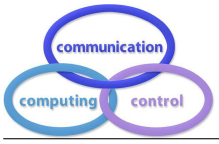
INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 21, Issue: 6, Month: December, Year: 2026
Article Number: 7422, https://doi.org/10.15837/ijccc.2026.6.7422



CCC Publications



Analysis of Sustainable Recycling Logistics via Multi-Agent Artificial Intelligence Decoded Business Analytics

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Abstract

Recycling projects powered by clean logistics face the fundamental challenge of improving performance while balancing environmental sustainability, technological change, and economic feasibility. Although multiple performance dimensions influence these projects, existing studies rarely provide a structured approach to identify which criteria and investment strategies should be prioritized under uncertainty. This lack of integrated prioritization frameworks represents a major gap in the literature. The purpose of this study is to develop a robust decision-making model that systematically evaluates performance criteria and strategic alternatives for clean logistics-based recycling projects. To address this gap, the proposed model integrates consensus-based expert selection with Manhattan distance-based centrality, cognitive maps for criterion weighting, orthogonal metric robust aggregation for strategy ranking, and newly developed Chipper fuzzy sets to handle uncertainty. The model offers methodological advantages by capturing expert consensus, causal relationships, and robust aggregation within a unified framework. The results indicate that technology adaptability and costs are the most influential criteria, while electric fleet operators and recycling park developers emerge as the most effective investment strategies. These findings suggest prioritizing flexible technologies and integrated low-emission infrastructure to enhance the long-term performance and sustainability of recycling projects powered by clean logistics.

Keywords: Clean logistics; Recycling project performance; Technology adaptability; Strategic prioritization; Fuzzy decision-making

1 Introduction

Recycling projects powered by clean logistics refer to integrated systems in which recycling activities are supported by low-emission transportation, clean energy use, and environmentally efficient logistics operations. These projects aim to reduce the environmental footprint of recycling processes while improving operational efficiency and long-term sustainability. Their importance lies in their ability to simultaneously address waste management challenges, climate change concerns, and resource efficiency goals. By relying on clean logistics, such projects can lower carbon emissions, reduce energy consumption, and enhance transparency across reverse supply chains [30]. Several strategic actions can be implemented to improve the performance of these projects. The use of an electric fleet operator enables the replacement of fossil fuel-based transport with low-emission vehicles, directly supporting environmental targets. The development of recycling parks allows for spatial integration of collection, processing, and distribution activities, which reduces logistics costs and energy losses. Recycling parts sellers play a critical role by creating secondary markets for recovered materials, thereby improving economic viability [32]. Tech failure insurers reduce operational risks by covering uncertainties related to new clean technologies. In addition, green tech startup incubators support innovation by accelerating the adoption of advanced recycling and clean logistics solutions, which strengthens system adaptability and long-term performance.

The selection of appropriate strategies for recycling projects powered by clean logistics requires careful consideration of multiple performance criteria. Carbon intensity is one of the most important criteria, as it reflects the environmental impact of logistics and recycling activities and directly relates to emission reduction goals. Material quality is another key factor, since higher-quality recyclable inputs improve recovery efficiency, reduce processing losses, and enhance economic outcomes [11]. Technology adaptability also plays a critical role, as recycling projects operate in dynamic environments where technologies must respond to changing regulations, material flows, and sustainability targets. Energy security is equally important, because reliable access to clean and stable energy sources ensures uninterrupted logistics and recycling operations while reducing dependence on volatile energy markets. Costs represent a fundamental economic criterion that affects the feasibility, scalability, and long-term sustainability of clean logistics-based recycling systems. High costs can limit investments in clean technologies, while well-managed cost structures support both environmental and financial performance [15]. Considering these criteria together allows decision makers to better understand trade-offs and interactions, leading to more balanced and effective strategy selection for recycling projects powered by clean logistics.

For recycling projects powered by clean logistics, identifying priority strategies is essential to achieve performance improvements in a timely and effective manner. Clear prioritization enables organizations to allocate resources efficiently and implement the most impactful actions without delay. When such priorities are not clearly defined, firms may face excessive operational and investment costs, which can severely weaken their financial performance and limit their ability to sustain clean logistics initiatives. These negative effects extend beyond individual organizations, as inefficient recycling systems can also generate broader social costs, including environmental degradation, employment instability, and reduced public trust in sustainability policies [12]. Despite the practical importance of prioritization, existing studies in the literature provide limited guidance on identifying the most critical performance criteria and strategies for clean logistics-based recycling projects. Many studies focus on isolated factors or adopt narrow analytical perspectives, which prevents a comprehensive understanding of strategic priorities. This limitation represents a significant research gap, as the absence of structured prioritization frameworks increases uncertainty in decision making and undermines the effectiveness of policy and managerial interventions. Addressing this gap is crucial to support more resilient, cost-effective, and socially beneficial recycling systems.

This study aims to develop prioritized strategies to enhance the performance of recycling projects powered by clean logistics through a novel decision-making framework. The motivation of the study stems from the lack of integrated models that simultaneously capture expert knowledge, complex criteria interactions, and uncertainty in strategic evaluations. Based on an extensive literature review, a comprehensive list of performance criteria and strategic alternatives is constructed. Expert opinions are collected from ten specialists with diverse backgrounds related to clean logistics and recycling systems.

The importance weights of experts are determined using a consensus-based expert selection approach combined with Manhattan distance-based centrality, ensuring that more reliable and experienced perspectives receive greater influence. Criterion weights are then calculated using the cognitive maps technique, which captures causal relationships among criteria. Strategies are ranked using an orthogonal metric robust aggregation approach to ensure stable and reliable results. In addition, newly developed Chipper fuzzy sets are integrated into the model to better represent uncertainty and expert judgment. This study addresses the following research questions: (1) Which performance criteria are most critical for recycling projects powered by clean logistics? (2) Which strategies should be prioritized to maximize project performance under uncertainty?

This study contributes to the literature by providing an integrated and robust decision-making framework tailored to recycling projects powered by clean logistics. It also introduces methodological advancements that enhance the reliability and interpretability of strategic evaluations. The proposed model offers several advantages over existing approaches. (1) The development and integration of Chipper fuzzy sets provide greater flexibility in representing uncertainty compared to traditional fuzzy sets, as they allow more nuanced expression of expert judgments and apply a decoding-based defuzzification process that reduces information loss. (2) The use of cognitive maps to determine criterion weights is particularly suitable for this study, as it captures causal relationships and feedback effects that are often ignored by conventional weighting techniques. This leads to a more realistic representation of complex decision environments. (3) The consensus-based expert selection with Manhattan distance-based centrality assigns higher influence to experts with greater experience and consistency, which improves the credibility of results. (4) The orthogonal metric robust aggregation technique enhances ranking stability by reducing sensitivity to extreme values and subjective bias, making it more effective than many traditional aggregation methods.

To make these contributions explicit, the novelty of this study is threefold. First, it develops a unified prioritization framework for recycling projects powered by clean logistics by linking expert consensus, causal criterion weighting, and robust strategy ranking in a single model. Second, it introduces CFSs as an uncertainty-handling mechanism and validates them through five alternative scoring scenarios. Third, it translates the model outputs into practical clean-logistics priorities by identifying the most influential performance criteria and the most effective strategic alternatives.

This study is structured as follows. The introduction presents the research background, motivation, and objectives related to recycling projects powered by clean logistics. The literature review examines existing studies on clean logistics, recycling performance, and decision-making approaches, and identifies key research gaps. The proposed methodology section explains the structure of the developed decision-making model, including expert selection, weighting techniques, fuzzy modeling, and aggregation procedures. The analysis results section presents the empirical findings and prioritized strategies derived from the proposed model. The discussion section interprets these results by linking them to existing literature and practical implications. Finally, the conclusion summarizes the main contributions of the study, highlights policy and managerial insights, and outlines directions for future research.

2 Literature Review

Carbon intensity is a key factor that significantly influences the performance of recycling projects powered by clean logistics. In theoretical terms, carbon intensity represents the level of emissions generated relative to operational output and serves as an important indicator of environmental efficiency within logistics-based recycling systems. Lower carbon intensity improves the performance of such projects by encouraging the use of cleaner transportation modes, energy-efficient routing, and low-emission technologies throughout reverse logistics networks, thereby enhancing both environmental and operational outcomes [8]. In addition, reduced carbon intensity contributes to better resource utilization by limiting unnecessary energy consumption during collection, transportation, and processing stages of recycling activities [33]. From a sustainability perspective, carbon intensity also affects the economic viability of recycling projects, as lower emission levels reduce regulatory pressures and compliance costs while strengthening the environmental credibility of clean logistics initiatives [30]. Moreover, carbon intensity operates as a comprehensive performance signal that reflects the effectiveness of integrating

clean energy solutions with logistics and recycling operations [32]. Empirical research further supports this relationship, as Khan et al. [16] directly show that recycling projects powered by clean logistics achieve higher environmental and operational performance when carbon intensity is actively managed through low-carbon transport and energy strategies. Similarly, Chen et al. [4] find that carbon intensity plays a decisive role in shaping the success of clean logistics-based recycling projects, demonstrating that lower carbon intensity is consistently associated with improved emission reductions, cost efficiency, and system resilience.

Material quality is a critical factor that significantly influences the performance of recycling projects powered by clean logistics. From a theoretical perspective, high material quality improves recycling efficiency by reducing contamination and limiting material losses during collection, transportation, and processing stages, which allows clean logistics systems to operate more effectively and with lower energy intensity [15]. Consistent material quality also supports smoother coordination across reverse logistics networks by enabling standardized handling, sorting, and storage practices, which enhances operational stability and throughput in clean logistics-based recycling projects [1]. In addition, material quality has a direct impact on economic performance, as higher-quality recyclable inputs increase recovery rates and reduce reprocessing and disposal costs, thereby strengthening the financial sustainability of recycling initiatives powered by clean logistics [17]. Moreover, strong material quality standards facilitate better integration between clean transportation, processing technologies, and recycling operations, allowing emission reduction and resource efficiency goals to be achieved more effectively [2]. Beyond these theoretical considerations, empirical studies explicitly emphasize the role of material quality in shaping project outcomes. Habbouche et al. [10] show that recycling projects powered by clean logistics achieve superior environmental and operational performance when material quality is actively monitored and managed across the reverse supply chain, leading to lower inefficiencies and more stable system performance. Similarly, Surana et al. [28] demonstrate that maintaining high and consistent material quality significantly enhances the overall effectiveness of clean logistics-driven recycling projects by improving process reliability, cost efficiency, and long-term system resilience.

Technology adaptability is a critical factor that strongly affects the performance of recycling projects powered by clean logistics. From a theoretical perspective, technology adaptability allows recycling systems to respond effectively to changing material streams, policy requirements, and sustainability targets by integrating flexible and upgradeable clean logistics solutions [18]. When technologies are adaptable, recycling projects can more easily adopt energy efficient transport systems, smart routing tools, and digital monitoring applications, which improves coordination and transparency across reverse logistics networks [6]. Technology adaptability also supports continuous improvement by enabling the integration of automation, data driven decision making, and real time performance tracking into clean logistics-based recycling operations [11]. Moreover, adaptable technological infrastructures reduce operational disruptions and allow recycling projects to align new recycling methods or clean energy sources with existing logistics systems, thereby strengthening both environmental and economic performance [31]. Empirical studies further highlight the central role of technology adaptability in shaping project outcomes. Huang et al. [14] show that recycling projects powered by clean logistics achieve higher overall performance when adaptable technologies are used to improve process efficiency, emission control, and system integration across logistics stages. Similarly, Holian et al. [12] demonstrate that technology adaptability directly enhances the effectiveness of clean logistics-driven recycling projects by enabling rapid technological adjustments, lowering operational risks, and supporting long-term sustainability and resilience.

