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Review paper

AI-Driven Frameworks and Sensor-Robotic Networks for Urban Waste Management: A Systematic Review Toward Sustainable Smart Cities

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Abstract

This study presents a systematic and quantitative review of artificial intelligence (AI) applications in modern waste management systems, with a focus on environmental chemistry, process optimization, and sustainability outcomes, supported by quantitative performance comparisons from recent literature. The review systematically evaluates AI-driven approaches across the entire waste lifecycle, including generation, monitoring, sorting, transportation, recycling, energy recovery, and final disposal. Emphasis is placed on machine learning (ML), computer vision, robotics, and wireless sensor networks for improving operational efficiency, cost reduction, and environmental performance. The analysis highlights recent advances in AI-assisted waste chemistry, including carbon emission prediction using FTIR-ML hybrid models, optimization of anaerobic digestion and biogas generation, and predictive modeling of plastic pyrolysis processes for hydrogen and biofuel recovery. AI-based surveillance systems using Convolutional Neural Networks (CNNs), Unmanned Aerial Vehicles (UAVs), and satellite data demonstrate high accuracy in illegal dumping detection and spatial waste monitoring, with reported classification accuracies exceeding 90-98% in several studies. Quantitative comparisons indicate improvements in collection efficiency, recycling accuracy, and cost reduction relative to conventional methods, with reported efficiency gains of approximately 20-40% and operational cost reductions ranging from 15-30%, depending on system scale. However, the review identifies critical limitations, including data scarcity, model interpretability challenges, high computational cost, and the “reality gap” between laboratory datasets and real-world waste conditions. The findings indicate that isolated AI solutions often fail to achieve scalable and context-adaptive performance due to fragmentation, limited data integration, and a lack of environmental feedback mechanisms. This study uniquely proposes a unified cyber-physical-environmental framework that integrates sensing, AI analytics, and environmental feedback mechanisms across the urban waste management lifecycle. The study concludes that integrated, explainable, and hybrid AI frameworks are essential to enable scalable, context-aware, and policy-relevant waste management systems. Such systems can significantly support circular economy strategies, climate change mitigation, and public health protection in rapidly urbanizing regions.

Keywords: Artificial Intelligence, Circular Economy, Machine Learning, Smart Cities, Solid Waste Management, Sustainable Waste Chemistry, Waste-to-Energy.

Introduction

According to recent evaluations by the World Bank and the United Nations Environment Programme (UNEP), global municipal solid waste (MSW) generation reached 2.3 billion tonnes in 2023 and, at current growth rates, continues to pose an escalating challenge to urban infrastructure as of 2026 [1-3]. This volume is expected to rise by almost 60% to reach an estimated 3.8 billion tonnes by 2050 if current "business-as-usual" patterns of production and consumption continue [1-2]. Additionally, it is projected that the overall yearly cost of waste management will nearly double by 2050, from $361 billion in 2020 to an estimated $640.3 billion by 2050, when hidden externalities associated with climate change, environmental degradation, and public health are taken into account [1-3]. Regrettably, 33% of solid waste is improperly handled and dumped in unmonitored landfills or illicit dumpsites [4]. Numerous health and environmental impacts, including groundwater contamination and public health risks, are associated with improper waste disposal [5]. Historically, waste management systems relied on basic collection practices with limited technological integration [6-7]. The waste was dumped at these specified locations once the vehicles were full. However, the waste management sector is undergoing a substantial transition to achieve sustainability and profitability, driven by the introduction of artificial intelligence (AI) [8-9]. Urban waste management systems typically consist of a series of interconnected processes, including waste generation, collection, transportation, sorting, recycling, incineration, landfilling, and waste-to-energy conversion. Each stage plays a critical role in determining the overall environmental and economic performance of the system. Modern waste management strategies increasingly emphasize resource recovery and circular economy principles, where materials are continuously reused and reintegrated into production cycles rather than disposed of as final waste [9].

AI is increasingly transforming waste management systems through the integration of machine learning, computer vision, robotics, and Internet of Things (IoT) technologies. For instance, computer vision models such as convolutional neural networks (CNNs) are widely applied for automated waste classification and sorting, while machine learning (ML) algorithms are used to predict waste generation patterns and optimize collection schedules. Robotic systems enhance sorting efficiency and reduce human exposure to hazardous materials, and IoT-enabled sensor networks facilitate real-time monitoring of bin fill levels, environmental conditions, and collection logistics [10-11]. According to Mukherjee et al. [12] and Yigitcanlar and Cugurullo [13], solid waste management could be revolutionized by incorporating robotics and AIinto the planning and running of urban waste treatment facilities. This would lead to increased operational effectiveness and more environmentally friendly waste management techniques [14-15]. Leading industrialized nations, including Canada, Switzerland, and New Zealand, are leveraging AI to refine waste management infrastructures, driving significant improvements in recycling efficiency and sustainable resource utilization [16-17]. However, in developing regions such as Bangladesh, including rapidly urbanizing cities like Dhaka, the implementation of such advanced systems remains constrained by limited infrastructure, data availability, and integration with informal waste sectors. These challenges highlight the need for context-aware and scalable AI-driven solutions tailored to diverse urban environments [17-18]. Waste management is increasingly relying on AI technology, particularly for sorting and processing solid waste [18-20]. AI is therefore essential for creating sustainable waste management models, especially for the shift to a "zero waste circular economy" that takes social, economic, and environmental aspects into account [15,21]. When analyzing the issues affecting various geographic regions and economic sectors, including smart cities, waste management should be taken into consideration. For example, scholars have put forth several models for sustainable waste management, including a model for megacities that takes recycling, reuse, and waste treatment into account [22]. Another model that considers unpredictable waste generation rates, facility operating costs, transportation expenses, and income was created by researchers to determine the optimal placement for solid waste management system components [23]. Liu et al. [24] examined data on landfills, waste management, and environmental safety in England, including the causes of illicit dumping, using data from the England panel [12-13]. Furthermore, Zhang et al. [25] highlighted the necessity of a new school of management in order to shift to a "zero waste circular economy."

Despite the growing body of literature on AI in waste management, existing studies remain largely fragmented and domain-specific. Many reviews focus on isolated components such as IoT-based monitoring, robotic sorting, or predictive modeling, without addressing the integration of these technologies across the full waste management lifecycle. Furthermore, limited attention has been given to the incorporation of environmental chemistry, including waste composition analysis and waste-to-energy optimization, within AI-driven systems. Existing frameworks often emphasize operational efficiency while overlooking environmental feedback mechanisms and system-level interactions [14-16]. As a result, there is a lack of comprehensive, scalable, and context-aware frameworks that unify sensing, analytics, decision-making, and environmental performance within a single architecture. This analysis aims to provide a comprehensive and systematic review of AI applications across the entire urban waste management lifecycle. Specifically, the review synthesizes recent advances in intelligent sensing, robotic sorting, predictive modeling, and AI-assisted waste-to-energy processes, with particular emphasis on the integration of waste chemistry and environmental performance. In addition, this study develops a cyber-physical-environmental framework that integrates data acquisition, machine-learning analytics, and operational decision-making within a unified system architecture. The scope of this review includes urban municipal waste systems within the context of smart cities and circular economy principles. Where available, quantitative performance indicators such as efficiency improvements, cost reduction, and emission mitigation are critically analyzed to provide a more evidence-based assessment of AI-driven waste management systems. Recent studies report that AI-based waste-sorting systems can achieve classification accuracies of 90-97%, while optimized routing algorithms can reduce operational costs and fuel consumption by approximately 20-30% [12-16]. The overarching conceptual framework for integrating AI across the urban waste management lifecycle, ranging from generation monitoring to chemical analysis, is synthesized in Fig. 1.

