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REVIEW

Remediation & Treatment

AI-driven circular economy optimization in waste management: A review of current evidence

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Abstract

The integration of artificial intelligence (AI) and machine learning (ML) in waste management has the potential to significantly advance circular economy objectives by enhancing efficiency, reducing waste, and optimizing resource recovery. However, realising these benefits depends on addressing significant technical, economic, and systemic barriers. AI technologies, such as intelligent waste-sorting systems and predictive models, are transforming how waste is processed and materials are reused. This article critically evaluates the potential and limitations of AI-driven approaches across the waste management lifecycle through a narrative review of peer-reviewed literature published between 2015 and 2025. AI offers a revolutionary approach to waste management, resource recovery, and environmental impact reduction by enabling the processing of massive datasets and automating complex decision-making. However, to fully realize AI's promise, critical issues, including scarce data availability, expensive implementation costs, the requirement for efficient human-AI cooperation, and ethical considerations regarding algorithmic transparency and workforce impacts, must be systematically addressed. Additionally, ethical concerns related to job displacement and the environmental footprint of AI technologies themselves require careful management. This review identifies significant research gaps, including the need for standardized datasets, explainable AI frameworks, and comprehensive lifecycle assessments of AI-driven interventions. Looking to the future, decentralized AI systems, AI-driven global waste trade optimization, blockchain-integrated tracking systems, and AI-enhanced product design offer promising avenues for further innovation. As AI continues to develop, its incorporation into waste management systems will be essential to accelerating the world's shift to a circular economy that is more resource-efficient and sustainable.

KEYWORDS

artificial intelligence, machine learning, recycling optimization, resource recovery, waste management

1 | INTRODUCTION

The global shift toward a circular economy (CE) represents a necessary transformation from the traditional linear model of production and consumption, often described as "take-make-dispose." This linear approach has contributed to significant environmental degradation and resource depletion.[1,2] However, transitioning to circular systems faces substantial technical, economic, and behavioral challenges that technology alone cannot solve. A circular economy aims to prolong the life cycles of resources, materials, and products while emphasizing waste management, cleaner production, and the closure of material loops.[3,4] By minimizing waste generation and promoting reuse, recycling, and energy recovery, a circular economy aims to achieve sustainability while reducing pressure on natural resources.[5]

To effectively implement circular economy principles, waste streams must be managed with unprecedented sophistication, a task where AI and ML technologies show promise but face significant real-world constraints. For example, managing organic waste using circular economy principles can transform waste streams into valuable resources, mitigating environment degradation and lowering greenhouse gas emissions.[6] This is where AI and ML technologies can make a profound impact.

AI technologies have demonstrated the potential to enhance efficiency and optimize processes across industries, from manufacturing to healthcare.[7] In waste management specifically, while AI and ML offer theoretical advantages for revolutionizing how waste is handled, reused, and repurposed,[8,9] practical implementation reveals significant gaps between laboratory performance and industrial-scale deployment. These technologies enable waste management systems to move beyond traditional methods by leveraging large datasets, improving decision-making, and automating complex tasks.[10] For instance, AI-based Material Circularity Assessment (MCA), which evaluates how well materials maintain their value through multiple use cycles, and Extended Producer Responsibility (EPR) strategies, which hold manufacturers accountable for end-of-life product management, can help manage e-waste by analyzing hazardous pollutants, promoting eco-design systems, and ensuring proper processing, recycling, and reuse.[11] However, a critical examination of published studies reveals that many performance claims are based on controlled laboratory conditions or limited pilot projects, with significant uncertainty about scalability, cost-effectiveness, and real-world robustness.

For example, while some studies report dramatic improvements such as waste reduction of 90%, landfill analysis improvements of 40%, and transportation reductions of 15%,[12] these figures derive from simulation models or small-scale implementations under specific conditions (e.g., pre-sorted waste, controlled environments, limited waste stream diversity). The particular contexts, assumptions, boundary conditions, and limitations of these studies are often inadequately disclosed, making it challenging to assess generalizability to diverse real-world waste management systems with varying infrastructure, waste composition, and operational constraints. Furthermore, few studies provide comprehensive cost–benefit analyses that account for the full lifecycle costs of AI system deployment, including hardware, software, data infrastructure, training, maintenance, and energy consumption.

Similarly, claims of classification accuracy exceeding 95%[13] should be contextualized: such performance levels are typically achieved under optimal conditions with clean, well-lit samples of known waste types. Real-world industrial sorting facilities face challenges, including variable lighting, contaminated materials, mixed compositions, sensor wear, and novel waste types not represented in training datasets, all of which can substantially degrade system performance. Long-term performance data from operational industrial facilities remains scarce in the literature.

AI can enhance lifecycle analysis (LCA) by processing large datasets to identify patterns in resource use, material composition, and energy consumption.[14,15] Research suggests that AI techniques may predict environmental impacts of products, though accuracy varies significantly depending on data quality, model architecture, and application context.[16] Beyond lifecycle analysis, AI technologies incorporating ML algorithms and computer vision show potential to improve waste sorting accuracy and speed.[17] However, practical deployment faces challenges, including high capital costs, maintenance requirements, and the need for continuous retraining as waste streams evolve.

Despite growing interest in AI for waste management, several critical gaps exist in current literature:

1. Most existing reviews focus on technical capabilities or environmental benefits in isolation, without systematically examining implementation barriers, cost-effectiveness, scalability challenges, or comparing AI approaches to optimized conventional methods.
2. Critical issues such as algorithmic transparency (explainability), ethical deployment frameworks, workforce transition strategies, and the environmental footprint of AI systems themselves have received limited attention.
3. There is insufficient analysis of the conditions under which AI-driven approaches provide clear advantages over well-implemented traditional or hybrid systems.
4. Standardized performance metrics, reporting frameworks, and comparative evaluation methodologies are lacking, making it difficult to assess the relative merits of different AI approaches.
5. The socio-technical dimensions of AI implementation, including stakeholder acceptance, regulatory frameworks, data governance, and organizational change management, remain underexplored.

This review addresses these gaps by providing a comprehensive, critical evaluation of AI's role in circular economy waste management, synthesizing evidence on both opportunities and constraints, and examining implementation barriers across technical, economic, institutional, and social dimensions. The review aims to:

1. Systematically map the current landscape of AI applications in waste management.
2. Critically evaluate the evidence base for claimed performance improvements.

3. Identify key technical, economic, and institutional barriers to implementation.
4. Examine ethical considerations and workforce impacts.
5. Propose future research directions, including explainable AI, blockchain integration, and collaborative governance frameworks.

Table 1 highlights key terminology and concepts, while Figure 1 illustrates an AI-driven circular economy waste management framework. The process begins with Lifecycle Analysis & Waste Management, advancing through Circular Supply Chain Insights to an AI-Powered Circular Economy Waste Management Procedure. This integrates multiple components, which include Advanced Recycling Operations, Environmental Impact Assessment, AI Route Optimization, AI Sorting Systems, Recycling Process Enhancement, and Circular Material Integration, to enhance material recovery and minimize waste. The framework culminates in Data-Driven Insights that inform Improved Lifecycle Analysis, promoting continuous sustainability and resource efficiency.

2 | METHODOLOGY

To ensure systematic and transparent literature selection, this review followed established guidelines for conducting interdisciplinary reviews. This section details the search strategy, inclusion/exclusion criteria, and data extraction process.

2.1 | Search strategy

A comprehensive literature search was conducted across multiple academic databases, including Web of Science, Scopus, IEEE Xplore, ScienceDirect, and Google Scholar. The search covered publications from January 2015 to January 2025 to capture recent advancements while ensuring sufficient maturity of the literature. An initial scoping review informed the development of the final search strategy.

