}\left(T_j^L\right)^{w_j}, \prod_{j=1}^{n}\left(T_j^U\right)^{w_j}\right], \\ &\left[1 - \prod_{j=1}^{n}\left(1 - I_j^L\right)^{w_j}, 1 - \prod_{j=1}^{n}\left(1 - I_j^U\right)^{w_j}\right], \\ &\left[1 - \prod_{j=1}^{n}\left(1 - F_j^L\right)^{w_j}, 1 - \prod_{j=1}^{n}\left(1 - F_j^U\right)^{w_j}\right] >\end{aligned} \tag{11}$$

Let A and B two IVNNs of the form $A =< [T_A^L(x), T_A^U(x)], [I_A^L(x), I_A^U(x)], [F_A^L(x), F_A^U(x)]\rangle$ and $B = < [T_B^L(x), T_B^U(x)], [I_B^L(x), I_B^U(x)], [F_B^L(x), F_B^U(x)]\rangle$. The Hamming distance value between A and B can be calculated as follows (Chi and Liu, 2013):

$$D_H(A, B) = \frac{1}{6}\left(\begin{array}{l}\left|T_A^L(x) - T_B^L(x)\right| + \left|T_A^U(x) - T_B^U(x)\right| + \left|I_A^L(x) - I_B^L(x)\right| + \\ \left|I_A^U(x) - I_B^U(x)\right| + \left|F_A^L(x) - F_B^L(x)\right| + \left|F_A^U(x) - F_B^U(x)\right|\end{array}\right) \tag{12}$$

while the Euclidean distance is given by:

$$D_E(A, B) = \sqrt{\left(\frac{1}{6}\left(\begin{array}{l}\left(T_A^L(x) - T_B^L(x)\right)^2 + \left(T_A^U(x) - T_B^U(x)\right)^2 + \left(I_A^L(x) - I_B^L(x)\right)^2 + \\ \left(I_A^U(x) - I_B^U(x)\right)^2 + \left(F_A^L(x) - F_B^L(x)\right)^2 + \left(F_A^U(x) - F_B^U(x)\right)^2\end{array}\right)\right)} \tag{13}$$

Ye and Du (2019) defined two new distance measures for IVNNs A and B as follows:

$$\begin{aligned}D_Y(A, B) = \frac{1}{3}\Big(&\max\Big[\left|T_A^L(x) - T_B^L(x)\right|, \\ &\left|T_A^U(x) - T_B^U(x)\right|\Big] + \max\left|I_A^L(x) - I_B^L(x)\right|, \\ &\left|I_A^U(x) - I_B^U(x)\right| + \max\left|F_A^L(x) - F_B^L(x)\right|, \\ &\left|F_A^U(x) - F_B^U(x)\right|\Big)\end{aligned} \tag{14}$$

$$\begin{aligned}D_Z(A, B) = \max\Big[&\frac{1}{2}\left(\left|T_A^L(x) - T_B^L(x)\right| + \left|T_A^U(x) - T_B^U(x)\right|\right), \frac{1}{2}\left(\left|I_A^L(x) - I_B^L(x)\right|\right. \\ &\left. + \left|I_A^U(x) - I_B^U(x)\right|\right), \frac{1}{2}\left(\left|F_A^L(x) - F_B^L(x)\right| + \left|F_A^U(x) - F_B^U(x)\right|\right)\Big]\end{aligned} \tag{15}$$

We will refer to these measures as the Y-based and Z-based distance measure hereafter. According to Chi and Liu (2013), the absolute positive and negative ideal solutions for IVNS are defined as $\pi^+ =< [1, 1], [0, 0], [0, 0] >$ and $\pi^- = < [0, 0], [1, 1], [1, 1] >$. According to Eq. (12), Hamming distance between an IVNN such as A, π^+, and π^- is given by:

$$D_H(A, \pi^+) = \frac{1}{6}\left(\begin{array}{l}\left|T_A^L(x) - 1\right| + \left|T_A^U(x) - 1\right| + \left|I_A^L(x) - 0\right| + \\ \left|I_A^U(x) - 0\right| + \left|F_A^L(x) - 0\right| + \left|F_A^U(x) - 0\right|\end{array}\right) \tag{16}$$

$$D_H(A, \pi^-) = \frac{1}{6}\left(\begin{array}{l}\left|T_A^L(x) - 0\right| + \left|T_A^U(x) - 0\right| + \left|I_A^L(x) - 1\right| + \\ \left|I_A^U(x) - 1\right| + \left|F_A^L(x) - 1\right| + \left|F_A^U(x) - 1\right|\end{array}\right) \tag{17}$$

Similarly, according to Eq. (11), the Euclidean distance between an IVNN such as A, π^+, and π^- is defined as follows:

Table 2
Linguistic terms for performance scoring and weighting.

Weight importance	Performance score	Interval-valued neutrosophic value
Not important (NI)	Certainly low (CL)	[0.1, 0.2], [0.1, 0.2], [0.8, 0.9]
Very low importance (VLI)	Very low (VL)	[0.2, 0.3], [0.3, 0.4], [0.7, 0.8]
Low importance (LI)	Low (L)	[0.3, 0.4], [0.4, 0.5], [0.6, 0.7]
Fairly low importance (FLI)	Below average (BA)	[0.4, 0.5], [0.5, 0.6], [0.5, 0.6]
Medium importance (MI)	Average (A)	[0.5, 0.5], [0.6, 0.7], [0.4, 0.5]
Fairly high importance (FHI)	Above average (AA)	[0.5, 0.6], [0.5, 0.6], [0.4, 0.5]
High importance (HI)	High (H)	[0.6, 0.7], [0.4, 0.5], [0.3, 0.4]
Very high importance (VHI)	Very high (VH)	[0.7, 0.8], [0.2, 0.3], [0.2, 0.3]
Extreme importance (EI)	Certainly high (CH)	[0.8, 0.9], [0.1, 0.2], [0.1, 0.2]

$$D_E(A,\pi^+)=\sqrt{\left(\frac{1}{6}\left(\begin{array}{l}\left(T_A^L(x)-1\right)^2+\left(T_A^U(x)-1\right)^2+\left(I_A^L(x)-0\right)^2+\\ \left(I_A^U(x)-0\right)^2+\left(F_A^L(x)-0\right)^2+\left(F_A^U(x)-0\right)^2\end{array}\right)\right)} \tag{18}$$

$$D_H(A,\pi^-)=\sqrt{\left(\frac{1}{6}\left(\begin{array}{l}\left(T_A^L(x)-0\right)^2+\left(T_A^U(x)-0\right)^2+\left(I_A^L(x)-1\right)^2+\\ \left(I_A^U(x)-1\right)^2+\left(F_A^L(x)-1\right)^2+\left(F_A^U(x)-1\right)^2\end{array}\right)\right)} \tag{19}$$

Finally, based on Eq. (14), the Y-based distance between an IVNN such as A, π^+, and π^- is given by:

$$\begin{aligned}D_Y(A,\pi^+)=\frac{1}{3}\Big(&\max\Big[\left|T_A^L(x)-1\right|,\\ &\left|T_A^U(x)-1\right|\Big]+\max\Big[\left|I_A^L(x)-0\right|,\\ &\left|I_A^U(x)-0\right|\Big]+\max\Big[\left|F_A^L(x)-0\right|+\left|F_A^U(x)-0\right|\Big]\Big)\end{aligned} \tag{20}$$

$$\begin{aligned}D_Y(A,\pi^-)=\frac{1}{3}\Big(&\max\Big[\left|T_A^L(x)-0\right|,\\ &\left|T_A^U(x)-0\right|\Big]+\max\Big[\left|I_A^L(x)-1\right|,\\ &\left|I_A^U(x)-1\right|\Big]+\max\Big[\left|F_A^L(x)-1\right|+\left|F_A^U(x)-1\right|\Big]\Big)\end{aligned} \tag{21}$$

while Eq. (15) defines the corresponding Z-based distance as follows:

$$\begin{aligned}D_Z(A,\pi^+)=\max\Big[&\frac{1}{2}\left(\left|T_A^L(x)-1\right|+\left|T_A^U(x)-1\right|\right),\ \frac{1}{2}\left(\left|I_A^L(x)-0\right|+\left|I_A^U(x)\right.\right.\\ &\left.\left.-0\right|\right),\ \frac{1}{2}\left(\left|F_A^L(x)-0\right|+\left|F_A^U(x)-0\right|\right)\end{aligned} \tag{22}$$

$$\begin{aligned}D_Z(A,\pi^-)=\max\Big[&\frac{1}{2}\left(\left|T_A^L(x)-0\right|+\left|T_A^U(x)-0\right|\right),\ \frac{1}{2}\left(\left|I_A^L(x)-1\right|+\left|I_A^U(x)\right.\right.\\ &\left.\left.-1\right|\right),\ \frac{1}{2}\left(\left|F_A^L(x)-1\right|+\left|F_A^U(x)-1\right|\right)\end{aligned} \tag{23}$$

