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AI-POWERED DYNAMIC ALLIANCES FOR CIRCULAR ECONOMY: A SIMULATION-BASED FRAMEWORK FOR ZERO INDUSTRIAL WASTE IN AJMAN, UAE

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Abstract

Achieving Zero Industrial Waste (ZIW) is a critical requirement for the transition to a circular economy. The existing approaches to industrial waste management remain constrained by fragmented waste streams, limited cross-sector coordination, and insufficient integration of intelligent technologies. A Public-Private Partnership (PPP) governance framework is developed and simulated in this study to operationalise ZIW through AI-enabled industrial symbiosis. A mixed-methods analysis was employed, combining qualitative stakeholder and governance analysis with a quantitative, AI-driven simulation of waste flows across five industrial sectors in Ajman, UAE, over 30 days. To manage non-reusable residuals, machine-learning-based matching algorithms optimised material compatibility, logistics, and timing, supported by predictive waste forecasting and waste-to-energy recovery pathways. Results indicate that 85% of total waste is directly repurposed through industrial symbiosis, achieving zero landfill disposal. Paper and wood achieved reuse rates exceeding 90%, while textile offcuts and organic wastes achieved 100% reuse. Approximately 70% of plastic waste was reused, and the remaining fraction was fully recovered through Waste-To-Energy. Using AI, 93% of matches were accurate, waste holding time was reduced by 40%, and an average of 12 new inter-industrial waste exchanges were enabled each month. A 32% reduction in CO2-equivalent emissions was achieved through residual waste recovery, which generated approximately 2 MWh/day of renewable energy. The integrated digital platform ensured full traceability and real-time visibility of waste streams, strengthening compliance, accountability, and transparency within the PPP framework.

Keywords: Ajman-UAE, AI, Effective zero waste, Public-private partnerships, Sustainable waste management, Waste-to-energy.

1. Introduction

The rapid industrialisation of the world has led to substantial economic growth and technological advancement; however, this progress has also been accompanied by a continuous increase in industrial waste generation, intensifying environmental degradation and posing serious health and environmental risks. Various industries produce industrial waste, such as manufacturing, chemical processing, and electronics, which can contain toxic solids, liquids, hazardous gases, and electronic waste that must be handled and disposed of carefully [1-3]. The empirical evidence indicates that improper waste management practices can lead to contamination of land, air, and water, adversely affecting biodiversity, public health, and local economies [4, 5]

In addition to soil contamination, respiratory diseases, and decreased agricultural productivity, unmanaged industrial waste contributes to significant negative externalities [6, 7]. These impacts are closely linked to traditional linear production models based on the "take-make-dispose" paradigm, which fail to account for long-term sustainability [8].

In response, sustainable industrial waste management (IWM) strategies have become increasingly popular, emphasising waste minimisation, reuse, and resource recovery. By encouraging closed-loop production systems that reduce reliance on virgin materials and minimise waste generation, the circular economy has emerged as a promising framework for addressing industrial waste challenges [9, 10]. As a result of the circular economy, industries are encouraged to adopt cleaner production techniques and environmentally friendly technologies in line with sustainable development objectives and the Sustainable Development Goals [11].

It has been demonstrated that operational approaches such as lean manufacturing, value stream mapping, and 5S methodologies are effective in reducing waste, optimising resource use, and improving product quality [12, 13]. Increasing operational efficiency can reduce environmental impacts and generate financial benefits for industries simultaneously [14]. Although awareness of sustainable IWM practices is growing, and conceptual models are available, implementation of sustainable IWM practices remains inconsistent due to technological limitations, regulatory fragmentation, and economic barriers [15].

To support evidence-based decision-making, Life Cycle Assessment (LCA) has been widely used to evaluate the environmental impacts of products and processes throughout their entire life cycle, from raw material extraction to the end-of-life management [16]. The LCA process allows for the identification of critical intervention points and provides data-driven insights that can be used to reduce emissions and optimise waste recovery strategies [17, 18]. Furthermore, it plays an important role in aligning industrial practices with environmental regulations and evolving consumer expectations regarding sustainability [19, 20]. However, the research landscape remains fragmented despite advances in IWM and LCA-based approaches, with limited integration between engineering optimisation models, policy frameworks, and circular economy principles [21, 22].

As a result, industrial waste management represents a critical intersection of environmental protection, public health, and economic development. To address the growing risks posed by industrial waste, a transition must be made from reactive disposal-oriented practices to proactive, integrated waste minimisation strategies that are both economically viable and environmentally sustainable. However, in the absence of holistic, scalable frameworks integrating sustainability principles, circular economy strategies, and advanced digital tools, such as life cycle assessment and real-time analytics, many current practices fail to recognise waste as a recoverable resource, resulting in limited progress toward sustainable industrial development [20, 23].