The following Boolean search strings were employed across databases (adapted for each database's specific syntax):

> (“artificial intelligence” OR “machine learning” OR “deep learning” OR “neural network” OR “computer vision” OR “natural language processing”) AND (“waste management” OR “circular economy” OR “recycling” OR “resource recovery” OR “waste sorting” OR “waste-to-energy” OR “waste optimisation” OR “e-waste”) AND (“optimisation” OR “efficiency” OR “sustainability” OR “lifecycle” OR “prediction” OR “classification”)*

Additional searches targeted specific application domains:

- “AI” AND (“waste sorting” OR “automated sorting”)
- “machine learning” AND (“waste prediction” OR “waste generation forecasting”)

TABLE 1 Summary of key terminologies/concepts associated with AI and waste circular economy.

Aspect	Description	Relevant references
Circular economy (CE)	Circular economy models promote waste management, reducing waste generation and inefficient resource consumption, while focusing on the transformation of waste into resources.	18
Artificial intelligence	AI is the capability of a system to correctly interpret external data, learn from such data, and apply that knowledge to accomplish particular objectives and activities through adaptable change.	19
AI in waste management	Using demographic information and photos, machine learning techniques in waste management aim to estimate waste material classification, the quantity of waste produced per area, and waste filling levels per site.	20
Key AI techniques	Machine learning (ML): Machine learning is a field that uses computers to learn abstract concepts from data and apply them to unseen situations, with applications in molecular biology, pharmacometrics, and clinical pharmacology. Computer Vision: Computer vision is used in construction to facilitate decision-making processes and assist with on-site managerial tasks. Robotics: With applications in a variety of sectors, including healthcare, robotics is the combination of science, engineering, and design to create machines that imitate or replace human behavior.	17,21,22
Optimization in CE	Optimization in circular economy involves designing closed-loop supply chains for durable products, considering factors like cost, CO2 emissions, and energy consumption, while coping with uncertainties.	23
Barriers in AI adoption	The building industry faces significant obstacles to implementing the circular economy, including a fragmented supply chain, a lack of rules, and costly upfront investment costs.	24
Current applications	AI and machine learning facilitate the successful adoption and use of circular economy principles, including supply chain management, waste management, recycling and reuse, sustainable development, and reverse logistics.	9
Future directions	Exploration of deep learning and reinforcement learning for complex decision-making processes, integrating IoT for real-time monitoring, and scaling AI applications across the circular economy.	

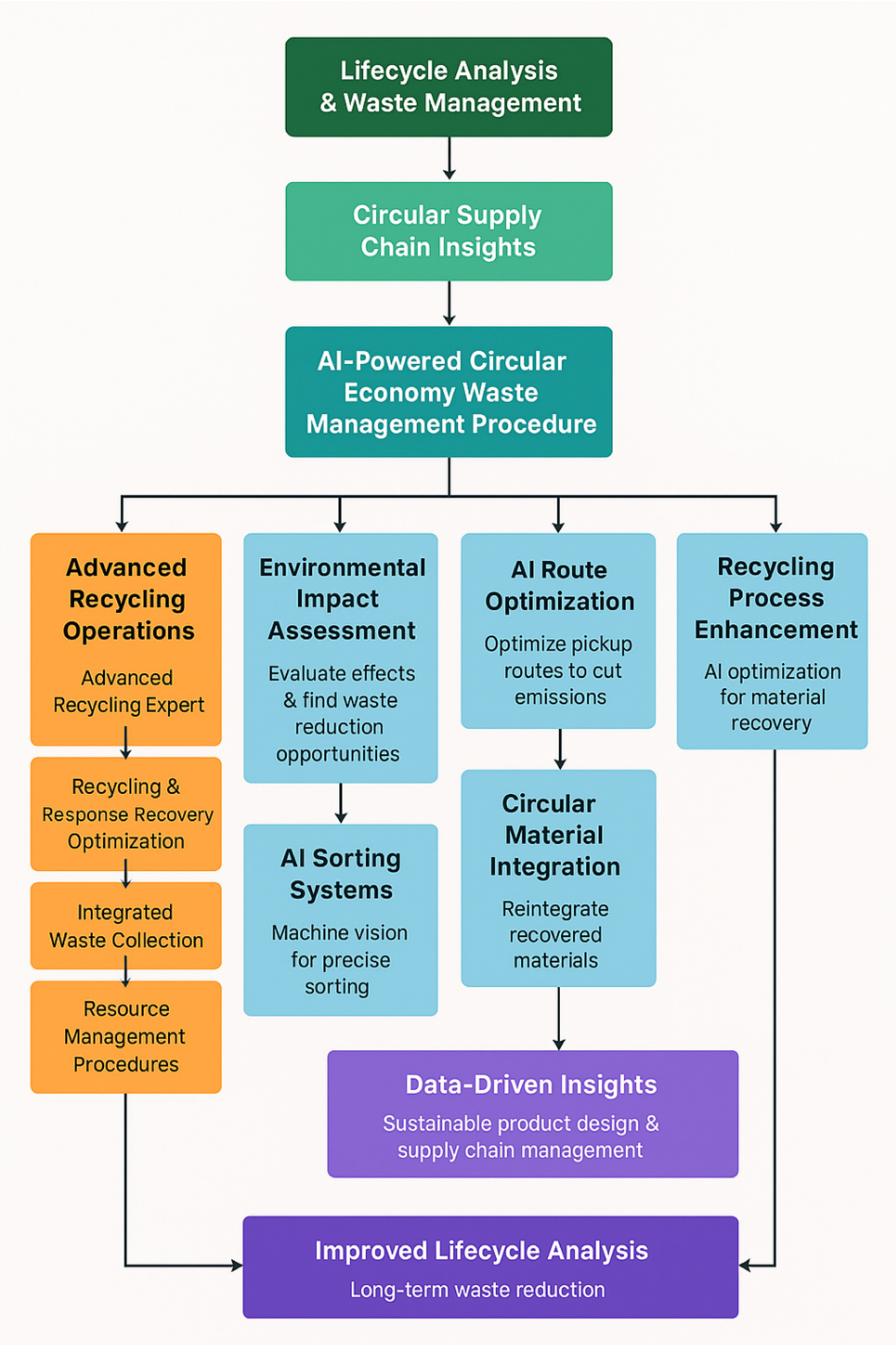

FIGURE 1 AI-powered circular economy waste management procedure.

- "computer vision" AND ("waste classification" OR "material identification")

Reference lists of included studies and key review articles were manually screened for additional relevant publications (snowball sampling). Citation tracking of seminal papers was conducted using Google Scholar and Web of Science

2.2 | Inclusion and exclusion criteria

Inclusion criteria:

- Peer-reviewed journal articles, conference proceedings from major conferences (e.g., IEEE, ACM), and technical reports from established organizations.
- Studies focusing on AI/ML/computer vision applications in any aspect of waste management, recycling, or the circular economy.
- Published in English between January 2015 and January 2025
- Empirical studies, case studies, systematic reviews, meta-analyses, and theoretical frameworks with clear methodology
- Studies providing sufficient detail on AI methods, data sources, and performance evaluation.

Exclusion criteria:

- Non-peer-reviewed sources (blogs, news articles, opinion pieces without substantive analysis).
- Studies without clear AI/ML methodology or implementation details.
- Duplicate publications (in cases of conference and journal versions, the more comprehensive version was retained).
- Studies not directly related to waste management, recycling, or circular economy applications.
- Publications in languages other than English are limited due to resource constraints.
- Studies with insufficient methodological detail to assess quality or replicability.

