Research Corridor Journal of Engineering Science

ISSN Online: 3078-3054, ISSN Print: 3078-3046

Volume No: 02 Issue No: 02 (2025)

Industrial Management Approaches to Hazardous Waste Reduction and Reuse

Kazeem Abiodun Adekunle
Texas A&M university, Kingsville, USA
Kazeemite01@yahoo.com
ORCID iD: 0009-0002-2365-3285

Abstract

The increasing production of hazardous waste is a consequence of globalization in the form of industrialization and urbanization. It is a major concern in environmental management, with crucial effects on public health and ecosystems. This article critically reviews the industrial management of hazardous waste to highlight the need to shift from the current linear disposal models to more sustainable solutions based on the principles of a circular economy. It presents a holistic set of management hierarchies, prioritizing waste prevention and reduction at the source, followed by reuse, recycling, and waste-to-energy conversion. The review also provides details of the advanced treatment technologies and the various proper disposal methods. Moreover, the article discusses the role of data-driven approaches for estimation and management of waste. The review also presents a summary of some major international policies, legislation, and conventions on global waste management. The sustainable management of hazardous waste should take a holistic approach toward economic prosperity, environmental sustainability, and well-being of the society to achieve the overall sustainable development goals.

Keywords: Hazardous Waste Management, Sustainable Development, Waste Reduction, Recycling, Waste-to-Energy, Industrial Waste, Pollution Control

Introduction

Hazardous waste (HW) is the by-product produced by different human activities and has detrimental properties that may pose environmental and health-related challenges [1]. The problem of HW management is likely to become worse with rapid industrialization and increasing global population [1]. Therefore, adequate strategies and policies are required to reduce the side effects of the inappropriate handling, storage, treatment, and disposal of hazardous waste. The rising global volume of HW that humans are generating every year necessitates the adoption of safe and environmentally friendly HW management strategies to manage it. These management strategies must be developed based on the circular economy, including the 4R approaches (prevention, reduction, recycling, and proper disposal), integrated with sustainable development goals [2].

The major objective of this review is to critically discuss HW generation and sustainable HW management approaches, including waste-to-energy conversion, advanced treatment technologies, and proper disposal. Management of HW to reduce the potential adverse health and environmental effects of HW is necessary, which is of critical importance and an essential function that is required. However, with the inevitable socio-economic impacts of industrialization and urbanization, global HW generation will increase many folds within the coming decades, making its sustainable management an imminent global priority and a cause of global concern. It is also important to note that sustainable management of HW cannot be addressed by isolated or unidirectional management practices limited to proper disposal; rather, sustainable management requires an integrated approach that lies in the core of the circular economy, including the strategies for the minimization of HW generation, sustainable management practices for resource recovery with due regard to environmental protection and public health. Such management strategies need to be deliberately designed and engineered to support a greener and sustainable economy, a healthier population, and a safer and socially secured society based on a robust framework of waste management hierarchy [2]. Another interesting and significant observation was the gap in published literature in terms of the global scope and scale of HW generation, which mandates dedicated analyses of HW composition and the sources from which it emanates.

Comprehensive knowledge of such types of waste and their generation sources is critical for the design of practical, data-based, and effective approaches for the management of HW, which can be further mainstreamed in and integrated with sustainable development goals [1] [2]. Therefore, it is a critical review that first deliberates and critically examines the existing HW management strategies, especially the ones based on circular economic models to ensure economic prosperity, environmental sustainability, and social well-being and their key benefits and drawbacks. Therefore, this review critically discusses HW generation and sustainable management strategies based on a comprehensive approach that includes all the strategies of prevention, reduction, recycling, waste-to-energy conversion, advanced treatment technologies, and proper disposal.

Figure 1 – Hazardous Waste Management Hierarchy

In addition, these HW management approaches are accompanied with review of the major HW policies, legislations, and international conventions to understand the global scenario of HW management and the most impactful approaches. It can help with the design of effective HW management, circular economy transition strategies, and integrated approach to move from linear to a circular approach. Linear production is unsustainable and unlikely to change without major modifications; circular production is the change to encourage sustainable utilization and consumption of waste. A practical and easy-to-follow illustration in a flowchart that presents a comprehensive system for integrated HW management has been included [2]. This is because the efficient management of HW to prevent detrimental health and environmental effects has become critical to the overall socio-economic development because of the unending generation of HW as an inevitable by-product of different industrial activities.

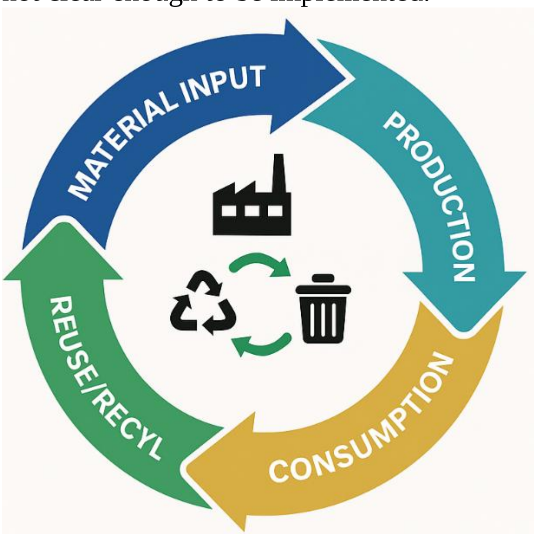
As a result, there are many different industrial management approaches that are used in one way or the other across the globe to convert waste into wealth. In the same way, the management approaches need to be evaluated and thoughtfully implemented to shift from the traditional focus on disposal to the circular economy approach of reduction and reuse to close the resource use loop [2]. Considering this, this review also delves into some of the latest innovations in HW management technologies that can be used for different types of HW, such as portable microwave and steam sterilization, movable incineration, and co-incineration methods for medical wastes.