Despite the extensive literature on industrial waste management, several critical gaps remain. Existing models rarely integrate environmental, economic, and operational dimensions within a unified framework, which limits their long-term scalability and effectiveness. Modern digital technologies, such as Artificial Intelligence (AI), Life Cycle Assessment (LCA), and lean manufacturing systems, still have limited application in industrial settings. In addition, industrial waste management is typically confined to academic or commercial domains, limiting its adoption on a broader scale. The management of emerging waste streams, such as electronic waste and hazardous chemical by-products, is insufficient despite their growing importance in contemporary industrial operations.

Governance is another critical limitation. The concept of industrial symbiosis is well established, but its implementation remains largely static and manually coordinated, making it unsuitable for managing real-time complexity, uncertainty, and scale. The integration of advanced artificial intelligence with circular economy principles under robust multistakeholder governance structures, in particular public-private partnerships (PPPs), remains largely unexplored. Furthermore, the government's role in digitally enabled circular systems is often narrowly defined as regulatory, ignoring its potential role as a facilitator, coordinator, and risk-sharing partner.

This study develops and evaluates an AI-powered, PPP-governed Integrated Smart Circular Waste Management System (IS-CVMS) designed to enable dynamic industrial alliances and operational achievement of ZIW in response to these gaps. Analysing current industrial waste management strategies, the study proposes an integrated framework that incorporates circular economy principles, artificial intelligence-driven decision-making, predictive waste forecasting, and waste-to-energy recovery. Using representative industrial data from Ajman, UAE, the study quantifies environmental and operational outcomes, including landfill diversion, energy recovery, and emissions reduction. This research provides a practical blueprint for sustainable industrial development and zero-waste industrial ecosystems through the translation of circular economy theory into a digitally enabled, governance-ready, and scalable system.

The objective of this study is to develop and validate an AI-enabled, PPP-governed framework capable of operationalising Zero Industrial Waste through dynamic industrial symbiosis. Research objectives include: (i) designing an integrated smart circular waste management system (IS-CVMS) that integrates artificial intelligence-driven decision-making into a multistakeholder governance structure; (ii) simulating inter-industrial waste exchanges using representative industrial data from Ajman, UAE; and (iii) quantitatively assessing environmental and operational outcomes, including landfill diversion, energy recovery, emission reduction, and system performance.

A mixed-methods approach is adopted in this study, involving a qualitative stakeholder and governance analysis as well as a quantitative, simulation-based model of industrial waste flows that is supported by machine-learning matching algorithms and predictive forecasting algorithms. In this manner, the scalability, effectiveness, and contribution of the framework to Zero Industrial Waste objectives can be rigorously evaluated.

2. Zero Industrial Waste Framework in the UAE

Alhosani et al. [24] proposed an integrated conceptual framework to eliminate industrial non-hazardous waste through PPPs. The study was conducted using Ajman, UAE, as a case study for analysing industrial solid waste, incorporating the government's role as a key player. According to the findings, categorising industries according to their primary activities and establishing an alliance community network to facilitate the substantial reuse of industrial waste within the community network can help achieve zero industrial waste. The concept was defined by establishing a central location where industries can share resources and implement sustainable practices. Figure 1 shows the basic framework. In this paper, an integrated framework powered by AI. Industrial waste streams are complex, diverse, and large in scale, making manual coordination inefficient. The purpose of this study is to address this limitation by introducing Artificial Intelligence (AI) as a core enabler. Real-time waste tracking, predictive analytics, and intelligent matching between Associated Waste Produced (AWP) and Needed Waste Inputs (NWI) facilitate waste-to-energy (WTE) recovery. Analysing historical waste data can forecast generation patterns, identify optimal reuse pathways, and enhance cross-industry collaboration. PPP-based systems benefit from automated compliance monitoring, anomaly detection, and transparent reporting through AI [22]. These capabilities position AI as the operational backbone of the proposed Integrated Smart Circular Waste Management System (IS-CVMS).

Looking at the conceptual framework in Fig. 1, it is emphasised that the entire system is designed to achieve **zero waste** through:

- Systematic classification and reuse of industrial waste,
- Digital integration across industries,
- Use of Waste to Energy only for unavoidable residuals,
- Strong governance and collaborative PPPs,

Emphasis on circularity, traceability, and accountability.

2.1. The role of public-private partnerships and the need

Through an innovative, cooperative system powered by Public-Private Partnerships (PPPs), this integrated conceptual framework aims to minimise non-hazardous industrial waste [25]. An Industrial Alliances Community Network (IACN) is a collaborative ecosystem where waste produced by one industry (Associated Waste Produced, AWP) serves as a resource for another industry (Needed Waste Inputs, NWI) by classifying industrial activities and waste streams. The dynamic reuse system reduces waste generation at the source, reduces reliance on landfills, and maximises resource efficiency [26]. The framework relies heavily on coordinated roles within PPPs, which provide the foundation for sustainable execution. Among these roles are stakeholders (industry, waste processors), regulators (policy makers), facilitators (connectors and technology providers), controllers (auditors and compliance monitors), and protectors (environmental and health agencies). By including Waste-to-Energy as a fallback, even residual, unutilised waste can contribute to the energy cycle instead of polluting the environment.