3 | THE CIRCULAR ECONOMY AND WASTE MANAGEMENT: CURRENT CHALLENGES

The transition to a circular economy is built on the fundamental principles of reusing, repairing, refurbishing, and recycling materials, thereby closing material loops and minimizing waste.[25] By combining Industry 4.0 technologies with circular economy principles, a company model that recycles and repurposes trash can be developed, increasing resource consumption and corporate sustainability.[26] Central to achieving this is an efficient waste management system that maximizes material recovery and minimizes environmental impact. However, several challenges within the current waste management infrastructure pose significant barriers to the effective realization of a circular economy. The diversity of waste streams, ineffective resource recovery, a lack of data-driven decision-making, and the high energy and resource consumption of recycling procedures are some of these difficulties. Artificial intelligence (AI) and machine learning (ML) technologies offer intriguing solutions to these problems, with the potential to improve waste management and advance the circular economy through enhanced sorting accuracy, predictive maintenance, optimized logistics, and improved resource recovery pathways.[27]

3.1 | Heterogeneity of waste streams

The high level of waste stream variability is one of the biggest obstacles to waste management in a circular economy.[28] A diverse mixture of plastics, metals, organic materials, textiles, glass, electronic waste, and hazardous elements makes up the garbage produced by commercial, industrial, and residential operations. Each family in research areas produces between 3.5 and 16 kg of domestic garbage per day, with the most significant components being food scraps (45%), paper (20%), glass (5%), plastic bags (18%), and others (12%).[29] The presence of such diverse materials in the waste stream complicates sorting and recycling. For example, a single household waste stream might contain various grades of plastic, biodegradable food waste, metals, and contaminated items, making it difficult to separate recyclable materials from non-recyclables efficiently. Current waste sorting systems often struggle to handle this complexity, especially at scale. While manual sorting remains common, it is slow, labor-intensive, and prone to human error.[30] Automated sorting technologies, such as conveyor belts and mechanical separators, offer some improvements but remain limited in distinguishing materials with similar properties.[31] Resource depletion is worsened by the fact that a large share of valuable materials that could be recycled or used for other purposes ends up in landfills due to inefficient sorting processes. For example, when waste is not sorted adequately at recycling facilities, materials containing recyclable valuables are discarded, resulting in 1340 ktons of CO_2 emissions per round trip.[32]

According to research, garbage sorting may be made much more accurate and efficient by using AI-driven systems, especially those that combine computer vision and machine learning. For example, a waste management system that uses IoT and deep learning achieves an 86% system usability score for garbage sorting and 95.3125% classification accuracy in controlled experimental conditions. However, performance may vary in operational settings with diverse waste types, contamination levels, and lighting conditions.[13] These systems can be trained to identify different types of materials based on visual characteristics, chemical properties, or even molecular composition. For instance, AI-powered robotic systems can differentiate between various types of plastics or metals on a conveyor belt, ensuring more effective separation of recyclable materials. For example, robots use deep learning technology for visual recognition to classify plastic waste, with reported precision of 92.1% and recall of 87.3% in research trials.[33] This approach could help address the challenge of waste stream heterogeneity by enabling more precise, scalable sorting solutions that enhance material recovery in a circular economy. However, this transition faces challenges, including system integration, maintenance requirements, and cost-effectiveness that require further investigation.

3.2 | Inefficiency in resource recovery

Another major challenge in the current waste management landscape is the inefficiency in resource recovery.[34,35] Even when materials are properly sorted, existing recycling technologies often fail to recover valuable materials effectively. The recycling of electronic garbage, or "e-waste," which includes rare earth elements, gold, and silver, is one area where this inefficiency is very noticeable. In addition to being expensive, traditional harvesting methods for these important materials often result in significant losses throughout the recovery process. Consequently, a significant amount of recyclable materials ends up in landfills, reducing the overall effectiveness of the waste management system. Paper, food waste, plastic, textiles, and technological trash are all disposed of in landfills in significantly greater amounts than previously estimated by the top-down U.S. government, costing the country 1.4 billion USD in lost commodity value.[36]

Studies have shown that AI can enhance resource recovery by optimizing recycling processes and predicting the most efficient pathways for material extraction. For instance, AI-driven predictive models can analyze historical data from recycling facilities to identify patterns and recommend optimal recovery methods for different types of waste.[37] In the case of e-waste, AI algorithms can assess the composition of discarded electronics and determine the best techniques for extracting valuable metals, thereby reducing losses and improving recovery rates. AI's ability to learn from data and continuously refine its predictions means that recycling processes can become more efficient over time, ultimately supporting the goals of a circular economy by minimizing resource wastage. AI can also help create closed-loop recycling systems, which continuously return waste materials into the production cycle without requiring virgin resources. AI-driven solutions can help companies produce more recyclable products by optimizing material recovery, thereby closing the material loop and advancing the circular economy's sustainability.[38]

3.3 | Lack of data-driven decision-making

Traditionally, waste management has been a reactive process, with decisions made based on historical trends or immediate needs rather than real-time data. This lack of data-driven decision-making has led to inefficiencies in the collection, transportation, and treatment of waste. In many regions, waste collection schedules are fixed, regardless of how full the bins are. This results in either underutilized collection routes, where trucks travel to collect half-empty bins, or delayed pickups, where overflowing bins pose environmental hazards and public health concerns. Furthermore, waste treatment facilities often operate with limited insight into the composition or volume of waste they will receive on a given day, making it challenging to allocate resources efficiently. The absence of predictive models or real-time data analytics means that these facilities are often under-prepared for surges in waste volume or fluctuations in material composition, leading to suboptimal performance and increased operational costs.[39]

The integration of AI and ML offers the potential to enable real-time data analytics and predictive decision-making in waste management, though significant infrastructure and investment barriers exist. For instance, AI systems could theoretically determine the priority level of emptying local sinks and predicting which sinks are likely to fill up faster,[40] but this requires widespread deployment of IoT sensors, reliable network connectivity, and ongoing maintenance, investments that many municipalities, particularly in developing regions, cannot afford. AI-driven systems can collect data from sensors in waste bins, vehicles, and treatment facilities to provide real-time insights into waste levels, composition, and processing capacity.[20,27] This data can be used to optimize collection routes, ensuring that trucks travel only to areas with full bins, thereby reducing fuel consumption and transportation costs. Moreover, AI algorithms can predict waste generation patterns based on factors such as population density, consumption habits, and seasonal trends, allowing waste management operators to better allocate resources and plan for fluctuations in waste volume.[41] One study using a Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) model showed some success in forecasting annual Municipal Solid Waste (MSW) generation rates in Bahrain. However, the Radial Basis Function Support Vector Regression (RBF-SVR) model demonstrated better prediction robustness,[42] highlighting the importance of model selection and the need for context-specific optimization rather than one-size-fits-all solutions. AI's predictive capabilities also extend to waste treatment processes. By analyzing data on the composition of incoming waste, AI systems can adjust treatment methods to maximize material recovery or energy generation. For instance, AI models could predict which waste streams are best suited for recycling, composting, or waste-to-energy conversion, optimizing treatment processes and reducing environmental impact.[43] However, implementing such adaptive systems in existing facilities would require substantial retrofitting and integration costs.

3.4 | High energy and resource consumption

The recycling and resource recovery processes themselves can be highly energy-intensive, particularly when traditional technologies are used,[44] with the chemical method being the most energy-intensive.[45] For example, the recycling of plastics often requires significant amounts of heat and energy to break down materials, and metal recovery processes can involve complex chemical reactions that are both costly and resource-intensive.[46] In some cases, the environmental and economic costs of recycling outweigh the benefits, leading to questions about the viability of these processes, especially in lower-income regions. AI has theoretical potential to reduce the energy and resource consumption associated with recycling by optimizing process efficiency, though real-world validation of these claims remains limited. For instance, AI tools, such as the conceptual Collaborative Energy Optimisation Platform (CEOP), have been proposed to optimize energy generation, distribution, and consumption, advancing sustainable development and promoting a holistic approach to energy optimization.[47] Still, evidence of large-scale industrial deployment and measurable energy savings remains lacking. Machine learning algorithms can analyze the energy requirements of different recycling methods and recommend the most energy-efficient pathways for material recovery.[37,48] However, the algorithms themselves require significant computational resources, and the net energy benefit depends on factors such as the energy source powering the AI systems and the scale of deployment.