The approach proposed defines an integrated distance measure that computes the arithmetic weighted average of the distance measures against π^+ and π^-. In this regard, the weight coefficients, λ, composing the weighted arithmetic formula are assigned a value of 0.25 for the Hamming, Euclidean, Y-based, and Z-based distance measures as follows:

$$d(A,\pi^+)=0.25\ D_H(A,\pi^+)+0.25\ D_E(A,\pi^+)+0.25\ (A,\pi^+)+0.25\ D_Z(A,\pi^+) \tag{24}$$

$$d(A,\pi^-)=0.25\ D_H(A,\pi^-)+0.25\ D_E(A,\pi^-)+0.25\ (A,\pi^-)+0.25\ D_Z(A,\pi^-) \tag{25}$$

The closeness index of an IVNN A against the negative and positive ideal solutions is given by:

$$\omega(A)=\frac{d(A,\pi^-)}{d(A,\pi^-)+d(A,\pi^+)} \tag{26}$$

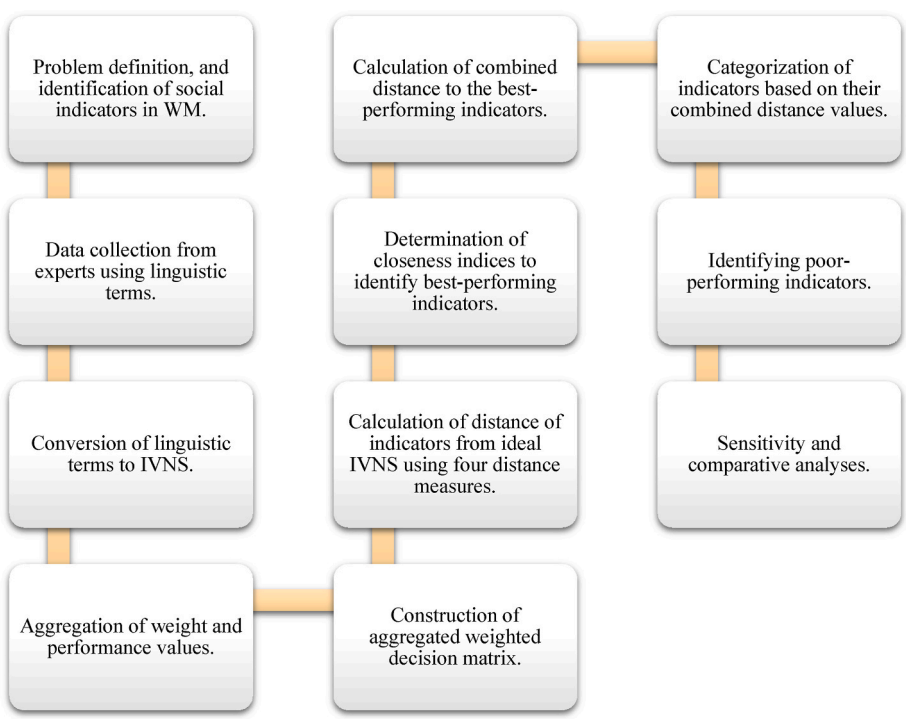

Fig. 1. Proposed approach.

4. Multi-distance IVNS approach

This section presents a detailed overview of the steps composing the algorithm proposed to detect social weaknesses and strengths in sustainable MWM systems. Similarly to other decision-making problems, the proposed method includes a set of indicators (criteria/factors) that are evaluated and prioritized based on relative weight coefficients and performance scores. The evaluation of criteria is performed after assigning the relative weight coefficients and performance scores. In this regard, the performance scores of the criteria generate a matrix named IVNS decision matrix (IVNSDM), while the weight coefficients define a matrix labeled IVNS weight matrix (IVNSWM).

The IVNSDM and IVNSWM matrices are filled by either one or several experts using the linguistic preferences described in Table 2 (Karaşan et al., 2019). Three important advantages of the proposed approach are its straightforward soft computing nature, its capability to tackle decision-making problems with IVNS, which are better suited than SVNS to analyze uncertainty, and its reliability on four different distance measures relative to the corresponding ideal solution. For a decision-making problem with n criteria, the IVNSDM is defined as follows.

Table 3
Social indicators of MWM from a sustainability perspective.

Category	Indicators	Reference
Working rights	Freedom of association and negotiation (C1)	(Ibáñez-Forés et al., 2019; Yıldız-Geyhan et al., 2017)
	Child labor (C2)	(Azimi et al., 2020; Ferrão et al., 2014; Ibáñez-Forés et al., 2019)
Equity	Labor regulations (C3)	(Ambati, 2019; Lu et al., 2017; Tsai et al., 2021; Yıldız-Geyhan et al., 2017)
	Labor from low-class communities (C4)	(Azimi et al., 2020; Wen et al., 2015)
	Gender equity (C5)	(Azimi et al., 2020; Ferrão et al., 2014; Ibáñez-Forés et al., 2019)
Working quality	Salary satisfaction (C6)	(Fragkou et al., 2014; Tsai et al., 2021)
	Working hours (C7)	(Azimi et al., 2020; de Souza et al., 2016; Yıldız-Geyhan et al., 2017)
	Legal employment (C8)	(Godfrey et al., 2017; Hajar et al., 2020; Torkayesh et al., 2021a)
	Workers with health insurance (C9)	(de Souza et al., 2016; Ibáñez-Forés et al., 2019)
Awareness	Environmental and social awareness and responsibility of workers (C10)	(Knickmeyer, 2020; Yıldız-Geyhan et al., 2017)
	Education level of workers (C11)	(Ibáñez-Forés et al., 2019; Yıldız-Geyhan et al., 2017)
	Hygiene lifestyle of workers (C12)	(Azimi et al., 2020; de Souza et al., 2016)
	Participation of citizens (C13)	Knickmeyer (2020)
Cooperation of government & employees	Public commitment to sustainability guidelines (C14)	(Hua et al., 2021; Tsai et al., 2021)
	Organizational corruption (C15)	(Al Sabbagh et al., 2012; Ibáñez-Forés et al., 2019; Santos et al., 2019)
	Local employment (C16)	(Hajar et al., 2020; Wen et al., 2015)
	Participation of non-governmental organizations (C17)	(Ak and Braida, 2015; Esmaeilian et al., 2018; Wen et al., 2015)

$$IVNSDM=\begin{bmatrix}\gamma_1\\ \gamma_2\\ \vdots\\ \gamma_n\end{bmatrix}=\begin{bmatrix}<\left[T^L_{\gamma_1}(x),T^U_{\gamma_1}(x)\right],\left[I^L_{\gamma_1}(x),I^U_{\gamma_1}(x)\right],\left[F^L_{\gamma_1}(x),F^U_{\gamma_1}(x)\right]>\\ <\left[T^L_{\gamma_2}(x),T^U_{\gamma_2}(x)\right],\left[I^L_{\gamma_2}(x),I^U_{\gamma_2}(x)\right],\left[F^L_{\gamma_2}(x),F^U_{\gamma_2}(x)\right]>\vdots\\ <\left[T^L_{\gamma_n}(x),T^U_{\gamma_n}(x)\right],\left[I^L_{\gamma_n}(x),I^U_{\gamma_n}(x)\right],\left[F^L_{\gamma_n}(x),F^U_{\gamma_n}(x)\right]>\end{bmatrix} \tag{27}$$

Similarly, the IVNSWM is defined as

$$IVNSWM=\begin{bmatrix}\nu_1\\ \nu_2\\ \vdots\\ \nu_n\end{bmatrix}=\begin{bmatrix}<\left[T^L_{\nu_1}(x),T^U_{\nu_1}(x)\right],\left[I^L_{\nu_1}(x),I^U_{\nu_1}(x)\right],\left[F^L_{\nu_1}(x),F^U_{\nu_1}(x)\right]>\\ <\left[T^L_{\nu_2}(x),T^U_{\nu_2}(x)\right],\left[I^L_{\nu_2}(x),I^U_{\nu_2}(x)\right],\left[F^L_{\nu_2}(x),F^U_{\nu_2}(x)\right]>\vdots\\ <\left[T^L_{\nu_n}(x),T^U_{\nu_n}(x)\right],\left[I^L_{\nu_n}(x),I^U_{\nu_n}(x)\right],\left[F^L_{\nu_n}(x),F^U_{\nu_n}(x)\right]>\end{bmatrix} \tag{28}$$

Both matrices in Eqs. 27 and 28 are used to construct an IVNS weighted decision matrix (IVNSWDM) by multiplying the performance scores and weight coefficients according to Eq. (29).

$$IVNSWDM=\begin{bmatrix}\gamma_1\nu_1\\ \gamma_2\nu_2\\ \vdots\\ \gamma_n\nu_n\end{bmatrix}=\begin{bmatrix}\psi_1\\ \psi_2\\ \vdots\\ \psi_n\end{bmatrix} \tag{29}$$

The ψ_1 values are calculated using Eq. (6) described in the preliminaries.