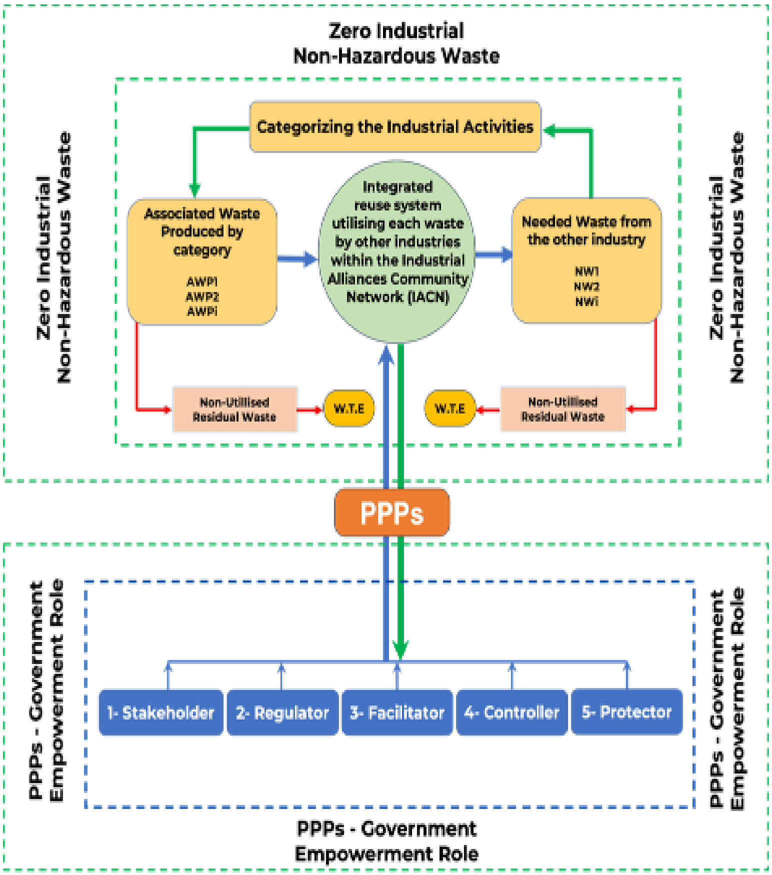

Fig. 1. Integrated conceptual framework to zero industrial non-hazardous waste empowered by PPPs [24].

2.2. AI in achieving zero industrial non-hazardous waste

AI must be integrated with this model despite its systemic strengths. Due to the complexity, diversity, and large scale of industrial waste streams, manual categorisation, monitoring, and exchange coordination are inefficient and prone to errors. The use of artificial intelligence has the potential to revolutionise this framework by enabling real-time tracking of waste, predicting waste generation, intelligently matching AWP and NWI categories, and optimising WTE decisions. To maximise cross-industry coordination and minimise downtime for waste management, machine learning models can analyse historical data to predict which industries can handle a particular waste type. In addition, AI has the potential to facilitate Life Cycle Assessments (LCA) and the deployment of lean systems, both of which are essential to assessing environmental impact and improving operational efficiency. Furthermore, AI enables regulators and controllers to enhance transparency and traceability through automated compliance checks, anomaly detection, and data-driven reporting [27].

Thus, AI enables PPPs to function more quickly and strategically, based on robust, real-time insights rather than delayed, fragmented information. As industries move toward Industry 5.0, digital integration and artificial intelligence-augmented decision making are not optional - they are essential to scalable, adaptive, and environmentally sustainable waste management solutions. From the above discussion, it can be concluded that the integrated framework powered by PPPs offers a promising approach for achieving zero non-hazardous industrial waste. Nevertheless, its true potential can only be realised through the introduction of artificial intelligence, which will enable static systems to become dynamic, intelligent, and circular industrial ecosystems.

3. Results and discussion

3.1. An integrated smart circular waste management system

The integrated smart circular waste management system, IS-CVMS, is a strategic, AI-driven framework designed to reduce industrial non-hazardous waste by converting it into valuable resources. In this model, waste produced by one industry (Associated Waste Produced - AWP) becomes a raw material for another industry (Needed Waste Input - NWI), thus promoting closed-loop industrial systems. To implement IS-CVMS, five interconnected steps are used: AI-based waste classification, real-time material matching, energy recovery through Waste-to-Energy for residuals, governance through Public-Private Partnerships (PPPs), and continuous monitoring through intelligent dashboards.