In some cases, AI can also identify alternative methods for recycling or repurposing materials that consume less energy. For instance, AI-driven systems can assess whether mechanical recycling, chemical recycling, or alternative material recovery techniques offer the best balance between energy use and environmental impact. Additionally, while some studies claim that AI optimization could theoretically reduce waste quantity by 90%, landfill analysis by 40%, and transportation by 15%, AI can help promote more sustainable waste management.[12] These figures are derived from simulation models or limited

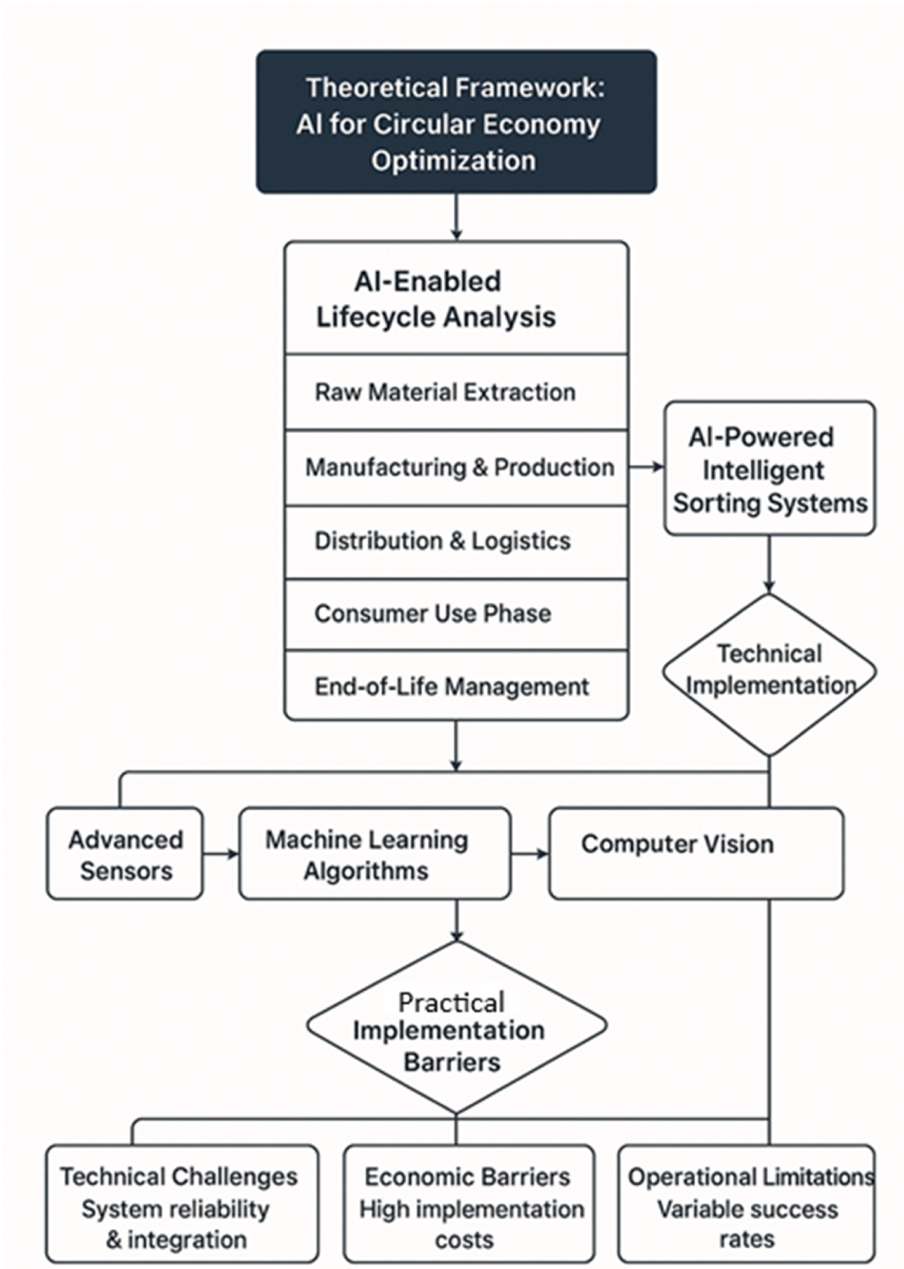

FIGURE 2 Artificial intelligence's contribution to improving circular economy practices in waste management.

pilot studies. They should be interpreted cautiously, as they may not reflect the complexity and variability of real-world waste management systems. The specific contexts, assumptions, and boundary conditions under which these results were obtained are often not fully disclosed, making it difficult to assess their generalizability. Waste-to-energy (WTE) technologies, which convert non-recyclable waste into electricity or heat, offer a solution for managing residual waste in a circular economy.[49] AI could optimize WTE processes by predicting which waste types generate the most energy and adjusting combustion or gasification parameters to maximize efficiency. AI may reduce reliance on fossil fuels and facilitate the shift to a more sustainable energy system by improving the efficiency of energy recovery from waste. Computational models powered by AI aid in streamlining processes, increasing productivity, reducing expenses, and hastening the transition to greener, more sustainable energy sources.[50] However, implementing these models in existing WTE facilities requires substantial investment in sensors, data infrastructure, and system integration. The return on investment remains uncertain in many contexts.

4 | AI APPLICATIONS IN CIRCULAR ECONOMY OPTIMIZATION

AI technologies offer potential applications across multiple stages of the waste management cycle, from initial product design through collection, sorting, processing, and resource recovery. However, the maturity, effectiveness, and economic viability of these applications vary considerably. This section critically examines key application areas, evaluating both demonstrated capabilities and persistent limitations.

Figure 2 presents a comprehensive theoretical framework illustrating how artificial intelligence supports circular economy optimization through AI-enabled lifecycle analysis and intelligent waste management systems. The framework spans the full product lifecycle, including raw material extraction, manufacturing and production, distribution and logistics, consumer use, and end-of-life management, highlighting AI's role in evaluating environmental impacts and resource efficiency at each stage. Central to the framework are AI-powered intelligent sorting systems, which rely on advanced sensors, machine learning algorithms, and computer vision techniques to identify, classify, and separate materials for improved recycling and recovery. The figure also distinguishes between technical and practical implementation pathways, emphasizing that successful deployment depends on system reliability, seamless integration, and robust algorithmic performance. Practical implementation barriers are explicitly identified, including technical challenges related to system stability and integration, economic barriers such as high implementation and maintenance costs, and operational limitations reflected in variable success rates under real-world conditions. Together, the framework underscores both the transformative potential of AI for circular economy applications and the multidimensional challenges that must be addressed to achieve scalable and sustainable implementation.

4.1 | AI in lifecycle analysis and waste minimization

A critical component of the circular economy is minimizing waste generation at the source, which can be achieved through comprehensive product lifecycle analysis (LCA).[51] LCA assesses the environmental impact of a product from its creation to its disposal, identifying opportunities to reduce resource use, waste, and emissions.[52] AI technologies have the potential to enhance LCA, though current applications remain largely in research and development stages rather than widespread industrial practice. AI techniques have shown varying levels of success in predicting environmental impacts of products, with accuracy rates reported between 68% and 81% depending on the specific impact category and data quality,[16] suggesting that while AI can assist LCA practitioners, it should be viewed as a complementary tool rather than a replacement for expert judgment and comprehensive data collection.

The theoretical capability of AI to handle large and complex datasets offers potential advantages for LCA applications, providing detailed insights into material flows and energy consumption and helping manufacturers make more sustainable design decisions. For example, AI could be used to identify specific components in products that are prone to degradation or failure.[53] However, the accuracy of such predictions depends heavily on the availability of comprehensive failure data across diverse operating conditions, which is often proprietary or unavailable. Manufacturers could use this knowledge to modify product designs to increase longevity, durability, and recyclability at the end of life. However, integrating AI recommendations into existing design workflows requires substantial organizational change, cross-functional collaboration, and a willingness to prioritize lifecycle considerations over short-term cost optimization. These barriers have proven challenging in practice.