Research Corridor Journal of Engineering Science
ISSN Online: 3078-3054, ISSN Print: 3078-3046
Volume No: 02 Issue No: 02 (2025)

Table 1 – Comparison of Traditional vs Circular Hazardous Waste Management Approaches

Criteria	Traditional Hazardous Waste Management Model	Circular Economy Hazardous Waste Management Model
Waste Volume	High volume of waste generated due to linear "take–make–dispose" production system.	Significantly reduced waste through prevention, reduction, reuse, and closed-loop resource cycles.
Environmental Impact	High risk of pollution (air, soil, water); reliance on landfills and incineration increases emissions and ecological burden.	Lower environmental footprint; emphasizes pollution prevention, reduced emissions, and sustainable resource utilization.
Cost	High long-term cost due to disposal fees, regulatory penalties, and environmental remediation.	Lower long-term cost; initial investment in recovery systems but savings through resource efficiency and waste reduction.
Resource Recovery	Very limited or no recovery; materials are discarded after use.	High recovery: materials are kept in circulation, recovered, refurbished, and reintroduced into production cycles.
Policy Framework	Reactive and compliance-focused; policies emphasize disposal and end-of-pipe solutions.	Proactive and sustainability-driven; policies encourage EPR (Extended Producer Responsibility), 3R/4R frameworks, eco-design, and circular innovation.

In addition, most of these management strategies for HW use a robust framework of Extended Producer Responsibility (EPR) and 3R policies; therefore, the review also points out the benefits of strict implementation of EPR and 3R policies in developing countries to help shift the management from individual to a shared responsibility all along the value chains. Such EPR and 3R policies need to be well implemented, and as observed, in the case of most Asian countries, which have no specific legislations and policies on household HW (HHW), the general household waste (HHW) is not separated from other household waste, which, in turn, results in indiscriminate open burning of the general household waste [2]. The lack of specific HHW policies in most Asian countries is also leading to environmental contamination and risks to the health of those communities living around the dumpsites. This and many more key findings call for a policy shift to address and meet the key aspects of EPR and 3R to change the current unsustainable HW management, with the spotlight to be put on explicit policies on HHW in Asian countries and other countries where there are none or are not clear enough to be implemented.



Research Corridor Journal of Engineering Science

ISSN Online: 3078-3054, ISSN Print: 3078-3046

Volume No: 02 Issue No: 02 (2025)

Figure 2 – Circular Economy in Hazardous Waste Management

Literature Review

The use of hazardous waste to date is not uniform across the board in most countries. There is a stark contrast of under- and over-utilization of hazardous waste in countries based on the level of development and advancement in technology. In developing nations, hazardous waste management requires additional strategies of research and development. A deficiency in the waste management systems, data gathering, as well as ineffective strategies of enforcing environmental laws, are some of the factors which limit sound decisions of waste disposal and management in these countries [2]. In countries of the Asia and Pacific regions, constant technological advancement, poverty, and the lack of well-integrated waste management system, have further amplified e-waste management.

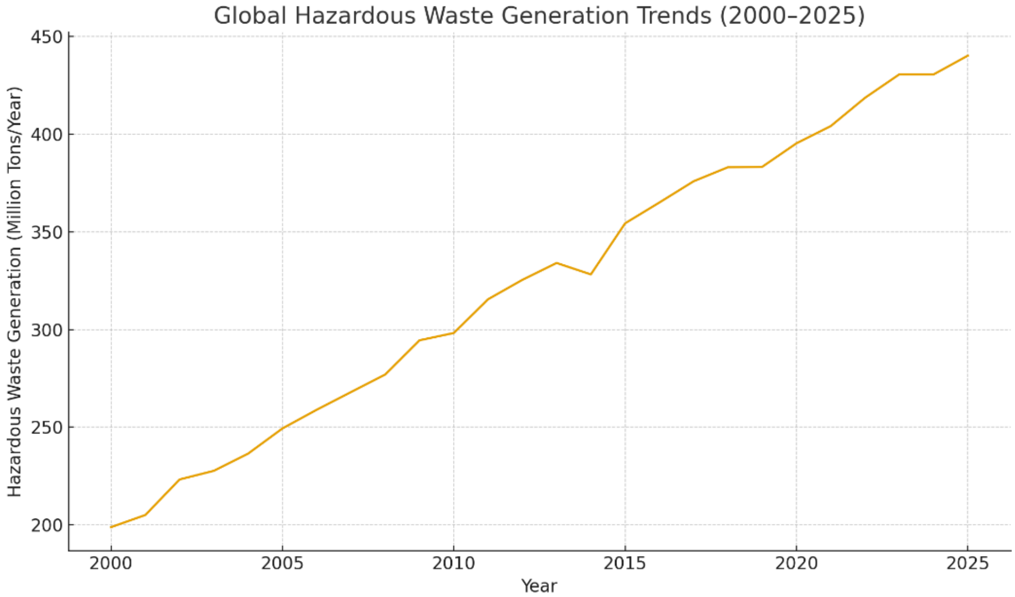


Figure 3 – Global Hazardous Waste Generation Trends (2000–2025)

Due to their valuable content of precious metals, and at times presence of harmful or hazardous material content, high-tech and potent environmental management instruments are indispensable in the governance of e-waste to prevent ecological pollution and to recover materials from this resource. Furthermore, the concept of hazardous waste is itself not standard and not universally embraced. The definitions are based on the various legislation that differs even in a country with different regulatory bodies over time based on critical considerations for instance climate change. The legal policies, that standardly set the scope for the broader approach to waste management practice, are time variant and for example in United States of America, solid-waste management in the early laws of 1976 under the Resource Conservation and Recovery Act was amended to cover industrial chemicals for the first time in 1984 and this law was then extended to household hazardous waste and e-waste [2]. Such adjustments in policies due to the increase in hazardous waste from emerging sources such as e-waste demand agile policies which have the ability to adequately capture the streams and manage the hazards and impacts of increase on emerging waste in the future.