Costs are a critical factor that strongly influence the performance of recycling projects powered by clean logistics. From a theoretical viewpoint, cost structures shape the feasibility and scalability of clean logistics-based recycling systems by determining whether low-emission transportation, clean energy use, and advanced logistics technologies can be sustained over time [25]. When costs are effectively managed, recycling projects are better positioned to optimize logistics routes, improve capacity utilization, and reduce unnecessary energy consumption, which directly enhances operational performance [26]. Cost efficiency also affects environmental outcomes, as high logistics or processing costs can limit investments in cleaner technologies and undermine emission reduction efforts within recycling systems [12]. Moreover, balanced cost structures support long-term project stability by

reducing financial risks and enabling continuous improvements in clean logistics practices, which contributes to overall system resilience [27]. Empirical evidence further highlights the importance of costs in shaping project performance. Mo et al. [23] show that recycling projects powered by clean logistics achieve higher economic and environmental performance when cost control mechanisms are aligned with clean transportation and energy strategies. Similarly, Hopson et al. [13] demonstrate that cost-related decisions play a decisive role in the success of clean logistics-based recycling projects, emphasizing that projects with optimized cost structures are more capable of maintaining low-emission operations while achieving stable financial performance.

Based on the comprehensive literature review conducted in this study, several key insights emerge regarding the performance of recycling projects powered by clean logistics. Existing studies consistently highlight the importance of environmental, technological, and operational factors such as carbon intensity, material quality, technology adaptability, and cost efficiency in shaping project outcomes. The literature also shows that clean logistics plays a central role in linking recycling activities with sustainability goals by reducing emissions, improving resource efficiency, and enhancing system reliability. However, despite these contributions, a significant research gap remains in the way these critical factors are evaluated and prioritized. Most existing studies examine these criteria in isolation or focus on limited performance dimensions, which restricts a holistic understanding of their relative importance and interdependencies within clean logistics-based recycling systems. This gap creates practical challenges, as decision makers may allocate resources inefficiently or overlook key trade-offs when designing or managing recycling projects, ultimately weakening environmental and economic performance. The absence of a structured priority assessment framework also limits the ability of policymakers and practitioners to develop targeted strategies that align technological, environmental, and cost-related objectives. Addressing this gap requires a systematic priority analysis that can capture expert judgments and reflect the complex interactions among performance criteria. Such an approach would provide clearer guidance for strategic decision making, support more effective policy design, and enhance the overall performance and sustainability of recycling projects powered by clean logistics.

3 Methodology

This part includes the formulations of decoding uncertainty with Cipher Fuzzy Sets (CFSs), consensus-based expert selection, Q-learning algorithms, cognitive maps, and orthogonal metric robust aggregation, respectively. For clarity, the methodological workflow is implemented in five sequential stages: (i) expert evaluations are converted into CFS values; (ii) consensus-consistent expert matrices are selected using Manhattan distance-based centrality; (iii) unbalanced evaluations are adjusted through Q-learning; (iv) criterion weights are derived with CF-cognitive maps; and (v) investment alternatives are ranked through CF-orthogonal metric robust aggregation. This stepwise structure shows how the output of each stage becomes the input of the next stage.

3.1 Decoding Uncertainty with CFSs

Experts' evaluations include bias due to pessimist or optimist. The evaluations can lead to exaggerated or noisy or nonlinear evaluations. For this reason, decision-making models based on the evaluations generated biased results, leading to effectiveness solutions. Therefore, classical fuzzy sets are unsuccessful since these sets utilize the raw evaluations. However, CFSs offer a novel set, enabling decision-making models to perform more reliable results. Directional evaluation, nonlinearity, and noise issues are resolved through data-driven decoding of belonging, non-belonging, and indeterminacy degrees. In the analysis, the truth of the evaluation is revealed via the triple coding value of belonging, non-belonging, and hesitancy for inverse cipher. The decoding numbers compute three-channel effective grade by single button and various positive evidence, negative absence, and confidence. In this resolution of uncertainty, a dynamic evaluation process is obtained through data-driven calibration of fuzzy coefficients. The graphs of CFSs are shown in Figure 1.

True triple is identified by Eq. (1).

$$(\mu^{\diagdown *}, v^{\diagdown *}, \pi^{\diagdown *}) \in [0,1]^3 \tag{1}$$

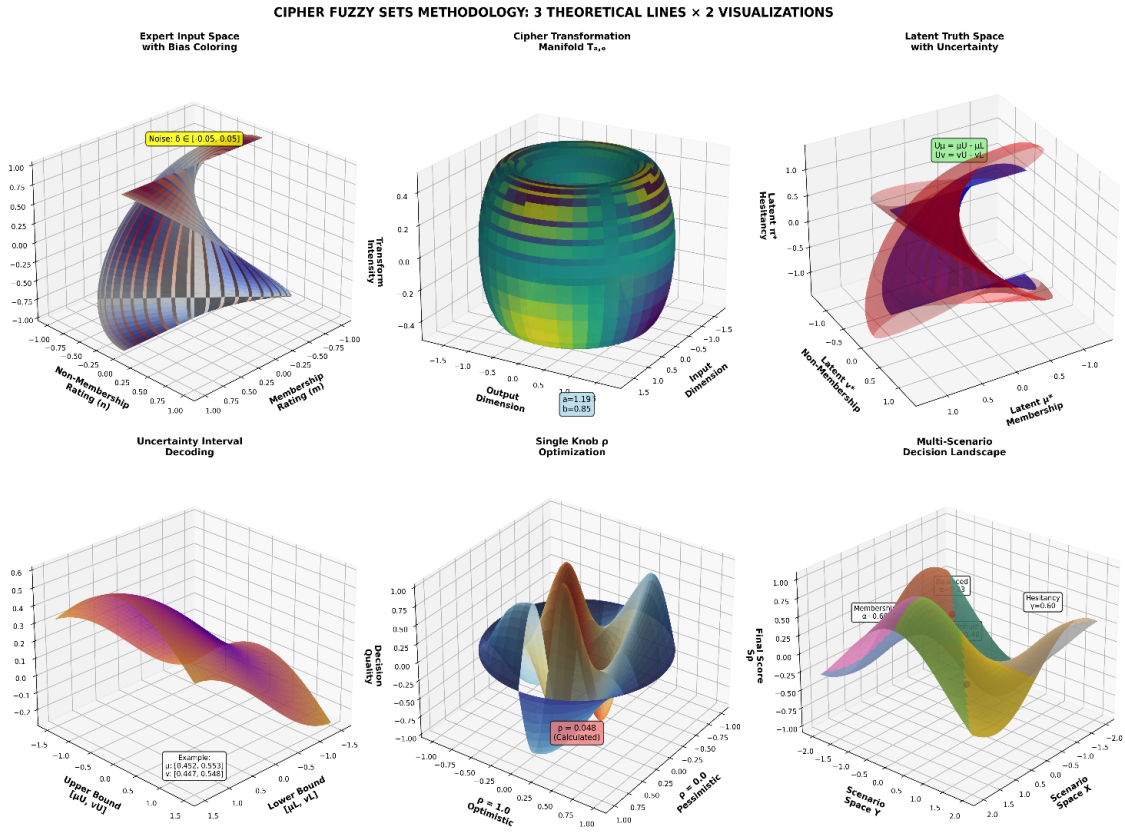


Figure 1: Graphs of CFSs

Wherein $\mu^{\backslash *}, v^{\backslash *}$ and $\pi^{\backslash *}$ represent the latent belonging, non-belonging, and hesitancy degrees for CFSs, respectively. Cipher and inverse cipher functions are computed with Eqs. (2)–(8).

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{2}$$

$$\operatorname{logit}(x) = \ln \frac{x}{1-x} \tag{3}$$

$$0 < x < 1 \tag{4}$$

$$T_{a,b}(x) = \sigma\left(a \operatorname{logit}(x) + b\right) \tag{5}$$

$$T_{a,b}^{-1}(x) = \sigma\left(\frac{\operatorname{logit}(x) - b}{a}\right) \tag{6}$$

$$T_{a_1,b_1}.T_{a_2,b_2} = T_{a_1a_2,\, a_1b_2+b_1} \tag{7}$$

$$(T_{a,b})^{-1} = T_{1/a,\, -b/a} \tag{8}$$

Encoding truth degrees of CFSs are estimated by Eqs. (9) – (20) for sampling noise.

$$T_{a_\mu b_\mu}\left(\mu^{\backslash *}\right) = \beta + \delta_\mu \tag{9}$$

$$T_{a_v b_v}\left(v^{\backslash *}\right) = \gamma + \delta_v \tag{10}$$

$$\beta = 1 - \gamma \tag{11}$$

$$\beta + \delta_\mu = \sigma\left(a_\mu \operatorname{logit}(\mu^{\backslash *}) + b_\mu\right) \tag{12}$$

$$\delta_\mu \in [-\varepsilon_\mu, \varepsilon_\mu] \tag{13}$$

$$\gamma + \delta_v = \sigma\left(a_v \operatorname{logit}(v^{\backslash *}) + b_v\right) \tag{14}$$

$$\delta_v \in [-\varepsilon_v, \varepsilon_v] \tag{15}$$

$$a_\mu = a_v = \frac{1}{4P_0(1-P_0)} \tag{16}$$

$$b_\mu = \text{logit}(P_0) \tag{17}$$
$$b_v = \text{logit}(1 - P_0) \tag{18}$$
$$P_0 = \text{median}\,\{m_{ij} : i \neq j\} \tag{19}$$
$$\varepsilon_\mu = \varepsilon_v = 0.05 \tag{20}$$

Encoding degrees of CFSs are mean by $T_{a_\mu b_\mu}\,(\mu^{\diagdown *})$ and $T_{a_v b_v}\,(v^{\diagdown *})$. β and γ refers the observed belonging and non-belonging values by experts, respectively. a is non-linearity. If a is lower than one, it identifies compression. Otherwise, it refers about expansion. b equal to directional bias coefficient. δ presents sampling noise from tolerance level (ε). Cipher inverse degrees of these are defined into the decoded widths with the help of Eqs. (21) – (32).

$$I_\beta = [\underline{m}, \overline{m}] \tag{21}$$
$$\underline{m} = \max\,(0, m - \varepsilon_\mu) \tag{22}$$
$$\overline{m} = \min\,(1, m + \varepsilon_\mu) \tag{23}$$
$$I_\gamma = \left[\underline{\gamma}, \overline{\gamma}\right] \tag{24}$$
$$\underline{\gamma} = \max\,(0, \gamma - \varepsilon_\mu) \tag{25}$$
$$\overline{\gamma} = \min\,(1, \gamma + \varepsilon_\mu) \tag{26}$$
$$\mu_L = \sigma\left(\frac{\text{logit}(\underline{m}) - b_\mu}{a_\mu}\right) \tag{27}$$
$$\mu_U = \sigma\left(\frac{\text{logit}(\overline{m}) - b_\mu}{a_\mu}\right) \tag{28}$$
$$v_L = \sigma\left(\frac{\text{logit}(\underline{\gamma}) - b_v}{a_v}\right) \tag{29}$$
$$v_U = \sigma\left(\frac{\text{logit}(\overline{\gamma}) - b_v}{a_v}\right) \tag{30}$$
$$U_\mu = \mu_U - \mu_L \tag{31}$$
$$U_v = v_U - v_L \tag{32}$$

Thus, data-driven hesitancy degree is estimated with Eqs. (33) – (35).

$$\pi = \prod (U_\mu, U_v) \tag{33}$$
$$\pi = \min\left\{1, \frac{U_\mu + U_v}{W_{\max}}\right\} \tag{34}$$

The newly proposed CFSs are validated in this study through a scenario-based sensitivity procedure. Instead of relying on a single defuzzification setting, five score configurations are used: balanced, membership-heavy, hesitancy-averse, hesitancy-ignored, and robust-balance. Comparing the results across these configurations allows the model to test whether the main priorities remain interpretable under different assumptions about belonging, non-belonging, and hesitancy, thereby providing an internal robustness check for the proposed fuzzy representation.

$$W_{\max} = \max_{\text{entries}}\,(U_\mu + U_v) \tag{35}$$

The decoded values are established by Eqs. (36) - (38) using single knob (ρ).

