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Machine Learning-Based Decomposed Fuzzy Set Model for Analyzing Key Performance Indicators in the Waste-to-Energy Supply Chain

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Abstract: Waste management through circular economy implementation is crucial for achieving sustainability and enhancing the performance of the waste-to-energy supply chain (WtESC). Therefore, developing key performance indicators (KPIs) and understanding their significance is essential for assessing WtESC performance. However, there is a lack of studies focused on developing and evaluating KPIs for WtESC. To address this gap, this study offers a novel machine learning (ML)-based decomposed fuzzy set (DFS)-analytical hierarchy process (AHP) model to assess the KPIs that can be used to evaluate the WtESC performance. Since decision-making based on experts' judgment often faces uncertainty and experts' experience significantly impacts the final decision, the advanced ML-based DFS-AHP model can effectively handle these challenges and enhance the model's reliability. In the proposed framework, decision makers' weights are computed using the ML approach based on expert information, which is integrated into the DFS-AHP model. The results indicate that the most important KPI for WtESC is 'CO_2 emissions intensity', which received a de-fuzzified composite weight of 0.1360. This KPI should be considered with a higher priority to ensure sustainability and improve WtESC performance. Consequently, the decision-makers should consider these findings when developing the performance index for WtESC, which may further assist in taking the necessary actions to improve WtESC's performance.

Keywords: Waste-to-energy supply chain; Machine learning; Decomposed fuzzy set; Decomposed fuzzy AHP; Key performance indicators; Sustainability.

1. INTRODUCTION

The rapid growth of the global economy puts excessive pressure on natural resources through solid waste generation, which can significantly damage the environment and necessitate a sustainable approach to waste management. For example, municipal solid waste generation is predicted to reach 3.8 billion tons by 2050 (UNEP, 2024). Considering global environmental issues, solid waste management (SWM), by adopting eco-friendly waste-to-energy (WtE) technology, has become the focus of the modern era. Researchers, policymakers, and industrialists increasingly focus on developing and redesigning WtE processes to minimize environmental impacts, allowing economic growth without harming the natural environment. Thus, the WtE supply chain (WtESC) is critical for ensuring better environmental, governance, social, and financial performance. In this sense, identifying key performance indicators (KPIs) for WtESC and developing a framework for assessing KPIs is vital for policymakers and decision-makers. However, existing studies mainly focus on traditional supply chains, which are not suitable for WtESC.

Furthermore, multi-criteria decision-making analysis (MCDA)-based weighting methods are often used to assess the significance of KPIs. For example, Moktadir *et al.,* (2020) offered the best-worst method for evaluating the importance of KPIs for operational excellence of manufacturing SC, Munmun *et al.,* (2024) examined the interactions of KPIs using Z-DEMATEL (decision-making trial and evaluation laboratory) for manufacturing SC towards performance management considering the COVID-19 pandemic, Jiang *et al.,* (2020) performed an MCDA analysis of KPIs for hospital service management using Z-DEMATEL, Gautam et al., (2025) identified and assessed the KPIs for green manufactured products using Pareto and the full consistency method (FUCOM). However, the diverse information of decision makers (DMs) is rarely considered when determining their levels of importance during the decision-making process. Instead, equal weight is often assigned, or the weights of DMs are determined using similarity measures or linguistic scales that can create unreliable or biased results. Furthermore, decision-making using classical models such as analytical hierarchy process (AHP), BWM, DEMATEL, and FUCOM, which rely on expert feedback, is susceptible to uncertainty, bias, and vagueness factors that should be avoided in any decision-making process by incorporating advanced fuzzy concepts. Considering the limited studies on KPIs for WtESC, as well as current methodological gaps in decision-making, this study addresses the following research questions (RQs).

a) What KPIs can be used to assess the performance of WtESC?
b) How can we measure the levels of significance of DMs considering their diverse information?
c) How can we handle the larger level of uncertainty considering both optimistic and pessimistic standpoints of DMs while assessing the significance of KPIs?