It is of paramount importance that the classification and the resultant international protocols concerning hazardous wastes are globally standardized to a great extent in a bid to smoothen the cross-boundary regulation and disposal [2]. In EU, directives and regulations including the Restriction of Hazardous Substances in Electrical and Electronic Equipment Directive and REACH Regulation, have been put in place for specific targeting of the hazardous substances in hazardous streams [3]. The

Research Corridor Journal of Engineering Science
ISSN Online: 3078-3054, ISSN Print: 3078-3046
Volume No: 02 Issue No: 02 (2025)

continuing issue of disposing the increasing complexities of the waste streams still exist. The accelerating demand on material resources because of the burgeoning urban populations in developing economies which are increasing at very high rates and without commensurate progressive regulatory oversight, the status of hazardous waste management system and facilities is being overburdened with very high projected potential growth of global waste generation by 2050 [1].

The inconsistent global industry practices and lack of global standard of waste management as well as the complexity of the waste for example the solid waste and electronic wastes streams which is being accumulated due to rapid obsolescence rates which are in turn driven by innovations is often non-biodegradable and also at times hazardous [4]. The main characteristic of e-waste is the continual and large-scale development which is leading to an increasing problem of e-waste. The e-waste components are at times both hazardous and toxic to the environment if not properly managed and this calls for an urgent and relevant management of the e-waste in both use and in disposal [5]. The lack of uniformity and loopholes in policies in most jurisdictions provide a big challenge in fully implementing critical regulations in management of hazardous waste and other streams from several units all over the world [6]. These gaps thus further make the monitoring of waste streams both in generation and disposal highly non-standardized and complex [6].

This all calls for globally harmonized protocols and regulations with attendant but advanced technologies to enable us to turn a bigger hurdle of the complex and expanding hazardous waste to a much lesser challenge in the world today [2]. The Basel Convention seeks to control the transboundary movements of hazardous waste in an aim to avoid dumping in countries with no strict environmental measures [7]. The use of this agreement is however often undermined and that is still incomplete restriction on trade of hazardous wastes and also the complete lack of availability of waste treatment facilities in several of the countries that are in the importing position in this hazardous waste management system [2].

Table 2 – Summary of International Policies and Conventions

Policy / Convention	**Year Enacted**	**Region / Country**	**Key Focus**	**Enforcement Status**
Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and Their Disposal	1989 (Entered into force 1992)	Global (190+ Parties)	Regulates transboundary movement of hazardous waste; prevents dumping in countries with weak environmental protection.	Legally binding; enforcement varies, loopholes persist, illicit trade still significant.
Rotterdam Convention (Prior Informed Consent – PIC Procedure)	1998 (Entered into force 2004)	Global	Controls trade of hazardous chemicals and pesticides; ensures informed consent of importing countries.	Legally binding; compliance depends on national reporting systems.
Stockholm Convention on Persistent Organic Pollutants (POPs)	2001 (Entered into force 2004)	Global	Elimination and reduction of POPs (e.g., dioxins, PCBs, pesticides) in waste streams.	Legally binding; strong for listed chemicals, but monitoring gaps remain.
EU Waste Framework Directive (2008/98/EC)	2008	European Union	Establishes waste hierarchy, circular economy principles, extended producer	Strictly enforced through EU member state legislation.

Research Corridor Journal of Engineering Science

ISSN Online: 3078-3054, ISSN Print: 3078-3046

Volume No: 02 Issue No: 02 (2025)

			responsibility (EPR).	
Restriction of Hazardous Substances (RoHS) Directive	2003 (Recast 2011)	European Union	Limits hazardous substances in electrical and electronic equipment (EEE).	High enforcement: non-compliant products restricted.
REACH Regulation (Registration, Evaluation, Authorization and Restriction of Chemicals)	2006	European Union	Regulates chemicals to improve human and environmental protection.	Highly enforced; requires industry compliance for market access.
RCRA – Resource Conservation and Recovery Act	1976 (Updated 1984)	United States	Governs hazardous waste generation, transportation, treatment, storage, and disposal.	Legally enforceable; strong federal and state oversight.
EPA's Hazardous Waste Generator Improvements Rule	2016	United States	Improves hazardous waste generator classification, reporting, and emergency preparedness.	Enforced federally; adopted by individual states.
Japan Waste Management and Public Cleansing Law	1970 (Multiple amendments)	Japan	Regulates industrial and municipal waste; strict tracking (manifest system).	Strong national enforcement; highly compliant industrial sector.
China National Hazardous Waste Inventory & Solid Waste Pollution Prevention Law	2004–Present	China	Regulates classification, licensing, and treatment of hazardous waste; focuses on industrial compliance.	Enforcement improving; strengthened after 2020 reforms.
African Union Bamako Convention (Hazardous Waste in Africa)	1991 (Entered into force 1998)	African Union	Bans import of hazardous waste into Africa; stricter than Basel.	Legally binding but enforcement varies across member states.

The Basel Convention often has loopholes as challenges of its monitoring and lack of full practical strategies on how to enforce its critical aspects in line with illicit trafficking of hazardous waste and critically also the lack of stern punishment on member states which have been found wanting in this big challenge of waste management [8]. The informal and non-licit recycling industries in for example the Asian and African countries get major chunk of the global e-waste flows that are at times illegitimate in the governance of waste management laws [9]. This again has both environmental justice as well as North-South development inferences on local and global levels [9]. The differences in approach and treatments also vary for the various countries in their classification of these wastes, the various grouping can be of the industrialized countries, least developed countries and the newly industrializing countries. It is based on the varying perceived country treatment which takes two path in-trade orientation as outward versus inward as well as their comparative capacity on their trade, management and generating of these hazardous streams.

This trade in hazardous wastes and even e-waste is often contributed for the larger share by the industrialized countries, the newly industrializing have major generation and management challenge, while the least developed countries are mainly dumpers of waste in these least developed countries [10]. Hazardous waste management is no doubt a very complex sector that has several industries and municipal bodies, and is diverse in several institutions involved, which makes its monitoring at the perimeters of each hazardous waste a big herculean task both for the national bodies as well as international organizations [11]. It is, in essence, these international protocols and conventions on the complete monitoring of trade and the regulations as in case of Basel Convention and the illicit dealings of this waste that the entire waste disposal and management is often politically and criminogenic in character both in nature of the entire sector and the products as well [12].