$$\widetilde{\mu} = (1 - \rho)\frac{\mu_L + \mu_U}{2} + \rho\mu_L \tag{36}$$
$$\widetilde{v} = (1 - \rho)\frac{v_L + v_U}{2} + \rho v_U \tag{37}$$
$$0 \leq \rho \leq 1 \tag{38}$$

Single knob for decoded degrees for each CFS is defined via Eqs. (39) – (41).

$$\rho = \frac{t_\mu(P_0) - t_v(P_0)}{t_\mu(P_0) - t_v(P_0) + v_U(P_0) - \mu_L(P_0)} \tag{39}$$

$$t_\mu = \frac{1}{2}\left(\mu_L + \mu_U\right) \tag{40}$$

$$t_v = \frac{1}{2}\left(v_L + v_U\right) \tag{41}$$

Decoded score function of CFSs is determined with the help of Eqs. (42) – (45).

$$S_\rho = \zeta\widetilde{\mu} + \xi\left(1 - \widetilde{v}\right) + \theta(1 - \pi) \tag{42}$$

$$\zeta, \xi, \theta > 0 \tag{43}$$

$$\zeta + \xi + \theta = 1 \tag{44}$$

$$0 \leq S_\rho \leq 1 \tag{45}$$

If these coefficients $(\zeta, \xi,\ \theta)$ are considered as equally, balanced scenario is constructed. For belonging-heavy scenario, coefficients are .6, .3 and .1, respectively. For hesitancy-averse, these coefficients are equal to $\zeta = .2, \xi = .2,\ \theta = .6$. When hesitancy is ignored, $\zeta = .5, \xi = .5,\ \theta = 0$. In the robust-balance scenario, $\zeta = .4, \xi = .4,\ \theta = .2$. In this situation, a CFS $(\widetilde{C})$ is created as Eq. (46).

$$\begin{aligned}\widetilde{C} = \Bigg\{ \Bigg(& u, (1-\rho)\frac{\mu_L + \mu_U}{2} + \rho\mu_L, \\ & (1-\rho)\frac{v_L + v_U}{2} + \rho v_U, \\ & \min\left\{1, \frac{U_\mu + U_v}{W_{\max}}\right\}\Bigg) \ \Bigg|\ u \in S\Bigg\}\end{aligned} \tag{46}$$

3.2 Consensus-based Expert Selection with Manhattan Distance-based Centrality

In decision-making analysis, consensus among experts is a factor that increases the reliability and applicability of results. In other words, the outlier rejection losses information is problem. For this, the consensus of evaluations from various experts is calculated with Manhattan distance-based centrality. The computation process is detailed follows [21].

Firstly, evaluations are collected and numerical evaluation matrices $(R = [r_{ij}])$ are obtained. Later, Manhattan distance among any two matrices is determined using Eq. (47).

$$d\left(R_a, R_b\right) = \sum_{i=1}^{n}\sum_{j=1}^{n}\left|{r_{ij}}^a - {r_{ij}}^b\right| \tag{47}$$

Wherein n equals to the dimension of these matrices. Then, dissimilarity values are summed via Eq. (48).

$$\mathrm{T}_a = \sum_{b=1,\, b\neq a}^{e} d(R_a, R_b) \tag{48}$$

Finally, best matrix (R_{a^*}) is selected with the help of Eq. (49).

$$a^* = \arg\min \mathrm{T}_a \tag{49}$$

3.3 Q-learning Algorithm for Unbalanced Expert Evaluations

The Q-learning algorithm's aim is to create balanced decision or relation matrix. The approach constructs balanced decision or relation matrix through an iterative training approach dependent penalty, reward factors, and learning ratio. The computation process is detailed follow [5].

Let Q be a CF-evaluation matrix. After selecting the best, reward degrees among the best and other CF-evaluation matrices are estimated by Eq. (50).

$$\mathbb{R}_{s,a} = r \cdot \left(Q_{s,a\,(\text{best})} - Q_{s,a\,(\text{other})}\right) \tag{50}$$

Wherein r presents to the reward factor for setting the quantify and positive feedback. The priority value of matrix with minimum experience is used as reward factor. Penalty degrees among the best and other evaluation matrices are established using Eq. (51).

$$\mathbb{P}_{s,a} = p \cdot \left(Q_{s,a\,(\text{other})} - Q_{s,a\,(\text{best})}\right) \tag{51}$$

Wherein p means the penalty factor for quantifying the negative feedback among experts. The factor is considered as the priority value of the matrix with maximum experience. Later, the CF-evaluation matrix is upgraded with Eq. (52), iteratively.

$$Q'_{s,a} = Q_{s,a\,(\text{best})} + \mathfrak{g} \cdot (\mathbb{R}_{s,a} - \mathbb{P}_{s,a}) \tag{52}$$

Wherein $\mathfrak{g}$ refers the learning ratio for ensuring efficient and stable learning process from new experiences. Next, the stabile CF-evaluation matrix is determined by Eqs. (53) and (54).

$$\Delta_{s,a} = \left|Q'_{s,a} - Q_{s,a}\right| \tag{53}$$

$$\Delta_{\max} = \max_{s,a}\{\Delta_{s,a}\} \tag{54}$$

When $\Delta_{\max}$ is smaller than threshold value, iteration stops.

3.4 CF-Cognitive Maps

Cognitive maps are an approach that determines criterion priorities iteratively. This approach is used as a powerful tool for solving complex real-world problem. The computation is detailed follow [24].

Firstly, evaluation about dependency levels of n criteria is collected. Next, CF-relation matrix is constructed with CFNs in Eq. (55).

$$H_t = \begin{bmatrix} 0 & h_{12} & \cdots & \cdots & h_{1n} \\ h_{21} & 0 & \cdots & \cdots & h_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_{n1} & h_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{55}$$

where $h_{ij} = \left(h_{\mu_{ij}}, h_{v_{ij}}, h_{\pi_{ij}}\right)$, and t denotes the number of scenarios. Later, decoded relation values are determined with Eqs. (42)–(45). Thus, the defuzzified relation matrix is created in Eq. (56). Each off-diagonal value N_{ij} is obtained by applying the decoded score function to the corresponding CFS relation value h_{ij} in the balanced expert matrices and then averaging the scenario-specific decoded scores. Therefore, N_{ij} values are derived from expert evaluations through the CFS defuzzification procedure, rather than assigned empirically or by ad hoc rules. The diagonal elements are set to zero because a criterion is not evaluated against itself.

$$N = \begin{bmatrix} 0 & N_{12} & \cdots & \cdots & N_{1n} \\ N_{21} & 0 & \cdots & \cdots & N_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ N_{n1} & N_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{56}$$

Next, the state vector at iteration s is defined in Eq. (57), and the vector is updated iteratively as shown in Eq. (58).

$$A(s) = [a_1(s), a_2(s), \ldots, a_n(s)] \tag{57}$$

$$A(s+1) = f\left(A(s) \cdot N\right) \tag{58}$$

Here, f is an element-wise sigmoid activation function, as shown in Eq. (59), and s denotes the iteration number.

$$f(x) = \frac{1}{1+e^{-x}} \tag{59}$$

The iterative approach is continued until $fA(s+1) = fA(s)$. Finally, the criterion weighting vector is defined by Eq. (60), where j denotes the criterion index and l is used only as the summation index.

$$W_j = \frac{fA(s)_j}{\sum_{j=1}^{n} fA(s)_j} \tag{60}$$

3.5 CF-Orthogonal Metric Robust Aggregation

This model includes the four various metrics such as Squared Euclidean deviation, root-Euclidean deviation, Chebyshev Euclidean deviation and linear correlation in ranking alternatives. More robust solutions are obtained thanks to this. The computation process is detailed follows [9].

Firstly, evaluation of m alternatives is collected. Decision matrix illustrated in Eq. (61) is created.

$$X_k = \begin{bmatrix} X_{11} & X_{12} & \cdots & \cdots & X_{1m} \\ X_{21} & X_{22} & \cdots & \cdots & X_{2m} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & \cdots & X_{nm} \end{bmatrix} \tag{61}$$

Subsequently, decoded decision values are calculated by Eqs. (42)–(45). Next, the decoded decision matrix is normalized using Eqs. (62) and (63). For clarity, the maximum and minimum operators are computed over alternatives $i = 1, \ldots, m$ for each fixed criterion j; B and C denote benefit and cost criteria, respectively.

$$r_{ij} = \frac{X_{ij}}{\max\limits_{i=1,\ldots,m} X_{ij}}, \quad \text{if } j \in B \tag{62}$$

$$r_{ij} = \frac{\min\limits_{i=1,\ldots,m} X_{ij}}{X_{ij}}, \quad \text{if } j \in C \tag{63}$$

Afterwards, normalized decoded decision values are multiplied by weighting vector with Eq. (64).

$$\tau_{ij} = w_j \times r_{ij} \tag{64}$$

Behind, ideal-best solutions are chosen regarding to Eq. (65).

$$b_j = \max_i \tau_{ij} \tag{65}$$

The four metrics among ideal-best solutions and weighted decoded decision values are computed using Eqs. (66) – (69), respectively.

$$\delta_i{}^{(2)} = \frac{1}{1 + \sum_{j=1}^{n} (b_j - \tau_{ij})^2} \tag{66}$$

$$\delta_i{}^{(M)} = \frac{1}{1 + \sqrt{\sum_{j=1}^{n} (b_j - \tau_{ij})^2}} \tag{67}$$

$$\delta_i{}^{(\infty)} = \frac{1}{1 + \max_{1 \le j \le n} |b_j - \tau_{ij}|} \tag{68}$$

$$\rho_i = \operatorname{corr}\left((\tau_{i1}, \ldots, \tau_{in}), (b_1, \ldots, b_n)\right) \tag{69}$$

Finally, the final ranks of alternatives are determined by Eq. (70).

$$s_i = \frac{1}{4}\left[\delta_i{}^{(2)} + \delta_i{}^{(M)} + \delta_i{}^{(\infty)} + \rho_i\right] \tag{70}$$

4 Analysis

The part includes the results of sustainable recycling logistics. Investment criteria set for recycling projects powered by clean logistics are carbon intensity (CIN), material quality (MQL), technology adaptability (TAD), energy security (ENS), and costs (CST). Similarly, investment alternatives for recycling projects powered by clean logistics are electric fleet operator (EFOP), recycling park developer (RCPD), recycling parts seller (RCPS), tech failure insurer (TFIN), and green tech startup incubator (GTSI). These investment criteria and alternatives are evaluated. The scale in Table 1 is used for evaluations.

Table 1: Evaluation Scales and Belongings

Scale	Linguistic	Belonging
1	Extremely Low (EL)	.1
2	Very Low (VL)	.2
3	Low (L)	.3
4	Moderately Low (ML)	.4
5	Neutral (N)	.5
6	Moderately High (MH)	.6
7	High (H)	.7
8	Very High (VH)	.8
9	Extremely High (EH)	.9

Firstly, the evaluation about investment criteria is collected using 9-point scales in Table 1. The results are given in Table 2.