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To address these RQs, a set of KPIs for the WtESC is identified from existing literature and consultation with DMs. DM importance levels are determined by employing an ML-based dimension reduction algorithm (DRA) that can handle diverse information about DMs. Finally, the optimistic and pessimistic viewpoints are considered when assessing the identified KPIs by offering an advanced decomposed fuzzy set (DFS)-AHP model. The reason behind integrating ML with the DFS-AHP model is that the ML-based model assists in determining the weight of experts considering DMs real information. At the same time, DFS-AHP aids in capturing the broader level of uncertainty by providing pessimistic and optimistic outlooks to DMs. In contrast, other fuzzy extensions, such as Pythagorean, q-rung, Fermatean fuzzy, etc., cannot offer optimistic and pessimistic viewpoints to DMs.

2. LITERATURE REVIEW

KPIs are defined as a set of criteria that can be used as parameters to assess the performance of a WtESC. Sustainable WtE conversion offers significant environmental, social, and economic (EnSE) benefits. However, to optimize the EnSE performance of WtESC, it is vital to construct KPIs. The developed KPIs can be used to examine the performance level of WtESC. Therefore, identifying relevant KPIs and developing efficient decision support models for WtESC are both crucial. By evaluating WtESC performance using the constructed KPIs, performance improvement strategies can be formed and implemented to enhance the WtESC performance. Hence, relevant KPIs (see Table 1) for the WtESC were identified through a literature review that considered Scopus, ScienceDirect, Google databases, and Web searches.

Table 1. KPIs for WtESC and their explanation.

KPIs	Explanation
CO_2 emissions intensity (KPI1) (Henry, 2024)	Reducing environmental impact is often a primary goal in WtE projects.
Levelized cost of energy (KPI2) (Henry, 2024)	It supports evaluating the economic viability and competitiveness of the energy generated from waste.
Energy conversion efficiency (KPI3) (Farjana & Ashraf, 2023; Henry, 2024)	High efficiency is crucial for maximizing output energy from waste, impacting both the environmental and economic performance of the WtESC.
Safety incident rate (KPI4) (Henry, 2024)	Ensuring safety is vital for sustainable operations and compliance with regulations.
Feedstock supply reliability (KPI5) (Cai et al., 2021)	Reliable WtESC is necessary for consistent and efficient supply chain operations.
Return on investment (KPI6) (Moktadir et al., 2024a)	It refers to the financial returns of the WtE project that can be used to assess financial performance.
WtE supply chain responsiveness (KPI7) (Richey et al., 2022)	It indicates flexibility and responsiveness for adapting to waste supply or demand changes.
Community acceptance index (KPI8) (Esgvoices, 2024)	Social acceptance can influence the WtESC's long-term success and ability to expand the WtE plant.
Job creation facility (KPI9) (Moktadir et al., 2024a)	While beneficial for social impact, job creation could also contribute to the social performance of WtESC.

3. RESEARCH METHODOLOGY

3.1 Research Design

The study develops a comprehensive ML-based novel MCDA model for assessing KPIs for WtESC that includes Phase I: Identification of KPIs from scholarly databases and web search, Phase II: Computation of DMs weights using DRA, and Phase III: Determination of importance weight of KPIs using DFS-AHP algorithm depicted in Fig. 1.

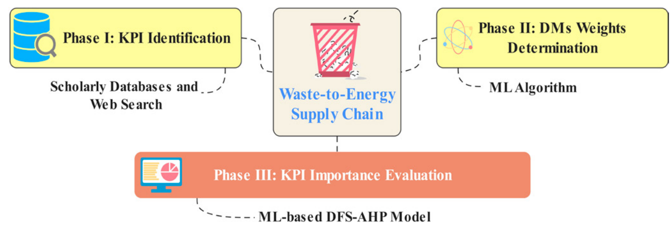

Fig. 1. Research framework.