Industries need to adopt a unified digital waste reporting system, supported by AI algorithms that can classify and match waste streams dynamically to achieve the goals of IS-CVMS. To create transparent regulatory environments and incentive mechanisms, the public and private sectors must work together. Smart logistics, traceable waste flows, and knowledge-sharing portals further enhance cross-sectoral reuse. As a result of data-driven decision-making and cooperative governance, success is ultimately measured by reduced reliance on landfills, higher reuse rates, energy recovery, and improved environmental performance. The proposed framework, the integrated smart circular waste management system (IS-CVMS), is shown in Fig. 2.

3.2. From conceptual to final framework: Evolution of IS-CVMS

Integrated Conceptual Framework to Zero Industrial Non-Hazardous Waste Empowered by PPPs presents a strategic vision for waste circularity through digital exchange and public-private partnerships. In this paper, the theoretical groundwork is outlined using principles from circular economy, industrial symbiosis, AI integration, and public-private collaboration. Waste is categorised as Associated Waste Produced (AWP) and matched with Needed Waste Inputs (NWI), while residuals are routed to Waste-to-Energy (WTE). Alhosani Zero Waste Framework or IS-CVMS (Integrated Smart Circular Waste Management System) builds upon this foundation. By bringing together smart manufacturing, WTE optimisation, knowledge portals, and real-time metrics, the concepts are operationalised into a digital, AI-driven platform. In this final version, theory is translated into a functional, scalable, and traceable industrial waste management system.

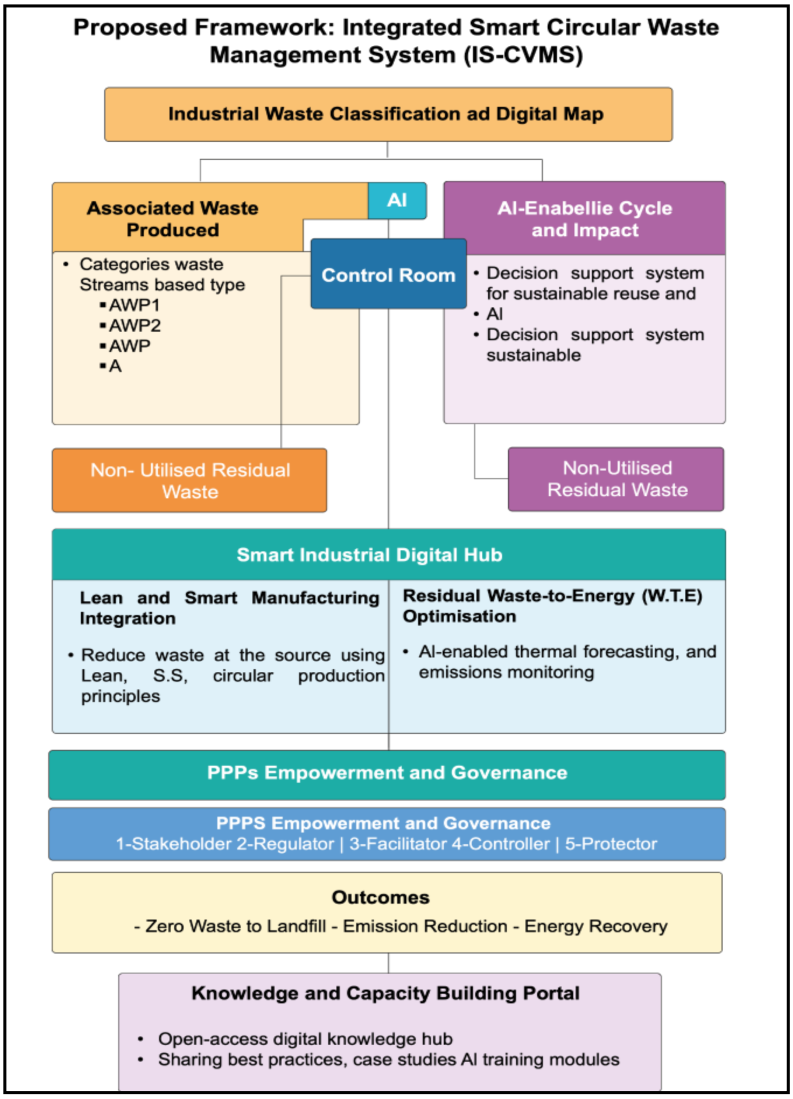

Fig. 2. Alhosani framework of integrated smart circular waste management system (IS-CVMS).