Table 2: Numerical Evaluation for Investment Criteria

Expert 1	CIN	MQL	TAD	ENS	CST	Expert 2	CIN	MQL	TAD	ENS	CST
CIN		7	9	8	7	CIN		7	8	6	7
MQL	8		8	6	7	MQL	9		6	6	6
TAD	8	6		6	6	TAD	8	7		6	6
ENS	9	6	9		5	ENS	9	6	9		5
CST	6	5	8	5		CST	8	6	8	6	

Continued on next page

Table 2 (continued)

Expert 3	**CIN**	**MQL**	**TAD**	**ENS**	**CST**	**Expert 4**	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		7	6	7	8	CIN		6	6	8	7
MQL	8		5	6	7	MQL	8		5	7	7
TAD	9	5		6	7	TAD	7	5		6	7
ENS	8	7	9		7	ENS	7	7	7		6
CST	8	8	8	5		CST	7	7	8	5	
Expert 5	**CIN**	**MQL**	**TAD**	**ENS**	**CST**	**Expert 6**	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		6	6	8	7	CIN		6	8	8	7
MQL	8		7	6	7	MQL	6		5	6	8
TAD	8	5		6	6	TAD	7	7		6	8
ENS	9	7	9		7	ENS	6	7	9		6
CST	8	7	7	7		CST	6	5	8	5	
Expert 7	**CIN**	**MQL**	**TAD**	**ENS**	**CST**	**Expert 8**	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		7	6	8	8	CIN		7	8	9	7
MQL	9		5	6	7	MQL	8		5	6	9
TAD	8	7		6	8	TAD	8	6		9	9
ENS	7	6	9		8	ENS	6	6	9		5
CST	6	7	8	5		CST	6	5	8	5	
Expert 9	**CIN**	**MQL**	**TAD**	**ENS**	**CST**	**Expert 10**	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		7	7	7	8	CIN		7	8	8	7
MQL	8		5	6	8	MQL	9		8	7	8
TAD	8	7		7	7	TAD	8	5		7	8
ENS	6	6	9		6	ENS	8	8	7		7
CST	6	5	8	5		CST	9	8	6	6	

At the same time, evaluation for investment alternatives is collected with similar procedure. The numerical evaluation of these alternatives is shown in Table 3.

Table 3: Numerical Evaluation for Investment Alternatives

Expert 1	**CIN**	**MQL**	**TAD**	**ENS**	**CST**	**Expert 2**	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	8	6	9	8	8	EFOP	9	8	9	8	8
RCPD	9	7	8	8	7	RCPD	8	9	8	8	8
RCPS	8	8	6	7	6	RCPS	8	8	8	7	8
TFIN	9	8	7	6	7	TFIN	9	9	8	7	8
GTSI	7	9	8	9	7	GTSI	9	9	9	9	7
Expert 3	**CIN**	**MQL**	**TAD**	**ENS**	**CST**	**Expert 4**	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	8	6	9	9	8	EFOP	8	6	9	8	8
RCPD	9	7	8	8	9	RCPD	6	7	6	6	6
RCPS	8	8	7	7	8	RCPS	8	8	8	7	8
TFIN	9	8	9	9	7	TFIN	7	8	6	7	6
GTSI	7	6	9	9	7	GTSI	6	7	9	8	6
Expert 5	**CIN**	**MQL**	**TAD**	**ENS**	**CST**	**Expert 6**	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	8	9	8	8	9	EFOP	9	6	9	8	8
RCPD	9	7	8	8	7	RCPD	8	7	8	8	7
RCPS	7	8	7	8	8	RCPS	8	8	8	7	8
TFIN	8	8	8	8	8	TFIN	9	8	9	7	9
GTSI	9	9	9	7	7	GTSI	7	8	9	9	7
Expert 7	**CIN**	**MQL**	**TAD**	**ENS**	**CST**	**Expert 8**	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	8	6	9	8	8	EFOP	9	6	9	8	8
RCPD	6	7	8	6	6	RCPD	6	7	8	8	7
RCPS	8	8	6	7	8	RCPS	8	9	9	7	9
TFIN	6	8	6	6	7	TFIN	9	8	7	9	7
GTSI	7	7	9	6	6	GTSI	9	9	9	9	7
Expert 9	**CIN**	**MQL**	**TAD**	**ENS**	**CST**	**Expert 10**	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	8	6	9	8	7	EFOP	9	6	9	8	9
RCPD	6	7	8	7	7	RCPD	9	6	8	9	9
RCPS	8	7	7	7	7	RCPS	9	6	6	9	8
TFIN	7	8	7	7	7	TFIN	8	7	6	7	8
GTSI	7	7	7	9	7	GTSI	8	7	8	8	9

4.1 Obtaining the Best Matrices

Firstly, Manhattan distances among these matrices in Table 2 and Table 3 are calculated with Eq. (47). Then, dissimilarities are summed using Eq. (48). The results for investment criteria are displayed in Table 4.

Table 4: Manhattan Distances and Total Dissimilarities for Investment Criteria

	E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**	**Total**
E1	0	12	20	20	16	17	18	16	15	24	158
E2	12	0	18	22	16	21	18	22	17	24	170
E3	20	18	0	12	12	21	12	24	15	20	154
E4	20	22	12	0	14	15	14	22	17	20	156
E5	16	16	12	14	0	23	18	28	23	18	168
E6	17	21	21	15	23	0	15	13	10	27	162
E7	18	18	12	14	18	15	0	18	11	24	148
E8	16	22	24	22	28	13	18	0	11	28	182
E9	15	17	15	17	23	10	11	11	0	27	146
E10	24	24	20	20	18	27	24	28	27	0	212

With same equations and processes, the distance is computed for investment alternatives, and the dissimilarities are summed. The results for investment alternatives are illustrated in Table 5.

Table 5: Manhattan Distances and Total Dissimilarities for Investment Alternatives

	E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**	**Total**
E1	0	18	15	23	20	13	19	17	14	24	163
E2	18	0	19	27	16	11	29	15	24	28	187
E3	15	19	0	24	21	12	24	18	19	25	177
E4	23	27	24	0	29	20	10	22	15	31	201
E5	20	16	21	29	0	19	27	21	26	26	205
E6	13	11	12	20	19	0	22	14	17	25	153
E7	19	29	24	10	27	22	0	24	15	29	199
E8	17	15	18	22	21	14	24	0	19	31	181
E9	14	24	19	15	26	17	15	19	0	26	175
E10	24	28	25	31	26	25	29	31	26	0	245

Finally, best matrices both investment for criteria and for alternatives are chosen with the help of Eq. (49). The three smaller total dissimilarities in Table 4 are Expert 9, Expert 7 and Expert 3 with 146, 148 and 154, respectively. In addition, the three smaller total dissimilarity values in Table 5 are Expert 6 with 153, Expert 1 with 163 and Expert 9 with 175. Thus, these evaluation matrices are determined as best matrices. In other words, the best matrices for investment criteria are presented in Table A1. At the same time, the best matrices for investment alternatives are summarized in Table A2.

4.2 Creating The Balanced Decoded Matrices

The best matrices for investment criteria are used observed consensus rating for criteria. The linguistic evaluation for investment criteria is shared in Table 6.

Table 6: Linguistic Evaluation for Investment Criteria

Expert 9 (Initial Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		H	H	H	VH
MQL	VH		N	MH	VH
TAD	VH	H		H	H
ENS	MH	MH	EH		MH
CST	MH	N	VH	N	

Continued on next page

Table 6 (continued)

Expert 7 (Q-learned expert-Second Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		H	MH	VH	VH
MQL	EH		N	MH	H
TAD	VH	H		MH	VH
ENS	H	MH	EH		VH
CST	MH	H	VH	N	
Expert 3 (Q-learned expert-Third Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		H	MH	H	VH
MQL	VH		N	MH	H
TAD	EH	N		MH	H
ENS	VH	H	EH		H
CST	VH	VH	VH	N	

Similarly, observed consensus ratings for investment alternatives are determined. The linguistic evaluation for investment alternatives is expressed in Table 7.

Table 7: Linguistic Evaluation for Investment Alternatives

Expert 6 (Initial Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	EH	MH	EH	VH	VH
RCPD	VH	H	VH	VH	H
RCPS	VH	VH	VH	H	VH
TFIN	EH	VH	EH	H	EH
GTSI	H	VH	EH	EH	H
Expert 1 (Q-learned expert-Second Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	VH	MH	EH	VH	VH
RCPD	EH	H	VH	VH	H
RCPS	VH	VH	MH	H	MH
TFIN	EH	VH	H	MH	H
GTSI	H	EH	VH	EH	H
Expert 9 (Q-learned expert-Third Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	VH	MH	EH	VH	H
RCPD	MH	H	VH	H	H
RCPS	VH	H	H	H	H
TFIN	H	VH	H	H	H
GTSI	H	H	H	EH	H

Subsequently, cipher inverse grades of fuzzy belonging and non-belonging for different observed various ratings of investment criteria are calculated by Eqs. (21) – (32). The results are presented in Table 8.

Table 8: Cipher Inverse Grades of Fuzzy Belonging and Non-Belonging for Different Observed Various Ratings of Investment Criteria

Expert 9 (Initial Expert) ($\mathbf{a:1.19, b:.85}$, $\mathbf{P_0}$: $\mathbf{.70}, \varepsilon:\mathbf{.05}$)						
m	$\mu_{\mathbf{L}}$	$\mu_{\mathbf{U}}$	$\mathbf{v_L}$	$\mathbf{v_U}$	$\mathbf{U}_{\mu}$	$\mathbf{U_v}$
$m:.5$	.293	.367	.633	.707	.074	.074
$m:.6$	.367	.452	.548	.633	.085	.085
$m:.7$	.452	.553	.447	.548	.100	.100
$m:.8$	.553	.678	.322	.447	.126	.126
$m:.9$	.678	.853	.147	.322	.175	.175

Continued on next page

Table 8 (continued)

Expert 7 (Q-learned expert-Second Expert) ($\mathbf{a}: \mathbf{1.19}, \mathbf{b}: \mathbf{.85}$, $\mathbf{P_0}$: $\mathbf{.70}, \varepsilon: \mathbf{.05}$)						
m	$\mu_{\mathbf{L}}$	$\mu_{\mathbf{U}}$	$\mathbf{v_L}$	$\mathbf{v_U}$	$\mathbf{U}_{\mu}$	$\mathbf{U_v}$
$m: .5$	.293	.367	.633	.707	.074	.074
$m: .6$	.367	.452	.548	.633	.085	.085
$m: .7$	.452	.553	.447	.548	.100	.100
$m: .8$	.553	.678	.322	.447	.126	.126
$m: .9$	.678	.853	.147	.322	.175	.175
Expert 3 (Q-learned expert-Third Expert) ($\mathbf{a}: \mathbf{1.19}, \mathbf{b}: \mathbf{.85}$, $\mathbf{P_0}$: $\mathbf{.70}, \varepsilon: \mathbf{.05}$)						
m	$\mu_{\mathbf{L}}$	$\mu_{\mathbf{U}}$	$\mathbf{v_L}$	$\mathbf{v_U}$	$\mathbf{U}_{\mu}$	$\mathbf{U_v}$
$m: .5$	.293	.367	.633	.707	.074	.074
$m: .6$	.367	.452	.548	.633	.085	.085
$m: .7$	.452	.553	.447	.548	.100	.100
$m: .8$	.553	.678	.322	.447	.126	.126
$m: .9$	.678	.853	.147	.322	.175	.175

Similarly, cipher inverse grades of fuzzy belonging and non-belonging for different observed various ratings of investment alternatives are established. The results are summarized in Table 9.

Table 9: Cipher Inverse Grades of Fuzzy Belonging and Non-Belonging for Different Observed Various Ratings of Investment Alternatives

Expert 6 (Initial Expert) ($\mathbf{a}: \mathbf{1.56}, \mathbf{b}: \mathbf{1.39}$, $\mathbf{P_0}$: $\mathbf{.80}, \varepsilon: \mathbf{.05}$)						
m	$\mu_{\mathbf{L}}$	$\mu_{\mathbf{U}}$	$\mathbf{v_L}$	$\mathbf{v_U}$	$\mathbf{U}_{\mu}$	$\mathbf{U_v}$
$m: .6$	.319	.380	.620	.681	.061	.061
$m: .7$	.380	.454	.546	.620	.074	.074
$m: .8$	.454	.555	.445	.546	.101	.101
$m: .9$	.555	.731	.269	.445	.175	.175
Expert 1 (Q-learned expert-Second Expert) ($\mathbf{a}: \mathbf{1.56}, \mathbf{b}: \mathbf{1.39}$, $\mathbf{P_0}$: $\mathbf{.80}, \varepsilon: \mathbf{.05}$)						
m	$\mu_{\mathbf{L}}$	$\mu_{\mathbf{U}}$	$\mathbf{v_L}$	$\mathbf{v_U}$	$\mathbf{U}_{\mu}$	$\mathbf{U_v}$
$m: .6$	.319	.380	.620	.681	.061	.061
$m: .7$	.380	.454	.546	.620	.074	.074
$m: .8$	.454	.555	.445	.546	.101	.101
$m: .9$	.555	.731	.269	.445	.175	.175
Expert 9 (Q-learned expert-Third Expert) ($\mathbf{a}: \mathbf{1.19}, \mathbf{b}: \mathbf{.85}$, $\mathbf{P_0}$: $\mathbf{.70}, \varepsilon: \mathbf{.05}$)						
m	$\mu_{\mathbf{L}}$	$\mu_{\mathbf{U}}$	$\mathbf{v_L}$	$\mathbf{v_U}$	$\mathbf{U}_{\mu}$	$\mathbf{U_v}$
$m: .6$	.319	.380	.620	.681	.061	.061
$m: .7$	.380	.454	.546	.620	.074	.074
$m: .8$	.454	.555	.445	.546	.101	.101
$m: .9$	.555	.731	.269	.445	.175	.175

In other step, decoded consensus values of CFSs for investment criteria are obtained using Eqs. (33) – (38). The results are illustrated in Table 10.