3.2 Dimension Reduction Algorithm

Data-driven methods like ML and artificial intelligence (AI) are increasingly used to tackle complex decision-making problems. However, MCDA frequently struggles to incorporate DMs diverse dimensional data, such as age, experience level, etc., when determining DMs weights rather than weight calculated by linguistic scale, significantly influencing the final decision. To address this, integrating ML techniques with advanced MCDA models offers a promising solution. This work presents a novel approach: the first integration of an ML algorithm with a novel DFS-AHP method. This combination effectively handles the challenges of incorporating dimensional data of DMs for approximating expert weights. The dimension reduction algorithm is outlined below (Eti et al., 2024):

Input: Demographic data of DMs, $\upsilon_{ij}, i \in [1,k], j \in [1,n]$; where k and n refer to the total number of DMs and the number of features of each DM, respectively.

Output: Weights of DMs, $\omega_i, i \in [1,k]$;

Start

Step 1.1: Developing the feature matrix of DMs.

$$\gamma_{ij} = [\upsilon_{ij}]_{k\times n}$$

Step 1.2: Computing the standardized matrix from γ_{ij}.

$$\pi_{ij} \leftarrow \frac{\upsilon_{ij}-\tilde{\upsilon}_j}{\sqrt{\sum_{i=1}^{k}(\upsilon_{ij}-\tilde{\upsilon}_j)^2}};\ \forall i \in [1,2,\dots,k];\ \forall j \in [1,2,\dots,n];$$

Step 1.3: Estimating the covariance matrix (τ_{ij}) from π_{ij}.

Step 1.4: Computing the eigenvalue (λ) of the covariance matrix (τ_{ij}).

$$Det\ (\tau_{ij} - \lambda I) = 0$$

Step 1.5: Calculating the eigenvector (ρ) for the highest eigenvalue (λ_{max}).

$$(\tau_{ij} - \lambda_{max} I) \times \rho = 0$$

Step 1.6: Converting the feature matrix to a new space (ζ).

$$\zeta \leftarrow \gamma_{ij} \times \rho$$

Step 1.7: Determining the final weight of DMs.

$$\omega_j \leftarrow \frac{\zeta_j}{\sum_{j=1}^{k}\zeta_j}, \forall j \in [1,2,\dots,k]$$

End

3.3 Decomposed Fuzzy Sets AHP

The DFS, a new development within the framework of intuitionistic fuzzy sets (Cebi *et al.,* 2022), expands the capacity to handle larger-scale uncertainty by capturing both pessimistic and optimistic views of DMs (Cebi *et al.,* 2023). The mathematical algorithm of DFS-AHP for assessing KPIs is explained below based on a study by Cebi *et al.,* (2023):

Step 2.1: Identification of KPIs ($KPI_1, KPI_2, \ldots, KPI_n$).

Step 2.2: Construction of a pairwise comparison matrix using the DFS linguistic scale found in Cebi *et al.,* (2023) among identified KPIs by each DM.

Step 2.3: Transformation of linguistic rating scale into DFS values to form the final comparison matrix for all DMs.

$$\tilde{M} = \left(\tilde{m}_{ii}^{k}\right)_{n\times n} = \left(\mathcal{O}\left(\mu_{ii}^{k}, \nu_{ii}^{k}\right), \mathcal{P}\left(\mu_{ii}^{k}, \nu_{ii}^{k}\right)\right)_{n\times n} \quad (1)$$

where the notations $\mathcal{O}$ and $\mathcal{P}$ denote optimistic and pessimistic DFS values.

Step 2.4: Checking the consistency of the final comparison matrix using the regression model ($S_s = 11\mu - 9\nu$) and procedure suggested by Saaty; S_s indicates the Saaty scale. The matrix is only considered if the value of the consistency ratio (*CR*) is less than 0.10 (i.e., *CR*<0.1).