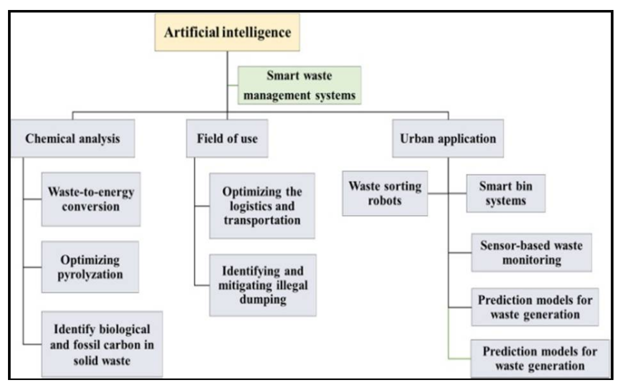

Figure 1. **Overview of AI-integrated waste management systems illustrating the interaction between waste generation, collection, sorting, processing, and resource recovery stages supported by intelligent technologies. The figure highlights the transition from conventional linear systems to data-driven, circular waste management approaches. (Source: Adapted from [26], licensed under Creative Commons Attribution (CC BY 4.0)).**

Five important aspects are depicted in the Fig. 1: the kind of waste that is produced, how AI is used in waste management, how it is used to optimize waste transportation, how it can be used to detect and reduce fraudulent disposal and waste treatment methods, and how it can be used to analyze the chemical makeup of waste. In addition to providing a concise and straightforward synopsis of the main points discussed in this evaluation, this optimized representation emphasizes how AI has the potential to revolutionize waste management practices. However, challenges related to model interpretability, particularly in black-box AI systems, remain significant, necessitating the use of explainable AI techniques such as SHAP and LIME for transparent decision-making. To address these limitations, this study proposes a unified cyber-physical-environmental framework that integrates sensing infrastructure, AI analytics, and environmental performance assessment across the urban waste management lifecycle. Unlike conventional cyber-physical systems that primarily focus on automation and logistics, the proposed framework incorporates environmental feedback loops, waste chemistry analysis, and decision-support mechanisms to enable more sustainable and adaptive waste management systems.

Methodology

This systematic review was conducted in strict accordance with the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement to ensure methodological rigor, transparency, and reproducibility.

Search Strategy and Information Sources

A comprehensive multi-stage literature search was performed across four primary academic databases: Web of Science, Scopus, IEEE Xplore, and Google Scholar. The search timeframe extended up to early 2026, focusing on the intersection of AI, robotics, and urban waste management. The search string utilized a combination of Boolean operators and keywords, including: ("AI-driven" OR "Machine Learning") AND ("Urban Waste Management" OR "Solid Waste") AND ("Sensor Networks" OR "IoT") AND ("Robotic Sorting" OR "Autonomous Systems"). To minimize selection bias, supplementary records were identified through website identification (n=15) and backward citation searching (n=55).

The inclusion of recent studies (2023-2026) ensures that the analysis reflects current technological developments and emerging trends in AI-driven waste management systems.

Eligibility Criteria

Studies were included if they met the following criteria: (i) focused on urban municipal solid waste; (ii) proposed or implemented AI, IoT, or robotic frameworks; and (iii) provided measurable data on system efficiency or pollution mitigation. On the other hand, research was disqualified if it lacked specialized technical frameworks for robotic or AI integration and was solely focused on non-urban industrial or radioactive waste studies that were not accessible in full text or did not provide sufficient information for analysis or synthesis.

The selection criteria were designed to ensure relevance to real-world urban waste management challenges and to capture studies that demonstrate measurable technical or environmental outcomes. The focus on urban municipal solid waste systems reflects the increasing complexity and scale of waste generation in rapidly urbanizing regions. The inclusion of AI, IoT, and robotic frameworks was prioritized to align with evaluating intelligent, data-driven waste management systems. Studies lacking quantitative or system-level implementation details were excluded to maintain analytical rigor and practical relevance.

Study Selection and PRISMA Flow

The systematic selection process is illustrated in Fig. 2. Initially, 1,745 records were identified from databases and 70 from other sources. A total of 990 records were removed during the pre-screening phase due to duplication (n=420), automation tool ineligibility (n=495), or other fundamental mismatches (n=75). As shown in Fig. 2, the remaining 825 records underwent title and abstract screening, resulting in 313 reports sought for retrieval. After assessing 305 reports for eligibility, 34 were excluded for specific reasons: focus on non-urban waste (n=14), lack of robotic/AI architecture (n=12), and insufficient pollution mitigation data (n=8).

To ensure reproducibility and consistency in study selection, the screening process followed a structured protocol based on predefined inclusion and exclusion criteria. The selection decisions were iteratively reviewed to minimize inconsistencies and subjective bias. The screening process was conducted iteratively, with repeated cross-checking of inclusion decisions to minimize inconsistencies and subjective bias.

Data Synthesis and Final Inclusion

Following the rigorous screening process depicted in Fig. 2, 271 studies were selected for final qualitative and quantitative synthesis. These studies provide the empirical basis for analyzing the efficiency of hybrid AI-sensor-robotic architectures in sustainable smart cities. The data extracted from these sources were categorized into predictive modeling, real-time monitoring via sensor networks, and automated resource recovery through robotics.