As discussed earlier, the proposed approach uses the IVNSWDM matrix to determine the distance of each element from the ideal solution, which is defined as the criterion with the best weighted-performance value among all criteria. In the next step, Eq. (26) is used to calculate the closeness index of each criterion $\omega(\psi_i)$. The criterion with the highest $\omega(\psi_i)$ value is considered the criterion with best performing value (ψ^*). The distance measures are defined in Eqs. (16-23) are then calculated, and Eqs. (24-25) are used to integrate the values obtained from the four distance measures. Fig. 1 presents a detailed step-by-step algorithm of the proposed approach.

5. Case study

This section presents a case study that investigates the social sustainability performance of the Turkish MWM system in Istanbul to show the applicability of the proposed approach to analyze real-life scenarios. Istanbul is the biggest city in Turkey with over 15 million, leading to a high waste generation rate, particularly during the recent decades. According to the Organization for Economic Co-operation and Development (OECD), the estimated amount of waste generated in Turkey was 35,017 tons in 2019, almost 90% of which was dealt with through landfilling (OECD, 2019). With its high population, MWM practices in Istanbul have been mostly limited to economic and environmental aspects. A review of previous studies on sustainable waste management for Istanbul leads to the conclusion that the primary goal of such studies was to address environmental and economic issues rather than social ones (Bahçelioğlu et al., 2020; Büyüközkan and Gocer, 2017; Coban et al., 2018). Due to the high population and waste generation rates, related governmental departments in Turkey have introduced strategic plans to implement sustainable practices named "National Action Plan for Waste Management 2023" and "Zero Waste." However, since social indicators play a significant role in developing a sustainable integrated MWM system that maximizes social benefits and minimizes disadvantages, this study investigates social sustainability indicators for the development of a sustainable MWM system in Istanbul.

In this regard, identifying weaknesses among the social indicators is important so that the required practices and strategies can be implemented accordingly. With this objective in mind, Table 3 represents a set

Table 4
Linguistic preferences of experts.

Indicators	Weight coefficient	Performance score
Freedom of association and negotiation (C1)	LI, NI, NI	VL, L, VL
Child labor (C2)	HI, VHI, EI	VL, BA, L
Labor regulations (C3)	HI, VHI, EI	VL, BA, VL
Labor from low-class communities (C4)	MI, HI, FHI	CL, L, L
Gender equity (C5)	FLI, HI, VHI,	BA, L, L
Salary satisfaction (C6)	EI, EI, EI	CH, CH, CH
Working hours (C7)	MI, MI, FHI	AA, A, BA
Legal employment (C8)	FLI, MI, MI	BA, VL, L
Workers with health insurance (C9)	EI, EI, EI	CH, CH, CH
Environmental awareness and responsibility of workers (C10)	FLI, FLI, MI	VL, L, A
Education level of workers (C11)	MI, MI, MI	H, H, H
Hygiene lifestyle of workers (C12)	FHI, FHI, HI	VH, A, A
Participation of citizens (C13)	LI, VLI, NI	L, L, A
Public commitment to sustainability guidelines (C14)	VHI, HI, FHI	A, H, A
Organizational corruption (C15)	MI, HI, FLI	L, BA, BA
Local employment (C16)	MI, VLI, NI	CH, VH, H
Participation of non-governmental organizations (C17)	EI, HI, FHI	BA, VH, A

of social indicators collected from the literature that contribute substantially to the social sustainability pillar. These indicators should allow authorities to analyze the MWM system in Istanbul and apply the corresponding measures to improve its social sustainability performance.

As illustrated in Table 3, social indicators are classified into five categories, namely, working rights, equity, working quality, awareness, and cooperation of government & employees. Within the first category, freedom of association and negotiation (C1) refers to the capacity of workers to organize meetings as well as the level of restriction imposed on association and collective procedures. Child labor (C2) measures the percentage of children aged 5–17 working in different waste management and MWM processes.

Within the second category, labor regulations (C3) describe the alignment of local regulations with labor standards. Labor from low-class communities (C4) denotes the level of involvement of low-class communities in waste management and MWM supply chain procedures. Gender equity (C5) measures the share of women and men in different departments and operations of MWM supply chains.

The third category summarizes the quality of MWM working conditions. Salary satisfaction (C6) denotes the satisfaction level of workers with their monthly salary in MWM supply chains. Working hours (C7) describes the satisfaction of workers with the amount of working hours in different MWM processes. Waste management is a critical environmental system particularly concerned with the use of illegal employment. Thus, legal employment (C8) compares the percentage of legally working employees in the MWM system relative to the national one. Since MWM processes and operations are deeply connected with health issues, workers with health insurance (C9) measures the average rate of workers who have health insurance as a percentage of the total number of workers in MWM.

Within the fourth category, environmental and social awareness and responsibility of workers (C10) highlights the importance of worker awareness regarding environmental and social goals and directives. The education level of workers (C11) reports the average academic and educational background of MWM workers. Hygiene lifestyle of workers (C12) evaluates their degree of cleanness and that of their environment through the MWM treatment processes. Participation of citizens (C13) describes the rate of citizen participation in achieving environmental and social targets within cities while accounting for their relative population.

The fifth and final category derives from the importance assigned to the concept of sustainability in different infrastructures and urban systems. In this regard, the commitment of citizens is measured by their public commitment to sustainability guidelines (C14). The remaining indicators composing the category focus on organizational corruption (C15), which describes the degree of corruption in organizational affairs based on public expenditure and related to MWM, local employment (C16), indicating the rate of employment in MWM processes derived from local labor sources, and participation of non-governmental organizations (C17), denoting the involvement of private organizations in addressing MWM problems.

Table 5
Aggregated weight importance and performance score.

Indicators	Aggregated IVNSWM	Aggregated IVNSDM
C1	<[0.172,0.273],[0.159,0.271],[0.727,0.828]>	<[0.235,0.335],[0.33,0.431],[0.665,0.765]>
C2	<[0.712,0.818],[0.2,0.311],[0.182,0.288]>	<[0.305,0.406],[0.391,0.493],[0.594,0.695]>
C3	<[0.712,0.818],[0.2,0.311],[0.182,0.288]>	<[0.273,0.374],[0.356,0.458],[0.626,0.727]>
C4	<[0.536,0.609],[0.493,0.594],[0.363,0.464]>	<[0.32,0.379],[0.288,0.412],[0.577,0.68]>
C5	<[0.584,0.689],[0.342,0.448],[0.311,0.416]>	<[0.335,0.435],[0.431,0.531],[0.565,0.665]>
C6	<[0.8,0.9],[0.1,0.2],[0.1,0.2]>	<[0.8,0.9],[0.1,0.2],[0.1,0.2]>
C7	<[0.5,0.536],[0.565,0.665],[0.4,0.5]>	<[0.469,0.536],[0.531,0.632],[0.431,0.531]>
C8	<[0.469,0.5],[0.565,0.665],[0.431,0.531]>	<[0.305,0.406],[0.391,0.493],[0.594,0.695]>
C9	<[0.8,0.9],[0.1,0.2],[0.1,0.2]>	<[0.8,0.9],[0.1,0.2],[0.1,0.2]>
C10	<[0.435,0.5],[0.531,0.632],[0.464,0.565]>	<[0.346,0.406],[0.416,0.519],[0.552,0.654]>
C11	<[0.5,0.5],[0.6,0.7],[0.4,0.5]>	<[0.6,0.7],[0.4,0.5],[0.3,0.4]>
C12	<[0.536,0.637],[0.464,0.565],[0.363,0.464]>	<[0.578,0.632],[0.416,0.528],[0.317,0.422]>
C13	<[0.204,0.305],[0.229,0.342],[0.695,0.796]>	<[0.374,0.435],[0.458,0.559],[0.524,0.626]>
C14	<[0.609,0.712],[0.342,0.448],[0.288,0.391]>	<[0.536,0.578],[0.524,0.626],[0.363,0.464]>
C15	<[0.507,0.578],[0.493,0.594],[0.391,0.493]>	<[0.368,0.469],[0.464,0.565],[0.531,0.632]>
C16	<[0.289,0.346],[0.262,0.383],[0.607,0.711]>	<[0.712,0.818],[0.2,0.311],[0.182,0.288]>
C17	<[0.658,0.771],[0.271,0.391],[0.229,0.342]>	<[0.552,0.632],[0.391,0.501],[0.342,0.448]>

The first column of Table 5 represents the name of the social indicators in abbreviated form. The second column describes the aggregated IVNSWM values, namely, the aggregated weight importance of the criteria. Finally, the last column corresponds to the aggregated IVNSDM values, that is, the aggregated performance score per criterion.