Step 2.5: Computation of aggregated weight of KPIs for each expert using the decomposed weighted geometric mean (DWGM) operator as follows (Cebi et al., 2022, 2023):

Assume $\tilde{\lambda}_i = \{\mathcal{O}(\alpha_i, \beta_i), \mathcal{P}(\wp_i, \chi_i)\}$ is a DFS value concerning $\xi_i = (\xi_1, \xi_2, \ldots, \xi_n)$; $\xi_i \in [0,1]$ as well as $\sum_{i=1}^{n} \xi_i = 1$. Hence, the DWGM can be defined as:

$$\mathrm{DWGM}(\tilde{\lambda}_1, \tilde{\lambda}_2, \ldots, \tilde{\lambda}_n) = \left\{ \begin{array}{l} \mathcal{O}\left(\prod_{i=1}^{n} \alpha_i^{\xi_i}, \left(1 - \prod_{i=1}^{n} (1-\beta_i)^{\xi_i}\right)\right), \\ \mathcal{P}\left(\frac{\prod_{i=1}^{n} \wp_i}{\sum_{i=1}^{n} \wp_i^{n-1} \xi_i (1-\wp_i) + \prod_{i=1}^{n} \wp_i}, \frac{\sum_{i=1}^{n} \xi_i \chi_i}{1 + \sum_{i=1}^{n}\left(\xi_i \chi_i - \frac{\chi_i}{n}\right)}\right) \end{array} \right\} \quad (2)$$

Step 2.6: Determination of aggregated DFS weight of KPIs for all DMs from the individual aggregated weight of DM using Eq. (2). In this case, the weight of DMs is computed from the ML model and denoted as $\omega_i = (\omega_1, \omega_2, \ldots, \omega_n)$; $\omega_i \in [0,1]$ as well as $\sum_{i=1}^{n} \omega_i = 1$.

Step 2.7: Calculation of de-fuzzified values of the DFS aggregated values for both individual and aggregated matrix for each DM and all DMs in the following ways. Assume $\tilde{\hbar}_i = \{\mathcal{O}(a_i, b_i), \mathcal{P}(c_i, d_i)\}$ is a set of aggregated DFS values, then the consistency index (*CI*) and score index (*SI*) can be computed as follows for each KPI:

$$CI(\tilde{\hbar}_i) = 1 - \ell^{h_i} = 1 - \left(\sqrt{\frac{(a_i-d_i)^2 + (b_i-c_i)^2 + (1-a_i-b_i)^2 + (1-c_i-d_i)^2}{2}}\right); 0 \le \mathrm{CI}(\tilde{\hbar}_i) \le 1 \quad (3)$$

The $CI(\tilde{\hbar}_i)$ value signifies the consistency level of DMs and decision matrices. Close to 1 means more consistency and vice versa.

$$\mathrm{SI}(\tilde{\hbar}_i) = \begin{cases} \frac{(a_i+b_i-c_i+d_i).\mathrm{CI}(\tilde{\hbar}_i)}{2.\ell}, & \mathrm{SI}(\tilde{\hbar}_i) > 0 \\ 0, & \mathrm{SI}(\tilde{\hbar}_i) \le 0 \end{cases} \quad (4)$$

where the value of ℓ is considered as 0.9 based on the linguistic scale found in a study by Cebi *et al.,* (2023), and it refers to the linguistic scale multiplier. Finally, the KPIs are ranked based on the normalized values of *SI*.