Table 10: Decoded Consensus Values for Investment Criteria

Expert 9 (Initial Expert) (ρ**:.048**)			
m	$\widetilde{\mu}$	$\widetilde{\mathbf{v}}$	π
$m: .5$	.329	.671	.424
$m: .6$	.408	.592	.484
$m: .7$	.500	.500	.573
$m: .8$	.612	.388	.717
$m: .9$	.762	.238	1.000
Expert 7 (Q-learned expert-Second Expert) (ρ**:.048**)			
m	$\widetilde{\mu}$	$\widetilde{\mathbf{v}}$	π
$m: .5$	.329	.671	.424
$m: .6$	.408	.592	.484
$m: .7$	.500	.500	.573
$m: .8$	.612	.388	.717
$m: .9$	.762	.238	1.000

Continued on next page

Table 10 (continued)

Expert 3 (Q-learned expert-Third Expert) (ρ:.048)			
m	$\widetilde{\mu}$	$\widetilde{\mathbf{v}}$	π
m : .5	.329	.671	.424
m : .6	.408	.592	.484
m : .7	.500	.500	.573
m : .8	.612	.388	.717
m : .9	.762	.238	1.000

Similarly, the decoded consensus values of CFSs for investment alternatives are computed using same procedure. The results are shared in Table 11.

Table 11: Decoded Consensus Values for Investment Alternatives

Expert 6 (Initial Expert) (ρ:.095)			
m	$\widetilde{\mu}$	$\widetilde{\mathbf{v}}$	π
m : .6	.346	.654	.347
m : .7	.413	.587	.425
m : .8	.500	.500	.579
m : .9	.635	.365	1.000
Expert 1 (Q-learned expert-Second Expert) (ρ:.095)			
m	$\widetilde{\mu}$	$\widetilde{\mathbf{v}}$	π
m : .6	.346	.654	.347
m : .7	.413	.587	.425
m : .8	.500	.500	.579
m : .9	.635	.365	1.000
Expert 9 (Q-learned expert-Third Expert) (ρ:.048)			
m	$\widetilde{\mu}$	$\widetilde{\mathbf{v}}$	π
m : .6	.408	.592	.484
m : .7	.500	.500	.573
m : .8	.612	.388	.717
m : .9	.762	.238	1.000

Behind, CFNs for investment criteria are displayed in Table A3 regarding to Eq. (46). Likewise, CFNs for investment alternatives are established. The results are presented in Table A4.

In Q-learning algorithm, both penalty and reward factors must be defined. For defining, total dissimilarities in Table 4 and 5 are normalized. Regarding to normalized total dissimilarities for investment criteria, the best is Expert 9 with .341. Expert 3 has the minimum importance with 0.323 for investment criteria. For Expert 7, it is .336. Likewise, the maximum weight is .356 with Expert 6. Expert 1 and Expert 9 have .334 and .311, respectively for investment alternatives. After calculating the values of factors, reward degrees across the best and other matrices are computed via Eq. (50). The reward result of relation matrix is presented in Table 12.

Table 12: Reward Results of Relation Matrix

Expert 9-Expert 7	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.00, .00, .00)	(.00, .00, .00)	(-.03, .03, -.03)	(.04, -.04, .05)	(.00, .00, .00)
MQL	(.05, -.05, .10)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(-.04, .04, -.05)
TAD	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(-.03, .03, -.03)	(.04, -.04, .05)
ENS	(.03, -.03, .03)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.07, -.07, .08)
CST	(.00, .00, .00)	(.06, -.06, .05)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
Expert 9-Expert 3	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.00, .00, .00)	(.00, .00, .00)	(-.03, .03, -.03)	(.00, .00, .00)	(.00, .00, .00)
MQL	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(-.04, .04, -.05)
TAD	(.05, -.05, .09)	(-.06, .06, -.05)	(.00, .00, .00)	(-.03, .03, -.03)	(.00, .00, .00)
ENS	(.07, -.07, .08)	(.03, -.03, .03)	(.00, .00, .00)	(.00, .00, .00)	(.03, -.03, .03)
CST	(.07, -.07, .08)	(.09, -.09, .09)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)

Similarly, the reward result for decision matrix is obtained. The results are illustrated in Table 13.

Table 13: Reward Result for Decision Matrix

Expert	CIN	MQL	TAD	ENS	CST
6-Expert 1					
EFOP	(-.04, .04, -.14)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
RCPD	(.04, -.04, .14)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
RCPS	(.00, .00, .00)	(.00, .00, .00)	(-.05, .05, -.08)	(.00, .00, .00)	(-.05, .05, -.08)
TFIN	(.00, .00, .00)	(.00, .00, .00)	(-.07, .07, -.19)	(-.02, .02, -.03)	(-.07, .07, -.19)
GTSI	(.00, .00, .00)	(.04, -.04, .14)	(-.04, .04, -.14)	(.00, .00, .00)	(.00, .00, .00)
Expert	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
6-Expert 9					
EFOP	(-.01, .01, -.09)	(.02, -.02, .04)	(.04, -.04, .00)	(.03, -.03, .04)	(.00, .00, .00)
RCPD	(-.03, .03, -.03)	(.03, -.03, .05)	(.03, -.03, .04)	(.00, .00, .00)	(.03, -.03, .05)
RCPS	(.03, -.03, .04)	(.00, .00, .00)	(.00, .00, .00)	(.03, -.03, .05)	(.00, .00, .00)
TFIN	(-.04, .04, -.13)	(.03, -.03, .04)	(-.04, .04, -.13)	(.03, -.03, .05)	(-.04, .04, -.13)
GTSI	(.03, -.03, .05)	(.00, .00, .00)	(-.04, .04, -.13)	(.04, -.04, .00)	(.03, -.03, .05)

Subsequently, penalty across the best and other matrices is estimated with Eq. (51). The penalty result of relation matrix is shown in Table 14.

Table 14: Penalty Result of Relation Matrix

Expert	CIN	MQL	TAD	ENS	CST
9-Expert 7					
CIN	(.00, .00, .00)	(.00, .00, .00)	(.03, -.03, .03)	(-.04, .04, -.05)	(.00, .00, .00)
MQL	(-.05, .05, -.10)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.04, -.04, .05)
TAD	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.03, -.03, .03)	(-.04, .04, -.05)
ENS	(-.03, .03, -.03)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(-.07, .07, -.08)
CST	(.00, .00, .00)	(-.06, .06, -.05)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
Expert	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
9-Expert 3					
CIN	(.00, .00, .00)	(.00, .00, .00)	(.03, -.03, .03)	(.00, .00, .00)	(.00, .00, .00)
MQL	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.04, -.04, .05)
TAD	(-.05, .05, -.10)	(.06, -.06, .05)	(.00, .00, .00)	(.03, -.03, .03)	(.00, .00, .00)
ENS	(-.07, .07, -.08)	(-.03, .03, -.03)	(.00, .00, .00)	(.00, .00, .00)	(-.03, .03, -.03)
CST	(-.07, .07, -.08)	(-.10, .10, -.10)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)

Likewise, the penalty result for decision matrix is determined. The results are given in Table 15.

Table 15: Penalty Result for Decision Matrix

Expert	CIN	MQL	TAD	ENS	CST
6-Expert 1					
EFOP	(.05, -.05, .15)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
RCPD	(-.05, .05, -.15)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)	(.00, .00, .00)
RCPS	(.00, .00, .00)	(.00, .00, .00)	(.05, -.05, .08)	(.00, .00, .00)	(.05, -.05, .08)
TFIN	(.00, .00, .00)	(.00, .00, .00)	(.08, -.08, .20)	(.02, -.02, .03)	(.08, -.08, .20)
GTSI	(.00, .00, .00)	(-.05, .05, -.15)	(.05, -.05, .15)	(.00, .00, .00)	(.00, .00, .00)
Expert	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
6-Expert 9					
EFOP	(.01, -.01, .10)	(-.02, .02, -.05)	(-.05, .05, .00)	(-.04, .04, -.05)	(.00, .00, .00)
RCPD	(.03, -.03, .03)	(-.03, .03, -.05)	(-.04, .04, -.05)	(.00, .00, .00)	(-.03, .03, -.05)
RCPS	(-.04, .04, -.05)	(.00, .00, .00)	(.00, .00, .00)	(-.03, .03, -.05)	(.00, .00, .00)
TFIN	(.05, -.05, .15)	(-.04, .04, -.05)	(.05, -.05, .15)	(-.03, .03, -.05)	(.05, -.05, .15)
GTSI	(-.03, .03, -.05)	(.00, .00, .00)	(.05, -.05, .15)	(-.05, .05, .00)	(-.03, .03, -.05)

Afterwards, the evaluation matrices are updated with Eq. (52). For this, learning rate is considered as .1. Upgraded CFNs of relation matrix are exhibited in Table A5. Similarly, upgraded CFNs of decision matrix are expressed in Table A6.

Then, the stabile evaluation is computed with Eqs. (53) and (54) for decision of iteration. The threshold value in these equations is equal to .02. The absolute difference of relation matrix for first iteration is presented in Table A7. Likewise, absolute difference of relation matrix for first iteration is defined. The results are described in Table A8.

According to differences, all CFNs are not smaller than threshold value. So, iterations are continued. The iterative absolute differences of decision matrix for Expert 6 and Expert 1 are illustrated in Table 16.

Table 16: Iterative Results of Decision Matrix for Expert 6 and Expert 1

Iteration 2				
Expert 6-Expert 1	**CIN**	**MQL**	**TAD**	**ENS**
EFOP	(.001, .001, .002)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)
RCPD	(.001, .001, .002)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)
RCPS	(.000, .000, .000)	(.000, .000, .000)	(.001, .001, .001)	(.000, .000, .000)
TFIN	(.000, .000, .000)	(.000, .000, .000)	(.001, .001, .003)	(.000, .000, .000)
GTSI	(.000, .000, .000)	(.001, .001, .002)	(.001, .001, .002)	(.000, .000, .000)

The iterative absolute differences of decision matrix for Expert 6 and Expert 9 are shown in Table 17.

Table 17: Iterative Results of Decision Matrix for Expert 6 and Expert 9

Iteration 2				
Expert 6-Expert 9	**CIN**	**MQL**	**TAD**	**ENS**
EFOP	(.000, .000, .001)	(.000, .000, .001)	(.001, .001, .000)	(.000, .000, .001)
RCPD	(.000, .000, .000)	(.000, .000, .001)	(.000, .000, .001)	(.000, .000, .000)
RCPS	(.000, .000, .001)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .001)
TFIN	(.001, .001, .002)	(.000, .000, .001)	(.001, .001, .002)	(.000, .000, .001)
GTSI	(.000, .000, .001)	(.000, .000, .000)	(.001, .001, .002)	(.001, .001, .000)

All absolute difference is lower than threshold value. Thus, stable cipher numbers for relation and decision matrices are created. Cipher numbers for relation matrices are shown in Table A9. At the same time, cipher numbers for decision matrices are exhibited in Table A10.

