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SCIENTIFIC OASIS

Decision Making: Applications in Management and Engineering

Journal homepage: www.dmame-journal.org
ISSN: 2560-6018, eISSN: 2620-0104

Risk Assessment Framework for Reverse Logistics in Waste Plastic Recycle Industry: A Hybrid Approach Incorporating FMEA Decision Model with AHP-LOPCOW- ARAS Under Trapezoidal Fuzzy Set

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ARTICLE INFO

Article history:
Received 2 October 2023
Received in revised form 2 June 2024
Accepted 17 June 2024
Available online 16 July 2024

Keywords:
Failure Mode Effect Analysis (FMEA); Analytic Hierarchy Process (AHP); LOgarithmic Percentage Change-driven Objective Weighting (LOPCOW); Additive Ratio Assessment (ARAS); Trapezoidal fuzzy set (TrFS)

ABSTRACT

In this study, a novel risk assessment framework designed for evaluating the challenges of plastic packaging waste management in the context of reverse logistics is introduced. The framework leverages Failure Mode Effect Analysis (FMEA) to address decision-making in a fuzzy environment. To augment the traditional FMEA risk criteria, encompassing severity (S), occurrence (O), and detection (D), three additional essential risk criteria are introduced: cost of failure (C), complexity of failure resolution (H), and impact on business (I). These newly incorporated criteria significantly enhance the capacity to convey the multifaceted risks inherent in reverse logistics for the plastic recycling sector. Furthermore, a comprehensive literature review and expert validation are conducted to identify ten distinct failure modes. To subjectively and objectively determine the risk criteria weightings, a combination of Analytic Hierarchy Process (AHP) and LOgarithmic Percentage Change-driven Objective Weighting (LOPCOW) is employed. Finally, the Additive Ratio Assessment (ARAS) approach is applied to prioritize such failure modes. Recognizing the inherent imprecision and uncertainty associated with human decision-making, the trapezoidal fuzzy set (TrFS) is adopted throughout all decision-making processes. To showcase the proposed framework effectiveness, the framework is applied as a case study to a waste plastic recycling manufacturer in Thailand.

1. Introduction

In the past decade, there has been growing global concern regarding environmental pollution attributed to plastic packaging waste. Current estimates indicate that the annual global accumulation of plastic packaging waste has reached an astonishing 14 million tons [1]. This surge in plastic waste is primarily driven by the widespread use of single-use plastic packaging products, exacerbating environmental issues [2]. The production and disposal of plastic packaging also contribute to the release of harmful chemical pollutants and greenhouse gases (GHGs), which pose substantial threats to both human and animal well-being while further accelerating the impacts of

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https://doi.org/10.31181/dmame812025984

climate change [3,4]. Notably, these environmental impacts impose a significant, yet often unaccounted for, cost on society, which is not reflected in the market prices of plastic packaging products [5]. Addressing the worldwide predicament of plastic packaging waste requires localized solutions. A pivotal factor contributing to this predicament lies in inadequate waste management systems and the lack of effective reverse logistics (RL) management, particularly in developing nations [6,7]. Recycling, a fundamental component of the closed-loop RL chain, plays a crucial role in promoting sustainable plastic waste management by curbing the volume of waste directed to landfills [8]. Given the emergence of new environmental regulations, resource depletion, the pressing challenges of global warming, a heightened emphasis on extended producer responsibility, and evolving economic paradigms, research on RL has garnered increasing attention from both academic and practical perspectives [4]. Effective RL management has economic, environmental, and social benefits. However, mishandling the closed-loop RL process can jeopardize firm profitability while negatively impacting the environment and society [9,10]. This vulnerability is primarily attributed to the multifaceted risks inherent to the closed-loop RL process chain [11]. Thus, it is imperative to systematically identify and quantify the risks associated with RL. Despite numerous prior studies attempting to assess RL risks, there is a notable dearth of related research within the context of the plastic recycling industry.

This study seeks to bridge this knowledge gap by developing a comprehensive quantitative risk assessment framework for reverse logistics specific to the plastic packaging recycling sector. The waste plastic recycling industry in Thailand is chosen as a representative case study to exemplify the applicability of the framework. Within this study, the quantitative risk assessment framework is envisioned as a Multicriteria Decision-Making (MCDM) process operating within a trapezoidal fuzzy environment. To achieve this goal, a hybrid approach is employed, seamlessly integrating the principles of Failure Mode and Effect Analysis (FMEA) with logarithmic percentage change-driven objective weighting (LOPCOW), Analytic Hierarchy Process (AHP), and Additive Ratio Assessment (ARAS). This comprehensive approach combines both subjective and objective weightings to calculate the weights of the FMEA risk criteria by incorporating AHP and LOPCOW, respectively. Furthermore, the ARAS approach is utilized to rank the failure modes of risks within the reverse logistics of the plastic recycling industry.

This study makes several contributions to the field of risk assessment in the plastic recycling industry. These contributions are as follows:

First, a novel risk assessment framework is introduced for the reverse logistics of the plastic recycling industry, incorporating the FMEA decision model. Unlike traditional FMEA risk criteria, which typically focus on severity (S), occurrence (O), and detection (D), the scope is extended in this study by introducing three additional criteria: cost of failure (C), complexity of failure resolution (H), and impact on business operations (I). This enhanced set of criteria enables a more accurate evaluation of the risks related to plastic packaging waste in reverse logistics.

Second, subjective and objective weighting methods are combined to derive combined weights for the FMEA risk criteria, enhancing the accuracy of the weighting process.

Third, AHP-LOPCOW-ARAS is incorporated under trapezoidal fuzzy sets, marking the first application of this approach to addressing MCDM problems in the context of risk assessment.

Finally, by using the waste plastic recycling industry in Thailand as a case study, insights are provided that may be applicable to other developing countries facing similar challenges in reverse logistics.

2. Materials

This section provides an overview of the relevant literature covering the following topics: reverse logistics in plastic packaging waste and the application of fuzzy MCDM in FMEA.

2.1 Reverse Logistics of Plastic Packaging Waste

There are several options for managing the disposal of plastic packaging, including landfill disposal, incineration, and recycling [6]. However, it is important to note that both incineration and landfill disposal methods have adverse effects on the environment and society [12]. Incineration, for instance, produces harmful pollutants such as dioxins and furans, which can severely impact human health [13]. Furthermore, landfill disposal of plastic packaging leads to the release of methane gas, contributing to global warming [14]. Furthermore, nonbiodegradable particles from plastic packaging waste can release toxic substances, contaminating soil and groundwater near landfill sites [12]. For these reasons, recycling plastic packaging waste is a more environmentally friendly and health-conscious option than using landfills or incineration [13]. Recycling involves the conversion of plastic packaging waste into new plastic raw materials [14,15]. Reverse logistics (RL) plays a crucial role in making the recycling process efficient. RL for plastic packaging waste encompasses a range of logistics activities aimed at managing the reverse flow of discarded plastic packaging, from end-users to recycling producers [16]. It is a complex waste management process that includes collection, transportation, sorting, warehousing, and recycling [17]. To effectively manage RL for plastic packaging waste, a proper logistical structure is necessary to facilitate reverse flow. Effective RL management of plastic packaging waste can yield economic, environmental, and social benefits [6,7]. Additionally, RL has evolved from merely an operational task to a strategic business approach [16]. However, improper RL management can exacerbate environmental and social issues such as air pollution, soil and ocean contamination, global warming, and community protests [11]. The process of using RL for plastic packaging waste and recycling is not without its challenges and risks. These include environmental risks [18,20], demand risks [21,22], technology risks [20,22], risks associated with reverse logistics information [20,21], collaboration risks among stakeholders [23] transportation risks [21, 24], inventory risks [21, 25], hygiene and safety risks [26,27], insufficient knowledge and skill risks [22,23], and demand risks [28,29], as well as risks associated with recycling production processes [21,22].

2.2 Risks Associated with the Reverse Logistics of Plastic Packaging Waste

A comprehensive literature synthesis reveals the following risks associated with the reverse logistics of plastic packaging waste.

Hazardous material mishandling risk: (Code: FM1)

Hazardous material mishandling in the reverse logistics of the plastic recycling industry is a significant concern with far-reaching consequences for both the environment and human health [19]. One key risk is the potential release of toxic chemicals into the environment. When plastics containing hazardous materials are mishandled, they can break, crack, or corrode, allowing these harmful substances to leach into the soil and groundwater [18]. This contamination can persist for many years, affecting ecosystems and wildlife and potentially entering the food chain, ultimately posing health risks to humans [20].

Contamination of recyclables risk: (Code: FM2)

The contamination of recyclables is a critical challenge in the reverse logistics of the plastic recycling industry. It occurs when non-recyclable materials or contaminants, such as food residue, chemicals, or non-plastic items, mix with collected plastic waste [30]. This contamination can occur at various points in the reverse logistics chain, from initial collection to sorting and processing, and poses several significant issues [11]. Furthermore, contamination affects the quality of recycled plastic. Plastics with high levels of contamination are often deemed unsuitable for recycling or have reduced market value, as they require more extensive cleaning and processing [13]. This results in higher costs for recycling facilities and lower revenues from the sale of recycled materials.

Energy-intensive recycling risk: (Code: FM3)

The plastic recycling industry is characterized by a significant challenge known as energy-intensive recycling within its reverse logistics system [12]. This issue revolves around the considerable energy demands necessary to convert collected plastic waste into viable recycled materials [16]. This energy consumption is distributed across several pivotal stages of recycling, encompassing the cleaning and sorting of plastic materials, as well as energy-intensive melting and reformation processes [31]. Numerous factors converge to amplify the energy intensity associated with plastic recycling. Energy-intensive recycling raises concerns about the environmental footprint of plastic recycling efforts. While recycling plastics reduces the demand for virgin materials and contributes to waste reduction, the environmental benefits may be diminished if the energy used in recycling exceeds that saved by avoiding the production of new plastics [1].

Worker health and safety risk (Code: FM4)

The collection, transportation, and processing of plastic waste can expose workers to various hazards that can lead to injuries, illnesses, or long-term health effects [2]. Chemical exposure is another critical concern. Plastic waste often contains hazardous substances, including toxic chemicals and heavy metals. In the absence of adequate personal protective equipment and precise handling protocols, workers become vulnerable to these substances, which can cause immediate health repercussions such as skin irritation and respiratory ailments [32]. Prolonged or extensive exposure may escalate these effects to more severe health conditions. Furthermore, the machinery and equipment used in plastic recycling facilities pose additional safety risks [33]. Workers operating shredders, balers, and conveyor belts may be at risk of accidents, such as entanglement, crushing, or falls, if safety measures and training are insufficient [1]. Noise pollution is a prevalent but often underestimated health risk in recycling facilities. The constant noise generated by machinery can lead to hearing impairment and other stress-related health problems if proper hearing protection and noise control measures are not implemented [34].

Recycled material transportation risk (Code: FM5)

Transportation risks in the reverse logistics of the plastic recycling industry are the challenges and vulnerabilities associated with the movement of plastic waste and recycled materials from collection points to processing facilities or recycling centers [11]. These risks can have significant impacts on the efficiency, cost-effectiveness, and environmental sustainability of reverse logistics operations [24]. First, there is the risk of inadequate transportation infrastructure. Recycling facilities and collection points may be located in regions with subpar road networks or limited access to transportation resources [19]. This can lead to delays, increased transportation costs, and disruptions in the recycling supply chain. Furthermore, poor infrastructure can result in increased wear and tear on vehicles, potentially leading to breakdowns and maintenance expenses. Second, the environmental impact of transportation is a crucial concern [33]. The transportation of plastic waste over long distances can result in increased fuel consumption and greenhouse gas emissions, contributing to environmental degradation. Excessive emissions can undermine an industry's commitment to sustainability and exacerbate climate change concerns [20]. To mitigate this risk, recycling facilities should strive to minimize transportation distances, optimize routes, and consider environmentally friendly transportation alternatives [7].

Recycled material inventory risk (Code: FM6)

Inventory risks in the reverse logistics industry of plastic recycling relate to the management of stockpiled or stored plastic waste and recycled materials, and they can have substantial implications for operational efficiency and profitability [35]. First, excess inventory poses a significant risk. Accumulating large volumes of plastic waste waiting to be processed or recycled can tie up valuable space and resources [11]. This can lead to increased storage costs and the potential for deterioration or contamination of stored materials. Excess inventory can also disrupt workflows, making it challenging to manage incoming waste effectively [35,36]. In contrast, inadequate inventory levels can lead to bottlenecks and delays in the recycling process. If recycling facilities run out of processed materials or fail to maintain a sufficient inventory of recycled plastics, they may be unable to meet customer demands or contractual obligations [1]. This can result in missed revenue opportunities, contractual penalties, and damage to the company's reputation.

Inadequate collection practice risk (Code: FM7)

Inadequate collection practices represent a significant risk within the reverse logistics landscape of the plastic recycling industry [37]. These practices involve non-optimal methods employed to gather plastic materials from a variety of sources, including households, businesses, and public spaces [2]. This inefficiency can manifest in various forms and has substantial implications for the industry's long-term sustainability [38]. Primarily, inefficient collection processes can lead to heightened fuel consumption and elevated emissions. In cases where collection routes lack meticulous planning and optimization, recycling vehicles might cover needlessly extensive distances, resulting in increased fuel expenditures and a more substantial carbon footprint [37]. This has implications not only for the industry's environmental footprint but also for its financial viability, as it adds supplementary operational costs that can potentially jeopardize the economic feasibility of recycling endeavors [1].

Reverse logistics information risk (Code: FM8)

Reverse logistics information risks in the plastic recycling industry encompass the challenges and vulnerabilities associated with managing the flow of data, documentation, and information throughout the process of collecting, transporting, and recycling plastic waste [39]. These risks have significant implications for the efficiency, transparency, and security of reverse logistics operations [40]. One prominent information risk is the impact on data accuracy and integrity. Inaccurate or incomplete information about the type, quantity, and origin of plastic waste can lead to operational inefficiencies and errors in sorting and processing [36]. This can result in the improper allocation of resources, reduced recycling rates, and increased contamination of recyclable materials [40].

Waste-to-Energy controversy risks (Code: FM9)

The controversy surrounding "Waste-to-Energy" (WtE) introduces a complex array of risks within the reverse logistics domain of the plastic recycling industry [11]. WtE entails the incineration of plastic waste to produce energy. Although this approach provides a feasible method for decreasing the accumulation of plastic waste in landfills, it also yields many environmental and health-related concerns, creating substantial risks [40]. Another significant concern is the impact of climate change. Burning plastic releases carbon dioxide, a potent greenhouse gas that contributes to global warming [36]. While some argue that WtE can offset the greenhouse gas emissions associated with the production of new plastics, the net environmental benefit of WtE remains contentious [40]. Critics contend that the energy-intensive nature of plastic production and recycling, combined with the emissions from incineration, may outweigh the benefits [11].

Machinery and equipment malfunction risk (Code: FM10)

Machinery and equipment malfunctions are critical risks inherent to reverse logistics operations within the plastic recycling industry [20]. Recycling facilities heavily depend on a diverse array of specialized machinery and equipment to effectively process the gathered plastic waste [27]. Failures in these pivotal components can trigger many challenges. First, machinery malfunctions can cause costly downtime [28]. When a key piece of equipment breaks down or requires repairs, the entire recycling process can be brought to a standstill [21]. This downtime not only impacts productivity but also incurs financial losses due to repair expenses and the revenue forfeited from delayed recycling operations [23]. Second, equipment malfunctions can compromise the quality of recycled materials [26]. If a machine designated for shredding or sorting plastic waste malfunctions, it may inadequately separate materials or inadvertently damage recyclables [20]. This can elevate the contamination levels within recycled materials, diminishing their worth and market appeal.