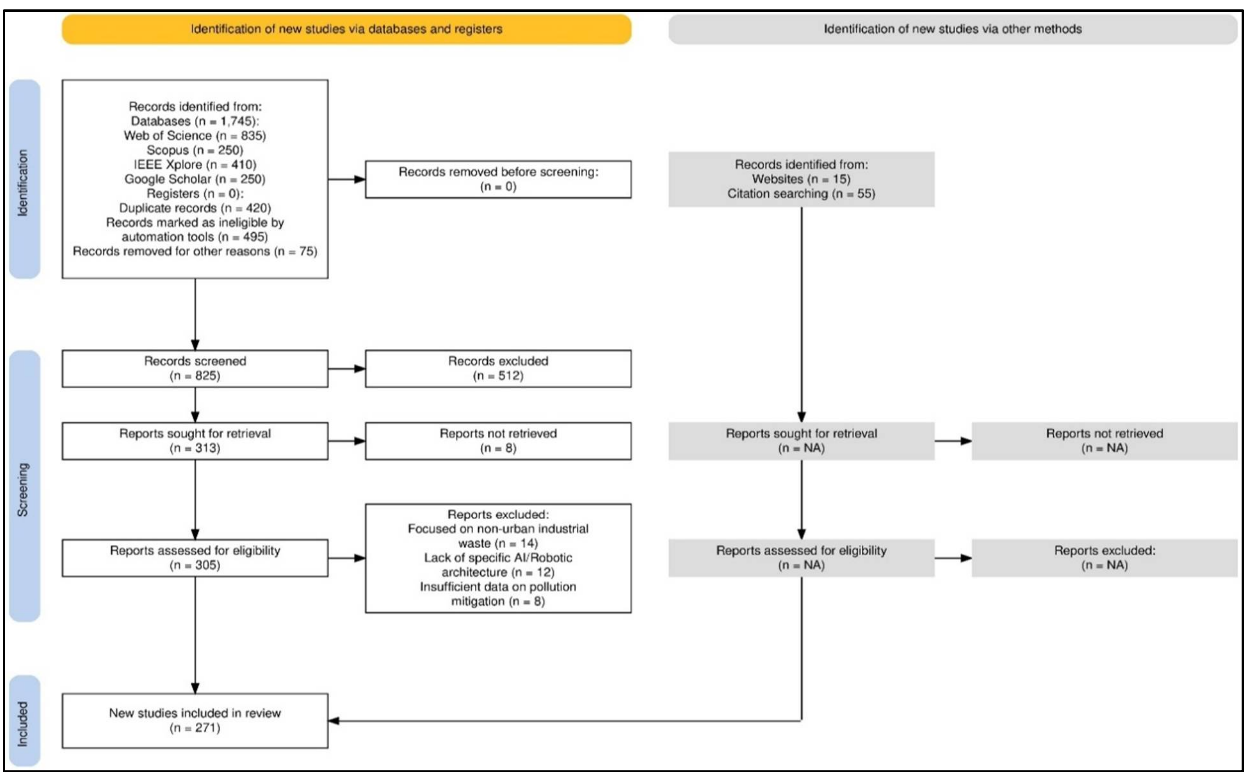

Figure 2. **PRISMA 2020 flow diagram illustrating the systematic identification, screening, eligibility, and inclusion process of studies considered in this review (n = 271). Source: Author's own construction based on PRISMA 2020 guidelines [27].**

Study Quality Assessment and Bias Evaluation

The quality of the selected studies was assessed based on methodological robustness, data availability, and relevance to AI-driven waste management systems. Studies were evaluated for the clarity of their proposed models, the presence of quantitative validation, and the applicability of their findings to real-world urban environments. Potential sources of bias were carefully considered. Publication bias may arise from the tendency to report successful implementations of AI models, while database bias may result from uneven coverage of regional studies. Additionally, regional bias was identified, as a significant proportion of studies originates from developed countries with advanced technological infrastructure. To mitigate these biases, multiple databases (Web of Science, Scopus, IEEE Xplore, and Google Scholar) were used, and backward citation tracking was conducted to identify additional relevant studies. The inclusion of diverse geographical contexts and a wide range of AI applications helped improve the representativeness and reliability of the review. The selected studies collectively provide a comprehensive representation of current advancements in AI-driven waste management systems, enabling comparative analysis across different technological approaches and operational contexts. This structured selection supports a more critical evaluation of performance, scalability, and real-world applicability in subsequent sections.

Types of Waste and Their Generation

Waste poses a significant threat to the environment through the potential contamination of air, soil, and water. Human-centered activities such as construction, agriculture, industrial production, environmental emissions, and ordinary consumption and disposal practices are the main causes of pollutant generation [28-29]. The consequences of improper waste handling are multifaceted, resulting in environmental pollution, public health risks, economic deficits, and the depletion of valuable resources. Several organizations have implemented strategic initiatives to address these issues.

The transition toward a sustainable future necessitates a multifaceted strategy that integrates circular practices, technological advancements, and profound social change. By prioritizing circularity through systematic recycling, composting, and the reuse of materials, industries can significantly reduce their environmental footprint and move away from traditional linear consumption models. This shift is further bolstered by the rapid adoption of green technologies and renewable energy sources, which provide the technical infrastructure required for a low-carbon economy. However, as noted by Osman et al. [30], these technical solutions must be underpinned by comprehensive public education and awareness campaigns; such social initiatives are critical for minimizing waste generation at the source and empowering individuals to make sustainable decisions in their daily lives. Waste classification is a complex process determined by the material, physical state, or point of origin [31]. Research identifies industrial activity as the primary source of global waste [32], often consisting of volatile compounds, wastewater, slag, and scrap. These materials frequently contain hazardous elements like heavy metals and radioactive substances, which pose severe environmental threats [33-34].

a) Classification by Source and Composition: The main source of waste streams worldwide is industrial waste, which is also commonly linked to the discharge of harmful materials [32-33]. Comparably, organic waste from farming, raising animals, treating wastewater, and the food industry has two characteristics: it has a high potential for being turned into compost or value-added products, but it can also be dangerous if it contains toxins like ammonia or chlorine [35].

b) Classification by Physical State and Characteristics: Waste is categorized by its physical state and properties, encompassing solid, hazardous, liquid, and recyclable streams. Solid waste, arising from manufacturing, mining, and agriculture, includes household, medical, electronic, and construction sub-types [31, 36-38]. Hazardous waste consists of flammable, corrosive, or radioactive materials often sourced from biomedical and electronic sectors [39]. Liquid waste is primarily industrial, composed of heavy metal (47.9%), organic (32.2%), and corrosive/alkaline (12.4%) variants, all of which pose severe public health risks if left uncontrolled [40-42]. Finally, recyclable waste, including paper, glass, and ceramics, can be diverted to serve as raw materials for new products [35, 43].

c) Management and Treatment Summary: The broader waste landscape spans diverse sources from individuals to transportation, requiring a variety of technical management treatments. Key methods utilized for processing these streams include recollection, incineration, landfilling, biological re-treatment, energy recovery, physical re-treatment, and pyrolysis [26, 44].

Smart Waste Management Technologies

The importance of smart waste management is increasing as cities expand and produce more waste [45]. Traditional methods can require staff to manually sort items and have specific collection periods. These operations may squander resources, result in problems, and increase expenses [46]. Alternatively, smart technologies make waste disposal more accurate, versatile, and easy. The main cause of this development is IoT. IoT connects sensors in waste trucks, waste stations, and waste cans to monitoring systems. The bins' level of filling, the frequency of their pickups, and real-time route optimization are all tracked by these tools [47-48]. In addition to using less petrol and reducing service delays, this data-driven strategy expedites collections. AI allows intelligent waste systems to make their own decisions, which further enhances their intelligence. AI systems assist in identifying trends in the production of waste, enhancing timetables, and identifying problems such as illegal dumping or malfunctioning machinery. More quickly and accurately than humans, robotic arms equipped with AIand visual recognition can locate, sort, and classify recyclable items in material recovery businesses [48]. When compared to fixed-route collection, AI-enabled intelligent routing and sensor-informed scheduling show quantifiable decreases in vehicle kilometers and fuel consumption; however, actual gains are contingent on baseline fleet utilization, data quality, and support capability. According to Edo et al. [49], computer-vision sorting systems can increase throughput and purity when compared to manual separation; however, they also demand a larger initial investment and specific operator upskilling to maintain performance.

One useful example of how AI and IoT may collaborate is smart dumpsters. These devices may weigh the waste being tossed away, identify the type of waste, and even award users for properly disposing of it. Additionally, by informing residences or businesses when pickups are anticipated, mobile apps that integrate with these systems might motivate individuals to participate [50].

When combined, these technologies enable adaptable waste infrastructure that can adjust to changing urban trends. When combined with cloud computing and data analytics, smart systems not only improve operational efficiency but also support sustainability assessment and long-term planning [51]. The idea that smart waste methods might be positioned as a component of larger urban livability and design-policy objectives is strengthened by recent research on smart urban infrastructure and AI-driven creativity in design [52]. The digital gap, standards, cost, and data security remain issues, particularly in developing countries [53]. The interconnectedness of smart recycling networks, residential infrastructure, and real-time collection logistics through IoT-enabled communication is illustrated in Fig. 3.