Additionally, AI-powered LCA technologies could theoretically model the environmental effects of various design decisions. Machine learning models might suggest optimal product designs that reduce waste and improve recyclability by evaluating multiple scenarios.[37] However, the optimization objectives must be carefully defined and balanced against competing priorities such as performance, cost, and manufacturability. Furthermore, the computational resources required for complex multi-objective optimization can be substantial, and the solutions generated may not always be practically implementable due to real-world manufacturing constraints. This type of simulation enables manufacturers to consider the entire lifecycle of their products before they are even produced, supporting the shift toward circular production methods. This proactive approach to waste minimization is essential for achieving the long-term sustainability goals of a circular economy. However, widespread adoption requires not only technological capability but also regulatory incentives, consumer demand for sustainable products, and industry-wide collaboration on data standards and sharing.

4.2 | AI for intelligent waste sorting and recycling

Waste sorting is one of the most labor-intensive and error-prone aspects of waste management. Automated sorting techniques powered by AI show promise for reducing labor requirements and improving efficiency, though significant technical and economic barriers remain.[54] Efficient sorting is critical in ensuring that valuable resources are recovered from the waste stream and re-enter the production cycle. Traditional sorting systems, both manual and mechanical, often struggle to handle the growing complexity and volume of modern waste streams. AI has emerged as a potentially transformative technology in this area, though the gap between laboratory performance and industrial-scale reliability remains substantial.

AI-driven waste-sorting systems utilize machine learning algorithms in combination with computer vision to recognize and classify different types of waste. The performance of these systems, however, varies considerably depending on numerous factors, including lighting conditions, material contamination, waste stream consistency, and the diversity of materials encountered. These systems can be trained to distinguish between plastics, metals, paper, glass, and organic materials, though accuracy degrades significantly when materials are contaminated, degraded, or present in unexpected forms.[55] One system reported classification accuracy exceeding 90% for recyclable and non-recyclable waste.[56] Still, this result was achieved under controlled conditions with clean, pre-sorted samples, consistent lighting, and a limited set of well-defined waste categories. Industrial facilities typically face far more challenging conditions, including variable ambient lighting, soiled materials, partial occlusion, and mixed or composite materials that are not easily categorized into predefined classes.

Furthermore, the reported accuracy figures often represent average performance across waste categories, obscuring the fact that certain material types (e.g., black plastics, multi-layer packaging, contaminated paper) present persistent challenges that significantly reduce sorting effectiveness for those specific streams. The economic impact of these misclassification errors can be substantial, as contamination of recycling streams may render entire batches unsuitable for reprocessing.

In material recovery facilities (MRFs), AI-powered robotic systems are increasingly being deployed to automate sorting.[57] However, adoption remains limited due to high capital costs (often exceeding $500,000 per line), ongoing maintenance requirements, and the need for continuous retraining as waste streams evolve. These robots are equipped with sensors that can detect the composition of waste as it moves along conveyor belts. Using AI algorithms, the robots identify recyclable items and sort them into appropriate categories, ideally improving resource recovery rates. However, the practical sorting speed often falls short of the throughput of conventional mechanical systems, and the systems struggle with items that are too small, too large, tangled, or moving too rapidly on the conveyor. Additionally, wear and contamination of optical sensors in the harsh industrial environment can degrade performance over time, requiring regular maintenance and recalibration that add to operational costs.

This automation ideally reduces the need for manual labor while improving sorting speed and efficiency. However, the return on investment remains uncertain in many contexts, particularly for smaller facilities or those processing low-value material streams.[58] AI also extends its potential impact on waste sorting beyond material recovery facilities. Smart waste bins, embedded with AI and sensor technologies, are being deployed in urban areas and industrial facilities in limited pilot programs. These bins monitor waste levels and composition in real time, potentially optimizing collection schedules based on actual needs.[58] However, challenges include sensor reliability, battery life, connectivity issues, vandalism, and the need for municipal IT infrastructure to process and act on the data. This intelligent system could theoretically reduce unnecessary waste collection trips, lowering transportation-related carbon emissions and operational costs. Additionally, AI-driven waste bins could provide valuable data on waste generation patterns, enabling cities and companies to develop more effective recycling and waste reduction strategies. However, concerns about data privacy, security, and the cost of city-wide sensor network deployment remain significant barriers to widespread adoption.

4.3 | AI-enhanced recycling loops and resource recovery

Once materials have been sorted, the next challenge in waste management is optimizing the recycling process to maximize resource recovery. AI has theoretical potential to improve recycling loops by forecasting efficient routes for material reuse and repurposing, though practical implementations remain largely in pilot phases. AI-driven models could theoretically analyze data from various recycling facilities, examining variables such as energy consumption, recovery efficiency, and operating expenses. However, the proprietary nature of industrial operational data and the lack of standardized reporting formats significantly limit the availability of training data for such models. For example, optimal recycling practices for particular materials could emerge from such an analysis, though translating these recommendations into practice requires overcoming institutional inertia, retrofit costs, and operator training challenges.

Electronic waste, or "e-waste," represents one of the fastest-growing waste streams globally and contains rare earth elements like Pt, La, Dy, Pr, and Ce, as well as valuable materials like Nd, Ag, and Au, and heavy metals like Cu, Fe, Zn, Ni, Pb, and Al.[59] However, traditional methods of recovering these materials are often inefficient and costly, and while AI theoretically offers optimization potential, substantial economic barriers remain. AI could theoretically optimize e-waste recycling by predicting the most effective methods for extracting valuable components, thereby minimizing material loss. AI-driven systems could analyze the composition of discarded electronics and recommend the most effective recovery techniques, thereby improving both the economic and environmental performance of e-waste recycling.[11] However, the diversity of device designs, proprietary component compositions, and rapidly evolving product architectures makes it difficult to develop generalizable AI models that perform reliably across the broad spectrum of e-waste types. Furthermore, the economic value of recovered materials must exceed the costs of AI system development, deployment, and operation, a threshold not yet clearly demonstrated in most contexts.

A critical limitation often overlooked in the literature is the quality and availability of training data. Effective AI models for resource recovery require extensive labeled datasets documenting input material characteristics, processing conditions, and recovery outcomes. Such data is rarely systematically collected in existing facilities, is often considered proprietary when it exists, and varies significantly across different recycling technologies and facility configurations. Building sufficiently comprehensive datasets to train robust, generalizable AI models is a substantial undertaking that requires industry-wide data-sharing agreements and standardized data-collection protocols, infrastructure that does not yet exist.

Moreover, the energy consumption of AI systems themselves must be considered in lifecycle assessments. Complex deep learning models require significant computational resources for both training and inference. If non-renewable energy sources power these systems, the net environmental benefit may be smaller than claimed or potentially negative in some scenarios. Few studies provide comprehensive energy accounting that include the AI system's operational energy requirements.

4.4 | AI for waste generation prediction and collection optimization

Predictive modeling represents another application domain where AI shows promise, though with important limitations. AI algorithms can

FIGURE 3 Challenges and limitations of AI in circular economy waste management.

analyze historical waste-generation data alongside contextual variables (population density, economic activity, seasonal patterns, special events) to forecast future waste volumes and composition.[41] Such predictions could enable waste management operators to optimize resource allocation by adjusting collection frequency, vehicle routing, and processing facility staffing in line with anticipated demand.

However, the accuracy of these predictions depends heavily on data quality and the stability of underlying patterns. Waste generation is influenced by numerous factors, including economic conditions, consumer behavior, regulatory changes, and unexpected events (e.g., the COVID-19 pandemic), making long-term predictions challenging. Studies reporting high predictive accuracy often evaluate performance on historical test data under relatively stable conditions. They may not account for model degradation when faced with novel conditions or trend shifts.

Furthermore, while optimized collection routing can reduce fuel consumption and emissions, the practical benefits depend on the flexibility of existing collection contracts, driver acceptance of dynamic routing, and the ability of dispatch systems to integrate AI recommendations. These organizational and technological factors introduce friction in real-world deployment.