2.3 Application of Fuzzy MCDM in FMEA

Among the plethora of risk analysis techniques, FMEA is a systematic tool widely embraced by both academia and industry for conducting comprehensive risk assessments. Traditional FMEA relies on three core risk criteria, severity (*S*), occurrence (*O*), and detection (*D*), each assessed using a 10-point scale to evaluate the risk associated with each Failure Mode (FM) [41]. These three scores are multiplied to yield the risk priority number (RPN), which is used to quantify the level of risk for each FM [42,43], with a higher RPN indicating a higher level of risk. However, traditional FMEA has several limitations and logical inconsistencies, including (*i*) the use of a 10-point scale, which introduces ambiguity and inaccuracy; (*ii*) the absence of a rigorous mathematical foundation for the multiplication of *S*, *O*, and *D* to calculate the RPN for FM prioritization; and (*iii*) disregard for the relative importance weights of the risk criteria (*S*, *O*, and *D*) during the RPN computation [44]. To rectify these shortcomings, the adoption of a multicriteria decision-making (MCDM) approach has emerged as a promising solution [45]. Decision-making within the context of FMEA often involves uncertainties and ambiguities inherent in human judgment. Fuzzy Set Theory (FST) has emerged as a strong tool for addressing these challenges [46,47]. In recent years, numerous studies have leveraged various forms of FST to mitigate uncertainty and enhance decision-making within the realm of FMEA as shown in Table 1, including the following.

Table 1
Recent research applies fuzzy FMEA approach

No.	Topic	Reference
1	Assessing risks in effluent treatment plants using fuzzy FMEA	[48]
2	Risk assessment for lean projects using fuzzy FMEA	[49]
3	Risk analysis based on FMEA in the oil and gas industry applying picture fuzzy sets	[50]
4	Analysis of FMEA failures in a CNC Machine using Interval type-2 fuzzy sets	[51]
5	Risk assessment for investments in renewable energy utilizing fuzzy FMEA	[52]
6	Health and safety risk assessment based on fuzzy FMEA	[53]
7	A fuzzy FMEA approach for quantitative dynamic risk assessment in ship operations	[54]
8	Utilizing rule-based Fuzzy FMEA for shipboard compressor system risk analysis to prevent major marine accidents	[55]
9	Automated prioritization of construction project requirements through Fuzzy FMEA and machine learning approaches	[56]
10	Evaluating a maintenance strategy in the paper industry integrating fuzzy FMEA-ANP-GP	[57]
11	FMEA for electric vehicles DC charging piles using canonical triangular interval type-2 fuzzy set linguistic	[58]
12	Assessment of hydroelectric earth dam failure modes using a fuzzy FMEA	[59]
13	Risk evaluation approach for LHD machine based on fuzzy-FMEA	[60]

3. Methods

This section presents the foundational mathematical concepts for the Trapezoidal Fuzzy Set (TrFS), AHP, and LOPCOW algorithms, as outlined below.

3.1 Mathematical Preliminaries of the Trapezoidal Fuzzy Set (TrFS)

A trapezoidal fuzzy set (TrFS) is a mathematical concept that plays a vital role in the domain of fuzzy logic, a branch of mathematics designed to handle imprecision and uncertainty. TrFS provides a versatile way to represent and work with fuzzy or vague information that may not be easily described by traditional binary sets [61]. Unlike crisp sets, which classify elements as either fully in or out of a set, a TrFS allows for a gradual transition between membership and non-membership, accommodating varying degrees of uncertainty. A TrFS is characterized by four parameters representing trapezoidal fuzzy numbers (TrFNs): the lower and upper bounds of the set and two intermediate points that define the transitions between full membership, partial membership, and non-membership [62]. The higher the membership degree at a particular point is, the more likely that the value belongs to the fuzzy set. By using TrFNs, researchers and engineers can capture the complexity of uncertain data and make informed decisions when precise information is scarce or inappropriate. Whether in finance, engineering, or expert systems, TrFNs are valuable tools for managing and processing uncertainty, contributing to more robust and adaptive solutions in an uncertain world. In this research, TrFNs are employed as a robust approach to address uncertain and imprecise data in reverse logistics risk assessment. For clarity, a visual representation of TrFNs is presented in Figure 1. Additionally, the mathematical expression describing the membership function of these numbers is provided as follows [63]:

$$\mu_N(x) = \begin{cases} (x-x_1)/x_2-x_1), x \in [x_1, x_2] \\ 1 \qquad , x \in [x_2, x_3] \\ (x_4-x)/\,(x_4-x_3)\,, x \in [x_3, x_4] \\ 0 \qquad ; otherwise \end{cases} \tag{1}$$

where $\{(x_1, x_2, x_3, x_4) | x_1, x_2, x_3, x_4 \in R;\ x_1 \leq \ x_2 \leq x_3 \leq x_4\}$

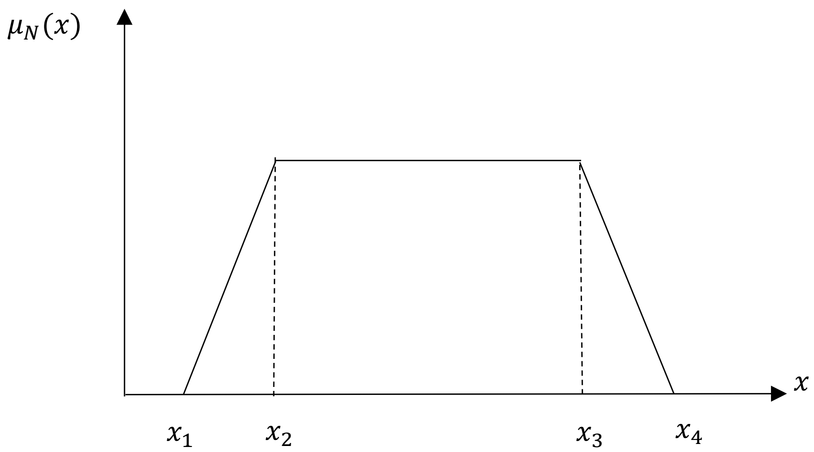

Fig. 1. Trapezoidal fuzzy number

Definition *1.* Let α and β represent two positive trapezoidal fuzzy numbers, characterized by the parameter sets $(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$ and $(\beta_1, \beta_2, \beta_3, \beta_4)$, respectively. The operational rules governing these two trapezoidal fuzzy numbers are detailed as suggested by Shemshadi *et al.,* [64].

$$\alpha(+)\beta = (\alpha_1, \alpha_2, \alpha_3, \alpha_4)(+)(\beta_1, \beta_2, \beta_3, \beta_4) = (\alpha_1+\beta_1, \alpha_2+\beta_2, \alpha_3+\beta_3, \alpha_4+\beta_4) \tag{2}$$

$$\alpha(-)\beta = (\alpha_1, \alpha_2, \alpha_3, \alpha_4)(-)(\beta_1, \beta_2, \beta_3, \beta_4) = (\alpha_1-\beta_1, \alpha_2-\beta_2, \alpha_3-\beta_3, \alpha_4-\beta_4) \tag{3}$$

$$\alpha(\otimes)\beta = (\alpha_1, \alpha_2, \alpha_3, \alpha_4)(\otimes)(\beta_1, \beta_2, \beta_3, \beta_4) = (\alpha_1\beta_1, \alpha_2\beta_2, \alpha_3\beta_3, \alpha_4\beta_4) \tag{4}$$

$$\alpha(\emptyset)\beta = (\alpha_1, \alpha_2, \alpha_3, \alpha_4)(\emptyset)(\beta_1, \beta_2, \beta_3, \beta_4) = \left(\frac{\alpha_1}{\beta_1}, \frac{\alpha_2}{\beta_2}, \frac{\alpha_3}{\beta_3}, \frac{\alpha_4}{\beta_4}\right) \tag{5}$$

$$k\alpha = (k\alpha_1, k\alpha_2, k\alpha_3, k\alpha_4) \tag{6}$$

$$\alpha^{-1} = \left(\frac{1}{\alpha_4}, \frac{1}{\alpha_3}, \frac{1}{\alpha_2}, \frac{1}{\alpha_1}\right) \tag{7}$$

Definition *2.* Let $X^1, X^2, \ldots, X^k$ and $k = 1,2,\ldots,p$, denote trapezoidal fuzzy matrices gathered from p experts for i alternatives considering j criteria, represented by $X^k = [x^k_{ij1}, x^k_{ij2}, x^k_{ij3}, x^k_{ij4}]$. Subsequently, the aggregation of the fuzzy rating score matrix from all the experts, denoted as $\tilde{x}^k_{ij} = (\tilde{x}^k_{ij1}, \tilde{x}^k_{ij2}, \tilde{x}^k_{ij3}, \tilde{x}^k_{ij4})$, can be expressed by Eq. (8), as described by Shemshadi *et al.,* [64].

$$\tilde{X}_{ij} = \begin{cases} \tilde{x}^k_{ij1} = \min\limits_k\{x^k_{ij1}\} \\ \tilde{x}^k_{ij2} = \frac{1}{p}\sum_{k=1}^{p} x^k_{ij2} \\ \tilde{x}^k_{ij3} = \frac{1}{p}\sum_{k=1}^{p} x_{ijk3} \\ \tilde{x}^k_{ij4} = \max\limits_k\{x_{ijk4}\} \end{cases} \tag{8}$$

Definition *3.* Let $X = [x_{ij}]_{m\times n}$ represent a trapezoidal fuzzy matrix; the normalized aggregated fuzzy rating matrix, denoted as $U = [u_{ij}]_{m\times n}$, can be expressed by Eq. (9) and Eq. (10).

$$u_{ij} = \left\{\left(\frac{x^-_{ij1}}{x_{ij1}}, \frac{x^-_{ij2}}{x_{ij2}}, \frac{x^-_{ij3}}{x_{ij3}}, \frac{x^-_{ij4}}{x_{ij4}},\right)\right\} \; for\ cost\ criterion \tag{9}$$

$$u_{ij} = \left\{\left(\frac{x_{ij1}}{x^+_{ij4}}, \frac{x_{ij2}}{x^+_{ij4}}, \frac{x_{ij3}}{x^+_{ij4}}, \frac{x_{ij4}}{x^+_{ij4}},\right)\right\} \; for\ benefit\ criterion \tag{10}$$

where $x^+_{ij4} = \max\limits_i\{x_{ij4}\}$ is the benefit criterion, while $x^-_{ij1} = \min\limits_i\{x_{ij1}\}$ is the cost criterion, and $u_{ij} = (u_{ij1}, u_{ij2}, u_{ij3}, u_{ij4})$.

Definition *4.* Let x represents a trapezoidal fuzzy number, denoted as $x = (x_1, x_2, x_3, x_4)$. To derive a precise value from a trapezoidal fuzzy number, a defuzzification process is necessary. The conversion of X into a corresponding crisp value can be expressed by Eq. (11), as proposed by Shemshadi *et al.,* [64].

$$\begin{aligned} \mathrm{Defuzz}(x_{ij}) &= \frac{\int \mu(x).x dx}{\int \mu(x) dx} \\ &= \frac{\int_{x_{ij1}}^{x_{ij2}}\left(\frac{x-x_{ij1}}{x_{ij2}-x_{ij1}}\right)\cdot x dx + \int_{x_{ij2}}^{x_{ij3}} x dx + \int_{x_{ij3}}^{x_{ij4}}\left(\frac{x_{ij4}-x}{x_{ij4}-x_{ij3}}\right)\cdot x dx}{\int_{x_{ij1}}^{x_{ij2}}\left(\frac{x-x_{ij1}}{x_{ij2}-x_{ij1}}\right) dx + \int_{x_{ij2}}^{x_{ij3}} dx + \int_{x_{ij3}}^{x_{ij4}}\left(\frac{x_{ij4}-x}{x_{ij4}-x_{ij3}}\right) dx} \\ &= \frac{-x_{ij1}x_{ij2} + x_{ij3}x_{ij4} + \frac{1}{3}(x_{ij4} - x_{ij3})^2 - \frac{1}{3}(x_{ij2} - x_{ij1})^2}{-x_{ij1} - x_{ij2} + x_{ij3} + x_{ij4}} \end{aligned} \tag{11}$$

Definition *5.* Let F represents a weighted normalization matrix of a trapezoidal fuzzy set, denoted as $F = [f_{ij}]_{m\times n} = [u_{ij}\otimes\omega_j^c]_{m\times n}$. The defuzzification of elements within F, denoted $d_{ij} = defuzz(u_{ij}\otimes\omega_j^c)$ can be expressed using Eq. (12), as proposed by Shemshadi *et al.,* [64].

$$d_{ij} = defuzz(u_{ij}\otimes\omega_j^c) = \frac{\int \mu(x).xdx}{\int \mu(x)dx} \quad (12)$$

$$= \frac{\int_{u_{ij1}\omega_{j1}^c}^{u_{ij2}\omega_{j2}^c}\left(\frac{x-\omega_{j1}^c}{u_{ij2}\omega_{j2}^c-u_{ij1}\omega_{j1}^c}\right)\cdot xdx + \int_{u_{ij2}\omega_{j2}^c}^{u_{ij3}\omega_{j3}^c} xdx + \int_{u_{ij3}\omega_{j3}^c}^{u_{ij4}\omega_{j4}^c}\left(\frac{u_{ij4}\omega_{j4}^c-x}{u_{ij4}\omega_{j4}^c-u_{ij3}\omega_{j3}^c}\right)\cdot xdx}{\int_{u_{ij1}\omega_{j1}^c}^{u_{ij2}\omega_{j2}^c}\left(\frac{x-u_{ij1}\omega_{j1}^c}{u_{ij2}\omega_{j2}^c-u_{ij1}\omega_{j1}^c}\right)dx + \int_{u_{ij2}\omega_{j2}^c}^{u_{ij3}\omega_{j3}^c} dx + \int_{u_{ij3}\omega_{j3}^c}^{u_{ij4}\omega_{j4}^c}\left(\frac{u_{ij4}\omega_{j4}^c-x}{u_{ij4}\omega_{j4}^c-u_{ij3}\omega_{j3}^c}\right)dx}$$

$$d_{ij} = \frac{-(u_{ij1}u_{ij2})(\omega_{j1}^c\omega_{j2}^c)+(u_{ij3}u_{ij4})(\omega_{j3}^c\omega_{j4}^c)+\frac{1}{3}(u_{ij4}\omega_{j4}^c-u_{ij3}\omega_{j3}^c)^2-\frac{1}{3}(u_{ij2}\omega_{j2}^c-u_{ij1}\omega_{j1}^c)^2}{-u_{ij1}\omega_{j1}^c-u_{ij2}\omega_{j2}^c+u_{ij3}\omega_{j3}^c+u_{ij4}\omega_{j4}^c}$$

where $\omega_j^c = [\omega_{j1}^c, \omega_{j2}^c, \omega_{j3}^c, \omega_{j4}^c]$ is the consolidated weights of the FMEA risk criteria.