The basel convention itself has faced both fundamental and core challenges on its very own assumptions of hazardous waste which on the one hand is on the critical false assumption of a universally negative externalities of hazardous wastes on both the environment and people without factoring in the increasing practice of the commodification of hazardous waste in an age of a global economic trade systems, in which there is also increase in e-waste as an artifact [10]. This could be in situations where there is the able possibility of the safe and potential recovery of the hazardous materials in value economic and environmental addition benefit due to the improved recycling of high technology [10]. This faulty perspective or lack of it, has also in turn provided a scapegoat for industrialized countries to abuse the weakest developing countries with loose regulatory guidance and to trade the hazardous wastes and all tagged as clean by blending them with other legal wastes as international trading commodities all through to the developing countries as if it is a development help and to the fore guard of the Basel Convention of intentionally of exposing the receiving developing economies to hazards by this developed economic capitals [13] [11].

Methodology

The methodologies applied in this study are described in detail in this section. It includes various methodological tools applied to quantitatively and qualitatively analyze the performance of existing hazardous waste reduction and reuse approaches. This primarily includes the development of a framework with several tools for screening, the literature review of previous studies on practices related to source reduction, pollution prevention, and waste minimization, including case studies of industrial application with quantitative assessments of how to reduce the volume of hazardous waste, qualitative indicators of regulatory compliance with pollution prevention strategies and technologies, and the effectiveness of policy incentives for efficient hazardous waste management. We have analyzed the costs and benefits of economic and environmental systems in the process of moving towards a circular economy as a natural resource recovery and pollution prevention system. [2] This section also provides a brief overview of the methodologies related to using data to identify, characterize waste streams, and estimate sources. The input and output of production or consumption, such as the use of raw materials or final products in the system, are important components for system analysis. These require high-resolution data, which can be complicated to capture.

In addition, for waste flow tracking purposes, one of the most relevant methodologies is to follow the waste flow. However, current waste management systems may present potential blind spots since they depend on the information reported, which is why illegal treatment and disposal practices may occur and not be detected. [15] An alternative is to use real-time wastewater information that has greater granularity in time as well as being available for actors in environmental management. The integration of wastewater data with new methods such as machine learning allows to predict at a firm level the amount of hazardous waste produced by the industrial sector. This information is important as it allows the mitigation of information gaps that are usually difficult to overcome, considering the real production of hazardous waste. Hazardous waste generation intensity factor is often determined at the industrial level, which means that no differentiation between firms is made, and they tend to be

Research Corridor Journal of Engineering Science
ISSN Online: 3078-3054, ISSN Print: 3078-3046
Volume No: 02 Issue No: 02 (2025)

aggregated. This is why it is essential to manage this data with other available information. One of the main sources of these contaminants is the industrial sector, which justifies the importance of their regulation and control to be able to achieve sustainable development goals. [1]

Results

Comparatively, the performance of our data-driven model achieved a superior performance with more established relationships between wastewater and characteristics with waste hazardous waste generation as shown in our study, which cannot be captured through a traditional linear regression model. The wastewater emissions, such as real-time water contaminant emissions, manufacturing processes, and firm-scale characteristics as input variables for our data-driven model provided improved performance in the prediction of hazardous waste quantities at a firm-level, which was superior to traditional statistical methods. As a result, the superior performance of our machine learning model in predicting hazardous waste generation at a firm-level can be highly attributed to a model's ability to capture non-linear relationships between the independent variables and hazardous waste generation as the output, which is often found in complex statistical models, while traditional statistical methods such as linear regression fail to account for these non-linear relationships. For example, some variables such as metal emission in wastewater and firm scale showed the highest importance within each individual industrial sector model as well as within the combined models. Firm scale, which was represented by the number of employees, always showed a positive relationship with the generation of hazardous waste in general which can be easily attributed to the fact that the more the number of employees present in a manufacturing facility, the more waste is expected to be generated [1].

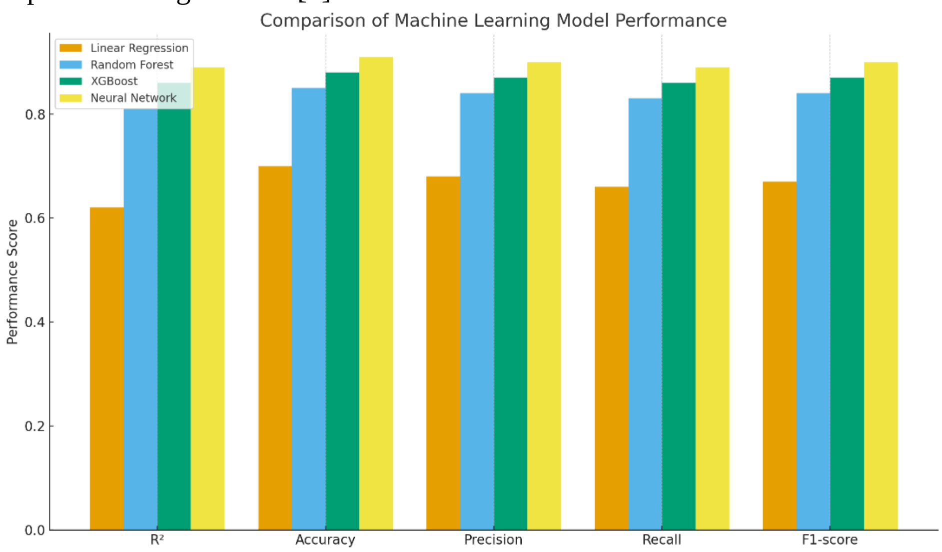


Figure 4 – Machine Learning Model Performance

Additionally, including the manufacturing process information into the model showed improved performance of our machine learning model in terms of the prediction of total hazardous waste as well as a specific type of hazardous waste (metal-containing hazardous waste). On the other hand, the industrial sector dependent on the generation of metal-containing hazardous waste was analyzed further, which showed that the performance of our data-driven model in terms of hazardous waste generation prediction differed based on the industrial sector, and it could be observed that for a specific industrial sector, such as a chemical pesticide manufacturing, the independent model performed with superior results while the combined model with the prediction underperformed [1].