4.3 Weighting of Investment Criteria

Firstly, decoded relation values are determined with Eqs. (42) – (45). Thus, defuzzified relation matrices by scenarios is created in Eq. (56). The averaged values of decoded relation matrices by scenarios are shared in Table 18.

Table 18: Averaged Values by Scenarios

Balanced	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	.000	.476	.474	.476	.503
MQL	.503	.000	.411	.444	.502
TAD	.503	.474	.000	.474	.476
ENS	.446	.445	.508	.000	.446
CST	.445	.414	.503	.411	.000
Membership-heavy	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	.000	.493	.489	.495	.579
MQL	.582	.000	.353	.419	.576
TAD	.582	.490	.000	.489	.495
ENS	.424	.420	.685	.000	.424
CST	.422	.361	.579	.353	.000
Hesitancy-averse	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	.000	.456	.457	.455	.415
MQL	.413	.000	.477	.473	.417
TAD	.413	.457	.000	.457	.455
ENS	.471	.473	.305	.000	.471
CST	.472	.475	.415	.477	.000

Continued on next page

Table 18 (continued)

Hesitancy-ignored	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	.000	.500	.496	.503	.612
MQL	.616	.000	.329	.408	.607
TAD	.616	.496	.000	.496	.503
ENS	.414	.410	.762	.000	.414
CST	.412	.339	.612	.329	.000
Robust-balance	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	.000	.485	.483	.487	.547
MQL	.548	.000	.378	.430	.544
TAD	.548	.483	.000	.483	.487
ENS	.433	.431	.609	.000	.433
CST	.432	.384	.547	.378	.000

Then, the state vector is defined with Eq. (57), and the vector is updated iteratively using Eqs. (58) and (59). Finally, the criterion weighting vector is defined by Eq. (60). The results by scenarios are summarized in Table A11. The investment criteria are ranked according to the weight rows of the scenarios. The comparative priority order of investment criteria according to scenarios is shown in Table 19.

Table 19: Comparative Priority Order of Investment Criteria

	Balanced	**Membership-heavy**	**Hesitancy-averse**	**Hesitancy-ignored**	**Robust-balance**
CIN	2	3	3	3	3
MQL	4	4	2	4	4
TAD	3	1	5	1	1
ENS	5	5	1	5	5
CST	1	2	4	2	2

Technology adaptability and costs emerge as the most important criteria for recycling projects powered by clean logistics, as they jointly determine both the operational effectiveness and long-term sustainability of these systems. High levels of technology adaptability enable recycling projects to respond quickly to changing regulatory requirements, material flows, and environmental targets by integrating flexible, upgradeable, and energy-efficient logistics and recycling technologies. At the same time, cost-related factors play a decisive role in shaping the feasibility, scalability, and continuity of clean logistics-based recycling initiatives, since excessive operational or investment costs can limit the adoption of advanced technologies and undermine financial performance. When technology adaptability is supported by well-managed cost structures, recycling projects are better positioned to achieve stable operations, reduce environmental impacts, and maintain competitive advantage. Therefore, prioritizing technology adaptability alongside cost efficiency is essential for maximizing the overall performance of recycling projects powered by clean logistics and for ensuring their economic and environmental viability in the long run.

The scenario comparison also functions as an empirical validation of the CFS-based weighting process. Four of the five configurations identify technology adaptability or costs among the two strongest criteria, while the hesitancy-averse configuration intentionally stresses uncertainty and shifts emphasis toward energy security and material quality. This pattern shows that the proposed CFS structure does not hide uncertainty-sensitive outcomes; instead, it separates stable priorities from scenario-dependent ones.

4.4 Ranking of Investment Alternatives

Firstly, using matrices, decoded decision values are calculated by Eqs. (42) – (45). The averaged values of decoded decision matrix by scenarios are reported in Table A12. Afterwards, the decoded decision matrix is normalized using Eqs. (62) and (63). All investment criteria are beneficial. Next, normalized decoded decision values are multiplied by weighting vector with Eq. (64). The weighted decision matrices by scenarios are presented in Table A13. Behind, ideal-best solutions are chosen regarding to Eq. (65). The results by scenarios are illustrated in Table 20.

Table 20: Ideal-best Solutions by Scenarios

	EFOP	RCPD	RCPS	TFIN	GTSI
Balanced	**.095**	**.094**	**.095**	**.094**	**.095**
Membership-heavy	**.115**	**.096**	**.117**	**.111**	**.116**
Hesitancy-averse	**.102**	**.107**	**.089**	**.103**	**.102**
Hesitancy-ignored	**.128**	**.097**	**.131**	**.123**	**.129**
Robust-balance	**.102**	**.095**	**.103**	**.100**	**.103**

The four metrics among ideal-best solutions and weighted decoded decision values are computed using Eqs. (66) – (69), respectively. Finally, the final ranks of alternatives are determined by Eq. (70). The results by scenarios are presented in Table A14. The investment alternatives are ranked according to the s values of the scenarios in Table A14. The comparative ranking of investment alternatives according to scenarios is shown in Table 21.

Table 21: Comparative Ranking of Investment Alternatives

	Balanced	Membership-heavy	Hesitancy-averse	Hesitancy-ignored	Robust-balance
EFOP	4	1	1	1	1
RCPD	2	2	2	2	2
RCPS	1	4	5	4	4
TFIN	5	3	3	3	3
GTSI	3	5	4	5	5

Electric fleet operator and recycling park developer emerge as the most effective investment alternatives for recycling projects powered by clean logistics, as they directly address both environmental performance and operational efficiency objectives. Investment in electric fleet operations enables a substantial reduction in carbon emissions and energy consumption by replacing conventional fossil fuel-based transportation with low-emission vehicles, while also improving cost predictability and regulatory compliance in logistics activities. At the same time, the development of recycling parks creates integrated infrastructures where collection, processing, and distribution activities are spatially coordinated, leading to lower logistics costs, reduced material losses, and more efficient resource utilization. Together, these two investment alternatives strengthen the structural foundation of clean logistics-based recycling systems by enhancing system reliability, scalability, and long-term sustainability. Prioritizing electric fleet operators and recycling park developers therefore allows decision makers to achieve higher environmental benefits, improved financial performance, and more resilient recycling projects in the context of clean logistics.

The alternative rankings provide an additional validation signal for the proposed CFSs. Electric fleet operator ranks first in four of the five scenarios, and recycling park developer remains the second-ranked alternative across all scenarios. This consistency indicates that the main strategic conclusion is robust to different CFS score configurations.

5 Discussion

The findings indicate that technology adaptability and costs are the most influential criteria affecting the performance of recycling projects powered by clean logistics, which implies that investment strategies should be designed with a strong focus on these two dimensions. This result suggests that projects achieving higher performance are those that can flexibly adopt new logistics and recycling technologies while simultaneously maintaining cost-efficient operations. Technology adaptability enables organizations to integrate energy-efficient transport systems, digital monitoring tools, and innovative recycling technologies in response to changing regulatory and market conditions [3]. However, the benefits of such adaptability can only be fully realized when cost structures are carefully managed, as high investment or operational costs may limit the effective use of advanced technologies. This

interaction highlights the need for balanced decision making that aligns technological innovation with financial feasibility [7]. The consistency of this finding with existing literature reinforces its validity, as previous studies similarly emphasize the joint role of adaptable technologies and cost control in achieving sustainable logistics and recycling performance. From a strategic perspective, policymakers and managers should prioritize incentives that support flexible technology adoption, such as subsidies for modular clean technologies, while also implementing cost-reduction mechanisms through shared infrastructure and economies of scale [20]. Such coordinated strategy and policy designs can enhance long-term performance and reduce financial risks.

The results further show that electric fleet operators and recycling park developers represent the most effective strategic investments for improving the performance of recycling projects powered by clean logistics. This finding indicates that performance gains are strongly linked to investments that simultaneously reduce emissions and improve operational integration. Electric fleet operators contribute by lowering carbon intensity, stabilizing energy costs, and improving compliance with environmental regulations, which directly enhances logistics efficiency [22]. Recycling Park developers support performance by creating centralized and integrated facilities where collection, processing, and redistribution activities are co-located, reducing transportation distances and material handling inefficiencies. The strong alignment of this result with prior literature highlights that infrastructure-based and transport-oriented strategies play a central role in clean logistics-driven recycling systems [29]. To effectively implement these strategies, decision makers should focus on long-term planning, regulatory alignment, and public–private partnerships that reduce investment risks [19]. Policy frameworks that encourage electric mobility adoption and support the development of recycling parks can further strengthen system resilience, enhance environmental outcomes, and ensure sustainable performance improvements.

6 Conclusion

This study sought to establish a comprehensive and systematic framework for prioritizing strategies that enhance the performance of recycling projects powered by clean logistics. To this end, an integrated decision-making model was developed by combining consensus-based expert selection, cognitive maps, orthogonal metric robust aggregation, and newly introduced Chipper fuzzy sets to address uncertainty and complex interrelationships among performance criteria. The empirical findings indicate that technology adaptability and costs exert the strongest influence on project performance, while investments in electric fleet operators and recycling park developers provide the greatest performance improvements. These results underline the need to coordinate flexible technological solutions with sound cost management practices to achieve sustainable and resilient recycling systems. The study contributes to the existing literature by filling an important gap in strategic prioritization for clean logistics-based recycling projects and by advancing methodological knowledge through the application of an innovative hybrid decision-making framework.

At the same time, several limitations of the study should be recognized. Conceptually, the analysis focuses on a specific set of criteria and strategic alternatives, which may limit the extent to which broader institutional, social, or behavioral dynamics are captured. The reliance on expert-based evaluations, even though carefully weighted, may introduce subjective bias into the results. From a methodological standpoint, the multi-layered structure of the proposed model may pose challenges for practitioners seeking rapid or simplified decision support. Future research could address these issues by incorporating additional criteria, integrating real-world performance data, and applying the framework in different regional or sectoral contexts to improve robustness and transferability. Further work may also focus on developing streamlined versions of the model that retain analytical strength while enhancing practical applicability.

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Appendix

Table A1: Best Matrices for Investment Criteria

Expert 9 (Initial Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		7	7	7	8
MQL	8		5	6	8
TAD	8	7		7	7
ENS	6	6	9		6
CST	6	5	8	5	
Expert 7 (Q-learned expert-Second Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		7	6	8	8
MQL	9		5	6	7
TAD	8	7		6	8
ENS	7	6	9		8
CST	6	7	8	5	
Expert 3 (Q-learned expert-Third Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN		7	6	7	8
MQL	8		5	6	7
TAD	9	5		6	7
ENS	8	7	9		7
CST	8	8	8	5	

Table A2: Best Matrices for Investment Alternatives

Expert 6 (Initial Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	9	6	9	8	8
RCPD	8	7	8	8	7
RCPS	8	8	8	7	8
TFIN	9	8	9	7	9
GTSI	7	8	9	9	7
Expert 1 (Q-learned expert-Second Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	8	6	9	8	8
RCPD	9	7	8	8	7
RCPS	8	8	6	7	6
TFIN	9	8	7	6	7
GTSI	7	9	8	9	7
Expert 9 (Q-learned expert-Third Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	8	6	9	8	7
RCPD	6	7	8	7	7
RCPS	8	7	7	7	7
TFIN	7	8	7	7	7
GTSI	7	7	7	9	7