Definition *6.* Let $X = [x_{ij}]_{m\times n}$ represents a trapezoidal fuzzy matrix; the geometric mean within each row of the matrix $(\widehat{r_i})$ can be expressed using Eq. (13), as proposed by Samia and Fares [65].

$$\widehat{r_i} = (\tilde{x}_{i1}\otimes\tilde{x}_{i2}\otimes \dots \otimes\tilde{x}_{in})^{\frac{1}{n}} \quad (13)$$

where $\tilde{x}_{i1}, \tilde{x}_{i2}, \dots \tilde{x}_{in}$ are TrFNs, $\widehat{r_i} = (r_{i1}, r_{i2}, r_{i3}, r_{i4})$

The applications of TrFS have been widely utilized to address numerous real-world and academic MCDM problems, as illustrated by the examples provided in Table 2.

Table 2
The examples of TrFS applications in existing studies

No.	Topic	Reference
1	Evaluation of wind power projects post-implementation using an enhanced ANP based on trapezoidal fuzzy set	[66]
2	Selecting security guard service company using geometric approach for ranking generalized trapezoidal fuzzy numbers	[67]
3	Selective disassembly sequence planning under uncertainty using trapezoidal fuzzy numbers	[68]
4	Emergency decision-making technique based on trapezoidal fuzzy best-worst method and zero-sum game	[69]
5	Efficiency analysis of water treatment plant using an integrated trapezoidal fuzzy	[70]
6	Water cycle health assessment based on trapezoid fuzzy TOPSIS model	[71]
7	Assessment of national innovation capabilities of OECD countries using trapezoidal interval type-2 fuzzy	[72]
8	Blockchain technology in construction organizations: risk assessment using trapezoidal fuzzy	[73]
9	Interval type-2 trapezoidal fuzzy multi-attribute decision-making method and its application to the corporate investment selection	[74]

3.2 AHP Algorithm

The AHP is a potent decision-making framework that enables both individuals and organizations to adeptly navigate intricate decision landscapes [75]. This can be achieved by organizing complex challenges into a hierarchical structure, applying relative significance to criteria, and employing pairwise comparisons to establish these priorities. This methodology harmoniously incorporates expert opinions and preferences into the decision-making process, positioning the AHP as an indispensable instrument for resolving multifaceted issues with numerous criteria while ensuring that decisions align seamlessly with overarching objectives and priorities [76]. The pseudocode for the AHP under the TrFS is outlined in Algorithm 1.

3.3 LOPCOW Algorithm

LOPCOW, an innovative objective weighting method introduced in recent literature, is a valuable approach for prioritizing assessment criteria within a specific hierarchical decision-making framework. This innovative methodology, developed by Ecer and Pamucar [77], offers numerous significant advantages. Distinguishing itself from other objective weighting methods, LOPCOW effectively handles negative values within raw data and alleviates substantial disparities in priority assignment among relevant criteria [77]. Furthermore, it excels in delivering comprehensive solutions for criteria in both hierarchical structures, regardless of whether they are classified as benefits or costs. Additionally, LOPCOW aids in harmonizing dimensional variations emerging from differences in data structures [78]. The LOPCOW pseudocode under TrFS is outlined in Algorithm 2.

3.4 ARAS Algorithm

The Additive Ratio Assessment (ARAS) method, a variant of MCDM, was first conceptualized by Zavadskas and Turskis [79]. Within the ARAS framework, a utility function is employed to quantify the intricate relative efficiency of a potential alternative. This utility function directly contrasts the alternative's performance against the cumulative impact of values and weights assigned to the significant criteria within a project. The ARAS approach offers several noteworthy advantages. First, it maintains a direct and proportional relationship with criterion weights [80]. Second, it has the ability to address highly intricate problems [79]. Third, it encompasses straightforward and efficient processes that consistently yield satisfactory, realistic, and reasonably accurate results when assessing and prioritizing various alternatives [80]. The pseudocode for ARAS under TrFS is outlined in Algorithm 3.

Algorithm 1: Pseudo Representation of AHP under TrFS

Input: (1) Index of criteria (j), number of criteria (n), C_j is criterion j^{th}, $j = 1,2,3,..,n$.
(2) Index of decision-maker (k), number of decision-makers (p), $k = 1,2,3,..,p$.
Output: Subjective weights of criteria (ω_j^s)

Begin

Step 1: Obtain linguistic pairwise comparison between C_j for all experts, and transform it into corresponding trapezoidal TrFN as outlined in Table 1.

Step 2: Conduct consistency check procedure by transforming to corresponding TrFN to consistency index numerators to obtain the consistency ratio

for $k = 1$ to p do

$$CR = \frac{CI}{RI}, \text{ where } CI = \frac{\lambda_{max}-n}{n-1} \tag{14}$$

If $CR > 0.1$ **then**

return to Step 1;

else

go to Step 3;

end

end

Step 3: Construct the TrFS pair-wise comparison matrix for each expert, using Eq. (15)

$$X^k = [x_{ij}^k]_{mxn} = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1}^m & x_{n2}^m & \cdots & x_{nn}^m \end{bmatrix} \end{array} \tag{15}$$

where $x_{ij}^k = \left(x_{ij1}, x_{ij2}, x_{ij3}, x_{ij4}\right)$, $x_{i=j}^k = (1,1,1,1)$, $x_{ji}^k = \left(\frac{1}{x_{ij4}}, \frac{1}{x_{ij3}}, \frac{1}{x_{ij2}}, \frac{1}{x_{ij1}}\right)$

Step 4: Aggregate the TrFS pair-wise comparison matrices into a group decision-making, denoted as $\tilde{X} = [\tilde{x}_{ij}]_{nxn}$, where $\tilde{x}_{ij} = \left(\tilde{x}_{ij1}, \tilde{x}_{ij2}, \tilde{x}_{ij3}, \tilde{x}_{ij4}\right)$, using Eq. (8).

Step 5: Calculate the geometric mean in each row of aggregated TrFS pair-wise comparison matrix**,** using Eq. (16)

$$\hat{r_i} = (\tilde{x}_{i1} \otimes \tilde{x}_{i2} \otimes \ldots \otimes \tilde{x}_{in})^{\frac{1}{n}} \tag{16}$$

where $\tilde{x}_{i1}, \tilde{x}_{i2}, \ldots, \tilde{x}_{in}$ are TrFNs, $\hat{r_i} = (r_{i1}, r_{i2}, r_{i3}, r_{i4})$

Step 6: Compute the TrFN subjective weighting for each row (ω_j^s), using Eq. (17)

$$\omega_j^s = \hat{r_i} \otimes (\hat{r_1} \otimes \hat{r_2} \otimes \ldots \otimes \hat{r_n})^{-1} \tag{17}$$

where $\omega_j^s = \left(\omega_{j1}^s, \omega_{j2}^s, \omega_{j3}^s, \omega_{j4}^s\right)$.

End

Algorithm 2: Pseudo Representation of LOPCOW under a trapezoidal fuzzy set

Input: (1) Index of alternative (i), number of alternatives (m), A_i is alternative i^{th}, $i = 1,2,3,..,m$.
(2) Index of criteria (j), n), C_j is criterion j^{th}, $j = 1,2,3,..,n$.
(3) Index of decision-makers (k), number of decision-makers (p),$k = 1,2,3,..,p$.
Output: Objective weights of criteria (ω_j^o)
Begin

Step 1: Obtain the linguistic evaluation of alternative i with respect to criterion j for all experts and transform them into corresponding trapezoidal fuzzy numbers, as outlined in Table 2-3.

Step 2: Construct the evaluation decision matrix for each expert as follows

$X^k = [x_{ij}^k]_{mxn}$

$$X^k = [x_{ij}^k]_{mxn} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1}^m & x_{n2}^m & \cdots & x_{nn}^m \end{bmatrix} \end{array}, \text{ where } x_{ij}^k = \left(x_{ij1}^k, x_{ij2}^k, x_{ij3,}^k\, x_{ij4}^k\right) \quad (18)$$

Step 3: Compute the aggregated evaluation decision matrix represented as $\tilde{X} = [\tilde{x}_{ij}]_{mxn}$ using Eq. (8), where $\tilde{x}_{ij} = \left(\tilde{x}_{ij1}, \tilde{x}_{ij2}, \tilde{x}_{ij3}\ \tilde{x}_{ij4}\right)$.

Step 4: Calculate the normalized aggregated matrix $U = [U_{ij}]_{mxn}$, using Eq. (9) and Eq. (10):

Step 5: Determine the percentage value (P_j) for each criterion, using Eq. (19)-Eq. (20):

$$RMS_j = \sqrt{\frac{\sum_{i=1}^{m} u_{ij}^2}{m}} \quad (19)$$

$$\sigma_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}(u_{ij} - \frac{1}{m}\sum_{t=1}^{m} u_{tj})^2} \quad (20)$$

$$P_j = \left| In\left(\frac{RMS_j}{\sigma_j}\right).100 \right| \quad (21)$$

where RMS_j and σ_j represent the root mean square value and the standard deviation of the joint normalized evaluations under the j^{th} criterion, respectively.

Step 6: Calculation the objective weights of criteria (ω_j^o), using Eq. (22)

$$\omega_j^o = \frac{P_j}{\sum_{j=1}^{n} P_j} \quad (22)$$

where $\omega_j^o = \left(\omega_{j1}^o, \omega_{j2}^o, \omega_{j3}^o\ \omega_{j4}^o\right)$.

End

Algorithm 3: Pseudo representation of ARAS under a trapezoidal fuzzy set

Input: (1) Index of alternative (i), number of alternatives (m), A_i is alternative i^{th}, $i = 1,2,3,..,m$.
(2) Index of criteria (j), n), C_j is criterion j^{th}, $j = 1,2,3,..,n$.
(3) index (k), number of decision-makers (p),$k = 1,2,3,..,p$.
Output: Ranking alternatives $(A_1, A_2, A_3, \dots, A_m)$
Begin

Step 1: Obtain the linguistic evaluation of alternative i with respect to criterion j for all experts and transform them into corresponding trapezoidal fuzzy numbers, as outlined in Tables (2)-(3). Subsequently, construct the decision matrix for each decision-maker, represented as $X^k = [x_{ij}^k]_{mxn}$, as shown in Eq. (23).

$$X^k = [x_{ij}^k]_{mxn} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1}^m & x_{n2}^m & \cdots & x_{nn}^m \end{bmatrix} \end{array}, \text{ where } x_{ij}^k = \left(x_{ij1}^k, x_{ij2}^k, x_{ij3,}^k\, x_{ij4}^k\right) \tag{23}$$

Step 2: Compute the aggregated decision matrix $\tilde{X} = [\tilde{x}_{ij}]_{mxn}$ using Eq. (8), where $\tilde{x}_{ij} = \left(\tilde{x}_{ij1}, \tilde{x}_{ij2}, \tilde{x}_{ij3}\, \tilde{x}_{ij4}\right)$.

Step 3: Identify the optimal value of criterion j, denoted as OV, using Eq. (24) for benefit criterion B and Eq. (25) for cost criterion C.

$$OV = \max_i \tilde{x}_{ij}, j \in B \tag{24}$$

$$OV = \min_i \tilde{x}_{ij}, j \in C \tag{25}$$

Step 4: Calculate the normalized aggregated matrix, $\bar{X}$, using Eq. (26) and Eq. (27)

$$\bar{x}_{ij} = \frac{\tilde{x}_{ij}}{\sum_{i=0}^m \tilde{x}_{ij}}, j \in B \tag{26}$$

$$\bar{x}_{ij} = \frac{\boldsymbol{x_{ij}^*}}{\sum_{i=0}^m \boldsymbol{x_{ij}^*}}, j \in C \text{ , where } x_{ij}^* = \frac{1}{\tilde{x}_{ij}} \tag{27}$$

Step 5: Conduct defuzzification on the weighted normalized decision matrix, defined as $\hat{x}_{ij}^{def} = defuzz\left(\bar{x}_{ij} \otimes \omega_j^c\right)$ using Eq. (12); ω_j^c can be obtained by Eq. (28).

$$\omega_j^c = \varphi\omega_j^s + (1-\varphi)\omega_j^o \quad (28)$$

Here, ω_j^c denotes the consolidated weight of each criterion derived from the TrFS AHP (Algorithm I) and the TrFS LOPCOW (Algorithm II). The coefficient γ represents the combined decision mechanism, which falls within the range of $\gamma \in [0, 1]$. For the sake of simplicity, without loss of generality, this study assumes a value of 0.5.

Step 6: Obtain the optimality function values (γ_i) by using Eq. (29)

$$\gamma_i = \sum_{j=1}^{n} \hat{x}_{ij}, i = 0,1, \dots, m \quad (29)$$

where γ_i represents the optimality function value of the i^{th} alternative.

Step 7: Calculate the degree of utility for alternative (K_i) via Eq. (30)

$$K_i = \frac{\gamma_i}{\gamma_{op}}, i = 1,2,3, \dots, m \quad (30)$$

where γ_{op} represents the optimal value of the alternative, $K_i \in [0,1]$

Step 8: Rank the alternatives in descending order based on K_i values.

End

3.5 Review the application of AHP, LOPCOW, and ARAS

The comprehensive review of AHP, Level LOPCOW, and ARAS provided valuable insights into their respective strengths and weaknesses in decision-making contexts.

AHP, a widely utilized method, emerged as a robust framework for structuring complex decision problems and prioritizing criteria. Its hierarchical structure facilitated the decomposition of decisions into manageable components, enabling decision-makers to systematically evaluate alternatives [75]. However, the review revealed that AHP may encounter challenges when dealing with subjective judgments and inconsistent pairwise comparisons, necessitating careful consideration of input data quality [76]. The applications of AHP under TrFN extensively utilized to address MCDM challenges in real-world scenarios, as illustrated by various examples provided in Table 3.

Table 3
The examples of AHP under TrFN applications in prior studies

No.	Topic	Reference
1	Work safety evaluation and early warning rating of hot and humid environments using a trapezoidal fuzzy AHP	[81]
2	Risk assessment of mega-city infrastructures related to land subsidence using improved trapezoidal FAHP	[82]
3	Identification of monkeypox risk factors using a hybrid trapezoidal fuzzy FUCOM-AHP approach	[83]
4	Development of a new trapezoidal fuzzy AHP-TOPSIS hybrid approach for manufacturing firm performance measurement	[84]
5	A framework to prioritize the public Expectations from water treatment plants based on Trapezoidal Type-2 Fuzzy AHP method	[85]
6	A hybrid decision support model using a Trapezoidal fuzzy-based multi-attribute preference model with AHP-Entropy for groundwater remediation selection	[86]
7	Cost-risk contingency framework for managing cost overrun in metropolitan projects using a trapezoidal fuzzy AHP and simulation	[87]

LOPCOW, focusing on the determination of overall weights for criteria, demonstrated effectiveness in integrating diverse perspectives and preferences into decision-making processes. Its emphasis on the holistic assessment of criteria allowed decision-makers to capture the overarching importance of each factor within the decision context. Despite its strengths, LOPCOW was found to be sensitive to variations in input data and may require additional calibration to mitigate potential biases. Nonetheless, its ability to provide a comprehensive overview of decision factors makes it a valuable tool for addressing complex decision problems [77]. To the best of the authors' knowledge, no prior studies have applied the LOPCOW methodology within the framework of TrFN. Nevertheless, LOPCOW has been employed in different fuzzy versions to address MCDM problems, as exemplified in Table 4.