Table 6
IVNSWDM, closeness index, and distance of indicators to C^*.

Indicators	IVNSWDM	$\omega(\xi_i)$	$d(C_i, C^*)$
C1	<[0.04,0.092],[0.437,0.585],[0.908,0.96]>	0.2678	0.574
C2	<[0.217,0.332],[0.513,0.651],[0.668,0.783]>	0.3405	0.422
C3	<[0.194,0.306],[0.485,0.626],[0.694,0.806]>	0.3383	0.435
C4	<[0.171,0.23],[0.639,0.762],[0.731,0.829]>	0.2558	0.505
C5	<[0.196,0.3],[0.626,0.741],[0.7,0.804]>	0.2843	0.468
C6	<[0.64,0.81],[0.19,0.36],[0.19,0.36]>	**0.7140**	0.000
C7	<[0.234,0.287],[0.796,0.877],[0.659,0.766]>	0.2490	0.518
C8	<[0.143,0.203],[0.735,0.83],[0.769,0.857]>	0.2033	0.549
C9	<[0.64,0.81],[0.19,0.36],[0.19,0.36]>	**0.7140**	0.000
C10	<[0.151,0.203],[0.726,0.823],[0.76,0.849]>	0.2099	0.543
C11	<[0.3,0.35],[0.76,0.85],[0.58,0.7]>	0.3034	0.469
C12	<[0.31,0.402],[0.687,0.794],[0.566,0.69]>	0.3359	0.422
C13	<[0.076,0.133],[0.582,0.71],[0.855,0.924]>	0.2289	0.571
C14	<[0.326,0.411],[0.687,0.793],[0.547,0.674]>	0.3458	0.415
C15	<[0.187,0.271],[0.728,0.823],[0.715,0.813]>	0.2374	0.507
C16	<[0.205,0.283],[0.41,0.574],[0.679,0.795]>	0.3638	0.421
C17	<[0.363,0.487],[0.557,0.697],[0.493,0.637]>	0.4142	0.328

5.1. Results

In the first step, three experts with professional experience in waste management were invited to participate in the case study. The team of experts includes two males – with more than 7 years of experience in waste management – and one female – with 5 years of experience in environmental management – who work as directors in a waste management company in Istanbul, Turkey. The experts and the company were selected based on their managerial and technical expertise in MWM systems. In order to collect the initial data, experts independently answered a questionnaire regarding the performance of the waste management system in terms of the social indicators selected. Their judgments were used as input data to construct the IVNSDM and IVNSWM matrices through the linguistic terms described in Table 2. Table 4 shows the opinions of the experts regarding the weight coefficient and performance scores of the social indicators.

The weight and performance opinions described in Table 4 are aggregated into IVNNs using the INWAA operator. The resulting expressions will be used to construct the aggregated IVNSWM and IVNSDM, respectively. An important assumption whose consequences will be analyzed through different sensitivity analyses is the fact that the opinions of experts are assumed to be equally important through the aggregation process. Table 5 presents the elements of the IVNSDM and IVNSWM matrices for each of the criteria being analyzed.

In order to provide additional intuition regarding the mathematical operations performed, an explicit description of the calculations involving C6 is provided below.

Table 7
Impact of decision-makers importance on the results.

Scenarios	DM1	DM2	DM3	Best	Satisfactory	Weak
Reference	1/3	1/3	1/3	C6, C9	C2,C3,C5,C11, C12,C14,C16,C17	C1,C4,C7,C8, C10,C13,C15
S1	1	0	0	C6, C9	C11,C12,C14, C16,C17	C1,C2,C3,C4, C5,C7,C8, C10,C13,C15
S2	0	1	0	C6, C9	C2,C3,C4,C5,C11, C14,C15,C16, C17	C1,C7,C8, C10,C12,C13
S3	0	0	1	C6, C9	C2,C3,C5,C11, C12	C1,C4,C7,C8, C10,C13, C14,C15, C16,C17
S4	0.5	0.25	0.25	C6, C9	C2,C3,C5,C11, C12,C14,C16,C17	C1,C4,C7,C8, C10,C13,C15
S5	0.25	0.5	0.25	C6, C9	C2,C3,C4,C5,C11, C12,C14,C15, C16,C17	C1,C7,C8, C10,C13
S6	0.25	0.25	0.5	C6, C9	C2,C3,C4,C5,C11, C12,C14,C16,C17	C1,C7,C8, C10,C13,C15
S7	0.6	0.2	0.2	C6, C9	C2,C3,C5,C11, C12,C14,C16,C17	C1,C4,C7,C8, C10,C13,C15
S8	0.15	0.7	0.15	C6, C9	C2,C3,C4,C5,C11, C12,C14,C15, C16,C17	C1,C7,C8, C10,C13
S9	0.1	0.1	0.8	C6, C9	C2,C3,C4,C5,C11, C12,C14,C17	C1,C7,C8, C10,C13, C15,C16

$$\nu_6 =< \left[\left(1-(1-0.8)^{\frac{1}{3}}*(1-0.8)^{\frac{1}{3}}*(1-0.8)^{\frac{1}{3}}\right), \left(1-(1-0.9)^{\frac{1}{3}}*(1-0.9)^{\frac{1}{3}}*(1-0.9)^{\frac{1}{3}}\right)\right],$$
$$\left[\left((0.1)^{\frac{1}{3}}*(0.1)^{\frac{1}{3}}*(0.1)^{\frac{1}{3}}\right), \left((0.2)^{\frac{1}{3}}*(0.2)^{\frac{1}{3}}*(0.2)^{\frac{1}{3}}\right)\right], \left[\left((0.1)^{\frac{1}{3}}*(0.1)^{\frac{1}{3}}*(0.1)^{\frac{1}{3}}\right), \left((0.2)^{\frac{1}{3}}*(0.2)^{\frac{1}{3}}*(0.2)^{\frac{1}{3}}\right)\right] >=< [0.8, 0.9], [0.1, 0.2], [0.1, 0.2] >$$

Since IVNSDM and IVNSWM have very similar linguistic terms, γ_6 is equal to ν_6.

The weighted performance scores are calculated using Eq. (29) to construct the IVNSWDM matrix, which combines the weighted importance and performance scores by multiplying two IVNN as described in Eq. (6). The multi-distance framework is used to obtain a combined distance value for each criterion based on the ideal ($< [1,1],[0,0],[0,0] >$) and negative-ideal solutions ($< [0,0],[1,1],[1,1] >$). For this purpose, Eqs. (16-23) are used to compute the four distance measures that will be combined using Eqs. (24-25).

The second column of Table 6 presents the IVNSWDM values, which have been computed using IVNSWM and IVNSDM, while the third column describes the closeness index, $\omega(\zeta_i)$, which has been obtained using the combined distances per indicator described in Eq. (26). Based on the results given in Table 6, C9 and C6 are the most significant indicators, displaying the highest value of the closeness index. These indicators are

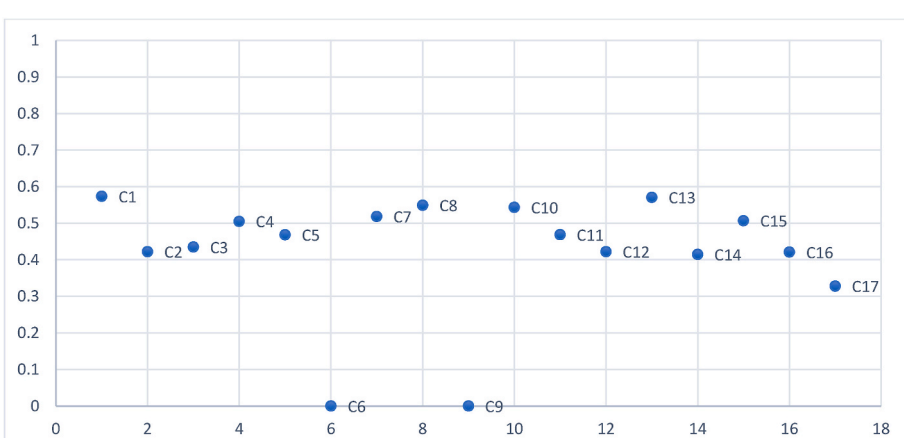

Fig. 2. Scatter plot of social indicators.