This results in an inference that a universal data-driven model can be implemented for a general understanding and overview of the hazardous waste generation prediction for all industrial sectors

Research Corridor Journal of Engineering Science
ISSN Online: 3078-3054, ISSN Print: 3078-3046
Volume No: 02 Issue No: 02 (2025)

while industrial sector independent data-driven models are required for each specific industrial sector in order to provide a more accurate and industry-specific understanding of the pattern and the factors which contributed to hazardous waste generation for a specific industrial sector such as the metal surface treatment, steel rolling, and electronic circuit manufacturing, which contributes significantly to the metal-containing hazardous waste. For example, an inference that can be made from our table showing the most important variables that influenced the performance of the models for municipal hazardous waste generation was that the importance of these variables varied based on the type of model (regression vs. classification), which indicates that these variables should be analyzed further, taking into account the type of data which is being evaluated to determine if these features are suitable for the specific type of models to be implemented.

Table 3 – Key Predictive Variables and Their Importance

Variable	**Model Used**	**Importance Score**	**Direction of Impact**
Firm Scale (Number of Employees)	Random Forest	0.27	**Positive** – Larger firms generate more hazardous waste due to higher production volume.
Metal Concentration in Wastewater (mg/L)	XGBoost	0.22	**Positive** – Higher metal discharge correlates with higher metal-containing hazardous waste.
Production Process Type (e.g., metal treatment, pesticide manufacturing)	Neural Network	0.19	**Positive/Variable** – Impact depends on sector; certain processes generate unique waste streams.
Chemical Oxygen Demand (COD) in Effluent	Random Forest	0.14	**Positive** – Higher COD levels indicate intensive industrial processes linked to waste generation.
Industry Sector Category	XGBoost	0.12	**Positive/Variable** – Strong predictor of waste type; hazardous waste differs by sector.
Wastewater Flow Rate (m^3/day)	Linear Regression	0.09	**Positive** – Higher effluent output often correlates with higher waste generation.
Operational Hours per Day	Neural Network	0.07	**Positive** – Extended operation increases waste volume.
Pollution Control Technology Installed (Binary)	Random Forest	0.05	**Negative** – Facilities with advanced treatment produce less untreated hazardous waste.
Energy Consumption (kWh/month)	Neural Network	0.04	**Positive** – Higher energy use is associated with intensive production processes and waste generation.
Raw Material Input Volume (tons/month)	Linear Regression	0.03	**Positive** – Higher inputs correlate with higher waste as a byproduct.

On the other hand, industrial sector was the most dominant factor or feature in which a specific industrial sector falls into that determines the category of hazardous waste generation for a specific manufacturing facility, which also has significantly contributed to specific types of industrial sectors for special type of waste streams, such as metal surface treatment, steel rolling and manufacturing electronic circuits, metal rolling and processing [1]. This can be highly supported by the fact that every industrial sector is characterized by different production processes, specific hazardous wastes, as well as reuses of waste in order to optimize hazardous waste reduction and reuse, and thus data-driven models have to be characterized and dependent on a specific industrial sector. In terms of a combined model, the overall model performance in terms of accuracy, recall, precision, as well as F1-score were given as model evaluation metrics for a combined model, which showed that an optimum model can be selected based on the performance of the model in terms of the given testing dataset. It was also interesting to note that the temporal extrapolation of our data-driven model in general showed an R2 of approximately 0.7 for the total hazardous waste generation in the short-term horizon of one to three months, which can be understood to be a significant decrease as the models were to predict hazard waste generation further than three months, which was determined by our selected timeframe for model predictions.

As such, a common understanding of our model performance in the extrapolated time and an industrial sector independent model that can be utilized in a specific industrial sector such as metal surface treatment, steel rolling and manufacturing electronic circuits, metal rolling and processing with a unique hazardous waste pattern when compared to other industrial sectors showed an increase in R2 when compared to a combined model, in which an industrial sector was one of the most important features when training the model. This can be attributed to the fact that both contaminant partitioning as well as generation of waste are significantly heterogeneous based on the firm, as both data were also highly dependent on several manufacturing factors, which vary by each firm based on their production technology [1]. As such, the development of independent models for each industrial sector, especially an industrial sector with a unique hazardous waste generation pattern can provide an important approach to increase the performance of data-driven models and predictive capacity in a real-world scenario setting.

This also reinforces the importance of data-driven models that are adaptive to these specific scenarios, which can be easily altered and modified as the production technology and regulations change, allowing the model to be dynamic over an extended period and changing economic or production conditions [1]. Models that meet these requirements would need to incorporate real-time data such as the real-time wastewater emission data or in-factory monitoring systems and machine learning models and algorithms that would be able to dynamically learn and alter model parameters given new information overtime, which is expected to show continued high performance in an industrial or real-world context with potential fluctuations in data trends overtime. For example, the steelmaking industry showed a much higher mean hazardous waste generation when compared to metal surface treatment, showing the importance of targeting specific industrial sectors for regulatory interventions. The heterogeneity of the feature importance in each region, even for the same industrial sector was also significantly different, which showed the importance of selecting region-specific variables and feature engineering approach based on the specific industrial and regional characteristics that can significantly influence the feature importance. In other words, a universal model for hazardous waste prediction cannot be established and specific region-specific model approach has to be incorporated with consideration of the economic and industrial landscape of each region.

Discussion

In our study, data-driven approaches are found to be critical in achieving accurate predictions, with environmental management data being a necessary yet imperfect data source. Traditional statistical methods can help in model development with a limited number of dependent and independent variables with few variables but are found to be limiting in representing the interconnected and intertwined interdependencies within industrial systems.