Table A3: CFNs for Investment Criteria

Expert 9 (Initial Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.000, .000, .000)	(.500, .500, .573)	(.500, .500, .573)	(.500, .500, .573)	(.612, .388, .717)
MQL	(.612, .388, .717)	(.000, .000, .000)	(.329, .671, .424)	(.408, .592, .484)	(.612, .388, .717)
TAD	(.612, .388, .717)	(.500, .500, .573)	(.000, .000, .000)	(.500, .500, .573)	(.500, .500, .573)
ENS	(.408, .592, .484)	(.408, .592, .484)	(.762, .238, 1.000)	(.000, .000, .000)	(.408, .592, .484)
CST	(.408, .592, .484)	(.329, .671, .424)	(.612, .388, .717)	(.329, .671, .424)	(.000, .000, .000)
Expert 7 (Q-learned expert-Second Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.000, .000, .000)	(.500, .500, .573)	(.408, .592, .484)	(.612, .388, .717)	(.612, .388, .717)
MQL	(.762, .238, 1.000)	(.000, .000, .000)	(.329, .671, .424)	(.408, .592, .484)	(.500, .500, .573)
TAD	(.612, .388, .717)	(.500, .500, .573)	(.000, .000, .000)	(.408, .592, .484)	(.612, .388, .717)
ENS	(.500, .500, .573)	(.408, .592, .484)	(.762, .238, 1.000)	(.000, .000, .000)	(.612, .388, .717)
CST	(.408, .592, .484)	(.500, .500, .573)	(.612, .388, .717)	(.329, .671, .424)	(.000, .000, .000)
Expert 3 (Q-learned expert-Third Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.000, .000, .000)	(.500, .500, .573)	(.408, .592, .484)	(.500, .500, .573)	(.612, .388, .717)
MQL	(.612, .388, .717)	(.000, .000, .000)	(.329, .671, .424)	(.408, .592, .484)	(.500, .500, .573)
TAD	(.762, .238, 1.000)	(.329, .671, .424)	(.000, .000, .000)	(.408, .592, .484)	(.500, .500, .573)
ENS	(.612, .388, .717)	(.500, .500, .573)	(.762, .238, 1.000)	(.000, .000, .000)	(.500, .500, .573)
CST	(.612, .388, .717)	(.612, .388, .717)	(.612, .388, .717)	(.329, .671, .424)	(.000, .000, .000)

Table A4: CFNs for Investment Alternatives

Expert 6 (Initial Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.635, .365, 1.000)	(.346, .654, .347)	(.635, .365, 1.000)	(.500, .500, .579)	(.500, .500, .579)
RCPD	(.500, .500, .579)	(.413, .587, .425)	(.500, .500, .579)	(.500, .500, .579)	(.413, .587, .425)
RCPS	(.500, .500, .579)	(.500, .500, .579)	(.500, .500, .579)	(.413, .587, .425)	(.500, .500, .579)
TFIN	(.635, .365, 1.000)	(.500, .500, .579)	(.635, .365, 1.000)	(.413, .587, .425)	(.635, .365, 1.000)
GTSI	(.413, .587, .425)	(.500, .500, .579)	(.635, .365, 1.000)	(.635, .365, 1.000)	(.413, .587, .425)

Continued on next page

Table A4 (continued)

Expert 1 (Q-learned expert-Second Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.500, .500, .579)	(.346, .654, .347)	(.635, .365, 1.000)	(.500, .500, .579)	(.500, .500, .579)
RCPD	(.635, .365, 1.000)	(.413, .587, .425)	(.500, .500, .579)	(.500, .500, .579)	(.413, .587, .425)
RCPS	(.500, .500, .579)	(.500, .500, .579)	(.346, .654, .347)	(.413, .587, .425)	(.346, .654, .347)
TFIN	(.635, .365, 1.000)	(.500, .500, .579)	(.413, .587, .425)	(.346, .654, .347)	(.413, .587, .425)
GTSI	(.413, .587, .425)	(.635, .365, 1.000)	(.500, .500, .579)	(.635, .365, 1.000)	(.413, .587, .425)
Expert 9 (Q-learned expert-Third Expert)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.612, .388, .717)	(.408, .592, .484)	(.762, .238, 1.000)	(.612, .388, .717)	(.500, .500, .573)
RCPD	(.408, .592, .484)	(.500, .500, .573)	(.612, .388, .717)	(.500, .500, .573)	(.500, .500, .573)
RCPS	(.612, .388, .717)	(.500, .500, .573)	(.500, .500, .573)	(.500, .500, .573)	(.500, .500, .573)
TFIN	(.500, .500, .573)	(.612, .388, .717)	(.500, .500, .573)	(.500, .500, .573)	(.500, .500, .573)
GTSI	(.500, .500, .573)	(.500, .500, .573)	(.500, .500, .573)	(.762, .238, 1.000)	(.500, .500, .573)

Table A5: Upgraded CFNs of Relation Matrix

Expert 9-Expert 7	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.00, .00, .00)	(.50, .50, .57)	(.49, .51, .57)	(.51, .49, .58)	(.61, .39, .72)
MQL	(.62, .38, .74)	(.00, .00, .00)	(.33, .67, .42)	(.41, .59, .48)	(.60, .40, .71)
TAD	(.61, .39, .72)	(.50, .50, .57)	(.00, .00, .00)	(.49, .51, .57)	(.51, .49, .58)
ENS	(.41, .59, .49)	(.41, .59, .48)	(.76, .24, 1.00)	(.00, .00, .00)	(.42, .58, .50)
CST	(.41, .59, .48)	(.34, .66, .43)	(.61, .39, .72)	(.33, .67, .42)	(.00, .00, .00)
Expert 9-Expert 3	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.00, .00, .00)	(.50, .50, .57)	(.49, .51, .57)	(.50, .50, .57)	(.61, .39, .72)
MQL	(.61, .39, .72)	(.00, .00, .00)	(.33, .67, .42)	(.41, .59, .48)	(.60, .40, .71)
TAD	(.62, .38, .74)	(.49, .51, .56)	(.00, .00, .00)	(.49, .51, .57)	(.50, .50, .57)
ENS	(.42, .58, .50)	(.41, .59, .49)	(.76, .24, 1.00)	(.00, .00, .00)	(.41, .59, .49)
CST	(.42, .58, .50)	(.35, .65, .44)	(.61, .39, .72)	(.33, .67, .42)	(.00, .00, .00)

Table A6: Updagraded CFNs of Decision Matrix

Expert 6-Expert 1	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.63, .37, .97)	(.35, .65, .35)	(.63, .37, 1.00)	(.50, .50, .58)	(.50, .50, .58)
RCPD	(.51, .49, .61)	(.41, .59, .43)	(.50, .50, .58)	(.50, .50, .58)	(.41, .59, .43)
RCPS	(.50, .50, .58)	(.50, .50, .58)	(.49, .51, .56)	(.41, .59, .43)	(.49, .51, .56)
TFIN	(.63, .37, 1.00)	(.50, .50, .58)	(.62, .38, .96)	(.41, .59, .42)	(.62, .38, .96)
GTSI	(.41, .59, .43)	(.51, .49, .61)	(.63, .37, .97)	(.63, .37, 1.00)	(.41, .59, .43)
Expert 6-Expert 9	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.63, .37, .98)	(.35, .65, .36)	(.64, .36, 1.00)	(.51, .49, .59)	(.50, .50, .58)
RCPD	(.49, .51, .57)	(.42, .58, .44)	(.51, .49, .59)	(.50, .50, .58)	(.42, .58, .44)
RCPS	(.51, .49, .59)	(.50, .50, .58)	(.50, .50, .58)	(.42, .58, .44)	(.50, .50, .58)
TFIN	(.63, .37, .97)	(.51, .49, .59)	(.63, .37, .97)	(.42, .58, .44)	(.63, .37, .97)
GTSI	(.42, .58, .44)	(.50, .50, .58)	(.63, .37, .97)	(.64, .36, 1.00)	(.42, .58, .44)

Table A7: Absolute Difference of Relation Matrix (First Iteration)

Expert 9-Expert 7	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.000, .000, .000)	(.000, .000, .000)	(.006, .006, .006)	(.008, .008, .010)	(.000, .000, .000)
MQL	(.010, .010, .019)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)	(.008, .008, .010)
TAD	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)	(.006, .006, .006)	(.008, .008, .010)
ENS	(.006, .006, .006)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)	(.014, .014, .016)
CST	(.000, .000, .000)	(.012, .012, .010)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)
Expert 9-Expert 3	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.000, .000, .000)	(.000, .000, .000)	(.006, .006, .006)	(.000, .000, .000)	(.000, .000, .000)
MQL	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)	(.007, .007, .010)
TAD	(.010, .010, .019)	(.011, .011, .010)	(.000, .000, .000)	(.006, .006, .006)	(.000, .000, .000)
ENS	(.014, .014, .015)	(.006, .006, .006)	(.000, .000, .000)	(.000, .000, .000)	(.006, .006, .006)
CST	(.014, .014, .015)	(.019, .019, .019)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)

Table A8: Absolute Difference of Decision Matrix (First Iteration)

Expert 6-Expert 1	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.009, .009, .029)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)
RCPD	(.009, .009, .029)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)	(.000, .000, .000)
RCPS	(.000, .000, .000)	(.000, .000, .000)	(.011, .011, .016)	(.000, .000, .000)	(.011, .011, .016)
TFIN	(.000, .000, .000)	(.000, .000, .000)	(.015, .015, .040)	(.005, .005, .005)	(.015, .015, .040)
GTSI	(.000, .000, .000)	(.009, .009, .029)	(.009, .009, .029)	(.000, .000, .000)	(.000, .000, .000)
Expert 6-Expert 9	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.001, .001, .019)	(.004, .004, .009)	(.008, .008, .000)	(.007, .007, .009)	(.000, .000, .000)
RCPD	(.006, .006, .006)	(.006, .006, .010)	(.007, .007, .009)	(.000, .000, .000)	(.006, .006, .010)
RCPS	(.007, .007, .009)	(.000, .000, .000)	(.000, .000, .000)	(.006, .006, .010)	(.000, .000, .000)
TFIN	(.009, .009, .028)	(.007, .007, .009)	(.009, .009, .028)	(.006, .006, .010)	(.009, .009, .028)
GTSI	(.006, .006, .010)	(.000, .000, .000)	(.009, .009, .028)	(.008, .008, .000)	(.006, .006, .010)

Table A9: Cipher Numbers for Relation Matrices

Expert 9(initial Q matrix)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.000, .000, .000)	(.500, .500, .573)	(.500, .500, .573)	(.500, .500, .573)	(.612, .388, .717)
MQL	(.612, .388, .717)	(.000, .000, .000)	(.329, .671, .424)	(.408, .592, .484)	(.612, .388, .717)
TAD	(.612, .388, .717)	(.500, .500, .573)	(.000, .000, .000)	(.500, .500, .573)	(.500, .500, .573)
ENS	(.408, .592, .484)	(.408, .592, .484)	(.762, .238, 1.000)	(.000, .000, .000)	(.408, .592, .484)
CST	(.408, .592, .484)	(.329, .671, .424)	(.612, .388, .717)	(.329, .671, .424)	(.000, .000, .000)
Expert 7 (Balanced Q matrix)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.000, .000, .000)	(.500, .500, .573)	(.494, .506, .567)	(.508, .492, .582)	(.612, .388, .717)
MQL	(.622, .378, .736)	(.000, .000, .000)	(.329, .671, .424)	(.408, .592, .484)	(.605, .395, .707)
TAD	(.612, .388, .717)	(.500, .500, .573)	(.000, .000, .000)	(.494, .506, .567)	(.508, .492, .582)
ENS	(.414, .586, .490)	(.408, .592, .484)	(.762, .238, 1.000)	(.000, .000, .000)	(.422, .578, .499)
CST	(.408, .592, .484)	(.340, .660, .434)	(.612, .388, .717)	(.329, .671, .424)	(.000, .000, .000)
Expert 3 (Balanced Q matrix)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
CIN	(.000, .000, .000)	(.500, .500, .573)	(.494, .506, .567)	(.500, .500, .573)	(.612, .388, .717)
MQL	(.612, .388, .717)	(.000, .000, .000)	(.329, .671, .424)	(.408, .592, .484)	(.605, .395, .707)
TAD	(.622, .378, .735)	(.489, .511, .563)	(.000, .000, .000)	(.494, .506, .567)	(.500, .500, .573)
ENS	(.421, .579, .499)	(.414, .586, .490)	(.762, .238, 1.000)	(.000, .000, .000)	(.414, .586, .490)
CST	(.421, .579, .499)	(.347, .653, .444)	(.612, .388, .717)	(.329, .671, .424)	(.000, .000, .000)