3.3. Breakdown of the final framework

Table 1 presents a structured breakdown of the Alhosani Zero Waste Framework (IS-CVMS) by highlighting each functional layer and its corresponding operational role. This multi-layered system transforms theoretical concepts, such as industrial symbiosis, artificial intelligence, and circular economy principles, into an actionable architecture. By categorising, redirecting, recovering, and governing industrial materials, each layer contributes to achieving zero waste. The table shows how each component of the framework interacts with the others, forming a seamless flow from data input to environmental and economic outcomes.

Table1. Alhosani (IS-CVMS) framework components.

Layer	Explanation
Classification Layer	Industries log waste types into an AI-powered system. Waste is categorised as AWP1, AWP2, AWPi, etc., based on type, reusability, and hazard.
AI Control Room	Acts as the brain of the system, matching AWP with NWI and routing unmatched waste to WTE.
AI Lifecycle & Impact Tool	Supports sustainability analysis and decision-making through environmental dashboards.
Digital Hub	Includes Lean Manufacturing Integration (waste minimisation at source) and WTE Optimisation (energy recovery and emission control).
PPPs Empowerment Layer	Implements the five stakeholder roles: Stakeholder, Regulator, Facilitator, Controller, and Protector.
Outcomes	Tracks metrics such as landfill diversion, CO_2 saved, and energy recovered, and displays them in dashboards.
Knowledge Portal	Provides a shared space for best practices, AI training, and technical documentation.

3.4. Verification and achieving zero waste by the are-CVMS framework

As part of the Alhosani Zero Waste Framework, the Integrated Smart Circular Waste Management System (IS-CVMS) offers a powerful, scalable pathway to achieve Zero Industrial Non-Hazardous Waste. In this verification walkthrough, each step is underpinned by artificial intelligence, governance, and smart reuse to ensure that 100% of waste is valued. Table 2 outlines the daily waste profiles of five key industries that form the basis for the IS-CVMS framework. In each entry, the type, quantity, reusability potential, and level of hazard are specified. Using this information, the AI system can categorise and assess the suitability of each waste stream for reuse or energy recovery, serving as a starting point for intelligent waste management and circular exchange across sectors.

Table 2. Industries and their waste streams (input).

Industry	Waste Type	Quantity/day	Reusability	Hazard	Example Use
Wood Furniture	Wood shavings	1 ton	High	Low	Pellet fuel
Publishing	Paper scraps	2 tons	High	Low	Packaging material
Plastic Moulding	Plastic trimmings	3 tons	Medium	Medium	Plastic bricks
Garments	Textile offcuts	1.5 tons	High	Low	Upholstery stuffing
Food Processing	Organic waste	4 tons	High	Low	Compost or animal feed

To assess the operational potential of the IS-CVMS framework, a data-driven simulation was developed using realistic estimates from five representative industries: wood furniture, publishing, plastic moulding, garments, and food processing. A typical industrial practice reported in the literature was used to estimate the daily waste generation and material reusability for each industry. To simulate how waste flows through the IS-CVMS system, the model applied standard waste-to-energy conversion rates and assumed a conservative reusability percentage. Steps are explained as follows:

- **Step 1: Industrial Waste Classification and Digital Mapping**

Each industry reports its daily waste characteristics to the AI-driven IS-CVMS platform, including material type, quantity, moisture level, and contamination indicators. To identify potential reuse opportunities, the AI system classifies waste into organic, synthetic, hazardous, and residual categories. Furthermore, the AI identifies at an early stage any waste unsuitable for reuse, ensuring it is routed efficiently to Waste-to-Energy facilities. Consequently, every unit of waste is either reused or prepared for responsible energy recovery, minimising the risk of untracked or improper disposal.

- **Step 2: AI-Powered Control Room (Central Decision Hub)**

Following the initial classification, the AI Control Room operates as the central optimiser, with its core functions outlined in Table 3. The IS-CVMS framework facilitates intelligent waste flows across industries by dynamically matching waste outputs with appropriate reuse pathways. Organic waste from food processing facilities is transported to nearby farms for composting, whereas textile offcuts are routed to furniture manufacturers for use as cushion filling. Scrap paper is delivered to packaging manufacturers, plastic trimmings are sorted, recyclable materials are sent to material recovery facilities, and contaminated plastic is sent to waste-to-energy plants. Wood shavings are also transferred to pellet manufacturing industries. Over 90% of waste is successfully repurposed through this integrated system, with only highly contaminated or surplus waste being diverted for energy recovery.

Table 3. Control room functions.

Function	Action
Matchmaking	AWP is linked to NWI instantly (e.g., paper scraps to packaging factories)
Prioritisation	Chooses optimal reuse based on distance, cost, and environmental gain
Alerts	Flag contamination, high hazard, or matching failures
Forecasting	Predicts peak waste seasons to pre-balance reuse capacity

- **Step 3: Smart Industrial Digital Hub**

Within the IS-CVMS framework, Lean 5S practices and AI waste tracking help garment factories reduce textile scrap by 10%. At the same time, smart sensors enable furniture factories to sort wood waste based on quality. By using artificial intelligence, non-reusable plastics and wood dust are assessed for their calorific value and efficiently routed to local Waste-to-Energy plants, with energy output and emission reductions predicted in advance. As a result of this approach, residuals are converted into renewable energy, which eliminates the need to dispose of them in landfills.