Table 4
The examples of LOPCOW under various fuzzy versions applications in prior studies

No.	Topic	Reference
1	A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector	[77]
2	Prioritizing industry 4.0-based material handling technologies in smart and sustainable warehouse management systems using neutrosophic LOPCOW-ARAS	[88]
3	Evaluation of third-party logistics service providers for car manufacturing firms using a novel integrated grey LOPCOW-PSI-MACONT model	[89]
4	Sustainability performance analysis of micro-mobility solutions in urban transportation with a novel IVFNN-Delphi-LOPCOW-CoCoSo framework	[90]
5	A new hybrid MCDM framework for third-party logistics provider selection under sustainability perspectives	[91]
6	A multi-criterion based analytic framework for exploring the impact of Covid-19 on firm performance in emerging market	[92]

ARAS method, known for its simplicity and efficiency, excels in prioritizing alternatives through ratio assessments. Its straightforward calculation and easy interpretation make it widely applicable [93]. However, it struggles with complex decision structures and conflicting preferences. While practical, its use demands careful consideration of context and trade-offs between simplicity and accuracy [94]. ARAS has been utilized in various fuzzy versions to tackle MCDM problems, as illustrated in Table 5.

Table 5
The examples of ARAS under various fuzzy versions applications in prior studies

No.	Topic	Reference
1	Geometric approach for ranking generalized trapezoidal fuzzy numbers and its application in selecting security guard service company	[93]
2	Interval type-2 Fuzzy ARAS method for recycling facility location problems	[94]
3	Smart watch evaluation with integrated hesitant fuzzy linguistic SAW-ARAS technique	[95]
4	Development of a firm export performance measurement model using a hybrid multi-attribute decision-making method	[96]
5	Resilient supplier selection to mitigate uncertainty: soft-computing approach	[97]
6	A decision-support approach under uncertainty for evaluating reverse logistics capabilities of healthcare providers in Iran	[98]

3.6 Proposed Research Framework

The proposed framework for risk assessment in the reverse logistics industry of plastic recycling can be divided into six phases as follows: Phase I: Identify and validate the failure modes; Phase II: Develop a decision model for risk assessment based on FMEA; Phase III: Calculate the subjective weights of FMEA risk criteria; Phase IV: Calculate the objective weights of FMEA risk criteria; Phase V: Compute the consolidated weights of the FMEA risk criteria; and Phase VI: Prioritize failure modes (*FMs*). This proposed framework is visually presented in Figure 2.

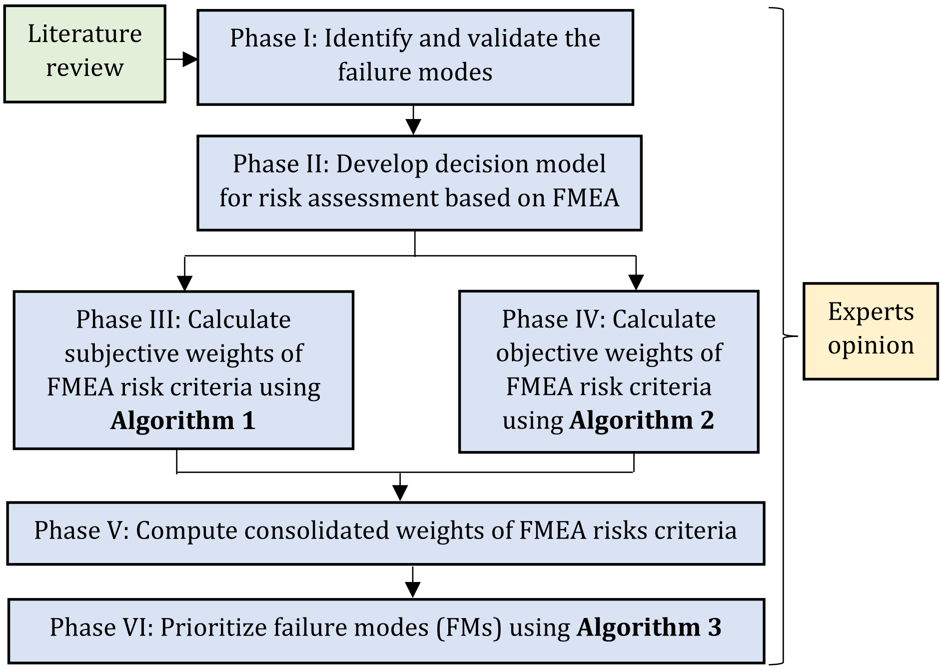

Fig. 2. Proposed research framework

3.7 Measurement Scales of TrFNs

The scale of relative importance used for pairwise comparisons of the AHP measurements, along with the corresponding TrFNs, is provided in Table 6. Additionally, the measurement scales for risk criteria under TrFNs are provided as follows: severity (*S*), occurrence (*O*), and detection (*D*) are detailed in Table 7, while cost of failure (*C*), complexity of failure resolution (*H*), and impact on business (*I*) are detailed in Table 8.

Table 6
Scale of relative importance employed for pairwise comparisons in AHP

Relative importance scale	Linguistic terms	TrFNs
1	Equally important	(1,1,1,1)
3	Weakly important	(2,5/2,7/2,4)
5	Essentially important	(4,9/2,11/2,6)
7	Very strongly important	(6,13/2,15/2,8)
9	Absolutely important	(8,17/2,9,9)
x =2,4,6,8 are intermediate scales (*x*-1, *x*-1/2, *x*+1/2, *x*+1)		

Table 7
Scale of risk criteria *S*, *O*, and *D* under TrFNs

Severity (*S*)	Occurrence (*O*)	Detection (*D*)	TrFNs
No(N)	Almost never (AN)	Almost detection (AD)	(0,0,1,2)
Very slight (VS)	Remote (R)	Very high (VH)	(0,1,2,3)
Slight (S)	Very slight (VS)	High (H)	(1,2,3,4)
Minor (Mi)	Slight (S)	Moderate high (MH)	(2,3,4,5)
Moderate (Mo)	Low (L)	Medium (M)	(3,4,5,6)
Significant (Si)	Medium (M)	Low (L)	(4,5,6,7)
Major (Ma)	Moderately high (MH)	Slight (S)	(5,6,7,8)
Extreme (E)	High (H)	Very slight (VS)	(6,7,8,9)
Serious (Se)	Very high (VH)	Remote (R)	(7,8,9,10)
Hazardous (H)	Almost certain (AC)	Almost impossible (AI)	(8,9,10,10)

Table 8
Scale of risk criteria *C*, *H*, and *I* under TrFNs

Cost of failure (*C*)	Complexity of failure resolution (*H*)	Impact on business (*I*)	TrFNs
No cost (N)	No difficulty (N)	No effect (N)	(0,0,1,2)
Almost no cost	Almost less difficulty (AD)	Almost less effect (AE)	(0,1,2,3)
Very low (VL)	Very low difficulty (VL)	Very low effect (VL)	(1,2,3,4)
Low (L)	Low difficulty (L)	Low effect (L)	(2,3,4,5)
Moderate low (ML)	Moderate low difficulty (ML)	Moderate low effect (ML)	(3,4,5,6)
Moderate (M)	Moderate difficulty (M)	Moderate effect (M)	(4,5,6,7)
Moderate high (MH)	Moderate high difficulty (MH)	Moderate high effect (MH)	(5,6,7,8)
High (H)	High difficulty (H)	High effect (H)	(6,7,8,9)
Very high (VH)	Very high difficulty (VH)	Very high effect (VH)	(7,8,9,10)
Extremely high cost (EH)	Extremely high difficulty (EH)	Extremely high effect (EH)	(8,9,10,10)

4. Results

4.1 Case Study

In this study, a real-world case study involving one of Thailand's prominent plastic recycling companies is employed to exemplify the application of the proposed framework. The selected company has more than 25 years of experience in plastic recycling and operates an innovative manufacturing facility situated in an economic zone along the southeastern coast of Rayong Province. This facility is equipped with state-of-the-art recycling technology and production lines specializing in the production of high-quality recycled plastic. With an annual production capacity of 35,000 tons of recycled polyethylene terephthalate (PET) resin, the company plays a pivotal role in the plastic packaging logistics closed-loop system. Given the inherent uncertainties, vulnerabilities, and recent disruptions encountered in the closed-loop system of plastic packaging logistics, the company has faced mounting logistics challenges and associated costs over the past two years, negatively affecting its reputation. To address these issues, the company's logistics director has devised a comprehensive risk assessment program tailored to the closed-loop logistics system. A dedicated FMEA working group comprising six experts is established within the case study company. Each expert has a wealth of knowledge and experience in reverse logistics within the context of plastic recycling. Details regarding these six individuals can be found in Table 9. The framework proposed in this study serves as a guiding tool for the systematic assessment of risks within the company's reverse logistics system.

Table 9
Details of the six experts

Code of experts	Current position	Experience (Years)	Responsibility relate reverse logistics in plastic waste
E1	Factory manager	12	His role involves coordinating with multiple departments, including logistics and quality control, to optimize operations, achieve production targets, and ensure alignment with sustainability goals.
E2	Logistics senior manager	6	His primary responsibility is to optimize the collection and transportation of plastic waste from diverse sources to recycling facilities, with a focus on minimizing costs and mitigating the environmental impact.
E3	Procurement senior manager	11	His role involves sourcing and procuring plastic waste feedstock from suppliers, skillfully negotiating favorable terms to enhance cost-efficiency. Furthermore, he works closely with suppliers to establish sustainable procurement practices and explores innovative sources of plastic waste, thus contributing significantly to the broader environmental objectives within the recycling industry.
E4	Production manager	5	His primary role involves the oversight of daily recycling facility operations, where he manages machinery and production processes to optimize output while upholding product quality standards. Furthermore, the production manager collaborates with various departments, including logistics and quality control, to enhance operational efficiency and align with the plastic recycling industry's sustainability and production objectives.
E5	Warehouse manager	6	His task involves the overseeing inventory control, ensuring precise tracking and reporting of stock levels to minimize waste and maintain a steady supply for production. He also plays a key role in enforcing recycling best practices, including proper material storage techniques to reduce contamination and promote the environmentally friendly reuse of plastic resources.
E6	Senior logistics engineer	5	Her role involves the data analysis and the implementation of cutting-edge logistics technologies aimed at enhancing efficiency, reducing transportation costs, and optimizing the overall performance of the reverse supply chain. This contribution aligns with the industry's sustainability objectives, fostering more eco-friendly practices in the plastic recycling sector.

4.2 Application of the Proposed Framework

The application of the proposed framework comprises six phases, as depicted in Figure 2. Further elaboration is provided below.

Phase I: Identify and Validate the Failure Modes

Through the comprehensive literature review outlined in Section 2.2, ten significant failure modes (*FMs*) that affect the operational efficiency of the reverse logistics of the plastic recycling industry are identified. To validate these ten *FMs*, a panel of experts from the plastic recycling industry is formed to review and confirm their relevance. The specifics of these experts are presented in Table 9. Following several rounds of discussion with these experts, the final selections of these ten *FMs* were confirmed as follows: hazardous material mishandling risk (*FM1*), contamination of recyclables risk *(FM2)*, energy-intensive recycling risk (*FM3*), worker health and safety risk (*FM4*), recycle material transportation risk (*FM*5), recycle material inventory risk (*FM*6), inadequate collection practice risk (*FM7*), reverse logistics information risk (*FM*8), waste-to-energy controversy risk (*FM9*), and machinery and equipment malfunction risk (*FM*10).

Phase II: Develop a Decision Model for Risk Assessment Based on FMEA

In this phase, a risk assessment decision model for reverse logistics in the plastic recycling industry is developed, as depicted in Figure 3. This comprehensive decision model is composed of six essential FMEA risk criteria, along with ten distinct failure modes (FMs), as outlined in Phase I. The six FMEA criteria include the severity (S), occurrence (O), detection (D), cost of failure (C), complexity of failure resolution (H), and impact on business (I). These six criteria can be categorized into two groups: benefit criteria (where larger values are preferable), which includes D; and cost criteria (where smaller values are preferable), which include S, O, C, H, and I.

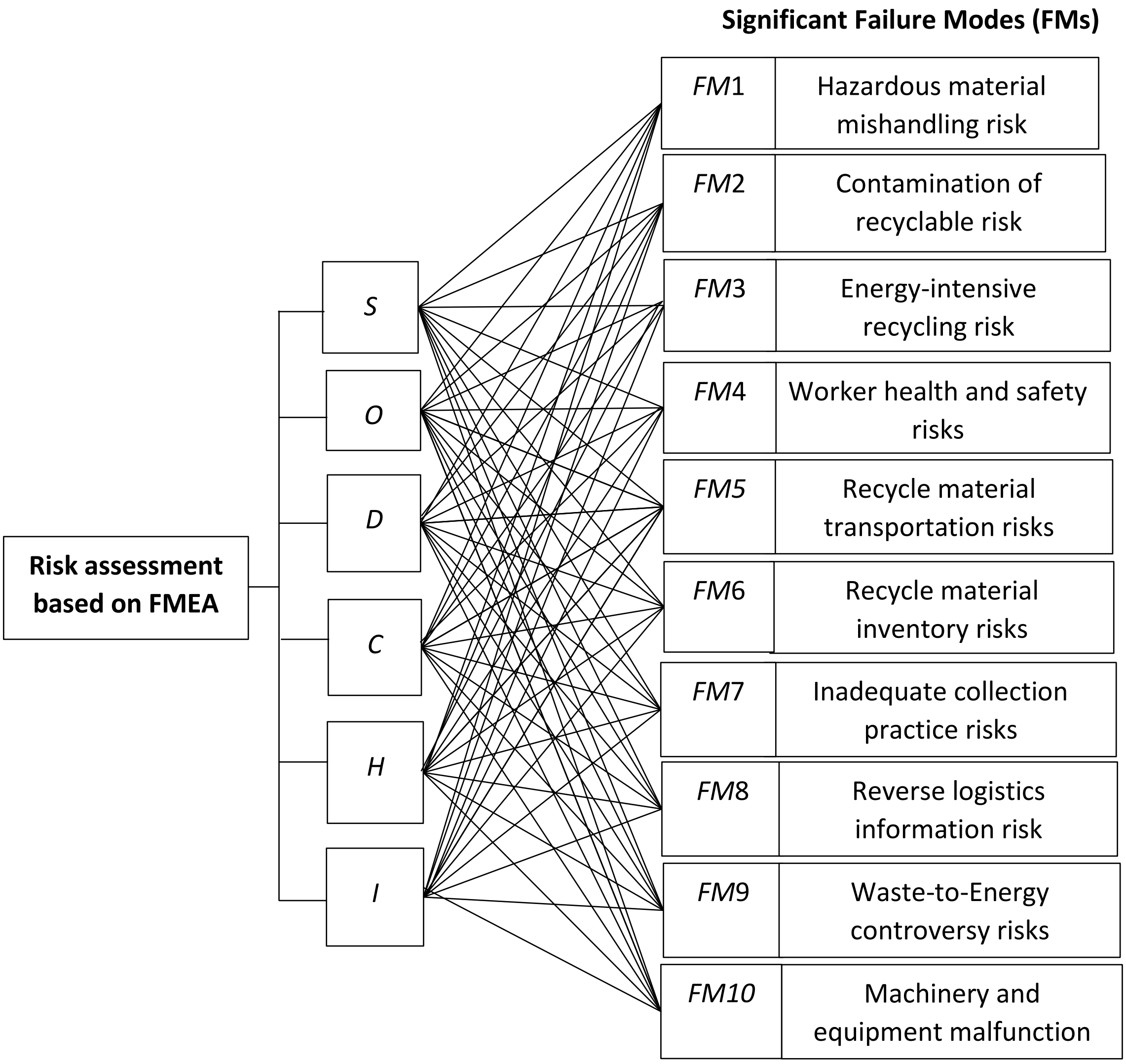

Fig. 3. Decision model for risk assessment based on FMEA

Phase III: Calculate the Subjective Weights of the FMEA Risk Criterion

The subjective weighting of each FMEA risk criterion (ω_j^s) is determined through the AHP using a trapezoidal fuzzy set procedure, as described in Algorithm 1. The process for calculating ω_j^s is described as follows:

Step 1: Obtain linguistic pairwise comparisons

Each industrial expert is tasked with assessing the relative importance of FMEA risk criteria through pairwise comparisons using the trapezoidal fuzzy linguistic terms provided in Table 1. All linguistic terms are converted into their respective TrFNs.