Table A10: Cipher Numbers for Decision Matrices

Expert 6(initial Q matrix)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.635, .365, 1.000)	(.346, .654, .347)	(.635, .365, 1.000)	(.500, .500, .579)	(.500, .500, .579)
RCPD	(.500, .500, .579)	(.413, .587, .425)	(.500, .500, .579)	(.500, .500, .579)	(.413, .587, .425)
RCPS	(.500, .500, .579)	(.500, .500, .579)	(.500, .500, .579)	(.413, .587, .425)	(.500, .500, .579)
TFIN	(.635, .365, 1.000)	(.500, .500, .579)	(.635, .365, 1.000)	(.413, .587, .425)	(.635, .365, 1.000)
GTSI	(.413, .587, .425)	(.500, .500, .579)	(.635, .365, 1.000)	(.635, .365, 1.000)	(.413, .587, .425)
Expert 1 (Balanced Q matrix)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.634, .366, .998)	(.346, .654, .347)	(.635, .365, 1.000)	(.500, .500, .579)	(.500, .500, .579)
RCPD	(.501, .499, .581)	(.413, .587, .425)	(.500, .500, .579)	(.500, .500, .579)	(.413, .587, .425)
RCPS	(.500, .500, .579)	(.500, .500, .579)	(.499, .501, .578)	(.413, .587, .425)	(.499, .501, .578)
TFIN	(.635, .365, 1.000)	(.500, .500, .579)	(.634, .366, .997)	(.413, .587, .425)	(.634, .366, .997)
GTSI	(.413, .587, .425)	(.501, .499, .581)	(.634, .366, .998)	(.635, .365, 1.000)	(.413, .587, .425)
Expert 9 (Balanced Q matrix)	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	(.635, .365, .999)	(.347, .653, .348)	(.635, .365, 1.000)	(.500, .500, .580)	(.500, .500, .579)
RCPD	(.500, .500, .579)	(.414, .586, .426)	(.500, .500, .580)	(.500, .500, .579)	(.414, .586, .426)
RCPS	(.500, .500, .580)	(.500, .500, .579)	(.500, .500, .579)	(.414, .586, .426)	(.500, .500, .579)
TFIN	(.634, .366, .998)	(.500, .500, .580)	(.634, .366, .998)	(.414, .586, .426)	(.634, .366, .998)
GTSI	(.414, .586, .426)	(.500, .500, .579)	(.634, .366, .998)	(.635, .365, 1.000)	(.414, .586, .426)

Table A11: Iterative State Vector and Weighting Vector by Scenarios

Balanced	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
$A(0)$	1	1	1	1	1
$A(1)$	1.897	1.809	1.896	1.806	1.927
$f(A(1))$	.870	.859	.869	.859	.873
$A(2)$	1.641	1.570	1.640	1.567	1.665
$f(A(2))$	.838	.828	.838	.827	.841
$A(3)$	1.581	1.512	1.580	1.509	1.604
$f(A(3))$	.829	.819	.829	.819	.833
$A(4)$	1.565	1.497	1.565	1.494	1.588
$f(A(4))$	.827	.817	.827	.817	.830
$A(5)$	1.561	1.493	1.560	1.490	1.584
$f(A(5))$	.826	.817	.826	.816	.830
$A(6)$	1.560	1.492	1.559	1.489	1.583
$f(A(6))$	.826	.816	.826	.816	.830
Weights	.2008	.1984	.2008	.1983	.2016
Membership-heavy	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
$A(0)$	1	1	1	1	1
$A(1)$	2.010	1.764	2.108	1.756	2.074
$f(A(1))$	.882	.854	.892	.853	.888
$A(2)$	1.752	1.551	1.832	1.544	1.805
$f(A(2))$	.852	.825	.862	.824	.859
$A(3)$	1.693	1.499	1.771	1.492	1.744
$f(A(3))$	.845	.817	.855	.816	.851
$A(4)$	1.678	1.485	1.755	1.479	1.729
$f(A(4))$	.843	.815	.853	.814	.849
$A(5)$	1.674	1.482	1.751	1.475	1.725
$f(A(5))$	.842	.815	.852	.814	.849
$A(6)$	1.673	1.481	1.750	1.475	1.724
$f(A(6))$	.842	.815	.852	.814	.849
Weights	.2019	.1953	.2042	.1951	.2035

Continued on next page

Table A11 (continued)

Hesitancy-averse	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
$A(0)$	1	1	1	1	1
$A(1)$	1.768	1.861	1.654	1.862	1.759
$f(A(1))$	.854	.865	.839	.866	.853
$A(2)$	1.514	1.588	1.421	1.589	1.505
$f(A(2))$	.820	.830	.805	.830	.818
$A(3)$	1.452	1.523	1.363	1.524	1.444
$f(A(3))$	.810	.821	.796	.821	.809
$A(4)$	1.436	1.506	1.348	1.507	1.428
$f(A(4))$	.808	.818	.794	.819	.807
$A(5)$	1.431	1.501	1.344	1.503	1.424
$f(A(5))$	.807	.818	.793	.818	.806
$A(6)$	1.430	1.500	1.343	1.501	1.422
$f(A(6))$	.807	.818	.793	.818	.806
Weights	.1997	.2023	.1962	.2024	.1994
Hesitancy-ignored	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
$A(0)$	1	1	1	1	1
$A(1)$	2.058	1.745	2.198	1.735	2.137
$f(A(1))$	.887	.851	.900	.850	.894
$A(2)$	1.799	1.541	1.914	1.533	1.865
$f(A(2))$	.858	.824	.872	.822	.866
$A(3)$	1.742	1.492	1.853	1.484	1.805
$f(A(3))$	.851	.816	.864	.815	.859
$A(4)$	1.727	1.479	1.837	1.471	1.789
$f(A(4))$	.849	.814	.863	.813	.857
$A(5)$	1.723	1.476	1.833	1.468	1.785
$f(A(5))$	.848	.814	.862	.813	.856
$A(6)$	1.722	1.475	1.832	1.467	1.784
$f(A(6))$	.848	.814	.862	.813	.856
Weights	.2023	.1941	.2056	.1938	.2042
Robust-balance	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
$A(0)$	1	1	1	1	1
$A(1)$	1.961	1.783	2.017	1.777	2.011
$f(A(1))$	.877	.856	.883	.855	.882
$A(2)$	1.705	1.559	1.750	1.554	1.745
$f(A(2))$	.846	.826	.852	.826	.851
$A(3)$	1.645	1.505	1.689	1.500	1.684
$f(A(3))$	.838	.818	.844	.818	.843
$A(4)$	1.630	1.491	1.673	1.486	1.668
$f(A(4))$	.836	.816	.842	.815	.841
$A(5)$	1.626	1.487	1.669	1.482	1.664
$f(A(5))$	.836	.816	.841	.815	.841
$A(6)$	1.625	1.486	1.668	1.481	1.663
$f(A(6))$	.835	.815	.841	.815	.841
Weights	.2014	.1966	.2028	.1964	.2027

Table A12: Averaged Values of Decoded Decision Matrix by Scenarios

Balanced	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.423	.449	.423	.474	.474
RCPD	.473	.467	.474	.474	.467
RCPS	.474	.474	.474	.467	.474
TFIN	.423	.474	.423	.467	.423
GTSI	.467	.473	.423	.423	.467
Membership-heavy	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.571	.377	.571	.492	.492
RCPD	.492	.430	.492	.492	.430
RCPS	.492	.492	.492	.430	.492
TFIN	.571	.492	.571	.429	.571
GTSI	.430	.492	.571	.571	.430

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Table A12 (continued)

Hesitancy-averse	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.254	.530	.254	.452	.452
RCPD	.452	.510	.452	.452	.510
RCPS	.452	.452	.452	.510	.452
TFIN	.254	.452	.255	.510	.255
GTSI	.510	.452	.255	.254	.510
Hesitancy-ignored	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.634	.346	.635	.500	.500
RCPD	.500	.413	.500	.500	.413
RCPS	.500	.500	.500	.413	.500
TFIN	.635	.500	.634	.413	.634
GTSI	.413	.500	.634	.635	.413
Robust-balance	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.508	.408	.508	.484	.484
RCPD	.484	.446	.484	.484	.446
RCPS	.484	.484	.484	.446	.484
TFIN	.508	.484	.508	.446	.508
GTSI	.446	.484	.508	.508	.446

Table A13: Weighted Decision Matrices by Scenarios

Balanced	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.085	.089	.085	.094	.095
RCPD	.095	.093	.095	.094	.094
RCPS	.095	.094	.095	.093	.095
TFIN	.085	.094	.085	.093	.085
GTSI	.094	.094	.085	.084	.094
Membership-heavy	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.115	.074	.117	.096	.100
RCPD	.099	.084	.101	.096	.087
RCPS	.099	.096	.100	.084	.100
TFIN	.115	.096	.117	.084	.116
GTSI	.087	.096	.117	.111	.087
Hesitancy-averse	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.051	.107	.050	.092	.090
RCPD	.090	.103	.089	.092	.102
RCPS	.090	.092	.089	.103	.090
TFIN	.051	.092	.050	.103	.051
GTSI	.102	.091	.050	.051	.102
Hesitancy-ignored	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.128	.067	.131	.097	.102
RCPD	.101	.080	.103	.097	.084
RCPS	.101	.097	.103	.080	.102
TFIN	.128	.097	.130	.080	.129
GTSI	.084	.097	.130	.123	.084
Robust-balance	**CIN**	**MQL**	**TAD**	**ENS**	**CST**
EFOP	.102	.080	.103	.095	.098
RCPD	.098	.088	.098	.095	.090
RCPS	.098	.095	.098	.088	.098
TFIN	.102	.095	.103	.088	.103
GTSI	.090	.095	.103	.100	.090

Table A14: Four Metrics and Ranking Values by Scenarios

Balanced	$\delta_i^{(2)}$	$\delta_i^{(M)}$	$\delta_i^{(\infty)}$	ρ_i	s_i
EFOP	1.000	.985	.990	-.147	.707
RCPD	1.000	.998	.999	.711	.927
RCPS	1.000	.999	.999	.922	.980
TFIN	1.000	.983	.990	-.962	.503
GTSI	1.000	.986	.990	.308	.821
Membership-heavy	$\delta_i^{(2)}$	$\delta_i^{(M)}$	$\delta_i^{(\infty)}$	ρ_i	s_i
EFOP	.999	.969	.978	.912	.965
RCPD	.998	.960	.972	.695	.906
RCPS	.998	.962	.973	.220	.789
TFIN	.999	.973	.973	.560	.876
GTSI	.998	.961	.972	.076	.752
Hesitancy-averse	$\delta_i^{(2)}$	$\delta_i^{(M)}$	$\delta_i^{(\infty)}$	ρ_i	s_i
EFOP	.996	.938	.951	.748	.908
RCPD	1.000	.983	.988	.639	.903
RCPS	.999	.978	.984	.367	.832
TFIN	.993	.923	.951	.583	.863
GTSI	.996	.937	.951	.553	.859
Hesitancy-ignored	$\delta_i^{(2)}$	$\delta_i^{(M)}$	$\delta_i^{(\infty)}$	ρ_i	s_i
EFOP	.998	.954	.971	.874	.949
RCPD	.996	.937	.957	.687	.894
RCPS	.996	.940	.959	.176	.768
TFIN	.998	.959	.959	.562	.869
GTSI	.996	.940	.957	.114	.752
Robust-balance	$\delta_i^{(2)}$	$\delta_i^{(M)}$	$\delta_i^{(\infty)}$	ρ_i	s_i
EFOP	1.000	.984	.985	.967	.984
RCPD	1.000	.983	.988	.676	.912
RCPS	1.000	.985	.988	.405	.844
TFIN	1.000	.988	.988	.603	.895
GTSI	1.000	.983	.988	-.068	.725



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Cite this paper as:
Dinçer, H.; Yüksel, S.; Eti, S. (2026). Analysis of Sustainable Recycling Logistics via Multi-Agent Artificial Intelligence Decoded Business Analytics. *International Journal of Computers Communications &Control*, 21(6), 7422, 2026.
https://doi.org/10.15837/ijccc.2026.6.7422