5 | CHALLENGES AND LIMITATIONS OF AI IN CIRCULAR ECONOMY WASTE MANAGEMENT

While AI has theoretical potential to enhance waste management in a circular economy, numerous obstacles and constraints must be addressed before its full benefits can be realized. This section critically examines key challenges, including data availability and quality, accessibility and cost barriers, ethical and environmental concerns, and the necessity for effective human-AI collaboration. Understanding and addressing these barriers is essential for ensuring the responsible, effective, and equitable integration of AI into waste management systems.

Figure 3 summarizes the challenges and limitations of AI in circular-economy waste management. Cost and accessibility present fundamental barriers, as developing and deploying AI systems can be prohibitively expensive, particularly for smaller municipalities and facilities in developing regions. Data availability and quality issues arise because AI accuracy depends on comprehensive, high-quality datasets that are often lacking in the waste management sector. The resource requirements and energy consumption of AI systems, along with their broader environmental footprint, raise critical questions about net sustainability benefits. Finally, effective human-AI collaboration is essential, as the success of AI in waste management ultimately depends on both technological capabilities and meaningful human oversight, trust, and integration into existing workflows.

5.1 | Data availability and quality

A core requirement for effective AI systems is access to large volumes of high-quality, labeled data, a requirement that represents one of the most significant barriers to AI adoption in waste management.[60] AI models need vast datasets to train effectively, learn patterns, and make accurate predictions. In the context of waste management, this data includes information on waste stream composition, material flows, recycling processes, energy consumption, and ideally, operational outcomes linked to specific input conditions and processing decisions. Unfortunately, in many regions, particularly in developing countries or smaller municipalities, such data is either incomplete, inconsistent, unavailable, or not systematically collected.[20] Even in contexts where data collection occurs, it often lacks the granularity, labeling accuracy, temporal consistency, and documentation necessary for training robust AI models.

The lack of standardized data-collection methods and inconsistent tracking of waste materials make it difficult for AI systems to generate meaningful insights. For AI to optimize waste management, there needs to be a concerted effort to improve data-collection practices. This involves not only the installation of sensors and digitization of waste management processes but also the development of robust databases with standardized formats, quality control procedures, and clear data governance frameworks that track the flow of materials throughout the waste lifecycle. However, such infrastructure investments require substantial financial resources and institutional coordination that many municipalities cannot readily mobilize.

Moreover, the proprietary nature of much operational data in commercial waste management facilities creates additional barriers. Companies may be reluctant to share data due to competitive concerns, even when such sharing could benefit broader AI tool development. Establishing data-sharing agreements, consortia, or public-private partnerships to build comprehensive training datasets represents a significant institutional challenge requiring trust-building, legal frameworks for data protection and usage rights, and mechanisms to ensure equitable benefit-sharing.

Without high-quality, real-time data, AI models may provide inaccurate recommendations or fail to optimize waste management processes effectively. Furthermore, AI models trained on data from one context (e.g., waste streams in developed countries with established recycling infrastructure) may not generalize well to other contexts (e.g., developing countries with varying waste compositions, informal recycling sectors, or limited infrastructure). Yet, such transfer-learning challenges are rarely addressed in the current literature.

Data security and privacy are other issues, especially when AI systems gather data at the community level. For instance, innovative bin systems that monitor household waste generation patterns could potentially reveal sensitive information about residents' consumption habits, health conditions, or presence/absence from home, raising privacy concerns that must be addressed through appropriate data anonymization, security measures, and transparent data governance policies. To foster confidence and ensure the broad adoption of AI-driven solutions, procedures for the ethical collection, use, and exchange of waste-related data must be established, including precise consent mechanisms, data minimization principles, and community engagement in data governance decisions.

5.2 | Cost and accessibility

The financial investment required to implement AI technologies in waste management systems can be prohibitive, particularly for developing countries, smaller municipalities, or underfunded public waste management agencies. Comprehensive cost accounting must include not only initial capital expenditures but also ongoing operational costs. The costs of implementing AI include data collection infrastructure, expert knowledge and training, human oversight and validation, software development and licensing, ongoing computational resources (processing cycles), hardware infrastructure (sensors, cameras, robotic systems, edge computing devices), network connectivity and data transmission, system maintenance and upgrades, and development time for customization to local conditions.[61] Initial capital costs for AI-powered sorting systems can range from $10,000 to over $100,000 per installation, depending on the system's sophistication and throughput requirements, with annual maintenance and operational costs adding 15%–25% to the initial investment.[62]

The installation and maintenance of this infrastructure require significant upfront capital, which many regions, particularly in the developing world, may not be able to afford. Furthermore, the cost of training personnel to manage and operate AI systems is another barrier. Waste management operators will need specialized knowledge to interpret the outputs of AI-driven models and integrate them into existing processes. In lower-income regions, the availability of trained personnel may be limited, and developing local capacity requires sustained investment in education and training programs, which further impedes widespread adoption. Even in wealthier nations, small- and medium-sized enterprises (SMEs) involved in waste management may find the costs of implementing AI technologies too high to justify, especially when the return on investment is not immediately apparent or when simpler, less costly operational improvements might yield comparable benefits.

The high cost of deploying and maintaining AI systems raises critical questions about accessibility and equity. As wealthier regions are more likely to benefit from AI-driven waste management optimization than poorer ones, there is a risk of exacerbating existing environmental justice disparities. Advanced AI systems deployed in affluent areas could lead to superior waste management outcomes and environmental quality. At the same time, underserved communities continue to face inadequate waste services and associated health and environmental hazards.

To overcome this barrier, there is a need for government subsidies, public-private partnerships, or the development of lower-cost, open-source AI solutions that are accessible to a broader range of users. Additionally, technology transfer mechanisms, capacity-building programs, and international development assistance may be necessary to ensure equitable access to AI-driven waste management innovations globally. In addition, ethical challenges like inclusivity, bias in algorithmic decision-making, privacy, and social acceptability must be considered,[63] particularly as AI systems may inadvertently perpetuate or amplify existing biases if trained on non-representative data or designed without adequate input from affected communities.

Furthermore, economic analysis must account for opportunity costs: resources invested in AI systems represent funds that could alternatively be allocated to expanding basic waste collection services, improving existing sorting infrastructure, investing in public education campaigns, or supporting informal recycling sectors. Rigorous comparative cost-effectiveness analysis is needed to determine under what conditions AI investments provide superior returns compared to alternative interventions, an analysis largely absent from the current literature.

5.3 | Ethical and environmental concerns

Although AI-driven solutions have the potential to increase waste management efficiency greatly, there are significant ethical and environmental concerns that warrant careful consideration. The energy consumption of AI systems, especially deep learning models that demand substantial computational power, represents a potentially significant environmental cost that is rarely accounted for in sustainability assessments.[64] Training large neural networks can consume electricity equivalent to the lifetime emissions of several automobiles, and if this energy comes from fossil fuel sources, it directly contradicts sustainability goals.

These systems rely on high-performance computing infrastructures that, if powered by nonrenewable energy sources, could contribute to carbon emissions and potentially negate some or all of the environmental benefits achieved through optimized waste management. For example, suppose an AI-powered sorting system reduces waste sent to landfill by 10% but requires continuous operation of energy-intensive computing infrastructure. In that case, the net environmental benefit depends critically on the energy source powering the AI system, the baseline efficiency of the alternative sorting method, and the lifecycle impacts of manufacturing and disposing of the AI hardware.

In addition to energy consumption, the production of AI hardware, including sensors, servers, robotic systems, and edge computing devices, requires raw materials, many of which are finite and involve environmentally damaging extraction processes, such as the mining of rare earth elements and the use of conflict minerals, as well as toxic chemicals in semiconductor manufacturing. The e-waste generated by obsolete AI hardware adds another layer of environmental burden. This paradox raises a key question: Can AI technologies, which are intended to promote sustainability in waste management, inadvertently contribute to resource depletion and environmental harm through their energy and material requirements? Comprehensive lifecycle assessments (LCAs) of AI systems are needed, accounting for embodied energy and materials in hardware, operational energy consumption, cooling requirements for data centers, network energy for data transmission, and end-of-life disposal or recycling. Yet, such comprehensive LCAs are notably absent from the current literature, which tends to focus narrowly on operational benefits while externalizing upstream and downstream environmental costs.