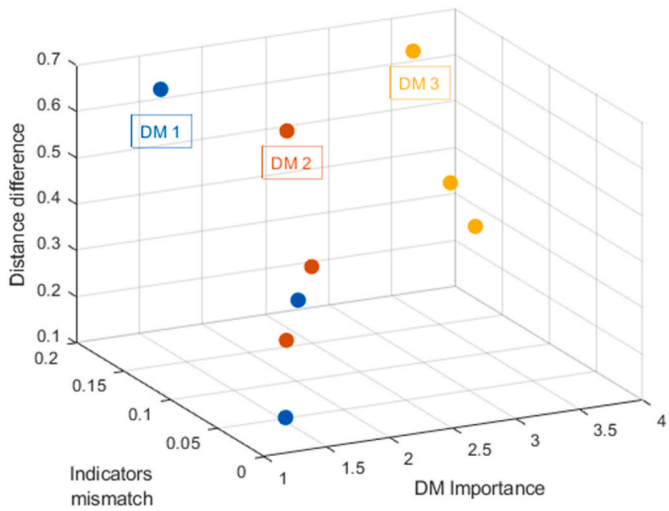

Fig. 3. The relative importance of decision-makers and evaluation differences.

therefore denoted by C^*. An example of the C6-based calculations performed within IVNSWDM and $\omega(\zeta_i)$ – based on the Euclidean measure – is provided below.

$$\psi_6 =< [0.8*0.8, 0.9*0.9], [0.1+0.1-0.1*0.1, 0.2+0.2-0.2*0.2], [0.1+0.1-0.1*0.1, 0.2+0.2-0.2*0.2] >=< [0.64, 0.81], [0.19, 0.36], [0.19, 0.36] >$$

$$\omega(\zeta_6)=\frac{d(<[0.64,0.81],[0.19,0.36],[0.19,0.36]>,<[0,0],[1,1],[1,1]>)}{d(<[0.64,0.81],[0.19,0.36],[0.19,0.36]>,<[0,0],[1,1],[1,1]>)+d(<[0.64,0.81],[0.19,0.36],[0.19,0.36]>,<[1,1],[0,0],[0,0]>)}=0.7140$$

The relative distance between the remaining indicators and the optimal ones is calculated using Eqs. (12-15). The resulting distances are then combined through Eqs. (24-25). The fourth column of Table 6 describes the distance of each indicator to C^*, with C6 and C9 trivially displaying a zero value. The calculations corresponding to the indicator C6 are summarized below.

$$D_H(C6,C6)=\frac{1}{6}\left(\begin{array}{l}|0.64-0.64|+|0.81-0.81|+|0.19-0.19|+\\|0.36-0.36|+\ |0.19-0.19|+|0.36-0.36|\end{array}\right)=0$$

$$D_E(C6,C6)=\sqrt{\left(\frac{1}{6}\left(\begin{array}{l}(0.64-0.64)^2+(0.81-0.81)^2+(0.19-0.19)^2+\\(0.36-0.36)^2+(0.19-0.19)^2+(0.36-0.36)^2\end{array}\right)\right)}=0$$

$$D_Y(C6,C6)=\frac{1}{3}\Big(\max\Big[|0.64-0.64|, |0.81-0.81|\Big]+\max[|0.19-0.19|, |0.36-0.36|]+\max[|0.19-0.19|, |0.36-0.36|])=0$$

$$D_Z(C6,C6)=\max\left[\frac{1}{2}(|0.64-0.64|+|0.81-0.81|),\ \frac{1}{2}(|0.19-0.19|+|0.36-0.36|),\ \frac{1}{2}(|0.19-0.19|+|0.36-0.36|)\right]=0$$

The rest of the indicators and their relative distance values can be intuitively visualized in Fig. 2.

A linguistic performance scale is defined such that indicators with a distance value of 0 display the "best performance," indicators with a distance value between 0.01 and 0.5 display a "satisfactory performance," those with a distance value between 0.501 and 1 display a "weak performance," and those with a distance value greater than 1 are considered as "poor performance" indicators. According to Fig. 2, salary satisfaction and workers with health insurance are identified as the best performing indicators for the sustainable MWM system of Istanbul.

Fig. 2 allows us to intuitively distinguish which indicators are not performing well compared to the best-performing ones. From a purely descriptive viewpoint, participation of non-governmental organizations (C17), local employment (C16), public commitment to sustainability guidelines (C14), hygiene lifestyle of workers (C12), education level of workers (C11), gender equity (C5), labor regulations (C3), and child labor (C2) display a satisfactory performance. On the other hand, freedom of association and negotiation (C1), labor from low-class communities (C4), working hours (C7), legal employment (C8), environmental awareness and responsibility of workers (C10), participation

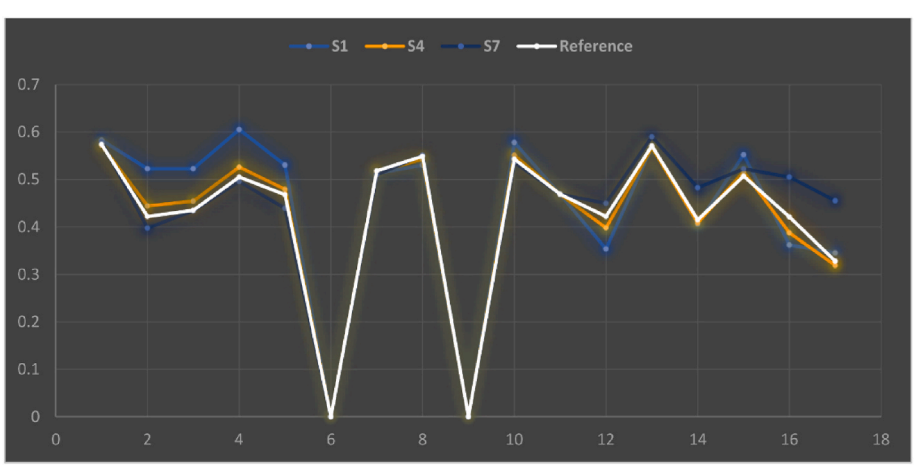

Fig. 4. $d(C_i, C^*|Sj)$ and $d(C_i, C^*|\textbf{reference})$ in the scenarios dominated by the first expert.

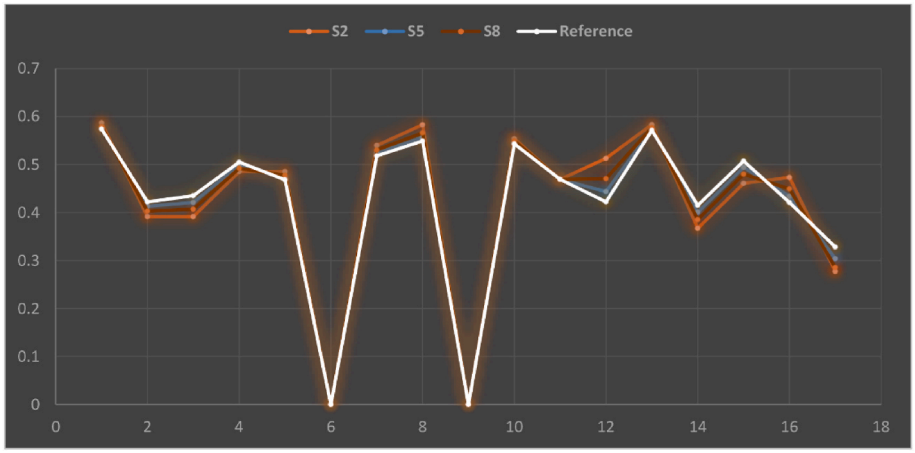

Fig. 5. $d(C_i, C^*|Sj)$ and $d(C_i, C^*|\textbf{reference})$ in the scenarios dominated by the second expert.

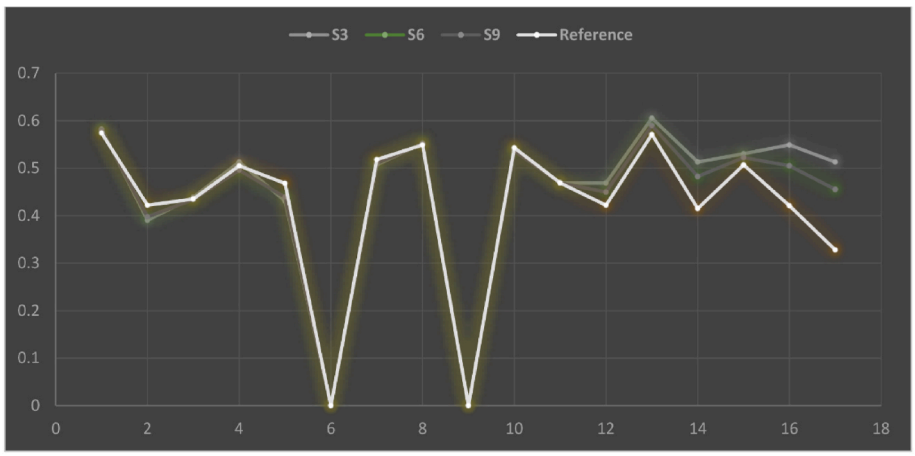

Fig. 6. $d(C_i, C^*|Sj)$ and $d(C_i, C^*|\textbf{reference})$ in the scenarios dominated by the third expert.

of citizens (C13), and organizational corruption (C15) display a poor performance. We will elaborate further on these results through the implications section below.