4. APPLICATION OF PROPOSED MODEL

This study focuses on the WtESC as it is a critical supply chain that needs to maintain optimal operational performance by completing the EnSE standards. Hence, in Phase I, we have identified the KPIs from existing literature and web searches considering WtESC in an emerging economies context that could be considered in the future for assessing WtESC performance. The proposed WtE technologies can be obtained from the previous study conducted by Moktadir *et al.,* (2024b). To implement an ML-based MCDA model, in Phase II, first, the demographic information of four DMs is collected from their online profiles. We purposively selected four relevant academics to ensure consistency in demographic data. In addition, one DM brings both academic and industry experience, confirming the diversity of the DM group. These DMs possess extensive experience and scholarly achievements in the supply chain domain, including WtESC and sustainability (See Table A1). Furthermore, we adopted an expert-based approach rather than data-driven methodologies, allowing us to rely on a smaller sample of DMs (Rezaei et al., 2012). The demographic information of DMs, such as age (υ_1), years of research and teaching experience (υ_2), education level (υ_3), number of professional memberships (υ_4), professional certifications (υ_5), the total number of Scopus-indexed publication (υ_6), Scopus h-index (υ_7), Scopus citation (υ_8), number of awards (υ_9), and the number of leadership positions held (υ_{10})are considered for the ML model. The demographic data of DMs is given in Appendix A in Table A1. The raw data is standardized using Step 1.2 and provided in Table 2. After that, using the dimension reduction algorithm mentioned in Section 3.2, the covariance matrix, eigenvalue of the covariance matrix, eigenvector for the highest eigenvalue, new space matrix, and final weight of DMs are computed. The final weight of DMs is given in Table 3.

Table 2. Standardized matrix of demographic information of DMs.

DMs	υ_1	υ_2	υ_3	$\upsilon_4, \ldots, \upsilon_8$	υ_9	υ_{10}
DM1	0.412	0.611	-0.151	, ...,	-0.195	0.496
DM2	0.333	-0.285	0.452	, ...,	-0.195	0.496
DM3	0.098	0.334	0.452	, ...,	0.846	-0.406
DM4	-0.843	-0.659	-0.754	, ...,	-0.456	-0.586

Table 3. DMs weight obtained from ML algorithm.

DMs	Score (ξ_i)	Weight (ω_i)
DM1	12492	0.2292
DM2	15821	0.2902
DM3	15340	0.2814
DM4	10857	0.1992

In Phase III, the DMs are invited to evaluate the listed KPIs using the DFS linguistic scale reported in a study by Cebi *et al.,* (2023). The initial matrix for DM1 is given in Appendix A in Table A2. After that, the initial comparison matrix for all DMs is converted to the final decision matrix using Eq. (1). Then, using the regression model ($S_s = 11\mu - 9\nu$), the *CR* of the final decision matrix is investigated following the protocol suggested in Saaty's AHP model. If the matrix is consistent, Eq. (2) is employed for all DMs to compute the aggregated score for KPIs for individual DM. For instance, the final decision matrix and aggregated value for DM1 are provided in Table A3 in Appendix A. Therefore, Eq. (2) mentioned in Step 2.5 is again applied to combine the aggregated score obtained from four DMs. In this case, the weight of DM is considered, which is determined by employing an ML model and denoted as $\omega_i = (\omega_1, \omega_2, \ldots, \omega_n)$; that fulfills the conditions of $\omega_i \in [0,1]$ and $\sum_{i=1}^{n} \omega_i = 1$. Finally, the de-fuzzified DFS values are computed from the aggregated DFS values by computing *CI* and *SI* values following the procedure mentioned in Step 2.7 in Eqs. (3)-(4). The aggregated values of four DMs, *CI*, and *SI* values of KPIs are provided in Table 3.

Table 3. The aggregated values of four DMs, CI, and SI of KPIs.

KPIs	DFS values				CI	SI
KPI1	0.6299	0.3701	0.0066	0.6579	0.6497	0.5960
KPI2	0.5616	0.4384	0.0583	0.5839	0.6306	0.5345
KPI3	0.5415	0.4585	0.1900	0.5759	0.7469	0.5751
KPI4	0.4739	0.5261	0.2469	0.4913	0.7291	0.5041
KPI5	0.5792	0.4208	0.0076	0.6017	0.5976	0.5293
KPI6	0.4263	0.5737	0.3139	0.4630	0.7565	0.4829
KPI7	0.4583	0.5417	0.1253	0.4792	0.5937	0.4465
KPI8	0.3788	0.6212	0.2455	0.4087	0.6383	0.4125
KPI9	0.2442	0.7558	0.6863	0.2671	0.9386	0.3029

The normalized value of SI and final ranking is depicted in Fig. 2. According to the results depicted in Fig. 2, the final ranking order of KPIs is sorted as follows: KPI1>KPI3>KPI2> KPI5>KPI4>KPI6>KPI7>KPI8>KPI9.