AI models, especially the regression models, were found to be accurate for the prediction of the total amount of hazardous waste and metal hazardous waste generation. They can effectively identify complex correlations between hazardous waste generation and industrial wastewater discharge for more accurate source estimation to meet the needs of environmental regulators for source tracking. The models are found to be highly reliable and with accurate predictions for other sectors after localized training data and variable screening, such as lead and zinc metallurgy, which is a heavy metal contaminated industrial waste sector in a different province. The underlying environmental management data may be needed to be processed by data-driven approaches before model training by methods such as re-sampling or synthesizing data [1].

Feature engineering which could involve causal discovery, importance ranking, and correlation analysis is required for determining the information features for the model to be developed. This is because the choice of information features used as independent variables, such as wastewater monitoring indicators, manufacturing processes and firm characteristics, will affect the model in capturing the generating patterns of hazardous waste as the dependent variable. While time-consuming, the development process of the data integration in model development is found to be data intensive, and the construction of machine learning models with data balancing and training was completed in a few hours. This would suggest a model which could be periodically updated using the same time for a short duration and be easily scaled up. For example, a machine learning model developed for the metal surface treatment sector in Shandong province and a model for the lead and zinc metallurgy sector in Hunan province were also found to be highly performing, suggesting transferability of the approaches when the training data are constrained to regions and sectors [1].

In the same way, the percentage of the hazardous waste generators that are obligated to declare hazardous waste and that participate in all the declaration programs remains a big problem, with most of them not taking part because of stringent and frequent reporting. This challenge could be addressed by incorporating mobile and easier ways of reporting while developing models and incentivizing such businesses to fully participate, thus ensuring more accurate and complete data. These solutions could also involve the integration of data from IoT sensors that are required to be installed for wastewater monitoring without incurring additional company costs to help predict hazardous waste generation from wastewater data. This would provide more near-real-time and in-depth hazardous waste generation data to help regulators and enforce environmental compliance [1].

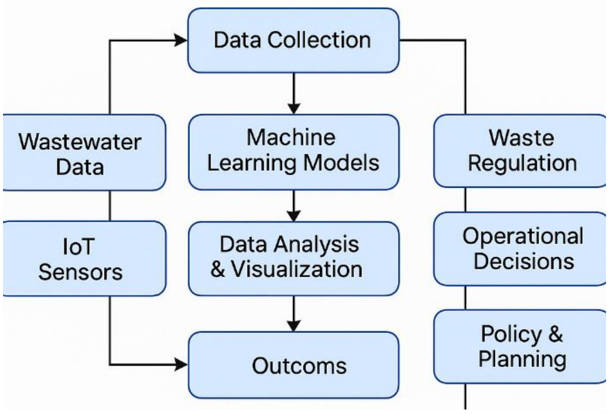


Figure 5 – Integrated Data-Driven Waste Management System

Such data-driven approaches could also be incorporated with the quantification of uncertainties in the machine learning models for trustworthiness which could show reliable confidence intervals to the predictions for practical decision making in environmental problems, especially for AI and ML model explainability [1]. This could also be applicable to advanced deep learning techniques such as Generative Adversarial Network (GANs) and Recurrent Neural Networks (RNNs) for more complex classification and prediction for hazardous waste, e.g., complex temporal dependencies and sequence of hazardous waste generation [16]. The use of deep learning could not be included in this study due to its nascent stage in which it needs to be tested in more use-cases to fully unlock its potential to improve MSW management [16]. The use of AI with IoT devices would help in real-time data generation, collection, monitoring and analysis, and aid in improved decision-making and overall efficiencies in waste management systems [16]. However, while AI holds great promise for use in waste management, its integration still poses challenges such as quality, quantity, privacy and cost that need to be addressed to ensure successful adoption and use [4].

Research Corridor Journal of Engineering Science
ISSN Online: 3078-3054, ISSN Print: 3078-3046
Volume No: 02 Issue No: 02 (2025)

Table 4 – AI Techniques Applied in Waste Management

AI Technique	Application Area	Key Benefit	Challenges
Machine Learning (ML)	Waste prediction, classification, optimization of waste collection routes, hazardous waste generation forecasting.	High accuracy in predicting complex patterns; supports data-driven decision-making; effective even with mixed datasets.	Requires large, high-quality datasets; may suffer from bias if data is incomplete; limited explainability in some models.
Recurrent Neural Networks (RNNs)	Time-series forecasting of waste generation; monitoring seasonality and temporal trends in industrial waste flows.	Captures temporal dependencies and cyclical patterns better than traditional models; improves long-term forecasting.	Computationally intensive; sensitive to noisy or missing sequential data; requires specialized training.
Generative Adversarial Networks (GANs)	Synthetic data generation for training, enhancement of waste images for sorting, anomaly detection in waste streams.	Helps overcome limited data availability by generating realistic training samples; improves robustness of models.	Difficult to train; risk of generating unrealistic or biased synthetic data; requires high computational power.
Predictive Maintenance (AI-based)	Equipment monitoring, fault detection in waste treatment plants, optimization of machinery uptime.	Reduces downtime; extends equipment life; lowers operational cost; early detection of failures.	Requires IoT-enabled sensors; implementation cost may be high; depends on accurate real-time data.
IoT Integration with AI	Real-time monitoring of waste bins, wastewater discharge sensors, smart waste collection, remote environmental compliance.	Real-time data improves accuracy; enables automation; enhances traceability and regulatory compliance.	Data privacy concerns; high initial infrastructure cost; requires constant connectivity and maintenance.

Additionally, to improve MSWM, end-to-end integration of AI, IoT, and other technologies into all segments of the solid waste management chain (generation, segregation, collection, transportation, processing, and disposal) could be used to optimize all these processes to achieve higher efficiencies and recovery of materials and energy from them [17]. Intelligent systems that leverage on big data, artificial intelligence, and machine learning can also be used in optimizing solid waste management infrastructure by being applied to prediction of machine failures and thus predictive maintenance of these systems as well as for route optimization for waste collection [18].