5.2. Sensitivity analysis

An important constraint is implicit in the definition of Eq. (10), namely, the aggregated IVNSWM and IVNSDM are constructed assuming equal importance among the three decision-makers. Nine scenarios are generated based on different combinations of the importance assigned to DM1, DM2, and DM3 to address this constraint and illustrate the consequences of modifying the relative importance assigned to each expert.

Table 7 presents information regarding the sensitivity analysis tests performed. The relative importance assigned to the decision-makers

Table 8
Aggregated SVNS weight importance and performance score.

Indicators	Aggregated SVNSWM	Aggregated SVNSDM
C1	<0.171,0.853,0.848>	<0.233,0.768,0.817>
C2	<1,0.153,0.134>	<0.302,0.708,0.748>
C3	<1,0.153,0.134>	<0.271,0.745,0.779>
C4	<0.628,0.372,0.395>	<0.317,0.75,0.699>
C5	<0.75,0.363,0.312>	<0.332,0.666,0.717>
C6	<1,0.05,0.052>	<1,0.05,0.052>
C7	<0.532,0.451,0.468>	<0.503,0.49,0.51>
C8	<0.465,0.532,0.549>	<0.302,0.708,0.748>
C9	<1,0.05,0.052>	<1,0.05,0.052>
C10	<0.432,0.565,0.599>	<0.343,0.686,0.686>
C11	<0.497,0.497,0.503>	<0.747,0.248,0.304>
C12	<0.654,0.316,0.367>	<0.704,0.4,0.338>
C13	<0.202,0.815,0.832>	<0.371,0.641,0.658>
C14	<0.781,0.252,0.266>	<0.599,0.424,0.425>
C15	<0.575,0.465,0.464>	<0.365,0.633,0.684>
C16	<0.286,0.781,0.728>	<1,0.153,0.134>
C17	<1,0.224,0.185>	<0.686,0.443,0.369>

Table 9
SVNSWDM, closeness index, and distance of indicators to C^*.

Indicators	SVNSWDM	$\omega(\zeta_i)$	$d(C_i, C^*)$
C1	<0.040,0.655,0.972>	0.278	0.593
C2	<0.302,0.108,0.781>	0.288	0.400
C3	<0.271,0.114,0.809>	0.261	0.418
C4	<0.199,0.279,0.818>	0.261	0.453
C5	<0.249,0.242,0.806>	0.274	0.432
C6	<1.00,0.002,0.100>	**0.933**	0.000
C7	<0.268,0.221,0.739>	0.300	0.407
C8	<0.141,0.377,0.886>	0.251	0.499
C9	<1.00,0.002,0.100>	**0.933**	0.000
C10	<0.148,0.388,0.874>	0.260	0.495
C11	<0.371,0.123,0.654>	0.373	0.346
C12	<0.461,0.126,0.581>	0.449	0.299
C13	<0.075,0.522,0.943>	0.260	0.553
C14	<0.468,0.107,0.578>	0.454	0.295
C15	<0.21,0.294,0.831>	0.266	0.455
C16	<0.286,0.119,0.765>	0.286	0.401
C17	<0.686,0.099,0.486>	0.602	0.207

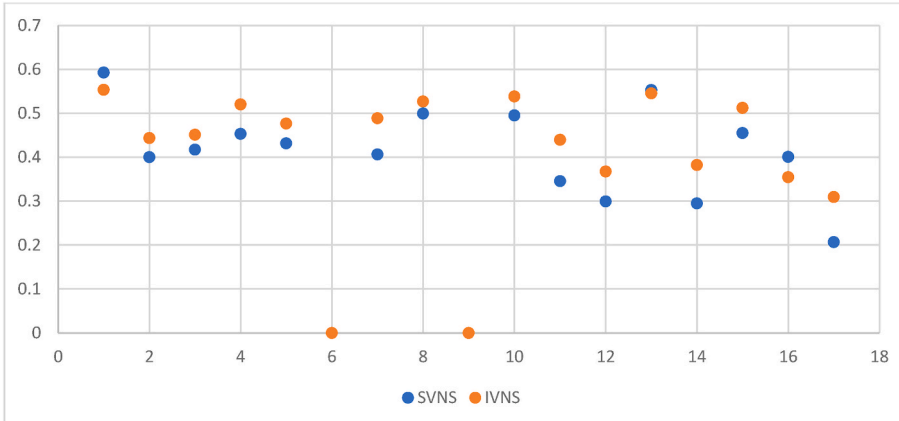

Fig. 7. Results of the SVNS-based approach compared to the IVNS-based approach.

within each scenario is described in the 2nd, 3rd' and 4th columns. Given the judgments of decision-makers, the best performing indicators are identical across scenarios, while those displaying satisfactory and weak performances vary across scenarios, as illustrated in the 6th' and 7th columns. Clearly, the relative performance of the indicators is conditioned by the weights assigned to determine the importance of decision-makers.

We extend the analysis to illustrate the strategic interactions that may be defined among experts as the relative importance assigned to each of them is modified. In this regard, we have introduced a relative importance variable assigned to each DM so as to differentiate across scenarios accordingly. In particular, the "DM importance" indicator assigned to the *i-th* DM, with $i = 1, 2, 3$, is defined as $i + \left|w_{ij} - 1/3\right|$, where w_{ij} represents the relative weight assigned to each DM within scenario Sj, $j = 1, 2, \ldots, 9$, and $1/3$ corresponds to the equal importance assigned in the reference framework. This distinction allows us to represent the DMs within different evaluation domains in Fig. 3; that is, the evaluations of the first DM are illustrated within the [1, 2] domain, those of the second within [2, 3], and those of the third DM within [3, 4].

The other two variables represented in Fig. 3 relate directly to the difference in the metrics obtained across scenarios. The "distance difference" is given by the sum of the absolute value differences between the distance of each indicator and the optimal one within each scenario relative to the distance of each indicator and the optimal one within the reference framework. More precisely, for each Sj scenario, $j = 1, 2, \ldots, 9$, the "distance difference" variable is given by $\sum_{i=1}^{17}\left|d(C_i, C^*|Sj) - d(C_i, C^*|\text{reference})\right|$, with $d(C_i, C^*|Sj)$ representing the distance of each indicator to C^* within the Sj scenario, while $d(C_i, C^*|\text{reference})$ accounts for the distance of each indicator to C^* within the reference framework. This variable is represented on the Z-axis of Fig. 3, where each distance is compared to the reference one while considering the scenarios where the first, second, and third experts are given relatively higher importance weights.

The "indicators mismatch" variable has been introduced to measure the differences between the satisfactory and weak classifications across the different scenarios described in Table 7. This indicator accounts for the number of mismatches between the weak and satisfactory indicators selected in each scenario and the reference one. The resulting number is divided by the total number of potential mismatches, i.e., 15, given that the best indicators coincide across scenarios. For instance, the S1 scenario displays a mismatch in three indicators, C2, C3, and C5, classified as weak while they are considered satisfactory in the reference framework.

The numerical results presented in Fig. 3 illustrate how the first expert displays a better performance in the "indicators mismatch" variable than the others, matching precisely the indicators allocated within each category. However, the first expert exhibits relatively significant distance differences in the values assigned to each indicator. The second expert displays more accurate evaluations in terms of distance differences relative to the reference but a more significant number of indicator mismatches, while the third expert exhibits a relatively weaker behavior in both indicators.

Table 10
Aggregated IVPFS weight importance and performance score.

Indicators	Aggregated IVPFSWM	Aggregated IVPFSDM
C1	[0.149,0.248],[0.644,0.743]	[0,0.149],[0.743,0.941]
C2	[0.644,0.743],[0.099,0.198]	[0,0.149],[0.743,0.941]
C3	[0.644,0.743],[0.099,0.198]	[0,0.149],[0.743,0.941]
C4	[0.396,0.495],[0.347,0.495]	[0,0.05],[0.842,0.941]
C5	[0.248,0.396],[0.495,0.644]	[0.248,0.396],[0.495,0.644]
C6	[0.842,0.941],[0,0.05]	[0.842,0.941],[0,0.05]
C7	[0.396,0.495],[0.347,0.495]	[0.495,0.644],[0.198,0.347]
C8	[0.248,0.396],[0.495,0.644]	[0.248,0.396],[0.495,0.644]
C9	[0.842,0.941],[0,0.05]	[0.842,0.941],[0,0.05]
C10	[0.248,0.396],[0.495,0.644]	[0,0.149],[0.743,0.941]
C11	[0.396,0.495],[0.347,0.495]	[0.644,0.743],[0.099,0.198]
C12	[0.495,0.644],[0.198,0.347]	[0.743,0.941],[0,0.149]
C13	[0.149,0.248],[0.644,0.743]	[0.149,0.248],[0.644,0.743]
C14	[0.743,0.941],[0,0.149]	[0.396,0.495],[0.347,0.495]
C15	[0.396,0.495],[0.347,0.495]	[0.149,0.248],[0.644,0.743]
C16	[0.396,0.495],[0.347,0.495]	[0.842,0.941],[0,0.05]
C17	[0.842,0.941],[0,0.05]	[0.248,0.396],[0.495,0.644]

Table 11
PFSWDM, closeness index, and distance of indicators to C^*.