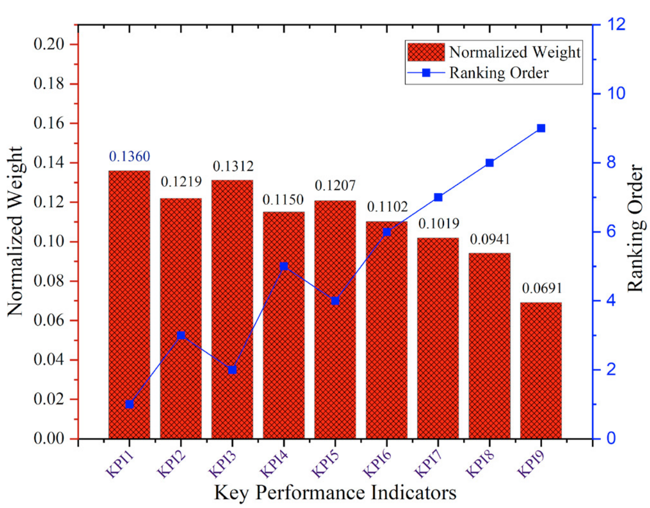

Fig. 2. Normalized weight and ranking of KPIs.

5. RESULTS AND DISCUSSION

The study aimed to identify and assess the KPIs for the WtESC using the novel ML-based DFS-AHP model. Based on the findings of the ML-based DFS-AHP model depicted in Fig. 2, the most crucial KPI is 'CO_2 emissions intensity (KPI1)', which received the highest normalized DFS weight of 0.1360. The lower the CO_2 emission from WtESC, the higher the performance of the WtE system and vice versa. This finding highlights the critical importance of minimizing CO_2 emissions from the WtE system towards achieving sustainable WtE operations. Therefore, prioritizing strategies and technologies that effectively reduce CO_2 emissions during waste conversion is crucial for improving the environmental sustainability and overall effectiveness of WtE systems (Su et al., 2023). This finding suggests that efforts to reduce CO_2 emissions intensity from WtESC should be a central focus for policymakers, industry stakeholders, and researchers involved in WtE development and management. In this regard, policymakers may consider advanced, cleaner, and more efficient technologies to foster the environmental performance of WtESC.

Next, the KPI "Energy conversion efficiency (KPI3)" received 2nd position in the final ranking, along with the de-fuzzified DFS normalized weight of 0.1312. This finding indicates that implementing efficient WtE conversion technology can significantly improve the overall performance of the WtESC as it directly relates to how effectively waste is transformed into usable energy. Higher efficiency means more energy is recovered from waste, reducing the need for other energy sources and minimizing the environmental impact associated with waste disposal. Improved energy conversion efficiency can also have positive economic implications. By maximizing energy output, WtE facilities can generate more revenue and become more economically competitive. Therefore, stakeholders involved in WtESC should adopt strategies and efficient technologies that enhance energy conversion efficiency. This could include investing in advanced WtE technologies, optimizing operational parameters, and implementing effective energy recovery systems that could improve the overall performance of WtESC.

Then, the analysis reveals that 'Levelized cost of energy (KPI2)', 'Feedstock supply reliability (KPI5)', and 'Safety incident rate (KPI4)' constitute the next tier of important KPIs for WtESC. These KPIs received de-fuzzified normalized weights of 0.1219, 0.1207, and 0.1150, respectively, indicating their significant contribution to the overall improvement of WtESC performance. While slightly less important than the top two KPIs, these KPIs still emphasize the importance of economic viability, consistent feedstock availability, and operational safety within WtE systems. Specifically, KPI2 underscores the need for economically competitive WtE solutions, while KPI5 highlights the importance of a stable and consistent waste stream to ensure continuous and efficient WtE operations. Finally, KPI4 underlines the critical need for prioritizing safety protocols and minimizing workplace accidents within WtE facilities, reflecting a strong commitment to worker well-being and operational integrity. To ensure the operational excellence of WtESC, stakeholders, policymakers, and decision-makers should consider these findings collectively and with the utmost care.