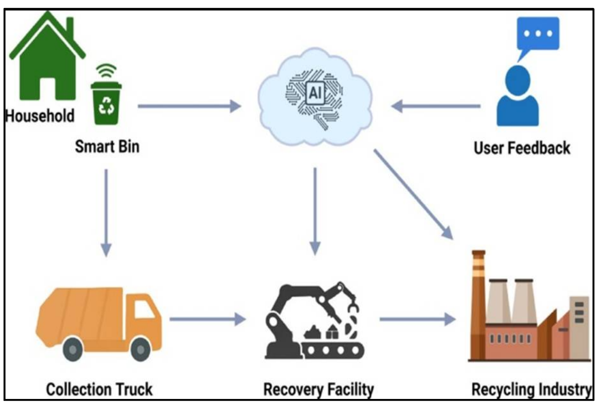

Figure 3. **Classification of municipal solid waste streams showing major categories such as organic, plastic, metal, paper, and hazardous waste, along with their respective processing pathways. This classification supports AI-based sorting and resource recovery strategies (Source: Adapted from [48], licensed under Creative Commons Attribution (CC BY 4.0))**

Smart waste management is not a stand-alone system; by guaranteeing higher-quality recyclables, lowering contamination, and improving traceability, it directly supports the objectives of the circular economy [54]. These technologies serve as the foundation for intelligent resource flow, connecting homes, businesses, and government systems in a networked feedback loop that promotes effectiveness, environmental stewardship, and public participation. The majority of advances that have been documented are from experimental or limited municipal implementations; without larger, longer-duration studies, generalizability is still unknown [55]. The figure illustrates how AI and IoT make it possible to gather data in real time from intelligent containers and collection trucks, which helps with automatic sorting in recovery facilities and logistics planning. Smart, circular waste systems depend on improved operational efficiency, material ownership, and community engagement, all of which are enhanced by this feedback loop. However, the performance of these systems is often influenced by data quality and environmental variability, which can reduce accuracy in real-world applications compared to controlled experimental settings.

Integration of Policies and The Development of Human Capital

Implementing circular economy and sustainable waste management systems calls for a workforce that is both competent and flexible, in addition to being a technological process. Development of human capital is essential for fostering creativity, guaranteeing operational effectiveness, and facilitating the long-term viability of waste recycling initiatives [56]. As modern technologies like AI, IoT, and biotechnology are incorporated into waste management systems, new skill sets are needed in a variety of industries. These include a multidisciplinary understanding of environmental policy and sustainable resource planning, technical proficiency with technological devices and sensor networks, and analytical abilities for data interpretation. To satisfy the demands of digital and decentralized systems, training programs and traditional labor roles must change [57-59]. In this industry, both formal and informal education are essential for workforce development. The integration of courses on environmental data science, sustainable engineering, and smart waste technologies into technical certifications, university curricula, and vocational programs is becoming more common [60]. Raising awareness and providing on-the-job training at the community level aid in closing the skills gap, especially in post-conflict areas or emerging economies where the abilities of institutions may be constrained [61].

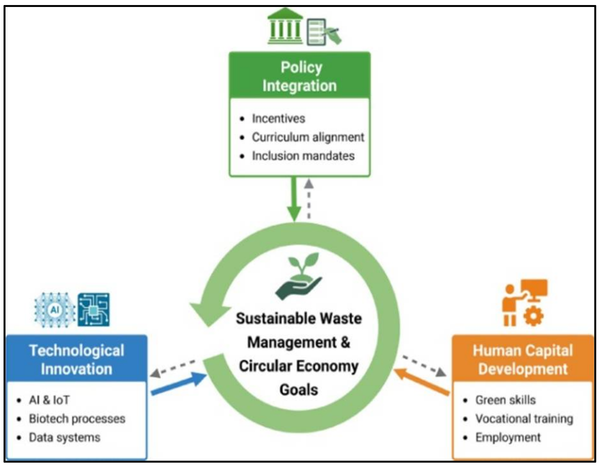

Figure 4. **Architecture of an AI-enabled smart waste management system integrating IoT sensors, data transmission networks, and machine learning models for monitoring, prediction, and optimization of waste collection and processing operations (Source: Adapted from [48], licensed under Creative Commons Attribution (CC BY 4.0)).**

Integrating policies is equally important. Labor development and national sustainability ambitions must be matched with regulatory frameworks to prevent waste recycling innovation from surpassing institutional readiness. Mandates for industry-academia cooperation in curriculum development, funding mechanisms for green hiring, and incentives for business-related training efforts are a few examples [62]. Additionally, inclusive development of policies can support social involvement, gender parity, and long-term job security. Programs that involve underrepresented groups, such as women, youth, and informal workers, can promote the objectives of the circular economy and improve social cohesion. Human capital is further enhanced by international cooperation and information transfer between nations through cooperative research projects, technological exchange, and best practices that are shared [63]. To illustrate the synergy between technological innovation and institutional readiness, Fig. 4 presents a systems-based model for the co-development of policy frameworks and human capital.

The alignment of waste innovation and workforce development can accelerate circular outcomes, as demonstrated by a number of national plans. The government of South Korea has set up specialist "Green Skills" training programs that collaborate with intelligent waste companies to provide practical experience in IoT systems, waste analytics, and robotics-based sorting. Under Korea's Green New Deal, these initiatives are backed by public funds and linked to national job creation goals [64-65]. In the recycling industry, local governments and universities in Japan collaborate to establish joint waste development centers that integrate worker reskilling, research, and small-business incubation. Localized adaptation of waste technologies, enhanced technical skill, and higher employment have all resulted from this integration. According to Moshkal et al. [66], these models show how industry, education, and policy may work together to create a workforce that is competent and prepared for sustainable waste management in the future. This figure shows how policy acts as a mediating framework to bring platforms, people, and purpose into alignment, and how technology innovation and the growth of human resources must be co-developed. The approach highlights how policy acts as a mediator to bring technological advancements, like automation and biotechnology, in line with institutional capacity and worker training. An adaptive, resilient waste handling ecosystem is created through feedback loops, which show how better technology adoption is fueled by increased human capital and then influences and reshapes supportive policies.

Comparative Performance of AI-Based Systems

AI-driven waste management systems demonstrate measurable improvements across operational, economic, and environmental performance indicators. However, their effectiveness varies depending on technology maturity, data availability, and local infrastructure conditions.

a) Efficiency Gains: AI-based routing and scheduling systems typically reduce collection distances and time by optimizing vehicle paths and predicting bin fill levels. Studies report efficiency improvements ranging from moderate to substantial, depending on system scale and data resolution.

b) Cost Reduction: Operational cost savings arise from reduced fuel consumption, optimized labor allocation, and improved asset utilization. Smart collection systems and automated sorting technologies contribute to lower long-term operational expenditure, although initial capital investment remains high.

c) Emission Reduction: AI-enabled route optimization and waste diversion strategies reduce greenhouse gas emissions through lower fuel use and decreased landfill deposition. Integration with recycling and energy recovery processes further contributes to carbon reduction.

d) Scalability: Cloud-based analytics, IoT infrastructure, and modular AI architectures support scalability from pilot projects to city-wide deployment. However, scalability is constrained by data infrastructure, maintenance capacity, and institutional readiness in many regions.

e) Limitations: Notwithstanding its advantages, AI-based solutions have several drawbacks, including high initial investment costs, reliance on trustworthy sensor data, algorithmic bias and unpredictability, threats to cyber security and data privacy, and limited adaptation to the informal waste sectors.