- **Step 4: PPP Governance and Empowerment**

Governance within the IS-CVMS framework ensures system integrity through clearly defined roles, as outlined in Table 4. This framework governance ensures transparency, compliance, and operational efficiency across all waste management processes. To ensure accountability at every stage, stakeholders, regulators, facilitators, controllers, and protectors are assigned specific roles. As a result of this structured oversight, waste flows, reuse activities, and energy recovery are managed in a legal, environmentally friendly, and ethical manner.

With the framework, real-time interventions can be made to reinforce compliance and sustainability in real time. When toxic plastics are detected, regulators immediately act to prevent environmental risks, while successful textile reuse efforts by garment firms are recognised and rewarded by regulators. As a result of these mechanisms, trust is built across industries, and the entire system operates transparently and sustainably.

Table 4. Governance within the Alhosani IS-CVMS framework.

Role	Responsibility
Stakeholder	Generates and accepts waste exchanges
Regulator	Monitors for environmental and legal compliance
Facilitator	Manages AI and digital logistics
Controller	Conducts audits, certifies compliance.
Protector	Oversees public health, emissions, and safety regulations

- **Step 5: Knowledge and Capacity Building Portal**

In this step, the Knowledge and Capacity Building Portal become the active learning engine. The platform continuously generates real-time dashboards that display key performance metrics, such as landfill diversion rates, energy recovered through Waste-to-Energy, and CO2 emissions saved, as industries upload and process their waste data. Dashboards help industries visualise their contributions to the circular economy.

Meanwhile, the system compiles monthly case studies from successful reuse operations (such as how crushed paper waste was repurposed into eco-friendly insulation materials). Other industries can replicate and improve on these examples.

Moreover, the portal offers training modules that integrate AI into waste tracking, optimise reuse potential, and apply best practices in industrial symbiosis. These modules ensure system-wide knowledge transfer and skill upgrading for industries, regulators, and facilitators.

The framework continuously improves, scales across sectors, and maintains a living, evolving zero-waste ecosystem through this dynamic exchange of knowledge, feedback, and best practices.

3.5. Outcome of the developed framework

At the end of the framework cycle, strong outcomes were recorded due to systematic waste classification, AI-driven decision-making, industrial matchmaking, energy recovery processes, and governance enforcement. Table 5 summarises those outcomes. 85% landfill diversion was achieved by accurately matching AWP (waste outputs) with NWI (needed inputs) across industries, while routing non-reusable materials to waste treatment plants instead of landfills. The generated energy (2 MWh/day) was generated by AI-optimised routing of residual waste streams with high calorific values, such as plastics and wood dust, to waste-to-energy facilities. Using real-time waste input updates and predictive demand forecasting, the dynamic matchmaking system continuously identifies new cross-sectoral reuse opportunities.

To achieve AI Match Accuracy (93%), we constantly train the AI Control Room on updated material characteristics, reuse histories, logistics optimisation, and environmental benefits. Reduction in emissions (32% versus baseline) was achieved by reducing landfill disposal (avoiding methane emissions) and substituting fossil energy with clean energy generated by controlled WTE. The IS-CVMS framework not only closes material loops but also improves environmental and economic performance at the ecosystem level.

Table 5. Summarises these results.

Metric	Achieved Result	Key Process Leading to Outcome
Landfill Diversion Rate	↑ 85%	AI-driven matchmaking + W.T.E fallback system
Energy Generated (WTE)	2 MWh/day	Calorific analysis + optimized W.T.E routing
New Industrial Waste Exchanges	12 per month	Dynamic AI matchmaking + predictive waste demand modelling
AI Match Accuracy	93%	Machine learning optimisation from continuous waste data training
Emission Reduction	32% versus baseline	Reduced landfill disposal + renewable energy production via WTE

3.6. How is zero waste achieved?

The purpose of this study is to achieve zero industrial waste through a combination of AI-enabled industrial symbiosis, predictive waste management, and coordinated Public-Private Partnership (PPP) governance. According to the simulation, 85% of industrial waste is diverted from landfills through intelligent matching between Associated Waste Produced (AWP) and Needed Waste Inputs (NWI), with textiles and organic waste achieving 100% reuse and paper and wood exceeding 90% reuse. A waste stream that cannot be reused because of quality or compatibility constraints is not discarded; instead, it is systematically routed to waste-to-energy (WTE) facilities, which generate approximately 2 megawatt hours of renewable energy per day. As a result of this closed-loop configuration, no landfills are required. The use of artificial intelligence-driven forecasting further reduces waste accumulation by predicting peak production periods, reducing waste holding time by 40%, and enabling continuous system optimisation. As a result of the high accuracy of AI matching (93%) and the formation of 12 new industrial waste exchange partnerships per month, Zero Waste can be achieved not by static recycling targets, but through a dynamic, data-driven process that adapts continuously to industrial conditions while maintaining environmental and economic performance.