Step 2: Conduct consistency check

The pairwise comparisons of the TrFNs provided by all the experts are transformed into crisp values. Following this transformation, consistency checks are conducted to ensure the reliability and validity of the pairwise comparisons within the decision-making process. When the consistency ratio (*CR*) exceeds 0.1, experts are asked to re-evaluate their pairwise comparisons for refinement.

Step 3: Construct trapezoidal fuzzy pairwise comparison matrices

The trapezoidal fuzzy pairwise comparison matrices are constructed based on the input from six experts. Considering the space constraints in the manuscript, an illustrative example of the trapezoidal fuzzy pairwise comparison matrix for the first expert (*E1*) is shown in Table 10 and Table 11.

Table 10
The pairwise comparison matrix in linguistics terms for the first expert (*E1*)

	S	O	D	C	H	I
S	E	VI	WI	WI	EI	EI
O	-	E	WI	WI	WI	WI
D	-	-	E	VI	AI	VI
C	-	-	-	E	VI	AI
H	-	-	-	-	E	EI
I	-	-	-	-	-	E

Table 11
The pairwise comparison matrix in TrFNs for the first expert (E1)

	S	O	D	C	H	I
S	(1,1,1,1)	(6,13/2,15/2,8)	(2,5/2,7/2,4)	(2,5/2,7/2,4)	(4,9/2,11/2,6)	(2,5/2,7/2,4)
O	(1/8,2/15,2/13,1/6)	(1,1,1,1)	(2,5/2,7/2,4)	(2,5/2,7/2,4)	(2,5/2,7/2,4)	(2,5/2,7/2,4)
D	(1/4,2/7,2/5,1/2)	(1/4,2/7,2/5,1/2)	(1,1,1,1)	(6,13/2,15/2,8)	(8,17/2,9,9)	(6,13/2,15/2,8)
C	(1/4,2/7,2/5,1/2)	(1/4,2/7,2/5,1/2)	(1/8,2/15,2/13,1/6)	(1,1,1,1)	(6,13/2,15/2,8)	(8,17/2,9,9)
H	(1/6,2/11,2/9,1/4)	(1/4,2/7,2/5,1/2)	(1/9,1/9,2/17,1/8)	(1/8,2/15,2/13,1/6)	(1,1,1,1)	(4,9/2,11/2,6)
I	(1/4,2/7,2/5,1/2)	(1/4,2/7,2/5,1/2)	(1/8,2/15,2/13,1/6)	(1/9,1/9,2/17,1/8)	(1/6,2/11,2/9,1/4)	(1,1,1,1)

Remark: Consistency ratio of expert *E1*, *CR* = 0.06

Step 4: Aggregate the TrFS pairwise comparison matrices

All the TrFS pairwise comparison matrices collected from the six experts are aggregated into a group decision matrix using Eq. (8), and the results are shown in Table 12.

Table 12
The aggregate the TrFS pair-wise comparison matrix

	S	O	D	C	H	I
S	(1,1,1,1)	(6,6.5,7.5,8)	(2,2.5,3.5,4)	(2,2.5,3.5,4)	(4,5.5,6.5,8)	(4,5.5,6.5,8)
O	(0.125,0.133, 0.153,0.166)	(1,1,1,1)	(2,2.5,3.5,4)	(2,2.5,3.5,4)	(2,2.5,3.5,4)	(2,2.5,3.5,4)
D	(0.25,0.285, 0.4,0.5)	(0.25,0.285, 0.4,0.5)	(1,1,1,1)	(6,7.5,8.25,9)	(8,8.5,9,9)	(6,7.5,8.25,9)
C	(0.25,0.285, 0.4,0.5)	(0.25,0.285, 0.4,0.5)	(0.111,0.122, 0.135,0.25)	(1,1,1,1)	(6,6.5,7.5,8)	(6,7.5,8.25,9)
H	(0.125,0.157, 0.4,0.5)	(0.25,0.285, 0.4,0.5)	(0.111,0.122, 0.135,0.25)	(0.125,0.133, 1.666,3.237)	(1,1,1,1)	(1,3.75,4.25,8)
I	(0.125,0.157, 0.188,0.25)	(0.25,0.285, 0.4,0.5)	(0.111,0.122, 0.15,0.25)	(0.111,0.122, 0.125,0.135)	(0.125,0.566, 0.579,1)	(1,1,1,1)

Step 5: Calculate the geometric mean in each row of the aggregated TrFS pairwise comparison matrix

Utilizing Eq. (16), the geometric mean in each row of the aggregated TrFS pairwise comparison matrix $(\widehat{r_i})$ is calculated, and the results are shown in Table 8. An example calculation of the geometric mean for the severity risk criterion (S), defined as $\widehat{r_S}$, is illustrated in Box I.

Calculating geometric mean in each row using Eq. (16)

$$\widehat{r_S} = [(1*6*2*2*4*4)^{\frac{1}{6}}, (1*6.5*2.5*2.5*5.5*5.5)^{\frac{1}{6}}, (1*7.5*3.5*3.5*6.5*6.5)^{\frac{1}{6}}, (1*8*4*4*8*8)^{\frac{1}{6}}]$$

$$\widehat{r_S} = (2.696, 3.273, 3.964, 4.489)$$

Box I

Step 6: Computes the TrFN subjective weighting of each criterion (ω_j^s)

Using Eq. (17), the TrFN subjective weighting of each risk criterion (ω_j^s) is calculated, and the results are shown in Table 13. An example calculation of the subjective weighting for the severity risk criterion (S), defined as $\omega_S^s = (\omega_{S1}^s, \omega_{S2}^s, \omega_{S3}^s, \omega_{S4}^s)$, is illustrated in Box II.

Calculating the TrFN subjective weighting of each criterion (ω_j^s), using Eq. (17)

$$\omega_{S1}^s = 2.696*(2.696+1.122+1.619+0.794+0.275+0.191)^{-1} = 0.403$$
$$\omega_{S2}^s = 3.273*(3.273+1.317+1.842+0.887+0.368+0.269)^{-1} = 0.411$$
$$\omega_{S3}^s = 3.964*(3.964+1.687+1.147+1.050+0.707+0.519)^{-1} = 0.438$$
$$\omega_{S4}^s = 4.489*(4.489+1.669+2.081+0.884+0.524+0.270)^{-1} = 0.452$$
$$\omega_S^s = (\omega_{S1}^s, \omega_{S2}^s, \omega_{S3}^s, \omega_{S4}^s) = (0.403, 0.411, 0.438, 0.452)$$

Box II

Table 13
TrFN geometric mean $(\widehat{r_i})$ and subjective weighting for each criterion (ω_j^s)

Risk criteria	Geometric mean in each row $(\widehat{r_i})$	TrFN subjective weighting for each criterion (ω_j^s)
S	(2.696,3.273,3.964,4.489)	(0.403,0.411,0.438,0.452)
O	(1.122,1.317,1.687,1.869)	(0.165,0.167,0.168,0.171)
D	(1.619,1.842,2.147,2.381)	(0.213,0.218,0.232,0.242)
C	(0.794,0.887,1.050,1.284)	(0.104,0.111,0.118,0.119)
H	(0.275,0.368,0.524,0.707)	(0.041,0.046,0.048,0.070)
I	(0.191,0.269,0.370,0.519)	(0.028,0.034,0.045,0.051)

Phase IV: Calculate the Objective Weights of the FMEA Risk Criteria

The objective weighting for each FMEA risk criterion (ω_j^o) is determined using the LOPCOW method under the trapezoidal fuzzy set approach, as described in Algorithm 2. The process for calculating ω_j^o is delineated in the following steps:

Step 1: Obtain the FM risk evaluation

Each industrial expert is tasked with assessing the risks associated with failure modes (*FMs*) using FMEA risk criteria and employing trapezoidal fuzzy linguistic terms, as presented in Table 7 and Table 8. Following this assessment, all linguistic terms are transformed into their respective TrFNs.

Step 2: Construct the evaluation decision matrix for each expert

The evaluation decision matrices with TrFNs are formulated based on input from six experts. Due to space limitations in the manuscript, an illustrative example of the trapezoidal fuzzy evaluation decision matrix for the first expert (*E1*) is presented in Table 14 and Table 15.

Table 14
An example of evaluation decision matrix for the first expert (E1)

	S	O	D	C	H	I
FM1	Si	MH	M	EH	H	H
FM2	Ma	H	MH	H	M	M
FM3	Ma	H	H	M	ML	M
FM4	E	MH	MH	H	M	H
FM5	S	H	M	ML	H	MH
FM6	Ma	MH	S	MH	M	M
FM7	Mo	MH	VS	L	H	ML
FM8	S	MH	MH	ML	L	M
FM9	S	MH	H	L	ML	M
FM10	Ma	MH	M	MH	M	MH

Table 15
An example of TrFS evaluation decision matrix for the first expert (*E1*)

Failure	Risk criteria					
mode	S	O	D	C	H	I
FM1	(1,2,3,4)	(5,6,7,8)	(3,4,5,6)	(8,9,9,10)	(6,7,8,9)	(6,7,8,9)
FM2	(5,6,7,8)	(6,7,8,9)	(2,3,4,5)	(6,7,8,9)	(4,5,6,7)	(4,5,6,7)
FM3	(5,6,7,8)	(6,7,8,9)	(1,2,3,4)	(4,5,6,7)	(3,4,5,6)	(4,5,6,7)
FM4	(6,7,8,9)	(5,6,7,8)	(2,3,4,5)	(6,7,8,9)	(4,5,6,7)	(7,8,9,10)
FM5	(7,8,9,10)	(6,7,8,9)	(3,4,5,6)	(3,4,5,6)	(6,7,8,9)	(5,6,7,8)
FM6	(5,6,7,8)	(5,6,7,8)	(5,6,7,8)	(5,6,7,8)	(4,5,6,7)	(4,5,6,7)
FM7	(3,4,5,6)	(5,6,7,8)	(6,7,8,9)	(2,3,4,5)	(6,7,8,9)	(3,4,5,6)
FM8	(1,2,3,4)	(5,6,7,8)	(2,3,4,5)	(3,4,5,6)	(2,3,4,5)	(4,5,6,7)
FM9	(1,2,3,4)	(5,6,7,8)	(1,2,3,4)	(2,3,4,5)	(3,4,5,6)	(3,4,5,6)
FM10	(5,6,7,8)	(5,6,7,8)	(3,4,5,6)	(5,6,7,8)	(4,5,6,7)	(5,6,7,8)

Step 3: Compute the aggregated evaluation decision matrix

The evaluation decision matrices obtained from the six experts are aggregated into a group decision matrix with TrFNs by using Eq. (8), and the resulting data are presented in Table 16.

Table 16
Aggregated evaluation decision matrix

Failure	Risk criteria					
mode	S	O	D	C	H	I
FM1	(1,4.66,5.66,8)	(5,7,8,10)	(0,2.33,3.33,6)	(6,8,9,10)	(6,7.33,8.33,10)	(6,7.66,8.66,10)
FM2	(5,6,7,8)	(6,7.33,8.33,10)	(1,3,4,6)	(5,6.33,7,33,9)	(4,5.33,6.33,8)	(4,5.66,6.66,8)
FM3	(5,6,7,8)	(6,7.66,8.66,10)	(1,3,4,6)	(3,4.66,5.66,7)	(3,4.33,5.33,7)	(3,5,6,8)
FM4	(1,5.66,6.66,10)	(5,7,8,10)	(1,3,4,6)	(6,7.33,8.33,10)	(3,4.66,5.66,7)	(6,7.66,8.66,10)
FM5	(6,7.66,8.66,10)	(5,6.66,7.66,9)	(2,3.66,4.66,6)	(3,4.33,5.55,7)	(5,6.66,7.66,9)	(5,6.33,7.33,9)
FM6	(2,4.66,5.66,8)	(5,6.33,7.33,9)	(3,5,6,8)	(4,6,7,9)	(3,4.66,5.66,7)	(3,4.66,5.66,7)
FM7	(3,4,5,6)	(5,6.66,7.66,9)	(4,6,7,9)	(2,3.66,4.66,6)	(4,6,7,9)	(3,4.66,5.66,7)
FM8	(1,2.66,3.66,6)	(5,6.33,7.33,9)	(1,3.66,4.66,8)	(2,3.33,4.66,6)	(2,3.33,4.33,6)	(3,56,8)
FM9	(1,3.33,4.33,6)	(4,5.66,6.66,8)	(1,2.33,3.33,5)	(2,3,4,5)	(3,4.44,5.33,7)	(3,56,8)
FM10	(1,5.33,6.33,10)	(4,5.33,6.33,8)	(2,3.33,4.33,5)	(3,4,5,6)	(4,6,7,9)	(5,6.66,7.66,9)

Step 4: Calculate the normalized aggregated evaluation decision matrix

The aggregated evaluation decision matrix is normalized with respect to the TrFNs through Eq. (9) and Eq. (10), and the results are displayed in Table 17.