Finally, the following four critical KPIs for the WtESC 'Return on investment (KPI6),' 'WtE supply chain responsiveness (KPI7)', 'Community acceptance index (KPI8)', and 'Job creation facility (KPI9)' obtained the DFS normalized score value of 0.1102, 0.1019, 0.0941 and 0.0691, consequently. KPI6 emphasizes the need for WtE projects to be financially viable and attractive to investors, ensuring long-term sustainability and development, as WtE projects often require significant investment. Hence, to ensure economic viability, the return on investment should be sufficient for the

WtE project, and a higher return on investment indicates its better economic performance. KPI7 focuses on the importance of efficient and adaptable waste management systems that can respond to changing waste streams and demands, whereas KPI8 underscores the critical role of public perception and social acceptance in the successful implementation and operation of WtE facilities. Finally, KPI9 reflects the potential of WtE projects to generate employment opportunities and contribute to local economies. These findings have noteworthy policy implications for policymakers in developing and implementing effective WtE technology. Policymakers should pay more attention to these KPIs to ensure the higher performance of the WtESC if the WtE technology is planned to be implemented for eco-friendly management of solid waste.

The theoretical implications of this study are notable as this study, for the first time, showed how the ML-based MCDA approach can be utilized to assess the KPIs for WtESC, covering broader levels of uncertainty. The specific policy implications of the study's findings could be summarized as follows:

Policymakers can prioritize specific areas for intervention and investment based on the relative importance of KPIs. For instance, the high weighting of CO_2 emission intensity suggests that policies should focus on incentivizing the adoption of advanced WtE technologies with lower emission profiles, such as those incorporating carbon capture and storage. Similarly, the emphasis on energy conversion efficiency indicates the need for policies that promote R&D in this area, as well as the implementation of best practices in WtE plant operation. Furthermore, the consideration of levelized energy cost, feedstock supply reliability, and safety incident rate underlines the importance of policies that support the economic viability of WtE projects, ensure stable waste streams, and enforce stringent safety standards. The importance of KPI6 suggests that policies should focus on creating a favourable investment climate for WtE projects. This can include providing financial incentives such as tax breaks, subsidies, feed-in tariffs, or loan guarantees to improve the economic viability and attract private sector investment. Policies should also streamline permitting processes and reduce bureaucratic hurdles to facilitate WtE project development to ensure maximum financial performance from WtESC.

Waste supply chain responsiveness (KPI7) highlights the need for integrated waste management strategies that ensure a reliable and consistent feedstock supply for WtE facilities. Policies such as supporting solid waste management programs, promoting public-private partnerships, and implementing regulations to ensure consistent waste delivery to WtE plants should be promoted with the utmost importance. In addition, waste segregation, collection, and transportation infrastructure should be developed to optimize the performance of the WtES. In addition, transparent communication, public consultations, and community involvement in the planning and development of WtE projects are crucial for WtESC's better performance. Finally, policies to support job creation should aim to maximize the local economic benefits of WtE projects. Furthermore, prioritizing local hiring, providing training programs for local workers, supporting the development of regional supply chains, and encouraging partnerships between WtE facilities and local businesses are also crucial for the higher performance of WtESC.