An average of 12 new inter-industrial waste exchange partnerships is formed each month, illustrating the framework's ability to stimulate sustained industrial collaboration and value creation. Beyond technical performance, the study demonstrates the critical role that empowered governance plays in achieving the objectives of the circular economy. In a digitally enabled PPP, the IS-CVMS framework positions government not only as a regulator but as a facilitator, coordinator, and system enabler as well. The proposed framework provides a scalable and transferable blueprint for regions seeking to align industrial development with circular economy objectives, environmental protection, and economic resilience.

4. Conclusions

This study developed and validated an AI-powered Integrated Smart Circular Waste Management System (IS-CVMS) to transform industrial waste management from static coordination to dynamic, intelligent, and governance-ready. Through waste classification, dynamic matching, predictive forecasting, and optimised waste-to-energy routing, the research proves Artificial Intelligence can operationalise industrial symbiosis within a robust PPP framework.

- According to the simulation results, the proposed system is technically feasible and environmentally friendly, achieving 85% landfill diversion, generating approximately 2 MWh/day of renewable energy from residual waste, and reducing CO2-equivalent emissions by 32%.
- With a 93% matching accuracy, the AI engine further validates the reliability of intelligent decision-making in managing heterogeneous and complex industrial waste streams.
- Zero Industrial Waste is not a static end-state, but rather a dynamic, continuously optimised process, enabled by real-time data, intelligent algorithms, and coordinated multistakeholder governance. IS-CVMS overcomes key limitations of traditional recycling and manual coordination approaches, especially for complex, variable waste streams, by integrating AI-driven waste matching, smart manufacturing principles, predictive logistics, and transparent digital oversight.

Overall, this research confirms that, when supported by artificial intelligence, coordinated governance, and continuous system learning, Zero Industrial Waste is a realistic and achievable objective, offering a meaningful path toward sustainable, circular industrial ecosystems. The IS-CVMS framework provides a validated and scalable approach to implementing Zero Industrial Waste, demonstrating AI's role as a system-level enabler of circular industrial performance and public-private collaboration.

Abbreviations

AWP	Associated Waste Produced
IACN	Industrial Alliances Community Network
IS-CVMS	Integrated Smart Circular Waste Management System
LCA	Life Cycle Assessment
NWI	Needed Waste Inputs
PPPs	Public-Private Partnerships
WTE	Waste-To-Energy
ZIW	Zero Industrial Waste

References

1. Peacock, C. (2022). The impacts of industrial waste. Retrieved October 5, 2025, from https://www.aquaread.com/blog/impacts-of-industrial-waste/

2. VLS Environmental Solutions. (2024). Combating pollution through industrial waste management. Retrieved October 5, 2025, from https://www.vlses.com/stay-in-the-know/newsroom/combatting-pollution-through-industrial-waste-management/
3. ACTenviro. (2023). A comprehensive guide to industrial waste management. Retrieved October 5, 2025, from https://www.actenviro.com/industrial-waste/
4. Ghazali, M.S.M.; Mupit, M.; Azni, M.E.; Yaacob, Z.; Ibrahim, K.N.; Sabri, M.Z.; Zahari, M.N.; and Hamzah, A.A. (2025). Food waste generation and economic implications during Ramadan in student rented houses: A pilot study. *Jurnal Ekonomi, Manajemen, Akuntansi dan Keuangan*, 6(4), 1-9.
5. Murshed, M. (2022). The impacts of fuel exports on sustainable economic growth: the importance of controlling environmental pollution in Saudi Arabia. *Energy Reports*, 8, 13708-13722.
6. Jerez, S.; Ventura, M.; Molina, R.; Pariente, M.I.; Martínez, F.; and Melero, J.A. (2021). Comprehensive characterization of an oily sludge from a petrol refinery: A step forward for its valorization within the circular economy strategy. *Journal of Environmental Management*, 285, 112124.
7. Chaturvedi, S.; and Khare, A. (2022). Solid wastes: characteristics, composition and adverse effects on environment and public health. *Asian Journal of Advanced Research and Reports*, 16(7), 9-30.
8. Ellen MacArthur Foundation. (2024). Circular economy introduction. Retrieved October 5, 2025, from https://www.ellenmacarthurfoundation.org/topics/circular-economy-introduction/overview
9. Patwa, N.; Sivarajah, U.; Seetharaman, A.; Sarkar, S.; Maiti, K.; and Hingorani, K. (2021). Towards a circular economy: an emerging economies context. *Journal of Business Research*, 122, 725-735.
10. Institute Veolia. (2021). Industry and waste: toward the circular economy. Retrieved October 5, 2025, from https://www.institut.veolia.org/en/publications/veolia-institute-review-facts-reports/industry-and-waste-toward-circular-economy
11. Obaideen, K.; Shehata, N.; Sayed, E.T.; Abdelkareem, M.A.; Mahmoud, M.S.; and Olabi, A.G. (2022). The role of wastewater treatment in achieving sustainable development goals (SDGs) and sustainability guidelines. *Energy Nexus*, 7, 100112.
12. Kumar, N.; Hasan, S.S.; Srivastava, K.; Akhtar, R.; Yadav, R.K.; and Choubey, V.K. (2022). Lean manufacturing techniques and its implementation: a review. *Materials Today*: *Proceedings*, 64, 1188-1192.
13. Zahraee, S.M.; Tolooie, A.; Abrishami, S.J.; Shiwakoti, N.; and Stasinopoulos, P. (2020). Lean manufacturing analysis of a heater industry based on value stream mapping and computer simulation. *Procedia Manufacturing*, 51, 1379-1386.
14. Siddiqua, A.; Hahladakis, J.N.; and Al-Attiya, W.A.K. (2022). An overview of the environmental pollution and health effects associated with waste landfilling and open dumping. *Environmental Science and Pollution Research*, 29(39), 58514-58536.