Overall, AI technologies provide strong performance advantages compared with conventional systems, but their success depends on integrated deployment strategies, policy support, and socio-technical alignment. From a techno-economic perspective, AI-enabled waste management systems typically require higher initial capital investment (CAPEX) due to the cost of sensors, robotics, and data infrastructure. However, these systems offer significant reductions in operational expenditure (OPEX) through improved efficiency, reduced fuel consumption, optimized labor utilization, and enhanced resource recovery. Several studies suggest that the payback period for such systems ranges from approximately 3 to 5 years, depending on system scale, infrastructure maturity, and data availability. This indicates that AI-driven waste management solutions are economically viable in the long term, particularly in large urban environments. Although AI-based systems consistently outperform traditional methods in terms of efficiency and accuracy, their adoption is constrained by higher initial costs and the need for advanced technical infrastructure. The findings synthesized in this review are consistent with reported literature, which indicates that AI-based waste management systems outperform conventional approaches in efficiency, cost reduction, and environmental performance. However, the degree of improvement varies significantly depending on data quality, system integration, and local infrastructure conditions.

Waste Management with Artificial Intelligence

AI has the potential to revolutionize municipal waste management by improving the efficiency of waste collection, processing, and categorization. Waste bins can be monitored, waste collection can be predicted, and waste processing facilities can operate more efficiently thanks to AI-based technology, including intelligent waste bins, classification robots, predictive models, and wireless detection. Table 1 provides a comparative analysis of these technologies, highlighting cost reductions and safety improvements. Municipalities may save costs, increase safety, and lessen the environmental effects of waste management by utilizing AI. The modular architecture of AI-driven systems, categorized into intelligent sensing, robotic sorting, and predictive analytics, is depicted in Fig. 5.

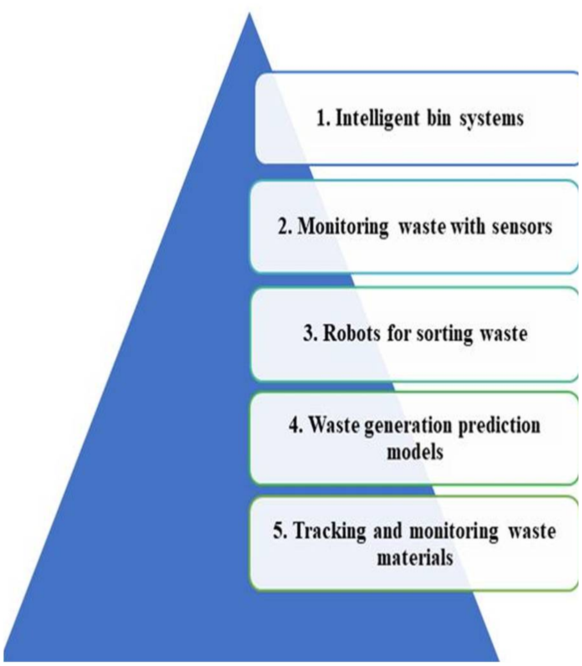

Figure 5. **Automated waste sorting system using computer vision and robotic manipulators, illustrating the process of image acquisition, material classification, and real-time separation of recyclable components. This system improves sorting accuracy and reduces human exposure to hazardous waste. Source: Author's own construction.**

Intelligent Bin Systems

Conventional waste management relies on manual inspections of waste bins, an inefficient process that often leads to overflowing containers and the breeding of disease-carrying organisms [67]. To address this within the framework of "smart cities," research has shifted toward intelligent waste bin systems focusing on automatic classification and real-time monitoring.

a) Key Technological Implementations

The transition from passive bins to intelligent systems is driven by diverse hardware and IoT configurations. Utilizing modules like the ESP8266, smart bins can automatically detect objects, set fill-level thresholds, and transmit status updates to web pages via Wi-Fi for remote analysis [68-69]. Level detection is typically achieved through ultrasonic sensors strategically placed at the top and bottom of bin covers [68-69]. More advanced designs include robotic bins that navigate along set lines using obstacle sensors to coordinate collection pauses [70], as well as automated sorting systems. These sorting units leverage Arduino and NodeMCU to separate metals from non-metals while monitoring liquid levels in real time and syncing data to the cloud for processing [71-72].

The primary objective of intelligent waste bin systems is to monitor fill levels in real time and provide timely alerts to users. Sensors are the main sources of the data, which is then sent across the network. Intelligent bin systems can improve the city's general environment, decrease the spread of illness, and improve waste collection efficiency. It is difficult to broadly market smart waste cans due to their relatively expensive implementation costs. Policymakers should consider implementing financial incentives to lower the price of smart waste bins and increase public access to them in order to solve this problem. Additionally, external elements like humidity and temperature might have an impact on these bins' normal performance. As a result, the waste bins need to be routinely inspected and maintained by committed staff. Thus, in the future, it will be essential to concentrate on creating and marketing smart waste bins.

Table 1. **Artificial intelligence in waste management. Prediction models, intelligent waste cans, and robots that sort waste are the primary uses of artificial intelligence in waste management. Sort and contrast the conclusions reached with the total of the important data.**

Type	Measure	Key information	Advantages and Results	Reference
Robot for sorting waste	Simultaneous mapping and localization using deep learning	Waste detection, navigation, relocation, sequencing, and map reconstruction.	Minimal prediction error is observed.	[26, 73, 74, 75, 76]
	Simultaneous mapping and localization in computer vision	Enables automated monitoring and navigation and effectively avoids obstructions. Find recyclables. Create a three-dimensional circumferential map for path planning, navigation, and robot positioning.	Robots for recycling now have a wider range of applications and are more reliable.	[26, 77, 78]
	Hyperspectral images in computer vision	Adaptive gripper mechanisms enable efficient handling of heterogeneous waste materials without requiring additional pneumatic or electrical systems.	Multi-view image capture and scanning for improved object detection.	[79-81]
	Near-infrared hyperspectral imaging for material identification and 3D surface mapping	Keep mortar, bricks/blocks, and concrete apart. automatically pick up things. Place in the appropriate recycling place. Handle bulky items without first treating them.	The accuracy of line recognition is about 100%, and the sorting efficiency may reach approximately 2,000 items per hour.	[82-83]
Waste production prediction model	Analysis of principal components	1. There is an improvement in predictive performance. 2. Change category variables to continuous ones.	The expected value was 1161.52 kg/square meter, whereas the average waste generation rate of the actual values was 1165.04 kg/square meter.	[26, 84-86]
	Exclusivity of predictors: Decomposition of integrated empirical patterns	An ANN should be analyzed using the predictor exclusivity and cross-prediction techniques. The result was a high-precision model for predicting municipal solid waste.	Significantly improves large-scale forecasting accuracy.	[87-88]
	Regression model with gradient augmentation	To forecast weekly waste generation, a gradient-enhanced regression model was created.	Presents New York's waste production patterns and gathers thorough statistics.	[89-90]
	Random forest algorithms are used in combination with support vector machines to improve prediction accuracy	Using small-scale classification datasets, a random forest model is suggested that can enhance prediction performance.	To enhance prediction performance, use small categorical datasets.	[91-94]
Intelligent waste bin	Ultrasonic sensors (IoT)	1. Monitoring waste levels. 2. Establish an internet connection. 3. Waste segregation.	Network of waste bins.	[72, 95, 96]
	High-frequency sensors	The integrated system prevents overflow, incorporates an automated lid-opening mechanism for touchless operation, and utilizes real-time sensor technology for autonomous waste-level detection.	Digital waste bin.	[68, 97]
	Red external ultrasonic sensor	1. Monitoring of the waste level. 2. Path tracking and navigation along predefined routes. 3. Recognize waste.	The system enables autonomous movement of waste bins for user interaction and collection efficiency.	[70-98]
	Network of sensors	The system enables autonomous movement of waste bins for user interaction and collection efficiency.	Utilized for gathering municipal waste.	[99-101]

Monitoring Waste with Sensors:

Sensor-based waste monitoring leverages advanced technology to track waste generation volumes, pinpoint sources, and evaluate the success of management strategies. Central to this is the Wireless Sensor Network (WSN), which consists of self-organized sensors designed to monitor specific physical or environmental parameters within a system [102].

a) WSN Architecture and Sensor Types

A typical WSN for solid waste treatment integrates a variety of sensors to optimize management and safety. Environmental monitoring is achieved through temperature, humidity, and gas sensors that track waste decomposition and hazardous emissions, while specialized "electronic noses" quantify real-time odor concentrations, particularly in wastewater contexts [103]. Logistics are streamlined using infrared sensors to monitor the fill levels of waste carriages, complemented by sound sensors that track associated noise pollution. In high-stakes industrial applications, such as cold crucible induction melting furnaces, non-contact microwave sensors enable the critical in-situ monitoring of nuclear waste glass melts [104].

b) Real-Time Process Control

By monitoring these parameters in real-time, these systems allow for significantly better control over waste treatment processes, ensuring that hazardous gases are detected early and that the physical state of the waste [7] (such as temperature and humidity) remains within safe or optimal processing limits [104]. Recent advancements in waste management focus on improving network architecture and energy sustainability to ensure continuous monitoring [105-106]. Karthikeyan et al. [107] proposed an intelligent system utilizing a Zigbee network structure, where terminal nodes on bins detect unfilled levels [108-109]. To address the energy constraints of these nodes, Raaju et al. [110] suggested integrating solar energy collection devices to extend the lifespan of the wireless sensor network.

c) Real-Time Data and Visualization

A significant challenge in earlier systems was the inability to display filling levels in real-time. To resolve this, specialized solar-powered wireless monitoring units were developed to measure and transmit the status of bins when empty [111]. Modern iterations of waste management systems emphasize autonomy and intuitive data visualization. Self-powered systems now transmit data from numerous sensor nodes to a central monitoring station, facilitating detailed analysis and comprehensive visualization of the network [112]. Furthermore, these systems utilize dynamic user interfaces, employing graphical features such as progressive bars to represent the real-time filling status of bins, which enhances the efficiency of monitoring and collection logistics.

d) The Role of Machine Learning

The rapid evolution of wireless sensor networks has shifted the focus toward not only monitoring levels but also notifying users through automated network alerts [113]. ML-based techniques are being used more and more in research to improve municipal solid waste management through process prediction and optimization. These cutting-edge methods are used in several crucial areas, such as waste generation and detection modeling, collection and classification workflow optimization, and material property analysis to guarantee process optimization.

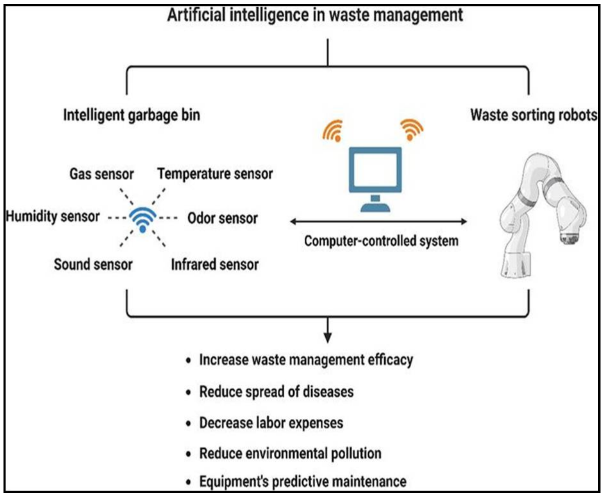

Figure 6. **Schematic representation of AI-driven waste sorting using computer vision and robotic systems, illustrating image acquisition, classification, and automated material separation. The system enhances sorting accuracy, reduces contamination, and improves recycling efficiency in real-world applications (Source: Adapted from [26], licensed under Creative Commons Attribution (CC BY 4.0)).**

As outlined in the performance data that goes with it, these features offer real-time waste bin monitoring to optimize waste disposal routes and prevent bin overflowing, and Fig. 6 shows the operational procedure for robotic arms guided by computer vision in material recovery facilities. Furthermore, efficient rubbish sorting can lower contamination and increase recycling efficiency. Robotic waste sorting, on the other hand, uses robotic arms to sort rubbish in recycling plants, enhancing sorting speed and accuracy while lowering the requirement for manual labor. Predictive maintenance, which minimizes downtime and prolongs equipment lifespans, may also make use of AI to forecast when waste-sorting equipment needs maintenance [7]. Finally, AI-based waste management optimization can improve the effectiveness of waste collection and processing by taking into account variables like traffic, weather, and population density.

Fig. 6 illustrates the integration of computer vision and robotic systems in automated waste sorting processes. The system operates by capturing visual data of mixed waste streams, which are processed using AI-based image recognition models to identify material types.

Based on classification outputs, robotic arms execute precise sorting actions in real time. This process significantly reduces contamination rates and improves recycling efficiency compared to manual sorting. Additionally, the integration of predictive maintenance models enables the system to anticipate equipment failures, thereby minimizing downtime and enhancing operational reliability.

Robots for Sorting Waste

Waste classification is a cornerstone of effective municipal solid waste management, and the integration of robotics can significantly enhance operational efficiency [114-116]. However, deploying robots in industrial settings is challenging, as they must possess advanced visual and operational capabilities to navigate heterogeneous and unpredictable environments [117-118].

a) Advanced Sensing and Target Identification: To improve classification accuracy, research is prioritizing the development of sophisticated hardware and algorithms. Hyperspectral imaging is increasingly utilized to precisely locate specific "regions of interest" within waste streams, facilitating superior material identification [83]. Furthermore, by integrating Simultaneous Localization and Mapping (SLAM) technology with instance segmentation, robotic systems can effectively navigate and manage complex field conditions.

b) Focus on Construction and Demolition (C&D) Waste: Waste management is particularly difficult on construction sites because of the large amounts of rubbish and the inherent safety hazards of human sorting.

Deep learning integration has been given priority in recent advancements to overcome these issues. In particular, instance segmentation has been used to enable robots to precisely identify the outlines of various objects for automated collecting [78, 119]. According to Yang et al. [120], the adoption of automated recovery systems has emerged as a crucial area of research for enhancing site safety and material recovery rates since manual classification is both dangerous and ineffective in these kinds of settings.

Current research focuses on the seamless integration of waste-sorting robots into established management infrastructures, particularly for pre-landfill processing [121]. A notable development in this area is the parallel robot model, which has a four-degree-of-freedom frame with a gripping feature built into it for high-speed sorting [79].

c) Performance Enhancement through Optoelectronics: Researchers are progressively fusing cutting-edge technology and complex algorithms to improve the accuracy of these systems. To identify and classify a variety of waste streams with high accuracy, new robotic systems use optical sensors and deep learning [122]. In order to increase operational speed and overall efficiency, continuous structural upgrades also focus on optimizing robotic arms, sensor suites, and classification algorithms.

d) Economic Viability and Practicality: While waste-sorting robots offer clear advantages in terms of precision and reduced labor costs, their adoption is sometimes hindered by the high capital and maintenance expenses compared to traditional manual methods. To overcome existing barriers, the scientific community is exploring affordable design strategies that utilize lower-cost materials to reduce manufacturing hurdles. Additionally, research is focusing on enhancing versatility, aiming to design robots capable of operating effectively across diverse and unpredictable environmental settings. Despite current economic debates, waste-sorting machines remain a focal point of research and are expected to play an indispensable role in future real-world environmental applications.