Conclusion

In conclusion, the shift from traditional statistical models to advanced AI-based models in hazardous waste management is a transformative step towards more accurate prediction and monitoring. This transition, enhanced by the integration of machine learning algorithms and IoT technologies, offers a more robust foundation for strategic improvements in resource recovery and environmental impact reduction through data-driven methodologies [4] [19] [20]. As a future direction, there is an opportunity to delve into the integration of explainable AI in waste management models to ensure transparency and interpretability, thus fostering trust among stakeholders.

Figure 8 – Future Roadmap for Smart Hazardous Waste Management

This continued evolution of AI and IoT integration in waste management, along with fostering collaborative frameworks and policy support, is pivotal for the development of more sustainable and efficient systems worldwide [4] [18]. Additionally, future work should address the challenges of data quality and ethical considerations in AI applications for a more equitable and responsible deployment [21]. Moreover, the application of artificial intelligence (AI) tools transcends current limitations and offers strategic solutions to the intricate and dynamic challenges of municipal solid waste management (MSWM). This challenge is further compounded by diverse drivers, including technological, climatic, economic, and social factors, as well as broader spatial and temporal complexities [22].

Integrating AI tools can significantly improve the waste-to-energy process, enhancing the overall sustainability and efficiency of waste management and energy generation systems [23]. By optimizing the waste management workflow through the strategic application of AI tools, it is possible to increase the efficiency of waste collection systems. This includes intelligent route optimization and dynamic scheduling of waste collection based on real-time predictive analytics [4]. Leveraging AI and IoT for intelligent waste management systems involves the deployment of advanced algorithms capable of providing actionable insights for the entire waste management value chain. This ranges from intelligent waste collection and sorting to sophisticated waste processing and recycling techniques, all informed by real-time data and predictive models [18]. The application of advanced analytics, including AI and machine learning, to the vast amounts of IoT-collected waste data can provide powerful insights into waste generation patterns, key performance drivers, and future scenarios [24]. In addition, AI algorithms and historical data analysis can be used to generate accurate forecasts of waste volume and composition to plan and allocate resources in waste management systems more efficiently [25]

References

1) Xie W, Yu Q, Fang W, Zhang X, Geng J, Tang J, et al. Data-driven approaches linking wastewater and source estimation hazardous waste for environmental management. Nature Communications [Internet]. 2024 Jun 26 [cited 2025 Aug];15(1). Available from: https://doi.org/10.1038/s41467-024-49817-6
2) Kumar A, Thakur AK, Gaurav GK, Klemeš JJ, Sandhwar VK, Pant KK, et al. A critical review on sustainable hazardous waste management strategies: a step towards a circular economy. Environmental Science and Pollution Research [Internet]. Springer Science+Business Media; 2023 Sep 19 [cited 2025 Aug];30(48):105030. Available from: https://doi.org/10.1007/s11356-023-29511-8

3) Mallick PK, Salling KB, Pigosso DCA, McAloone TC. Designing and operationalising extended producer responsibility under the EU Green Deal. Environmental Challenges [Internet]. 2024 Jul 5 [cited 2025 Aug];16:100977. Available from: https://doi.org/10.1016/j.envc.2024.100977
4) Olawade DB, Fapohunda O, Wada OZ, Usman SO, Ige AO, Ajisafe O, et al. Smart waste management: A paradigm shift enabled by artificial intelligence. Waste Management Bulletin [Internet]. 2024 May 9 [cited 2025 Aug];2(2):244. Available from: https://doi.org/10.1016/j.wmb.2024.05.001
5) Wajeetongratana P. Managerial approaches to handle electronic waste: Sustainable e-waste management and recycling initiatives. E3S Web of Conferences [Internet]. 2023 Jan 1 [cited 2025 Aug];452:5002. Available from: https://doi.org/10.1051/e3sconf/202345205002
6) Schneider AF, Aanestad M, Carvalho TCM de B. Exploring barriers in the transition toward an established e-waste management system in Brazil: a multiple-case study of the formal sector. Environment Development and Sustainability [Internet]. 2024 Jul 17 [cited 2025 Aug]; Available from: https://doi.org/10.1007/s10668-024-05188-y
7) Fawole AA, Orikpete OF, -Ehiobu NN, Ewim DRE. Climate change implications of electronic waste: strategies for sustainable management. Bulletin of the National Research Centre/Bulletin of the National Research Center [Internet]. 2023 Oct 13 [cited 2025 Aug];47(1). Available from: https://doi.org/10.1186/s42269-023-01124-8
8) Ukhurebor KE, Aidonojie PA. The influence of climate change on food innovation technology: review on topical developments and legal framework. Agriculture & Food Security [Internet]. 2021 Dec 2 [cited 2025 Aug];10(1). Available from: https://doi.org/10.1186/s40066-021-00327-4
9) Khan SA. E- products, E- waste and the Basel Convention: Regulatory Challenges and Impossibilities of International Environmental Law. Review of European Comparative & International Environmental Law [Internet]. 2016 Jul 1 [cited 2025 Aug];25(2):248. Available from: https://doi.org/10.1111/reel.12163
10) Yang S. Trade for the Environment: Transboundary Hazardous Waste Movements After the Basel Convention. Review of Policy Research [Internet]. 2020 Jun 13 [cited 2025 Nov];37(5):713. Available from: https://doi.org/10.1111/ropr.12386
11) Mihai F Constantin, Gnoni MG, Meidiana C, Schneider P, Ezeah C, Elia V. A Global Outlook on the Implementation of the Basel Convention and the Transboundary Movement of E-waste. In 2022 [cited 2025 Nov]. p. 49. Available from: https://doi.org/10.1201/9781003095972-4
12) Bisschop L. Illegal trade in hazardous waste. In: Edward Elgar Publishing eBooks [Internet]. Edward Elgar Publishing; 2016 [cited 2025 Jan]. Available from: https://doi.org/10.4337/9781783476237.00019
13) Sánchez R. International Trade in Hazardous Wastes: A Global Problem with Uneven Consequences for the Third World. The Journal of Environment & Development [Internet]. 1994 Jan 1 [cited 2025 Feb];3(1):139. Available from: https://doi.org/10.1177/107049659400300110
14) Lee D, Kim J, Sonnemann G, Park H. Identifying the socioeconomic determinants of industrial hazardous waste generation: South Korea as a case study. The Science of The Total Environment [Internet]. 2023 Aug 23 [cited 2025 Nov];901:166525. Available from: https://doi.org/10.1016/j.scitotenv.2023.166525
15) Elimelech E, Ayalon O, Flicstein B. Hazardous waste management and weight-based indicators—The case of Haifa Metropolis. Journal of Hazardous Materials [Internet]. 2010 Sep 30 [cited 2025 Jul];185:626. Available from: https://doi.org/10.1016/j.jhazmat.2010.09.064