Table 17
Normalized aggregated evaluation decision matrix

FM	RISK CRITRIA					
	S	O	D	C	H	I
FM1	(0.647,0.750, 0.762,1.000)	(0.761,0.792, 0.800,0.800)	(0.000,0.389, 0.476,0.667)	(0.375,0.444, 0.500,1.000)	(0.333,0.455, 0.520,0.600)	(0.500,0.609, 0.654,0.700)
FM2	(0.200,0.500, 0.667,0.727)	(0.666,0.727, 0.760,0.800)	(0.250,0.500, 0.571,0.667)	(0.200,0.474, 0.545,0.556)	(0.500,0.625, 0.684,0.750)	(0.750,0.824, 0.850,0.875)
FM3	(0.200,0.524, 0.696,0.750)	(0.666,0.696, 0.783,0.800)	(0.250,0.500, 0.571,0.667)	(0.200,0.643, 0.706,0.714)	(0.666,0.769, 0.813,0.857)	(0.875,0.933, 0.944,1.000)
FM4	(0.550,0.600, 0.762,1.000)	(0.761,0.792, 0.800,0.825)	(0.250,0.500, 0.571,0.667)	(0.409,0.480, 0.500,1.000)	(0.667,0.714, 0.765,0.857)	(0.500,0.609, 0.654,0.700)
FM5	(0.166,0.423, 0.600,0.800)	(0.700,0.800, 0.826,0.889)	(0.500,0.611, 0.667,0.766)	(0.166,0.692, 0.714,0.750)	(0.400,0.500, 0.565,0.667)	(0.600,0.737, 0.758,0.778)
FM6	(0.500,0.647, 0.750,0.842)	(0.800,0.842, 0.864,0.889)	(0.750,0.833, 0.857,0.889)	(0.500,0.543, 0.556,0.571)	(0.666,0.714, 0.765,0.857)	(1.000,1.000, 1.000,1.000)
FM7	(0.333,0.733, 0.800,1.000)	(0.800,0.833, 0.845,0.857)	(1.000,1.000, 1.000,1.000)	(0.333,0.818, 0.833,0.857)	(0.500,0.556, 0.619,0.667)	(1.000,1.000, 1.000,1.000)
FM8	(0.842,1.000, 1.000,1.000)	(0.800,0.842, 0.864,0.889)	(0.250,0.611, 0.667,0.889)	(0.833,0.900, 0.923,1.000)	(1.000,1.000, 1.000,1.000)	(0.875,0.933, 0.944,1.000)
FM9	(0.846,0.941, 0.955,1.000)	(0.941,0.950, 0.965,1.000)	(0.250,0.389, 0.476,0.556)	(1.000,1.000, 1.000,1.000)	(0.666,0.769, 0.813,0.857)	(0.875,0.933, 0.944,1.000)
FM10	(0.578,0.600, 0.733,1.000)	(1.000,1.000, 1.000,1.000)	(0.500,0.556, 0.619,0.667)	(0.450,0.556, 0.619,0.667)	(0.500,0.556, 0.619,0.667)	(0.600,0.700, 0.739,0.778)

Step 5: Determine the percentage value (P_j) for each criterion

The percentage values (P_j) for each criterion are determined with the TrFNs through Eqs. (19)-(21), as shown in Table 18. Example calculations of the parameter values RMS_j, σ_j, and P_j for the severity risk criterion (S), defined as RMS_s and P_s, are provided in Box III, Box IV, and Box V, respectively.

Calculating TrFNs of RMS_s, where $RMS_S = (RMS_{S1}, RMS_{S2}, RMS_{S3}, RMS_{S4})$, using Eq. (20)

$$RMS_{S1} = \sqrt{\frac{(0.647)^2 + (0.020)^2 + (0.020) + (0.550)^2 + (0.166)^2 + (0.500)^2 + (0.333)^2 + (0.842)^2 + (0.846)^2 + (0.578)^2}{10}}$$

$$RMS_{S2} = \sqrt{\frac{(0.750)^2 + (0.500)^2 + (0.524)^2 + (0.600)^2 + (0.423)^2 + (0.647)^2 + (0.733)^2 + (1.000)^2 + (0.941)^2 + (0.600)^2}{10}}$$

$$RMS_{S3} = \sqrt{\frac{(0.762)^2 + (0.667)^2 + (0.696)^2 + (0.762)^2 + (0.600)^2 + (0.762)^2 + (0.800)^2 + (1.000)^2 + (1.000)^2 + (1.000)^2}{10}}$$

$$RMS_{S4} = \sqrt{\frac{(1.000)^2 + (0.727)^2 + (0.750)^2 + (1.000)^2 + (0.800)^2 + (0.842)^2 + (1.000)^2 + (1.000)^2 + (1.000)^2 + (1.000)^2}{10}}$$

$$RMS_S = (RMS_{S1}, RMS_{S2}, RMS_{S3}, RMS_{S4}) = (0.543, 0.694, 0.815, 0.918)$$

Box III

Calculating TrFNs of $\sigma_S = (\sigma_{S1,}\sigma_{S2,}\sigma_{S3,}\sigma_{S4})$, using Eq. (20)

For σ_{S1}; $u_{ij}^{S1} = (0.647, 0.200, 0.200, 0.550, 0.166, 0.500, 0.333, 0.842, 0.846, 0.578)$

$$\frac{1}{m}\sum_{t=1}^{m} u_{tj} = \frac{0.647 + 0.200 + 0.200 + 0.550 + 0.166 + 0.500 + 0.333 + 0.842 + 0.846 + 0.578}{10} = 0.486$$

$$\sigma_{S1} = \sqrt{\frac{(0.647 - 0.486)^2 + (0.200 - 0.486)^2 + (0.200 - 0.486)^2 + \cdots + (0.578 - 0.166)^2}{10 - 1}} = 0.254$$

For σ_{S2}; $u_{ij}^{S2} = (0.750, 0.500, 0.524, 0.600, 0.423, 0.647, 0.733, 1.000, 0.941, 0.600)$

$$\frac{1}{m}\sum_{t=1}^{m} u_{tj} = \frac{0.750 + 0.500 + 0.524 + 0.600 + 0.423 + 0.647 + 0.733 + 1.000 + 0.941 + 0.600}{10} = 0.671$$

$$\sigma_{S2} = \sqrt{\frac{(0.750 - 0.671)^2 + (0.500 - 0.671)^2 + (0.524 - 0.671)^2 + \cdots + (0.600 - 0.671)^2}{10 - 1}} = 0.187$$

For σ_{S3}; $u_{ij}^{S3} = (0.762, 0.667, 0.696, 0.762, 0.600, 0.750, 0.800, 1.000, 1.000, 1.000)$

$$\frac{1}{m}\sum_{t=1}^{m} u_{tj} = \frac{0.762 + 0.667 + 0.696 + 0.762 + 0.600 + 0.750 + 0.800 + 1.000 + 1.000 + 1.000}{10} = 0.804$$

$$\sigma_{S3} = \sqrt{\frac{(0.762 - 0.804)^2 + (0.667 - 0.804)^2 + (0.696 - 0.804)^2 + \cdots + (1.000 - 0.804)^2}{10 - 1}} = 0.147$$

For σ_{S4}; $u_{ij}^{S4} = (1.000, 0.727, 0.750, 1.000, 0.800, 0.824, 1.000, 1.000, 1.000, 1.000)$

$$\frac{1}{m}\sum_{t=1}^{m} u_{tj} = \frac{1.000 + 0.727 + 0.750 + 1.000 + 0.800 + 0.824 + 1.000 + 1.000 + 1.000 + 1.000}{10} = 0.912$$

$$\sigma_{S4} = \sqrt{\frac{(1.000 - 0.912)^2 + (0.727 - 0.912)^2 + (0.750 - 0.912)^2 + \cdots + (1.000 - 0.912)^2}{10 - 1}} = 0.118$$

Box IV

Calculating TrFNs of P_S, where $P_S = (P_{S1}, P_{S2}, P_{S3}, P_{S4})$, using Eq. (19)

$$P_{S1} = \left| ln\left(\frac{0.543}{0.254}\right) * 100 \right| = 75.977, where\ RMS_{s1} = 0.543\ , \sigma_{S1} = 0.254$$

$$P_{S2} = \left| ln\left(\frac{0.694}{0.187}\right) * 100 \right| = 131.136, where\ RMS_{S2} = 0.694\ , \sigma_{S2} = 0.187$$

$$P_{S3} = \left| ln\left(\frac{0.815}{0.147}\right) * 100 \right| = 171.275, where\ RMS_{S3} = 0.815\ , \sigma_{S3} = 0.147$$

$$P_{S4} = \left| ln\left(\frac{0.918}{0.118}\right) * 100 \right| = 205.151, where\ RMS_{S4} = 0.918\ , \sigma_{S4} = 0.118$$

Box V

Step 6: Calculate the objective weights of criteria (ω_j^o)

The objective weights of criteria (ω_j^o) for each criterion are calculated with the TrFNs through Eq. (21), and the results are displayed in Table 18. An illustrative computation of the objective weights for the severity risk criterion (S), represented as ω_S^o, is presented in Box VI.

Calculating TrFNs of ω_S^o, where $\omega_S^o = (\omega_{S1}^o, \omega_{S2}^o, \omega_{S3}^o, \omega_{S4}^o)$, using Eq. (22)

$$\omega_{S1}^o = \frac{(75.977)}{(75.977+164.553+15.603+70.950+114.739+117.722)} = 0.135$$

$$\omega_{S2}^o = \frac{(131.136)}{(131.136+178.001+78.332+115.105+132.160+153.553)} = 0.167$$

$$\omega_{S3}^o = \frac{(171.275)}{(171.275+196.678+108.073+126.417+146.914+173.867)} = 0.186$$

$$\omega_{S4}^o = \frac{(205.151)}{(205.151+218.360+140.185+129.185+169.219+188.654)} = 0.195$$

Box VI

Table 18
The percentage value (P_j) for each criterion

Criteria	$\mathbf{RMS_j} = \sqrt{\frac{\sum_{i=1}^{m} \mathbf{u_{ij}^2}}{\mathbf{m}}}$	$\mathbf{P_j} = \left\lvert \mathbf{In}\left(\frac{\mathbf{RMS_j}}{\boldsymbol{\sigma_j}}\right) * \mathbf{100} \right\rvert$	Objective weights $(\boldsymbol{\omega_j^o} = \frac{\mathbf{P_j}}{\sum_{j=1}^{n} \mathbf{P_j}})$
S	(0.543, 0.694,0.815,0.918)	(75.977,131.136,171.275,205.151)	(0.135,0.167,0.186,0.195)
O	(0.542,0.547,0.647,0.691)	(164.553,178.001,196.678,218.360)	(0.186,0.190,0.197,0.233)
D	(0.343,0.422,0.487,0.572)	(15.603,78.332,108.073,140.185)	(0.120,0.159,0.175,0.188)
C	(0.558,0.629,0.647,0.670)	(70.950,115.105,126.417,129.185)	(0.123,0.127,0.137,0.146)
H	(0.592,0.607,0.623,0.687)	(114.739,132.160,146.914,169.219)	(0.159,0.160,0.168,0.205)
I	(0.632,0.715,0.775,0.873)	(117.722,153.553,173.867,188.654)	(0.159,0.179,0.195,0.210)

Phase V: Compute Consolidated Weights of FMEA Risks Criteria

By utilizing Eq. (27) with $\varphi = 0.5$, the consolidated weights (ω_j^c) for the FMEA risk criteria within the TrFN framework are derived through a synergistic integration of subjective weights (ω_j^s) obtained from the TrFN AHP, as outlined in Table 13, and objective weights (ω_j^o) extracted from the TrFN LOPCOW, as detailed in Table 18. The corresponding outcomes are presented in Table 19. Subsequently, these consolidated TrFN weights are transformed into precise numerical values using Eq. (11), with the results summarized in both Table 19 and Figure 4.

A comprehensive computation of the consolidated TrFN weight parameters for the severity risk criterion (S), designated ω_S^c, is provided in Box VIII. The conversion of ω_S^c to a crisp number is further illustrated in Box VII. The weighted ranking of risk criteria, as displayed in Table 19, is as follows: S (0.273) > O = I (0.186) > D (0.146) > C (0.133) > H (0.096).

Calculating TrFNs of ω_S^c, where $\omega_S^c = (\omega_{S1}^c, \omega_{S2}^c, \omega_{S3}^c, \omega_{S4}^c)$, using Eq. (28)

$$\omega_{S1}^c = (0.5 * 0.403) + (1 - 0.5) * (0.135) = 0.270$$
$$\omega_{S2}^c = (0.5 * 0.411) + (1 - 0.5) * (0.167) = 0.289$$
$$\omega_{S3}^c = (0.5 * 0.438) + (1 - 0.5) * (0.186) = 0.312$$
$$\omega_{S4}^c = (0.5 * 0.452) + (1 - 0.5) * (0.195) = 0.324$$

Box VII

Calculating crisp numbers of consolidated weights of risk criteria, employing Eq. (12)

$$\mathrm{Defuzz}(\omega_S^c) = \frac{-(0.270 * 0.289) + (0.312 * 0.324) + \frac{(0.324 - 0.312)^2}{3} - \frac{(0.289 - 0.270)^2}{3}}{-(0.270) - (0.289) + (0.312) + (0.324)}$$

$$\mathrm{Defuzz}(\omega_S^c) = 0.273$$

Box VIII

Table 19
Consolidated weights of FMEA risks criteria

Risk criteria	TrFN Subjective weights $(\boldsymbol{\omega}_j^s)$	TrFN Objective weights $(\boldsymbol{\omega}_j^o)$	TrFN Consolidated weights $(\boldsymbol{\omega}_j^c)$	Consolidated weights $(\mathbf{w}_j^c)$ in crisp numbers	Rank
S	(0.403,0.411,0.438,0.452)	(0.135,0.167,0.186,0.195)	(0.270,0.289,0.312,0.324)	0.273	1
O	(0.165,0.167,0.168,0.171)	(0.186,0.190,0.197,0.233)	(0.186,0.190,0.197,0.233)	0.186	2
D	(0.213,0.218,0.232,0.242)	(0.120,0.159,0.175,0.188)	(0.120,0.159,0.175,0.188)	0.146	3
C	(0.104,0.111,0.118,0.119)	(0.123,0.127,0.137,0.146)	(0.113,0.119,0.127,0.132)	0.113	4
H	(0.041,0.046,0.048,0.070)	(0.159,0.160,0.168,0.205)	(0.100,0.103,0.106,0.108)	0.096	5
I	(0.028,0.034,0.045,0.051)	(0.159,0.179,0.195,0.210)	(0.094,0.107,0.120,0.131)	0.186	2

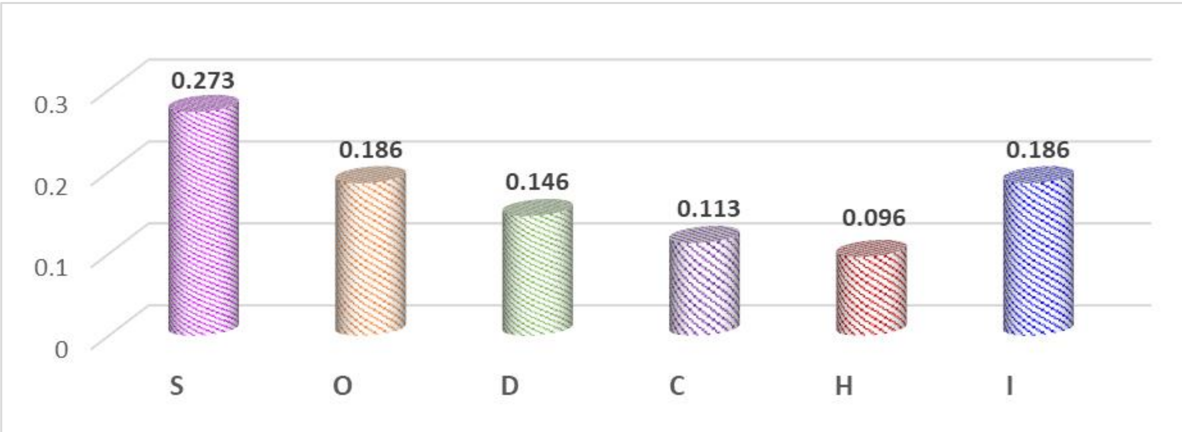

Fig. 4. The combined weights of risk criteria

Phase VI Prioritize failure modes (FMs)

ARAS, outlined in Algorithm 3, is employed for the prioritization of reverse logistics in plastic recycling. This process is presented as follows:

Step 1: Obtain the FM risk evaluation (see the results in Phase IV, Step 1)

Step 2: Construct the evaluation decision matrix for each expert (see the results in Phase IV, Step 2)

Step 3: Compute the aggregated evaluation decision matrix (see the results in Phase IV, Step 3)

Step 4: Identify the optimal value of each risk criterion

The optimal value of each criterion (OV) is determined based on its nature. Accordingly, the risk criteria S, O, C, H, and I are categorized as cost criteria, whereas D is categorized as a benefit criterion. Eq. (23) and Eq. (24) are applied to ascertain the optimal value for each criterion, and the results are presented in Table 20.