Waste Generation Prediction Models

The field of waste generation prediction is seeing a significant rise in research, with a variety of models being developed to more accurately forecast waste volumes [123]. These approaches range from traditional statistical methods to advanced artificial intelligence, including machine learning, deep learning, and fuzzy models. AI algorithms are particularly favored for their superior reliability, driven by their unique capacity to handle data input, autonomous learning, and precise prediction [124].

a) Machine Learning and Neural Networks: Certain algorithms have been found by researchers to be particularly effective at simulating the intricacies of waste management systems. Because of their resilience and fault tolerance, ANNs are frequently used. They are especially good at capturing the nonlinear interactions seen in multi-variable urban contexts [94]. Models like Multilayer Perceptron (MLP), Support Vector Regression (SVR), Linear Regression, Decision Trees, and Genetic Algorithms have shown improved predictive accuracy for smaller datasets with a high proportion of categorical variables [85, 125].

b) Regional and Historical Data Strategies: The availability of historical records has a significant impact on the selection of a prediction model. Cities can combine several datasets to create Gradient Boosting Regression models in data-rich environments like New York City. These models have shown excellent performance, with accuracy rates as high as 88% [89]. On the other hand, in settings with little historical documentation and little data, researchers must use thorough approaches that consider every possible predictor in order to fully comprehend regional variations and how they affect waste trends. A model's ability to accurately estimate urban waste frequently depends on how well it takes regional differences into account. By analyzing a model's dependence on specific predictive factors, researchers can better understand how geographical and demographic differences influence waste generation patterns [88].

c) The Role of AI: The rapid evolution of AI has made it a primary tool in forecasting waste generation [126-127]. The most commonly implemented AI systems in this field include: ANN, SVM / SVR, and other methods.

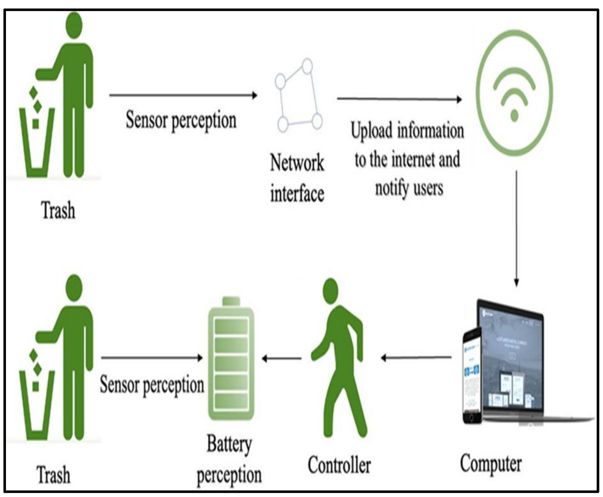

Figure 7. **An example of a solid waste management system's wireless sensor network architecture (Source: Adapted from [26], licensed under Creative Commons Attribution (CC BY 4.0)).**

Fig. 7, which depicts the waste bin with a sensor connected, illustrates the iterative process of data collection, feature selection, and model training for urban waste generation forecasting. When waste comes in, the sensor can identify it based on factors like weight, dampness, and smell. Simultaneously, it can monitor the amount of filling in waste cans and identify their surroundings. As data is supplied over the internet, users may keep an eye on the condition of waste bins on the platform in real time.

Tracking and Monitoring Waste Materials

AI has become a transformative force in waste classification and recycling by enabling more precise material identification [128-129]. ML techniques allow for the accurate sorting of plastics, metals, and paper, while AI-based monitoring systems detect anomalies such as contamination or misclassification, alerting personnel in real-time [121, 130].

a) Optimization and Process Monitoring: AI is an essential tool for systemic improvement that goes beyond simple classification. It drives process optimization by analyzing recycled data to recommend structural improvements [131]. According to Ponis et al. [132], these systems are also necessary for the accurate tracking and measurement of waste along the supply chain, guaranteeing that materials are handled efficiently at every turn. Additionally, by using sound recognition and spectrum analysis to pinpoint the origins of noise pollution, AI improves environmental perception and gives decision-makers the ability to see and control local noise distributions [133].

b) Smart Logistics and Data Integration: The practical application of AI in waste logistics incorporates a number of location and identification technologies to increase operational effectiveness. To monitor containers and optimize collection truck routes, geospatial systems integrate RFID, GPS, and GIS [134-136]. To automate container-level detection, machine learning and image processing approaches are combined. Additionally, real-time state monitoring and automatic classification are made possible by hardware solutions, such as gas sensors and intelligent terminals, which drastically save labor expenses [137-138]. While these technologies demonstrate strong performance in pilot studies, their effectiveness at a large scale depends on infrastructure readiness, data integration, and long-term maintenance capabilities.

c) Future Research Directions: The field is moving toward more integrated, multidisciplinary platforms, even if AI has greatly improved pollution tracing and information collecting [139]. The integration of remote sensing to give dynamic, long-term updates for urban home waste management is becoming a more significant area of future research. Additionally, integrating specialized knowledge is becoming more and more important, combining AI systems with human expert understanding to improve intelligent decision support. The creation of centralized, platform-based prediction models is also a top focus; these platforms use real-time sensor data to continuously train and improve models that are intended to address challenging environmental issues.

A Cyber – Physical - Environmental Framework for AI-Driven Urban Waste Management

To overcome the fragmentation observed in existing studies, this paper proposes a unified cyber-physical-environmental framework for AI-driven urban waste management [140-141]. The framework conceptualizes waste management as an interconnected system composed of four tightly coupled layers: sensing, intelligence, decision-making, and actuation, operating across the entire waste lifecycle. The physical layer includes waste sources, bins, collection vehicles, treatment facilities, and energy recovery systems. These components generate real-time data through sensors measuring fill levels, weight, temperature, gas emissions, moisture, and chemical composition. The conceptual cyber-physical-environmental framework, depicted in Fig. 9, demonstrates how artificial intelligence, data networks, sensing infrastructure, and decision-making processes are integrated throughout the urban waste management lifecycle. The paradigm emphasizes the need for explainable, scalable, and context-aware AI systems by highlighting feedback loops, operational limitations, and environmental repercussions.

As illustrated in Fig. 8, the proposed cyber-physical-environmental framework integrates sensing, data processing, intelligent decision-making, and operational actions within a unified system architecture. The inclusion of environmental feedback loops enables continuous adaptation and optimization of AI-driven waste management processes. The operational workflow of the proposed framework can be described in a sequential manner. First, the sensing layer collects real-time data from waste sources using sensors measuring fill levels, weight, temperature, gas emissions, and chemical composition. Second, the data are transmitted through IoT networks and cloud infrastructure for storage and preprocessing. Third, the intelligence layer applies machine learning and optimization algorithms to perform classification, prediction, and anomaly detection. Fourth, the decision-making layer interprets the analytical outputs to generate actionable insights, such as optimized collection routes or sorting strategies. Finally, the actuation layer implements these decisions through physical systems, including robotic sorting units, automated collection vehicles, and process control mechanisms in waste treatment facilities. This closed-loop system enables continuous feedback, learning, and adaptive optimization.