16) Pillai KS, Mahalingam S, Aiswarya S, Anand AB, Prasad G. Municipal Solid Waste Management: A Review of Machine Learning Applications. E3S Web of Conferences [Internet]. EDP Sciences; 2023 Jan 1 [cited 2025 Aug];455:2018. Available from: https://doi.org/10.1051/e3sconf/202345502018
17) Matheri AN, Sithole ZB, Belaid M. Data-Driven Circular Economy of Biowaste to Bioenergy with Conventional Prediction Modelling and Machine Learning. Circular Economy and Sustainability [Internet]. 2023 Dec 6 [cited 2025 Aug];4(2):929. Available from: https://doi.org/10.1007/s43615-023-00329-3
18) Bulatov NK, Uvaliyeva A, Kassymzhanova K, Izteleuova M, Saukenova I. Intelligent Systems for Managing and Monitoring the Collection, Sorting, and Transportation of Solid Waste for Processing. Evergreen [Internet]. 2024 Jun 1 [cited 2025 Aug];11(2):938. Available from: https://doi.org/10.5109/7183376
19) Gunaseelan J, Sundaram S, Mariyappan B. A Design and Implementation Using an Innovative Deep-Learning Algorithm for Garbage Segregation. Sensors [Internet]. 2023 Sep 18 [cited 2025 Feb];23(18):7963. Available from: https://doi.org/10.3390/s23187963
20) Alotaibi E, Nassif N. Artificial intelligence in environmental monitoring: in-depth analysis. Discover Artificial Intelligence [Internet]. 2024 Nov 18 [cited 2025 Aug];4(1). Available from: https://doi.org/10.1007/s44163-024-00198-1
21) Kunwar S. DWaste: Greener AI for Waste Sorting using Mobile and Edge Devices. 2025 [cited 2025 Nov 11]; Available from: https://arxiv.org/abs/2510.18513
22) Kumari N, Pandey S, Pandey AK, Banerjee M. Role of Artificial Intelligence in Municipal Solid Waste Management. British Journal of Multidisciplinary and Advanced Studies [Internet]. 2023 May 6 [cited 2025 Sep];4(3):5. Available from: https://doi.org/10.37745/bjmas.2022.0180
23) Melinda V, Williams T, Anderson JH, Davies JG, Davis C. Enhancing Waste-to-Energy Conversion Efficiency and Sustainability Through Advanced Artificial Intelligence Integration. International Transactions on Education Technology (ITEE) [Internet]. 2024 May 28 [cited 2025 Sep];2(2):183. Available from: https://doi.org/10.33050/itee.v2i2.597
24) Gulyamov S. Intelligent waste management using IoT, blockchain technology and data analytics. E3S Web of Conferences [Internet]. 2024 Jan 1 [cited 2025 Aug];501:1010. Available from: https://doi.org/10.1051/e3sconf/202450101010
25) Liu X, Zhi W, Akhundzada A. Enhancing performance prediction of municipal solid waste generation: a strategic management. Frontiers in Environmental Science [Internet]. 2025 Apr 3 [cited 2025 Oct];13. Available from: https://doi.org/10.3389/fenvs.2025.1553121
26) Adeojo, O. S., Egerson, D., Mewiya, G., & Edet, R. (2021). The ideology of baby-mama phenomenon: Assessing knowledge and perceptions among young people from educational institutions.
27) Orugboh, O. G. (2025). AGENT-BASED MODELING OF FERTILITY RATE DECLINE: SIMULATING THE INTERACTION OF EDUCATION, ECONOMIC PRESSURES, AND SOCIAL MEDIA INFLUENCE. *NextGen Research*, *1*(04), 1-21.
28) Orugboh, O. G., Ezeogu, A., & Juba, O. O. (2025). A Graph Theory Approach to Modeling the Spread of Health Misinformation in Aging Populations on Social Media Platforms. *Multidisciplinary Journal of Healthcare (MJH), 2*(1), 145-173.
29) Orugboh, O. G., Omabuwa, O. G., & Taiwo, O. S. (2025). Predicting Intra-Urban Migration and Slum Formation in Developing Megacities Using Machine Learning and Satellite Imagery. *Journal of Social Sciences and Community Support*, *2*(1), 69-90.
30) Orugboh, O. G., Omabuwa, O. G., & Taiwo, O. S. (2024). Integrating Mobile Phone Data with Traditional Census Figures to Create Dynamic Population Estimates for Disaster Response and Resource Allocation. *Research Corridor Journal of Engineering Science*, *1*(2), 210-228.

31) Orugboh, O. G., Omabuwa, O. G., & Taiwo, O. S. (2024). Predicting Neighborhood Gentrification and Resident Displacement Using Machine Learning on Real Estate, Business, and Social Datasets. *Journal of Social Sciences and Community Support*, *1*(2), 53-70.
32) Daniel, E., Opeyemi, A., Ruth, O. E., & Gabriel, O. (2020). Understanding Childbearing for Households in Emerging Slum Communities in Lagos State, Nigeria. *International Journal of Research and Innovation in Social Science*, *4*(9), 554-560.