Table 20
The optimal value of each criterion (*OV*)

	Risk criteria					
	S	O	D	C	H	I
Type of criteria	Cost	Cost	Benefit	Cost	Cost	Cost
Optimal value (*OV*)	(1,2.66,3.66,6)	(4,5.33,6.33,8)	(4,6,7,9)	(2,3,4,5)	(2,3.33,4.33,6)	(3,4.66,5.66,7)

Step 5: Calculate the normalized aggregated matrix

The normalized aggregated matrix is calculated utilizing Eq. (25) for the benefit criterion and Eq. (26) for the cost criterion, with the results presented in Table 21.

Table 21
Normalized aggregated matrix

Failure mode	Risk criteria					
	S	O	D	C	H	I
OV	(0.114,0.134, 0.135,0.147)	(0.102,0.106, 0.109,0.109)	(0.664,0.133, 0.145,0.200)	(0.128,0.243, 0.333,0.416)	(0.113,0.169, 0.207,0.289)	(0.105,0.246, 0.281,0.388)
FM1	(0.084,0.086, 0.088,0.135)	(0.082,0.083, 0.084,0.088)	(0.000,0.056, 0.063,0.099)	(0.046,0.051, 0.056,0.064)	(0.048,0.059, 0.063,0.068)	(0.056,0.065, 0.068,0.074)
FM2	(0.027,0.061, 0.076,0.086)	(0.073,0.079, 0.080,0.082)	(0.050,0.072, 0.076,0.099)	(0.055,0.065, 0.069,0.071)	(0.072,0.081, 0.083,0.085)	(0.084,0.088, 0.089,0.092)
FM3	(0.027,0.065, 0.070,0.086)	(0.073,0.075, 0.077,0.082)	(0.050,0.072, 0.076,0.099)	(0.088,0.090, 0.091,0.092)	(0.090,0.976, 0.099,0.100)	(0.092,0.099, 0.100,0.112)
FM4	(0.068,0.069, 0.073,0.135)	(0.082,0.083, 0.084,0.088)	(0.050,0.072, 0.076,0.099)	(0.046,0.056, 0.061,0.064)	(0.093,0.095, 0.097,0.099)	(0.056,0.065, 0.068,0.074)
FM5	(0.023,0.051, 0.056,0.068)	(0.086,0.087, 0.088,0.09)	(0.088,0.089, 0.096,0.100)	(0.091,0.092, 0.095,0.096)	(0.058,0.065, 0.069,0.075)	(0.067,0.079, 0.081,0.082)
FM6	(0.068,0.084, 0.086,0.089)	(0.088,0.091, 0.092,0.095)	(0.074,0.224, 0.121,0.150)	(0.068,0.070, 0.071,0.073)	(0.090,0.092, 0.095,0.097)	(0.105,0.108, 0.110,0.112)
FM7	(0.045,0.088, 0.098,0.114)	(0.086,0.087, 0.088,0.911)	(0.066,0.133, 0.145,0.200)	(0.107,0.109, 0.113,0.137)	(0.072,0.073, 0.075,0.078)	(0.102,0.105, 0.107,110)
FM8	(0.114,0.130, 0.135,0.147)	(0.078,0.088, 0.910,0.930)	(0.050,0.074, 0.086,0.089)	(0.107,0.118, 0.123,0.137)	(0.112,0.113, 0.115,0.117)	(0.090,0.092, 0.100,0.112)
FM9	(0.104,0.114, 0.118,0.135)	(0.091,0.102, 0.105,0.109)	(0.050,0.056, 0.063,0.119)	(0.116,0.128, 0.135,0.138)	(0.090,0.097, 0.099,0.110)	(0.092,0.099, 0.101,0.112)
FM10	(0.068,0.073, 0.077,0.135)	(0.102,0.106, 0.109,0.112)	(0.080,0.083, 0.900,0.112)	(0.055,0.061, 0.066,0.071)	(0.070,0.072, 0.075,0.078)	(0.067,0.075, 0.077,0.082)

Step 6: Compute the weighted normalized decision matrix

Utilizing the normalized aggregated matrix outlined in Table 17, the weighted normalized decision matrix is calculated using Eq. (12), and the results are illustrated in Table 22. An illustrative value of the weighted normalization for FM1 concerning the severity criterion (S), denoted as d_{FM1}^{s}, is illustrated in Box VIII.

Compute d^{s}_{FM1} employing Eq. (12)

$$=\frac{-(0.084*0.086)*(0.270*0.289)+(0.088*0.135)*(0.312*0.324)+\frac{(0.135*0.324-0.088*0.312)^2}{3}-\frac{(0.086*0.289-0.084*0.270)^2}{3}}{-(0.084*0.270)-(0.086*0.289)+(0.088*0.312)+(0.135*0.324)}$$

$$d^{s}_{FM1}=0.001$$

Box VIII

Table 22
Weighted normalized decision matrix

	S	O	D	C	H	I
OV	0.001	0.023	0.062	0.018	0.016	0.000
FM1	0.001	0.017	0.017	0.007	0.005	0.000
FM2	-0.001	0.016	0.017	0.008	0.005	0.000
FM3	-0.001	0.016	0.017	0.011	0.005	0.000
FM4	0.002	0.017	0.017	0.007	0.002	0.000
FM5	-0.001	0.018	0.013	0.012	-0.143	0.000
FM6	0.000	0.018	-0.046	0.009	0.003	0.000
FM7	-0.002	0.018	0.062	0.015	-0.004	0.000
FM8	-0.200	0.018	0.027	0.015	0.018	0.000
FM9	0.000	0.021	0.014	0.016	-0.004	0.000
FM10	0.001	0.022	0.011	0.008	0.004	0.000

Step 7: Obtain the optimality function values (γ_i)

The optimality function values (γ_i) of ten failure modes (FMs) is obtained using Eq. (28), and the results are presented in Table 23.

Step 8: Calculate the degree of utility for failure modes

The degree of utility for each failure mode (K_i) is calculated using Eq. (29), and the results are presented in Table 23.

Step 9: Rank the failure modes (FMs) in descending order

The ten FMs are ranked in descending order based on their degree of utility (K_i), and the results are presented in Table 23.

Table 23
The ranking results of failure modes (*FMs*)

	OV	FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8	FM9	FM10
$\boldsymbol{\gamma}_{\mathbf{i}}$	-0.090	0.047	0.044	0.047	0.045	-0.102	-0.016	0.089	-0.121	0.048	0.046
$\mathbf{K}_{\mathbf{i}}$	1	-0.527	-0.495	-0.526	-0.501	1.141	0.181	-0.990	1.357	-0.531	-0.518
RANK	-	8	4	7	5	2	3	10	1	9	6

4.3 Sensitivity Analysis

The sensitivity of the proposed framework is systematically assessed through a comprehensive three-stage experimentation process. In the first stage, a comparative ranking is conducted among AHP-LOPCOW-ARAS, AHP-ARAS, and LOPCOW-ARAS under the TrFS, as outlined in Section 4.3.1. In the second stage, the combined weight of each risk criterion ($\boldsymbol{\omega}_j^{c}$) is adjusted by altering the value of γ, as detailed in Section 4.3.2. Finally, the comparative analysis of other novel MCDM ranking methods is carried out as, presented in Section 4.3.3.

4.3.1 Comparative Ranking among AHP-LOPCOW-ARAS, AHP-ARAS, and LOPCOW-ARAS

In the first stage of the sensitivity analysis, a comparative evaluation of the ranking results for ten *FMs* associated with the reverse logistics of the waste plastic recycling industry is conducted. The rankings are generated through the proposed framework (AHP-LOPCOW-ARAS under TrFS) and are compared with rankings obtained by considering solely the subjective weights of criteria (AHP-ARAS under TrFS) and solely the objective weights of criteria (LOPCOW-ARAS under TrFS). The comparative rankings among FMs using these three MCDM approaches are presented in Table 24 and Figure 5. Notably, "Reverse logistics information risks" (*FM8*) consistently maintains its top-ranking position across all methods, as presented in Table 24.

To assess the correlation among the ranking results of FMs derived from three MCDM approaches, the Spearman correlation coefficient (ρ) is computed as outlined in Eq. (31). The results reveal that the correlation coefficients between the proposed framework and the other two employed methods are as follows: AHP-ARAS and AHP-LOPCOW-ARAS (ρ = 0.879), LOPCOW-ARAS and AHP-LOPCOW-ARAS (ρ = 0.867) and AHP-ARAS and LOPCOW-ARAS (ρ = 0.903), with an average of ρ = 0.883, as presented in Table 25. A correlation coefficient (ρ) ≥ 0.8 signifies a very strong correlation among the MCDM methods used, as highlighted in Table 26. These results reveal that while there are slight variations in the ranking results among all methods, these differences have a minimal impact on the overall outcomes. This indicates that the proposed framework demonstrates a high level of consistency and stability in decision-making.

$$\boldsymbol{\rho} = \mathbf{1} - \frac{\mathbf{6}\sum \boldsymbol{D}^{\mathbf{2}}}{\boldsymbol{N}(\boldsymbol{N}^{\mathbf{2}}-\mathbf{1})} \tag{31}$$

Here, ρ represents the Spearman correlation coefficient, D^2 denotes the square of the difference in ranks for each data pair between the two Multi-Criteria Decision Making (MCDM) methods, and N is the total number of data pairs.

Table 24
The comparative rankings among FMs using three MCDM approaches

Comparative MCDM methods	K_i									
	FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8	FM9	FM10
AHP-LOPCOW-ARAS (Proposed framework)	-0.527	-0.495	-0.526	-0.501	1.141	0.181	-0.990	1.357	-0.531	-0.518
Rank	8	4	7	5	2	3	10	1	9	6
AHP-ARAS	0.537	0.816	0.401	0.562	0.632	0.876	0.498	4.128	0.387	0.526
Rank	6	3	9	5	4	2	8	1	10	7
LOPCOW-ARAS	0.435	0.478	-0.546	0.429	0.483	0.498	0.382	0.712	0.424	0.454
Rank	6	4	10	7	3	2	9	1	8	5

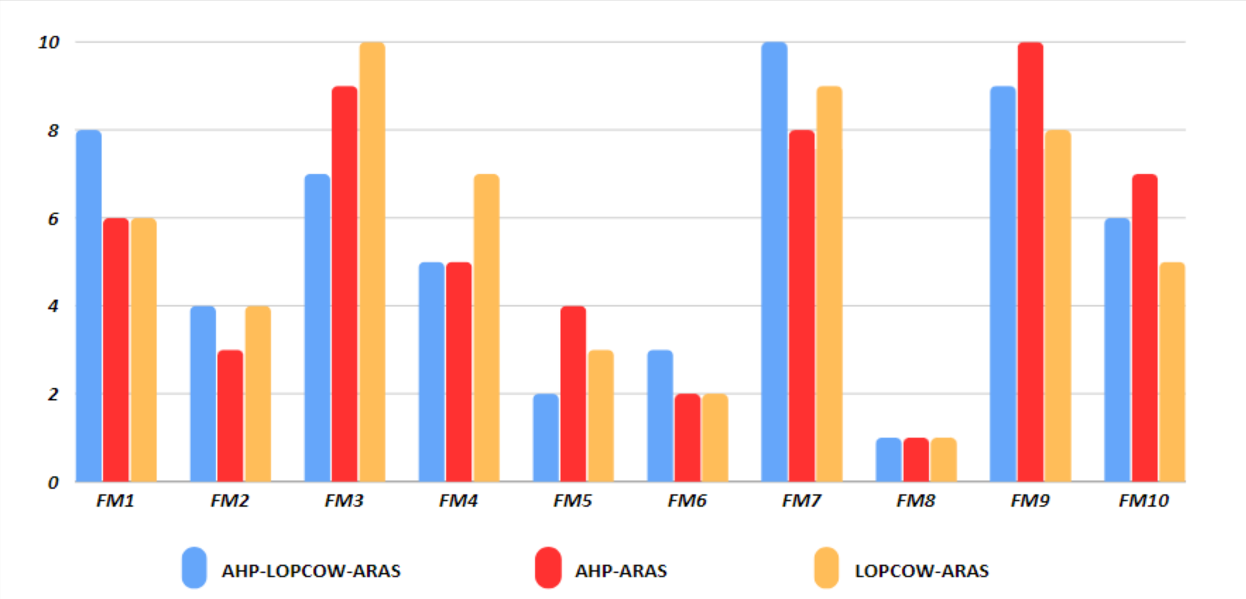

Fig. 5. The comparative rankings among FMs using three MCDM approaches

Table 25
The Spearman's correlation coefficients among employed MCDM approaches

	AHP-ARAS	LOPCOW-ARAS	AHP-LOPCOW-ARAS
AHP-ARAS	1.000	0.903	0.879
LOPCOW-ARAS	-	1.000	0.867
AHP-LOPCOW-ARAS	-	-	1.000

Table 26
Criteria of correlation strength utilizing Spearman's correlation coefficient

Spearman's correlation coefficients	Degree of conformity
$\rho < 0.2$	Very weak
$0.2 \leq \rho < 0.4$	Weak
$0.4 \leq \rho < 0.6$	Moderate
$0.6 \leq \rho < 0.8$	Strong
$\rho \geq 0.8$	Very strong

4.3.2 Adjusting the Value of Parameter $\boldsymbol{\varphi}$ in the Combined Weights

The parameter φ, a component of the combination weights in Eq. (27) and varies within the range of $\{0,0.1,0.2,0.3,\ldots,1.0\}$. Consequently, even distinct scenarios are created to evaluate and rank ten FMs using the proposed framework (AHP-LOPCOW-ARAS under a TrFs). The ranking results of the eleven scenarios are presented in Table 27 and Figure 6. As indicated in Table 27, "reverse logistics information risks" (*FM8*) and "recycle material transportation risks" (*FM5*) maintain the first and second ranks among FMs, respectively. Additionally, the correlations of the test scenarios with the baseline scenario (ρ), with values of 0.685, 0.685, 0.685, 0.745, 0.745, 1.00, 0.855, 0.855, 0.758, 0.758, and 0.875, are presented in Table 28. According to Table 26, it indicates that the strength of the correlations ranges from strong to very strong, suggesting that the proposed decision-making framework is robust and stable.