15. Williams, H. (2023). *Circular economy and waste management practices*. Retrieved October 5, 2025, from https://www.harriswilliams.com/our-insights/epi-circular-economy-revolutionizing-waste-management-practices
16. Paiva, C.L.; and Ugaya, C.M.L. (2024). Environmental impacts assessment in packaging and its contribution to reducing food waste. *Cleaner and Circular Bioeconomy*, 8, 100083.
17. Ecochain. (2024). Life cycle assessment (LCA) – everything you need to know. Retrieved November 5, 2025, from https://ecochain.com/blog/life-cycle-assessment-lca-guide/
18. Latimer, J. (2024). What is life cycle assessment? Retrieved November 5, 2025, from https://www.vaayu.tech/insights/what-is-lca
19. Osman, A.I.; Mehta, N.; Elgarahy, A.M.; Hefny, M.; Al-Hinai, A.; Al-Muhtaseb, A.; and Rooney, D.W. (2022). Hydrogen production, storage, utilisation and environmental impacts: a review. *Environmental Chemistry Letters*, 20(1), 153-188.
20. Fu, H.; He, W.; Feng, K.; Guo, X.; and Hou, C. (2024). Understanding consumers' willingness to pay for circular products: A multiple model-comparison approach. *Sustainable Production and Consumption*, 45, 67-78.
21. Strezov, V.; and Cho, H.H. (2020). Environmental impact assessment from direct emissions of Australian thermal power generation technologies. *Journal of Cleaner Production*, 270, 122515.
22. Smol, M.; Adam, C.; and Preisner, M. (2020). Circular economy model framework in the European water and wastewater sector. *Journal of Material Cycles and Waste Management*, 22, 682-697.
23. Murthy, V.; and Ramakrishna, S. (2022). A review on global E-waste management: urban mining towards a sustainable future and circular economy. *Sustainability*, 14(2), 647.
24. Alhosani, K.M.; Kaied, Y.O.; Darwish, A.S.; Al-Kayiem, H.H.; and Farrell, P. (2025). A framework for public-private partnerships empowerment towards zero industrial waste in the UAE. *Journal of Engineering Science and Technology*, 20(Special Issue 1), 95-117.
25. Casady, C.B.; Cepparulo, A.; and Giuriato, L. (2024). Public-private partnerships for low-carbon, climate-resilient infrastructure: Insights from the literature. *Journal of Cleaner Production*, 470, 143338.
26. Abdolmaleki, H.; Ahmadi, Z.; Hashemi, E.; and Talebi, S. (2025). A review of the circular economy approach to the construction and demolition wood waste: A 4 R principal perspective. *Cleaner Waste Systems*, 11, 100248.
27. Jean, G. (2025). Explainable AI in manufacturing: Enhancing trust, transparency, and regulatory compliance. Retrieved November 5, 2025, from https://www.researchgate.net/profile/Guillaume-Jean-6/publication/390023479_Explainable_AI_in_Manufacturing_Enhancing_Trust_Transparency_and_Regulatory_Compliance/links/67dc38cffe0f5a760f5b05de/Explainable-AI-in-Manufacturing-Enhancing-Trust-Transparency-and-Regulatory-Compliance.pdf