6. CONCLUSIONS

The performance management of WtESC is critical and requires special care compared to traditional supply chains. Hence, to guide the industrial managers, it is crucial to construct a set of KPIs for performance measurement of WtESC, a special supply chain where waste is treated and converted into value-added products in a thermochemical environment. Therefore, the scientific contributions of this study are that, for the first time, it constructs KPIs for WtESC and offers a comprehensive ML-based DFS-AHP framework for the evaluation of KPIs that may support policymakers and decision-makers to take necessary actions towards achieving optimal performance in WtESC. The main advantages of offering an ML-based MCDA model are that the ML algorithm helped to determine the DMs level of importance considering diverse demographic data and integrated DMs weight in the DFS-AHP approach provided more reliable results as decision-making based on DMs feedback often neglected to consider the level of importance considering their performance. The literature review helped to identify the most important nine KPIs for WtESC, whereas the ML algorithm supported finding the weight of DMs. According to the findings of ML-based DFS-AHP, the two most important KPIs are "CO_2 emissions intensity (KPI1)" and "Energy conversion efficiency (KPI3)". These findings reveal that CO_2 emission intensity and energy efficiency are the most important KPIs for WtESC to ensure optimal performance and long-term sustainability. Therefore, to advance the operational performance of WtESC, policymakers must play a significant role in taking proactive and reactive actions, including advanced technology integration, R&D, etc., that may help to improve the overall operational performance of WtESC.

Though this study presents a pathway for WtES to use a set of KPIs for measuring performance and policymaking towards operational excellence, it also suffers some limitations. For instance, this study considered the WtESC, which may not fit other supply chains. In addition, technological aspects such as Robotics, Industry 5.0, and AI integration in the performance management of WtESC are avoided and could be considered in future evaluations. A life cycle-based real data-driven model can be considered in future studies for analyzing the performance of WtESC. Furthermore, the proposed framework can be applied to the performance assessment of other supply chain contexts.

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Appendix A: Supporting Information

Table A1. Demographic information of DMs.

DMs	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}
DM1	42	17.5	PhD	1	3	141	41	5542	4	8
DM2	41.5	12	Postdoc	2	0	171	51	7078	4	8
DM3	40	15.8	Postdoc	1	3	170	44	6849	8	3
DM4	34	9.7	MSc	1	1	76	36	4895	3	2

Table A2. An initial decision matrix constructed by DM1.

KPIs	KPI1		,…,		KPI9	
	$\mathscr{O}$	$\mathscr{P}$	$\mathscr{O}$	$\mathscr{P}$	$\mathscr{O}$	$\mathscr{P}$
KPI1	EEI	EEI	,…,	,…,	AMI	AMU
KPI2	EEU	EEI	,…,	,…,	StMI	StMU
KPI3	WMU	WMI	,…,	,…,	VSI	VSU
KPI4	MU	MI	,…,	,…,	AMI	AMU
KPI5	SMU	SMI	,…,	,…,	PMI	PMU
KPI6	StMU	StMI	,…,	,…,	WMI	SMU
KPI7	WMU	WMI	,…,	,…,	WMI	WMU
KPI8	VSU	VSI	,…,	,…,	PMI	PMU
KPI9	AMU	AMI	,…,	,…,	EEI	EEI

Table A3. DFS final decision matrix computed by DM1.

KPIs	KPI1				.	Aggregated value (DWGM)			
	$\mathscr{O}$		$\mathscr{P}$			$\mathscr{O}$		$\mathscr{P}$	
KPI1	0.50	0.50	0.50	0.50	.	0.620	0.380	0.127	0.628
KPI2	0.50	0.50	0.50	0.50	.	0.578	0.422	0.243	0.583
KPI3	0.40	0.60	0.60	0.40	.	0.569	0.431	0.191	0.578
KPI4	0.35	0.65	0.65	0.35	.	0.465	0.535	0.192	0.489
KPI5	0.45	0.55	0.55	0.45	.	0.594	0.406	0.060	0.611
KPI6	0.30	0.70	0.70	0.30	.	0.446	0.554	0.437	0.450
KPI7	0.40	0.60	0.60	0.40	.	0.418	0.582	0.354	0.439
KPI8	0.25	0.75	0.75	0.25	.	0.410	0.590	0.262	0.433
KPI9	0.20	0.80	0.80	0.20	.	0.263	0.737	0.656	0.283