Indicators	IVPFSWDM	$\omega(\xi_i)$	$d(C_i, C^*)$
C1	[0,0.037],[0.859,0.974]	0.072	0.680
C2	[0,0.11],[0.745,0.943]	0.137	0.635
C3	[0,0.11],[0.745,0.943]	0.137	0.635
C4	[0,0.025],[0.862,0.955]	0.073	0.679
C5	[0.061,0.157],[0.656,0.81]	0.215	0.567
C6	[0.708,0.885],[0,0.07]	**0.844**	0.000
C7	[0.196,0.319],[0.393,0.579]	0.400	0.408
C8	[0.061,0.157],[0.656,0.81]	0.215	0.567
C9	[0.708,0.885],[0,0.07]	**0.844**	0.000
C10	[0,0.059],[0.813,0.966]	0.096	0.664
C11	[0.255,0.368],[0.359,0.524]	0.442	0.367
C12	[0.368,0.605],[0.198,0.373]	0.588	0.233
C13	[0.022,0.061],[0.81,0.894]	0.117	0.643
C14	[0.294,0.466],[0.347,0.512]	0.478	0.332
C15	[0.059,0.123],[0.696,0.813]	0.193	0.583
C16	[0.333,0.466],[0.347,0.497]	0.490	0.321
C17	[0.208,0.372],[0.495,0.645]	0.372	0.426

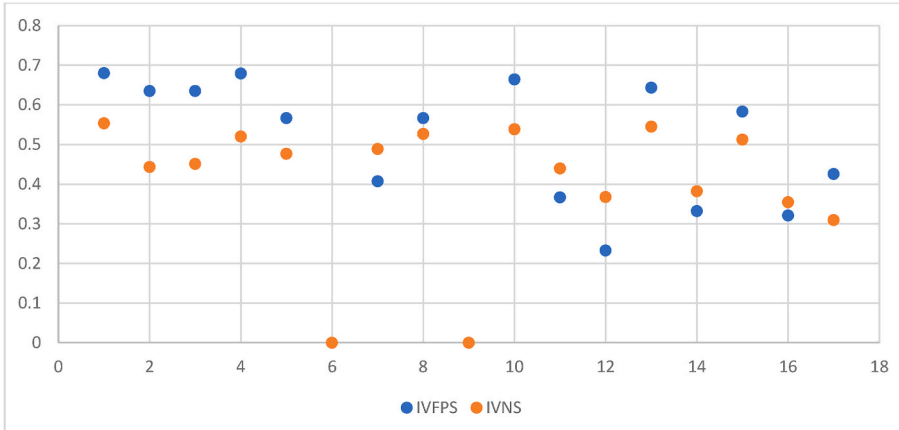

Fig. 8. Results of the IVPFS-based approach compared to the IVNS-based approach.

Thus, as can be observed, the first expert has a greater influence in determining the indicators selected, with the second conditioning the relative evaluations assigned. Note how different combinations of weighting power assigned to the experts can modify the solutions, requiring a careful selection of the experts and the relative weights assigned, particularly when determining the indicators that will be categorized as weak.

Finally, the higher alignment of the evaluations provided by the second expert in terms of distance differences can be observed when comparing the scenarios composing Fig. 5 with those illustrated in Figs. 4 and 6. These figures divide the different scenarios according to the relative weight assigned to each expert and compare the patterns generated by the corresponding $d(C_i, C^*|Sj)$ and $d(C_i, C^*|\text{reference})$ distances. Figs. 4–6 illustrate the differences arising in the scenarios dominated by the first and third experts, i.e., those where these experts are assigned higher weights, which display a higher variability – particularly among the last indicators – than those described in Fig. 5, where the second expert is assigned higher weights.

5.3. Comparative analysis

The proposed methodology provides a flexible environment for experts to express their judgments with high accuracy under uncertain conditions. Despite this quality, a comparative analysis is conducted to illustrate the performance of the proposed approach relative to other types of uncertainty sets. More precisely, the input data of the study is used to address the same problem through two different uncertainty sets, namely, distance-based SVNS (Chaw et al., 2020; Rani et al., 2021; Rani and Mishra, 2020) and distance-based Interval-valued Fuzzy Pythagorean Sets (IVFPS) (Hendiani et al., 2021; Peng, 2019; Peng and Yang, 2016).

Through the current section, we use a unique distance measure, i.e., the Euclidean one, to categorize the indicators within the IVNS, SVNS, and IVFPS approaches. The reason for this modification – relative to the four distance measures applied to the IVNS-based approach through the previous sections – is that the Y-based and Z-based distance measures defined by Ye and Du (2019) are specifically developed for IVNS and cannot be applied to SVNS and IVFPS. As a result, we have considered only the Euclidean distance measure, which is common to all the approaches, to perform the corresponding comparative analyses. For this purpose, the information given in the form of IVNS linguistic terms is adjusted to the exact or closest linguistic term within SVNS and IVFPS, described in Tables A1 and A2 in Appendix A, respectively.

Similar to the proposed methodology, two decision matrices are generated for the SVNS-based approach, namely, the SVNS weighted matrix (SVNSWM) and the SVNS decision matrix (SVNSDM). The results obtained are reported in Table 8. Then, we integrate SVNSWM and SVNSDM to generate the SVNS weighted decision matrix (SVNSWDM) presented in Table 9. Note that the SVNS-based approach also identifies C6 and C9 as the best performing indicators. In order to facilitate comparisons between both sets of results, Fig. 7 illustrates the distance from each indicator to the best-performing ones using the proposed IVNS approach and SVNS.

As illustrated in Fig. 7, most SVNS-based results are similar to the proposed approach. However, some indicators display slight differences. For instance, SVNS categorizes C4, C7, C10, and C15 as satisfactory, while our approach classifies them as weak performing indicators. The main differences in the results obtained between both methods stem from the reliance of SVNS on single values for the membership functions of the neutrosophic sets. At the same time, IVNS allows decision-makers and experts to express their uncertain judgments in a more flexible environment. Therefore, we may consider the results derived from the IVNS-based approach to be more reliable than those of the SVNS-based approach.

The second comparative analysis is based on IVPFS, which assigns interval-valued numbers to the membership functions similarly to IVNS. As in the previous case, two decision matrices are generated, the IVPFS weighted matrix (IVPFSWM) and the IVPFS decision matrix (IVPFSDM). The results obtained are reported in Table 10. IVPFSWM and IVPFSDM are integrated to generate the IVPFS weighted decision matrix (IVPFSWDM), which is described in Table 11. Note how the IVPFS-based approach also identifies C6 and C9 as the best performing indicators. To facilitate comparisons between both sets of results, Fig. 8 illustrates the distance from each indicator to the best-performing ones using the proposed IVNS approach and IVPFS.

As illustrated in Fig. 8, the IVPFS-based approach classifies C2, C3, and C5 as weak performing indicators, while the proposed methodology classifies them as good performing ones. Similarly, our approach classifies C7 as a weak-performing indicator, while the IVPFS-based approach categorizes it as a good-performing one. The remaining results derived from the IVPFS-based approach are similar to the proposed methodology. The differences between both methodologies rely on the fact that IVFPS are based on two membership and non-membership functions, while IVNS provides a more flexible environment for the experts to express their judgments through three different functions.

Finally, note how both neutrosophic approaches deliver closer results than the Pythagorean one, the latter providing less similar distance values despite its interval-based characterization. Figures A1 and A2 in Appendix A section describe the distance from each indicator to the best-performing ones when four measures are used to categorize the indicators within the IVNS approach. The Euclidean distance is applied to categorize the indicators within the SVNS, and IVFPS approaches. Note how the main results described in the current section remain valid. A slight increase in the differences between indicators – relative to Figs. 7

and 8 – can be observed when considering four distance measures instead of using only the Euclidean one. Thus, the characteristics of the linguistic terms defining the approaches together with the distance measures implemented generate the observed variability.