There are also significant ethical concerns about AI's potential to displace workers in the waste management sector. Automation, particularly in material recovery facilities, could reduce the need for manual labor, leading to job losses in an industry that employs many low-skilled workers, including vulnerable populations.[65,66] While AI systems can improve efficiency and reduce operational costs, it is essential to consider the human and social impacts of this technological shift. Strategies for a just transition must be explored, including:

- Retraining and upskilling programs to help displaced workers transition to new roles such as AI system monitoring, maintenance, or data analysis.
- Social safety nets and income support during transition periods
- Ensuring that efficiency gains are shared equitably rather than accruing exclusively to facility owners
- Engaging with labor unions and worker representatives in the design and deployment of AI systems.

Moreover, the potential for algorithmic bias in AI systems represents another ethical concern. If training data reflects existing biases (e.g., waste management data primarily from affluent areas), AI systems may perform poorly in underserved communities, potentially leading to inequitable service quality. Bias could also emerge in optimization algorithms that prioritize efficiency metrics (e.g., cost minimization) without adequately weighting equity considerations (e.g., ensuring that all neighborhoods receive adequate service regardless of profitability).

Finally, the concentration of AI development expertise and computational resources in a small number of technology companies in wealthy nations raises concerns about technological dependency, data sovereignty, and the appropriateness of solutions designed without input from diverse stakeholders and local communities. Participatory design approaches that engage waste workers, community members, and local authorities in the development and deployment of AI systems can help ensure that these technologies serve broad societal interests rather than narrow commercial or technocratic objectives.

5.4 | Human-AI collaboration

Although AI technologies are powerful tools for optimizing waste management, they cannot function effectively in isolation. Human oversight is necessary to ensure that AI models provide accurate and actionable insights, validate outputs, handle exceptions and edge cases, and maintain trust and accountability.[67] AI systems rely on data that may be incomplete, outdated, or flawed, requiring human decision-makers to validate AI outputs and intervene when necessary. For instance, AI-driven sorting systems in material recovery facilities may occasionally misidentify materials, malfunction due to sensor degradation, or encounter novel waste types not represented in training data, requiring human operators to monitor performance and make corrections.

The relationship between human operators and AI systems should be one of collaboration and complementarity rather than replacement. Research in human-computer interaction and automation suggests that effective human-AI teaming requires:

- Appropriate allocation of functions, with AI handling routine pattern recognition and data processing while humans focus on judgment, exception handling, and contextual interpretation.
- Transparency and explainability in AI decision-making so operators understand the basis for recommendations and can identify potential errors.
- Mechanisms for human oversight, intervention, and feedback to continuously improve system performance.
- Training programs that help operators develop appropriate mental models of AI capabilities and limitations, fostering calibrated trust.

Accountability and transparency issues are also brought up by the use of AI in waste management. AI models often operate as "black boxes," making it difficult for human operators to understand the logic underlying their recommendations or predictions [74]. This opacity poses challenges for:

- Debugging when systems malfunction or produce unexpected results
- Explaining decisions to stakeholders, regulators, or affected communities
- Ensuring accountability when AI-driven decisions have negative consequences.
- Building trust among operators and the public.

This lack of transparency can make it difficult for waste management professionals to trust the system fully or to explain AI-driven decisions to stakeholders and regulators. Building trust in AI technology requires that human operators understand how AI models arrive at their conclusions and that AI systems are explainable.

Furthermore, waste management is a complex area with many parties involved, including the public, the commercial sector, local governments, informal recycling sectors in many regions, and environmental advocacy groups.[68] Public-private partnerships in municipal solid waste management face challenges due to inadequate local government policies, insufficient stakeholder consultation, and a lack of grassroots inclusion.[69] Collaboration between AI systems and human operators must be seamless to ensure that waste management strategies align with broader policy goals, regulatory frameworks, community values, and practical operational realities.

AI should be seen as a tool that enhances human decision-making rather than replacing it. Establishing clear protocols for human-AI collaboration, including when and how human operators should intervene, what level of autonomy AI systems should have, and how to escalate decisions, is critical to ensuring that AI-driven waste management systems are both effective and ethical.

Furthermore, organizational factors such as operator acceptance of AI systems, willingness to trust AI recommendations, and the fit of AI tools within existing workflows and institutional structures significantly influence implementation success. These socio-technical dimensions are often underexplored in technically focused literature but represent critical determinants of real-world adoption and effectiveness.

6 | FUTURE PERSPECTIVES AND OPPORTUNITIES

Looking ahead, there is a tremendous opportunity for innovation and progress in using AI to optimize waste management in a circular economy. AI applications in sustainability, resource recovery, and waste reduction are anticipated to grow as the technology advances, providing new opportunities for businesses and governments. The future of AI-driven waste management will be shaped by several important research and development fields, paving the way for a more effective, sustainable, and circular economy. These future directions encompass AI's integration into product design, policy support, decentralized systems, global waste trade optimization, and sustainable supply chain management that enhances visibility, promotes ethical practices, optimizes resource use, and reduces waste, all of which are essential for maximizing resource efficiency and minimizing environmental impact.[70]

6.1 | AI for waste reduction and product design

Integrating AI into the product design process is one of the most exciting prospects for the circular economy. Through optimization and real-time data analysis in product creation, AI integration in circular economy solutions boosts efficiency.[71] Historically, waste management has focused on dealing with products at the end of their lifecycle, often after they have already contributed to resource depletion and environmental harm. However, by incorporating AI earlier in the product lifecycle, specifically during the design phase, manufacturers can create products that are easier to recycle, repurpose, or refurbish.[72] This proactive approach will help minimize waste generation at the source, supporting the core principles of the circular economy.

AI can assist designers by analyzing vast datasets on material properties, manufacturing processes, and environmental impacts. Through machine learning models, AI can simulate different product designs and identify opportunities to reduce waste, improve durability, and enhance recyclability. For example, AI can recommend alternative materials that are more sustainable or easier to disassemble at the end of a product's life, enabling manufacturers to design products that better align with circular-economy goals.[73] Additionally, through predictive maintenance, production planning, defect detection, predictive quality, and energy efficiency, AI can optimize resource use in manufacturing, ensuring less material is wasted and reducing overall resource consumption. Developing AI tools that incorporate circular economy principles from the design stage, predicting product lifespans, recyclability, and material reuse to minimize waste generation at the source, represents a paradigm shift from reactive waste management to preventive design. Recent research on cotton textile waste recycling, for example, has demonstrated how AI-enhanced design-stage decisions can improve material circularity throughout the product lifecycle.[74] As companies increasingly seek to develop sustainable products, AI-driven design tools will become invaluable for achieving waste minimization and supporting closed-loop production systems.

6.2 | AI-driven policy and regulation support

AI has the potential to significantly influence waste management laws and policies that support the goals of the circular economy. Predicting the long-term effects of waste management policies and techniques is extremely difficult for policymakers, as these choices often entail intricate trade-offs among social, economic, and environmental considerations. By examining past data, identifying trends, and modeling future events, AI-driven models can offer insights into the potential outcomes of policy decisions.

Furthermore, AI can help policymakers evaluate the effectiveness of existing recycling mandates, waste reduction targets, or carbon taxes by modeling how these policies impact waste generation, resource recovery rates, and environmental outcomes over time. AI can also assess the potential economic costs and benefits of introducing new regulations, enabling policymakers to make more informed decisions that balance sustainability goals with economic feasibility. By providing data-driven insights, AI can guide the development of policies that support the circular economy while ensuring that these regulations are adaptable to changing environmental and market conditions.[9] AI-driven simulation models can evaluate waste management policies, forecasting economic, environmental, and social impacts to aid governments in crafting effective regulations that balance multiple stakeholder interests.