Table 27
Criteria of correlation strength utilizing Spearman's correlation coefficient

	Φ	RANKING									
		FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8	FM9	FM10
SCENARIO 1	0	8	7	5	10	2	3	9	1	6	4
SCENARIO 2	0.1	7	8	4	6	2	5	9	1	10	3
SCENARIO 3	0.2	8	7	5	9	2	10	3	1	4	6
SCENARIO 4	0.3	8	7	5	9	2	10	3	1	4	6
SCENARIO 5	0.4	8	7	5	9	2	10	3	1	4	6
SCENARIO 6 (BASED LINE)	0.5	8	4	7	5	2	3	10	1	9	6
SCENARIO 7	0.6	7	5	9	3	2	6	10	1	8	4
SCENARIO 8	0.7	5	4	6	7	2	3	10	1	8	9
SCENARIO 9	0.8	5	6	4	7	2	3	8	1	10	9
SCENARIO 10	0.9	5	6	4	7	2	3	8	1	10	9
SCENARIO 11	1	6	8	7	5	2	3	10	1	4	9

Table 28
The correlation of test scenarios with the baseline scenario

	Scenario										
	1	2	3	4	5	6	7	8	9	10	11
Based line (Scenario 6)	0.685	0.685	0.079	0.079	0.079	1.000	0.855	0.855	0.758	0.758	0.673
Correlation strength (ρ)			Strong			Based line	Very strong			Strong	

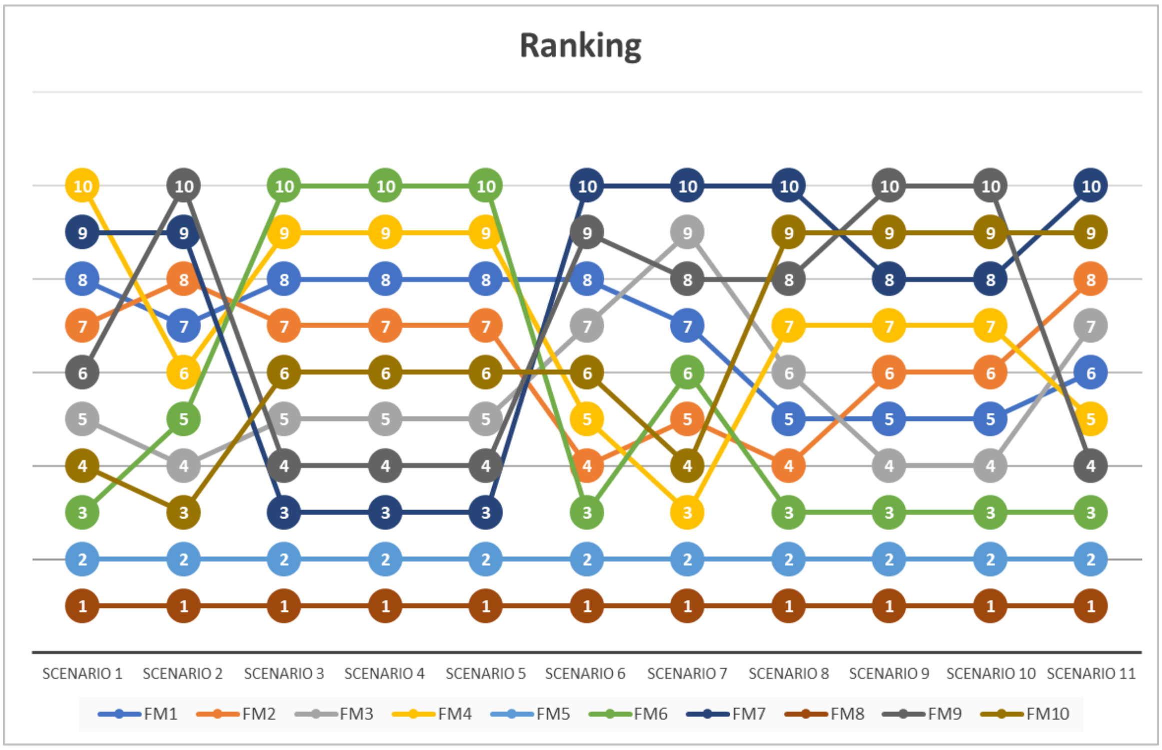

Fig.6. The ranking outcomes for eleven scenarios under varying φ parameters

4.3.3 Comparative analysis of other novel MCDM ranking methods

In the third phase of the sensitivity analysis, this study a comparative evaluation of FMs' ranking outcomes. The rankings are derived through the implementation of the proposed framework and are compared against rankings obtained from other established MCDM methodologies. To attain this objective, a collection of innovative MCDM methods under TrFS including TOPSIS, EDAS, CODAS, and WASPAS is utilized. The reason to select these particular methods is based on their proven effectiveness in addressing a variety of real-world MCDM challenges, consistently producing reliable and equitable results.

Upon completion of the ranking process, as depicted in Table 29 and Figure 7, it is evident that "Reverse logistics information risk" (*FM8*) consistently holds its top-ranking position across all applied methods. While there are minor variations in the ranking outcomes among the different methods, these discrepancies have minimal influence on the overall results. Spearman's correlation coefficients (ρ), outlined in Table 30, have been calculated to evaluate the deviation between the ranking results generated by all utilized MCDM methods. The findings reveal an average correlation coefficient of 0.778 across the employed MCDM methods.

Furthermore, the correlation coefficients between ARAS (the proposed method) and the other employed methods are as follows: 0.867, 0.890, 0.821, 0.878, and 0.769, with an average of 0.821. A correlation coefficient ρ of ≥ 0.8 indicates a remarkably strong correlation with the other MCDM methods, as elucidated in Table 26. This underscores that the proposed framework demonstrates a high degree of consistency and stability in decision-making, achieving a satisfactory level of reliability.

Table 29
The FMs ranking outcomes from established MCDM approaches

Failure Mode (FM)	ARAS (Proposed method)	TOPSIS	EDAS	CODAS	WASPAS
FM1	8	7	6	6	7
FM2	4	5	5	5	6
FM3	7	9	8	8	10
FM4	5	6	7	4	4
FM5	2	2	3	2	3
FM6	3	4	2	3	2
FM7	10	8	9	10	9
FM8	1	1	1	1	1
FM9	9	10	10	7	5
FM10	6	3	4	9	8

Table 30
The Spearman's correlation coefficients among employed MCDM methods

	ARAS	TOPSIS	EDAS	CODAS	WASPAS	Average
ARAS	1.000	0.867	0.890	0.878	0.769	0.851
TOPSIS	-	1.000	0.939	0.660	0.624	-
EDAS	-	-	1.000	0.721	0.660	-
CODAS	-	-	-	1.000	0.915	-
WASPAS	-	-	-	-	1.000	-

Average correlation coefficient among employed MCDM methods = 0.778

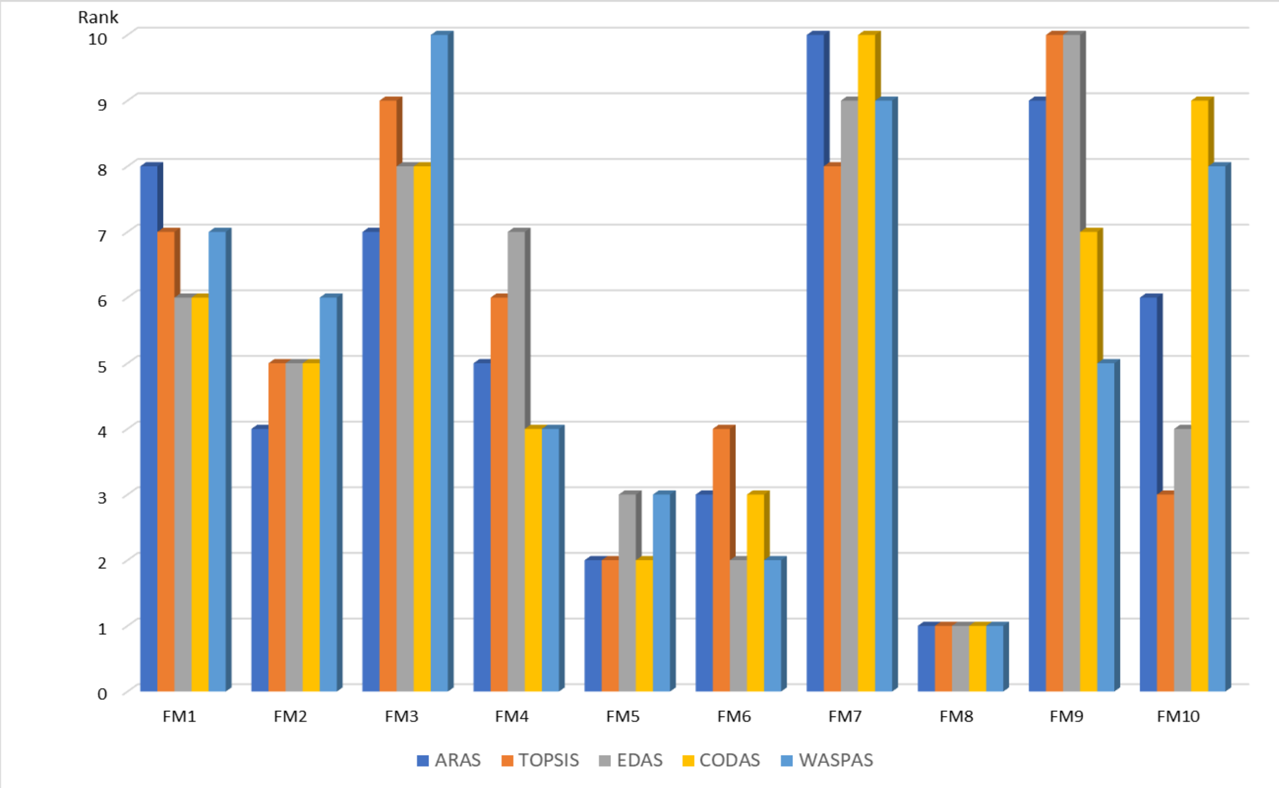

Fig.7. The comparison of FMs ranking from established MCDM approaches

5. Discussions and Conclusion

5.1 Discussions

Drawing from the findings of this case study, the analysis is centered on evaluating the efficacy of the proposed approach for prioritizing failure modes (*FMs*) within the context of reverse logistics in the plastic recycling industry. This discussion focuses on the three specific failure modes deemed the most significant.

The results indicate that "reverse logistics information risks" (*FM8*) is the highest risk failure mode. These risks have a substantial influence on the efficiency, transparency, and security of reverse logistics operations [9]. Particularly noteworthy is the risk associated with data accuracy and integrity. When information concerning the type, quantity, and origin of plastic waste is inaccurate or incomplete, operational inefficiencies and errors can occur during the sorting and processing stages [39]. This can result in misallocated resources, reduced recycling rates, and heightened contamination levels within recyclable materials.

The second-highest risk failure mode is "Recycle material transportation risks" (*FM5*). Efficient and secure transportation is essential for maintaining the sustainability and environmental benefits of recycling. Recycled materials often traverse considerable distances to reach processing facilities or manufacturers. Risks associated with transportation, such as accidents, spills, or mishandling, have the potential to cause environmental harm, contaminating recyclables and increasing carbon emissions due to rerouting or cleanup activities [19]. Ensuring the safe and responsible transportation of recycled materials is imperative for preserving the environmental gains achieved through recycling [11].

Finally, the third highest risk failure mode is "Recycle material inventory risk" (FM6). These risks hold significant importance due to their potential to profoundly impact the efficiency and effectiveness of recycling operations. First, precise inventory management is pivotal for ensuring an uninterrupted and dependable supply of recycled materials to manufacturers and end-users. When inventory is not managed effectively, the risk of material shortages or overstocking arises, both of which can disrupt production processes and result in financial losses [40]. For instance, a shortage of recycled materials can lead to production delays and missed delivery deadlines, while overstocking can utilize valuable warehouse space and capital that could be allocated elsewhere [11]. Adequate inventory management maintains a well-balanced supply chain and ensures the smooth operation of recycling operations. Moreover, the quality of recycled materials is intrinsically linked to inventory management. The quality of recycled materials can vary based on factors such as their source, processing methods, and storage conditions. If inventory risks are not adequately mitigated, there is a heightened risk of contamination, deterioration, or damage to recycled materials, which subsequently diminishes their usability and market value [1]. For example, improper storage practices may expose materials to moisture or contaminants, rendering them unsuitable for recycling or resale.

5.2 Conclusion and future research

Both academics and practitioners have underscored the vital role played by the recycling supply chain in addressing issues related to plastic packaging waste. Manufacturers involved in recycling plastic confront many risks intertwined with supply chain operations, requiring adept management and proactive strategies to minimize adverse effects on their business performance. Nevertheless, there is a lack of quantitative research focusing on risk factors and the corresponding proactive measures for risk mitigation within the recycling supply chain. In this study, a novel risk assessment framework designed for evaluating the challenges in managing plastic packaging waste within the context of reverse logistics is introduced. The framework leverages failure mode effect analysis (FMEA) as its foundation and is tailored to address decision-making in a fuzzy and uncertain environment. To address the inherent imprecision and uncertainty associated with human decision-making, a trapezoidal fuzzy set (TrFS) is adopted throughout all stages of the decision-making process. To illustrate the applicability of the proposed framework, the plastic packaging recycling industry in Thailand is employed as a case study. Through an extensive literature review and expert validation, ten failure modes related to the reverse logistics of plastic packaging waste are identified.

Additionally, by engaging in consultations with industry experts, a set of six FMEA risk criteria is constructed, encompassing severity (*S*), occurrence (*O*), detection (*D*), cost of failure (*C*), complexity of failure resolution (*H*), and impact on business (*I*). Both subjective and objective weighting for these FMEA risk criteria are utilized using the AHP and LOPCOW methods, respectively, under the TrFS approach. The resulting combined weightings, integrating both subjective and objective assessments, illuminate the relative significance of the FMEA risk criteria. Subsequently, the ARAS under the TrFS is employed to rank all eleven identified failure modes. This analysis revealed that the three most significant risk factors are "reverse logistics information risk" (*FM8*), "recycle material transportation risk" (*FM5*), and "recycle material inventory risk" (*FM6*). To ensure the robustness and reliability of our proposed framework, a sensitivity analysis is performed by varying the proportion of subjective and objective weightings. The results of these analyses affirm the dependability and stability of the proposed framework when applied to risk assessment within the context of the reverse logistics of the plastic recycling industry. Moving forward, we recommend further research in several directions. First, applying our framework to assess reverse logistics risks in other contexts, such as solid waste, electronic waste, and health care waste, would be valuable. Additionally, conducting comparative studies between the Intuitionistic Fuzzy Set approach and other fuzzy set approaches, such as neutrosophic, hesitant, Pythagorean, and q-rung orthopairs, could shed light on the most suitable method for addressing imprecise and uncertain information in specific contexts.

Nomenclature list	
AHP	Analytic hierarchy process
ARAS	Additive Ratio Analysis
CR	Consistency ratio
FMs	Failure modes
FMEA	Failure Mode Effect Analysis
FST	Fuzzy set theory
GHG	Greenhouse gases
LOPCOW	Logarithmic Percentage Change-driven Objective Weighting
MCDM	Multi-criteria decision-making
RL	Reverse logistics
RPN	Risk priority number
Trapezoidal fuzzy numbers	TrFNs
Trapezoidal fuzzy set	TrFS

Author Contributions

Conceptualization, D.S.; methodology, D.S. validation, D.S.; formal analysis, D.S.; investigation, D.S.; resources D.S. and J.K.; writing—original draft preparation, D.S.; writing—review and editing, D.S.; visualization, D.S. and J.K.; supervision, D.S.; The authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Data Availability Statement

The data used to support the findings of this study are included within the article.

Conflicts of 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.

Acknowledgement

This research was not funded by any grant.

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