6. Managerial implications

This section discusses the main motivation defining the proposed approach and, more importantly, elaborates on the results obtained to understand its methodological and conceptual fundamentals. Due to the high complexity involved in understanding and modeling social sustainability and its related indicators within MWM systems, we have proposed a novel multi-distance IVNS approach based on the simplest possible soft computing operations. Linguistic terms were used to facilitate the retrieval of opinions from decision-makers in real-life scenarios. One of the main features of the model relates to the selection of IVNS. Neutrosophic set were initially defined via SVNS, which assigns three crisp values for truth, indeterminacy, and falsity membership functions. However, real-world events exhibit a high degree of uncertainty when dealing with complex decision-making scenarios, implying that assigning crisp values to membership functions does not provide a sufficiently flexible framework for decision-makers to express their opinions. IVNS constitutes a reliable uncertainty set that determines membership functions using interval values. Since this approach utilizes a distance value to determine which indicators perform weakly, a robust distance evaluation framework has been defined using four distance measures.

The results obtained indicate that salary satisfaction and health insurance are the best-performing indicators for the MWM system of Istanbul. This behavior implies that related organizations could efficiently provide workers with the satisfaction levels required in terms of salary and health insurance. However, given the complexity of the MWM system, encompassing legal and illegal interactions within its associated organization and other informal sectors, there are noticeable weak performing indicators. For instance, labor from low-class communities is one of these weak performing indicators, which is also considered one of the fundamental problems in every MWM system. According to the opinion of the experts, waste management organizations in Istanbul cannot reduce or eliminate their hiring from low-class communities. This is mainly due to the lower salaries, part-time work, and the provision of lower amenities that people from higher social classes are not willing to accept. The environmental awareness and responsibility of workers is another weak performing indicator for Istanbul, highlighting important deficiencies regarding the lack of training, seminars, and workshops for workers. The participation of citizens is also weak for the city of Istanbul. However, most big cities in the world face similar involvement problems. In order to improve the performance of this indicator, municipalities or associated organizations should develop interactive programs as incentives to increase the involvement of citizens in creating a sustainable MWM system. Freedom of association and negotiation between workers and managers performs weakly within organizations. The weak performance of this indicator denotes that workers are not usually asked for their opinions on new projects. However, since workers are more in contact with waste collection and disposal operations, there exists a great need to involve them and gather their opinions for strategical planning purposes.

7. Conclusion

We have proposed a novel multi-distance IVNS approach to identify social failure indicators within MWM systems in real-life decision-making scenarios. The proposed approach utilizes IVNS instead of SVNS to incorporate uncertainty and vagueness through interval numbers – instead of single values – in the three membership functions of the neutrosophic sets. A combined distance measure has been defined to evaluate the performance of the indicators relative to the ideal solutions.

The current study is the first to develop a multi-distance IVNS approach and apply it to analyze social failure indicators in MWM systems. A real case study involving three experts from the city of Istanbul, Turkey, has been presented to show the applicability of the proposed approach. A categorical scale has been defined to label the performance of the indicators regarding their combined distances from the ideal solutions.

A total of 7 out of 17 social indicators were considered weak-performing, implying that the MWM system of Istanbul has a considerable amount of work to do to improve their relative performances. In particular, the proposed approach delivered the following main results regarding the performance of this MWM system:

- Salary satisfaction and workers with health insurance are the most significant social indicators determining the success of the system.
- Freedom of association and participation of citizens constitute the main social indicators triggering failures in the system.

Among the main limitations of our decision-making approach, we must highlight that the manual categorization of the indicators is subject to biases. Moreover, since the proposed approach is based on experts' opinions, the results are conditioned by their flexibility and capacity to handle linguistic terms. In this regard, Z-numbers, extended Z-numbers, and Neutrosophic Z-numbers can be used to increase the accuracy of experts when expressing their intuitive opinions. In addition, a weighting method could be introduced to determine the weights assigned to the different techniques and decrease subjectivity and biasedness in the data.

The current study can be extended in several directions. One of them consists of applying the proposed methodology to detect social, environmental, and economic failure indicators in other systems that aim to implement sustainability and circular economy practices. Another future research direction would focus on applying other advanced uncertainty sets within large-scale decision-making models, providing an enhanced framework of analysis to deal with uncertain evaluations. In this regard, machine learning and data mining algorithms could be used to address large-scale problems with incomplete data and classify indicators into different performance categories.

CRediT authorship contribution statement

Ali Ebadi Torkayesh: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Madjid Tavana:** Methodology, Writing – original draft, Writing – review & editing, Visualization. **Francisco J. Santos-Arteaga:** Methodology, Writing – original draft, Writing – review & editing, Visualization.

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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Appendix A

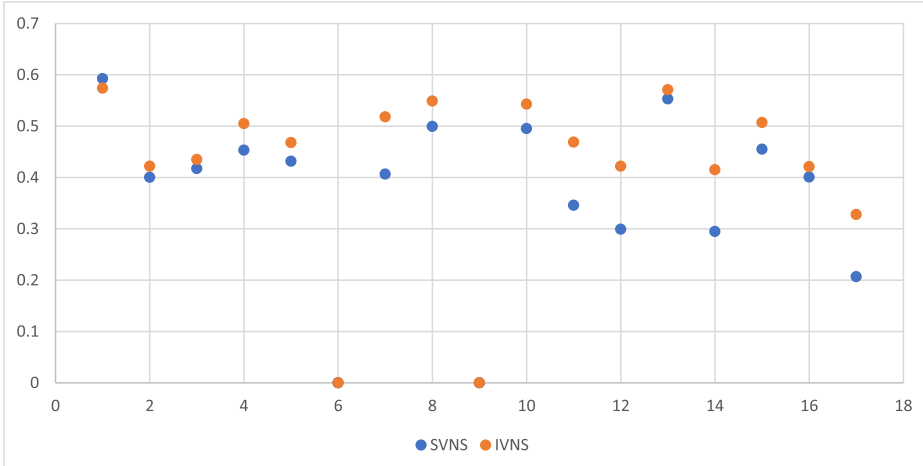

Fig. A1. Comparing the Euclidean SVNS to the four measures IVNS-based approach.

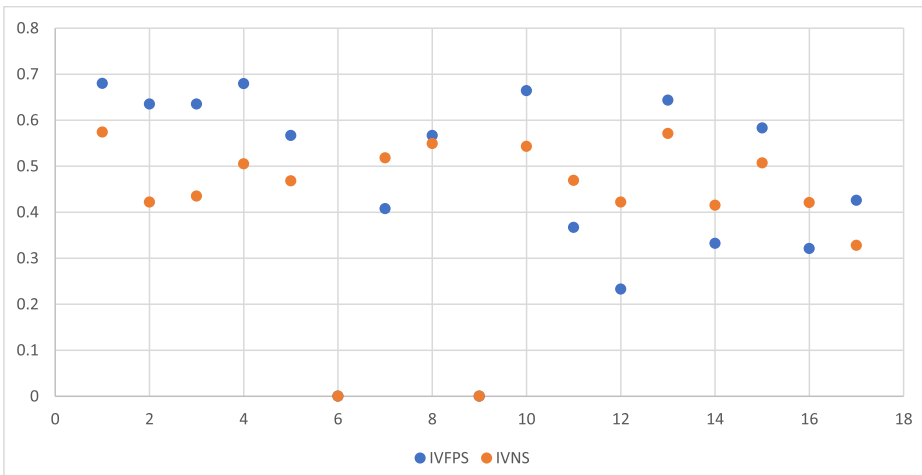

Fig. A2. Comparing the Euclidean IVPFS to the four measures IVNS-based approach.

Table A1
SVNS linguistic terms for performance assessment.

Linguistic terms	SVNS
Not important (NI)	<0.10,0.90,0.95>
Very low importance (VLI)	<0.20,0.80,0.85>
Low importance (LI)	<0.30,0.70,0.75>
Fairly low importance (FLI)	<0.40,0.60,0.65>
Medium importance (MI)	<0.50,0.50,0.50>
Fairly high importance (FHI)	<0.60,0.35,0.40>
High importance (HI)	<0.75,0.25,0.30>
Very high importance (VHI)	<0.90,0.15,0.15>
Extreme importance (EI)	<1.00,0.05,0.05>

Table A2
IVPFS linguistic terms for performance assessment.

Linguistic terms	IVPFS
Not important (NI)	([0.00,0.05],[0.85,0.95])
Very low importance (VLI)	([0.00,0.15],[0.75,0.95])
Low importance (LI)	([0.15,0.25],[0.65,0.75])
Fairly low importance (FLI)	([0.25,0.40],[0.50,0.65])

(*continued on next page*)

Table A2 (*continued*)

Linguistic terms	IVPFS
Medium importance (MI)	([0.40,0.50],[0.35,0.50])
Fairly high importance (FHI)	([0.50,0.65],[0.20,0.35])
High importance (HI)	([0.65,0.75],[0.10,0.20])
Very high importance (VHI)	([0.75,0.95],[0.00,0.15])
Extreme importance (EI)	([0.85,0.95],[0.00,0.05])

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