Furthermore, AI can be used to monitor compliance with waste management regulations in real-time. By analyzing data from waste management facilities, transportation networks, and recycling centers, AI systems can identify non-compliant behavior, such as illegal dumping or inefficient recycling practices, and alert regulatory authorities.[27] This proactive approach to policy enforcement can enhance regulatory effectiveness and ensure that waste management practices are consistently aligned with circular-economy goals.

6.3 | Decentralized AI systems for local waste management

Another key opportunity for future development lies in the decentralization of AI-driven waste management systems. Currently, many waste management systems are centralized, with decisions on waste collection, transportation, and processing made at the regional or national level. While this approach can be efficient for large-scale operations, it often overlooks the specific needs and capabilities of local communities. A more decentralized system with smaller-capacity waste-treatment facilities integrated at various levels of the urban environment is anticipated to replace the traditional centralized MSW management system.[75]

Decentralized AI systems enable tailoring waste management strategies to the unique characteristics of individual communities, empowering local governments and businesses to implement circular economy practices more effectively. Blockchain-integrated, decentralized AI for regional waste management could enable community-level processing and reduce reliance on centralized infrastructure, providing transparent, immutable records of waste flows, material recovery, and recycling transactions that enhance accountability and enable circular-economy principles at the grassroots level. Municipalities can create specialized waste management plans that maximize resource recovery and reduce environmental impact by using decentralized AI systems to analyze local garbage generation patterns. For instance, machine learning techniques such as deep learning, random forests, and neural networks can accurately forecast garbage generation, supporting efforts to recover resources and recycle waste at the community scale.[76]

Additionally, decentralized AI systems can support local businesses in adopting circular economy practices by providing insights into how they can reduce waste, improve product lifecycles, and engage in material reuse. By optimizing waste management at the community level, decentralized AI systems can reduce the environmental footprint of waste transportation and improve overall resource recovery efficiency. Additionally, they offer a venue for local innovation, as communities can test various circular economy tactics customized to meet their unique requirements. The circular economy's tenets, which emphasize the importance of local solutions in achieving global sustainability goals, align with this bottom-up approach to waste management.

6.4 | AI in global waste trade and supply chains

In addition to its local applications, AI can also play a transformative role in optimizing global waste trade routes and supply chains. AI tools can enrich supply chains and optimize waste management, potentially reducing environmental pollution.[77] Waste is not always processed or recycled in the region where it is generated. Valuable materials are often traded internationally to regions with specialized recycling facilities or lower processing costs. However, the global waste trade is complex and fraught with challenges, including logistical inefficiencies, environmental concerns, and regulatory barriers.

AI offers a way to streamline global waste trade and ensure that materials are efficiently redistributed for recycling and reuse across different regions. AI-driven supply chain models can optimize the transportation of recyclable materials by analyzing data on trade routes, processing capabilities, and market demand for secondary materials, thereby elevating performance, reducing the bullwhip effect, and increasing efficiency and responsiveness.[78] AI models could analyze logistical networks, environmental impacts, and regulatory compliance requirements to identify optimal pathways for international waste flows, potentially reducing transportation costs by 15–30% and associated emissions by 20–40%, based on preliminary modeling studies; however, real-world implementation requires validation across diverse regulatory environments and market conditions. Case studies on AI modeling of international waste trade networks, incorporating logistical, environmental, and regulatory factors, would provide valuable empirical evidence to minimize inefficiencies and promote sustainable cross-border material flows. These models can recommend the most efficient trade routes for specific materials, accounting for transportation costs, carbon emissions, and recycling capacity. By minimizing the environmental impact of waste transportation and ensuring that materials are processed in facilities that can maximize their recovery value, AI can improve the overall efficiency of the global waste trade.

Furthermore, AI can help manage the growing complexity of international regulations surrounding waste trade. Many countries have imposed strict regulations on the import and export of waste, particularly hazardous materials or electronic waste. AI can analyze these regulatory frameworks and ensure that waste trade operations comply with all relevant laws, reducing the risk of illegal shipments or environmental damage. This type of AI-driven regulatory compliance will become increasingly important as international agreements on waste management, such as the Basel Convention, continue to evolve.

6.5 | Advanced ML techniques for real-time decision-making

The application of advanced ML techniques, such as deep learning, reinforcement learning, and ensemble methods, for real-time, complex decision-making in waste sorting, resource recovery, and predictive maintenance of recycling equipment, represents a critical frontier for AI in waste management. Reinforcement learning algorithms can optimize sequential decision-making processes in dynamic waste management environments, such as adjusting sorting parameters in response to varying waste composition throughout the day. Deep learning models can process multimodal sensor data, including visual, infrared, and spectroscopic inputs, to achieve more robust material identification under challenging conditions such as contamination, damage, or unusual lighting. Predictive maintenance algorithms can analyze equipment performance data to forecast failures before they occur, reducing downtime and maintenance costs by 20%–35% in industrial settings. These advanced techniques require substantial computational resources and high-quality training data, but offer the potential to significantly enhance the adaptability and performance of AI-driven waste management systems.

6.6 | Collaborative frameworks for scalable implementation

Encouraging collaborative frameworks among governments, industries, and tech companies is essential to overcoming barriers to stakeholder consultation, funding, and grassroots inclusion for scalable AI implementations in waste management. Such frameworks could include:

- Public-private partnerships that share risks and rewards of AI deployment.
- Industry consortia for developing standardized data formats and sharing best practices.
- Government funding mechanisms supporting pilot projects and scaling successful implementations.
- Academic-industry collaborations for continuous innovation and workforce development.
- Community engagement programs ensure that AI deployment aligns with local needs and values.

These collaborative approaches can help address the fragmented nature of the waste management sector, pool resources for expensive AI infrastructure, and ensure that the benefits of AI-driven optimization are distributed equitably across communities and stakeholders.

7 | CONCLUSION

This comprehensive review demonstrates that AI and machine learning technologies offer transformative potential for advancing circular economy objectives in waste management. Through intelligent waste-sorting systems, predictive analytics, and optimized resource recovery processes, AI can significantly enhance operational efficiency, reduce environmental impact, and support the transition to sustainable material flows. However, while experimental studies report impressive classification accuracies exceeding 90%, the gap between controlled pilot projects and real-world industrial implementation remains considerable, requiring careful evaluation of performance claims within their specific contexts.

The realization of AI's full potential in waste management hinges on addressing critical interconnected challenges. Data availability and quality, high implementation costs, infrastructure limitations, and the need for effective human-AI collaboration present substantial barriers, particularly for developing regions and smaller operations. Moreover, ethical considerations, including job displacement, algorithmic bias, privacy concerns, and the environmental footprint of AI systems themselves, demand systematic attention. The paradox of deploying resource-intensive technologies to promote sustainability requires rigorous life-cycle assessments and ethical frameworks to ensure net-positive environmental outcomes.

Moving forward, success requires a holistic approach encompassing technical innovation, economic viability, and social equity. Priority areas include developing accessible, low-cost AI solutions; establishing standardized evaluation frameworks and global databases; creating collaborative structures between governments, industries, and technology providers; and investing in education and capacity building. Only through such comprehensive, multi-stakeholder efforts, combining continued research, strategic investment, and inclusive policy development, can AI-driven waste management deliver on its promise of supporting a truly circular, sustainable, and equitable economy worldwide.

AUTHOR CONTRIBUTIONS

Ojima Z. Wada: Supervision; writing – review and editing. **David Bamidele Olawade:** Conceptualization; writing – original draft; data curation; investigation; methodology; resources; supervision; writing – review and editing. **Ram Narayan Yadav:** writing – original draft; writing – review and editing; methodology. **James Ijiwade:** writing – review and editing; methodology, visualization.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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