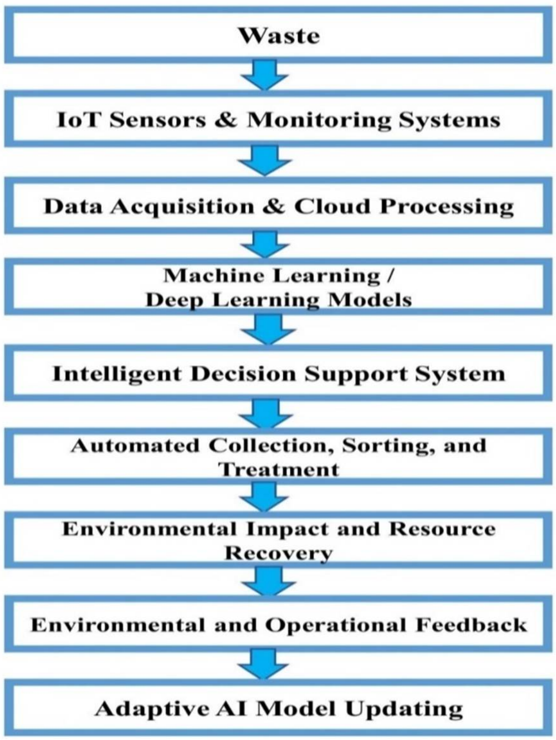

Figure 8. **Integrated cyber-physical-environmental framework for AI-driven waste management, illustrating the interaction between sensing systems (IoT sensors), data processing (cloud and AI models), decision-making layers, and actuation mechanisms (collection, sorting, and treatment), along with environmental feedback loops for adaptive system optimization. Source: Author's own construction.**

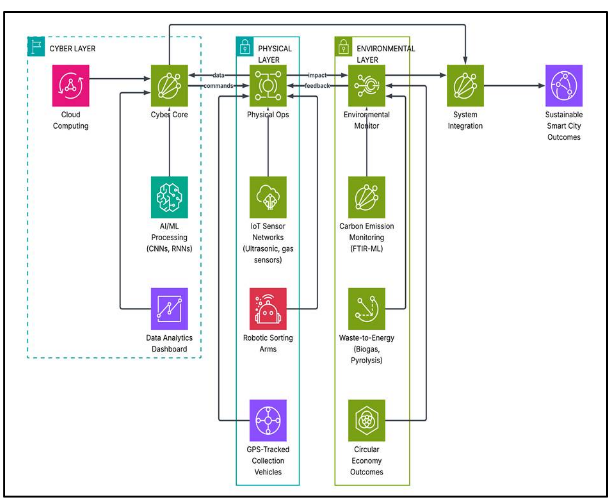

Figure 9. **Cyber-physical-environmental framework for AI-driven urban waste management. Source: Author's own construction.**

The cyber layer consists of wireless sensor networks, IoT platforms, cloud infrastructure, and data pipelines that transmit, store, and preprocess heterogeneous waste data [142-143]. This layer enables continuous monitoring and system-wide visibility. The intelligence layer applies machine learning, deep learning, and optimization algorithms to perform waste classification, generation forecasting, route optimization, anomaly detection, chemical property estimation, and energy output prediction. This layer transforms raw data into actionable knowledge. The decision and actuation layer closes the loop by translating AI outputs into operational actions, including dynamic route scheduling, robotic sorting, process control in waste-to-energy systems, illegal dumping alerts, and policy-relevant decision support [144]. Critically, the framework highlights key failure points, including data bias, model opacity, energy consumption of AI systems, and the mismatch between laboratory-trained models and real-world urban waste conditions [141]. By explicitly integrating technical, environmental, and operational dimensions, this framework provides a scalable foundation for designing explainable, resilient, and context-aware AI-enabled waste management systems.

Validation and Positioning of the Cyber-Physical-Environmental AI Framework

The proposed cyber-physical-environmental AI framework is positioned as an integrated architecture that connects sensing, analytics, decision support, and environmental outcomes across the waste management value chain. To validate its relevance and robustness, it is compared with established smart waste management frameworks and mapped against sustainability performance indicators.

First, relative to traditional cyber-physical waste systems, the proposed framework extends beyond operational automation by explicitly incorporating environmental performance layers such as emission monitoring, material circularity, and energy recovery. Conventional models focus primarily on routing, bin-fill prediction, or logistics optimization. In contrast, the present framework integrates waste characterization, process optimization, and environmental impact prediction within a unified decision architecture. Second, the framework aligns with key global sustainability benchmarks, including the United Nations Sustainable Development Goals (SDG) and circular economy principles. The sensing layer contributes to SDG 11 (sustainable cities) through optimized collection. The analytics and optimization layer contributes to SDG 12 (responsible consumption and production) through waste minimization and resource recovery. The environmental monitoring layer supports SDG 13 (climate action) through emission reduction and carbon tracking. Third, three exemplary application scenarios are used to illustrate conceptual validation: AI routing, transfer station optimization, and urban municipal waste systems, such as IoT-enabled bins, which lower fuel consumption, operating costs, and overflow incidents. Biogas output and nutrient recovery are enhanced by organic waste valorization systems, such as AI-assisted anaerobic digestion and composting control. For instance, computer vision sorting and pyrolysis optimization in plastic waste recovery systems increase polymer recovery rates and decrease landfill leakage.

Across these scenarios, the framework shows consistent performance gains in efficiency, emissions reduction, and resource recovery potential. Finally, compared with earlier models, the framework uniquely integrates environmental feedback loops into operational decision-making. This allows continuous learning and adaptive optimization, which is essential for dynamic and heterogeneous waste streams in rapidly urbanizing regions. Overall, the framework is validated conceptually as a scalable and transferable architecture that can support data-driven circular waste management systems in both developed and developing contexts.

Critical Discussion and Comparative Analysis

Comparative performance of AI models

AI models applied in waste management systems demonstrate varying performance depending on data complexity, operational scale, and implementation context. Deep learning models, particularly convolutional neural networks and long short-term memory networks, consistently achieve high accuracy in waste classification and time-series prediction tasks, often exceeding 90% in controlled environments. However, these models require large datasets, significant computational resources, and careful tuning.

In contrast, traditional machine learning approaches such as decision trees, support vector machines, and random forests are computationally efficient and easier to deploy but may exhibit lower performance when handling heterogeneous waste streams or complex temporal patterns. Hybrid approaches that integrate ML with domain-specific knowledge or sensor fusion techniques offer a balanced solution, improving robustness while maintaining computational feasibility. Compared to traditional machine learning models, deep learning approaches typically demonstrate higher classification accuracy (often above 90%), particularly in image-based waste sorting tasks. However, their performance advantage diminishes in low-data environments, where simpler models may achieve comparable results with significantly lower computational cost.

Contradictions and limitations in existing studies

Despite promising results reported in the literature, several contradictions exist between laboratory-scale findings and real-world implementations. Multiple studies report high classification accuracy under controlled conditions; however, performance often declines in practical environments due to mixed waste streams, sensor noise, and variability in waste composition. Additionally, models trained on region-specific datasets may not generalize effectively to different geographical or socio-economic contexts. These discrepancies highlight the need for more robust, scalable, and context-adaptive AI models in waste management systems.

Practical implementation challenges:

The implementation of AI-driven waste management systems faces several practical challenges, particularly in developing urban environments. Key barriers include limited data availability, a lack of standardized data collection infrastructure, high initial investment costs, and integration with existing waste management systems. In cities such as Dhaka, the presence of informal waste collection sectors further complicates the deployment of fully automated systems, requiring hybrid solutions that combine technological innovation with socio-economic considerations.

Scalability and system integration issues

Scalability remains a critical concern in transitioning from pilot-scale implementations to city-wide deployment. While AI models perform effectively in controlled or small-scale scenarios, scaling these systems requires robust data pipelines, high computational capacity, and seamless integration with municipal infrastructure. Challenges such as data heterogeneity, system interoperability, and maintenance requirements can limit large-scale adoption. Addressing these issues requires the development of flexible architectures capable of adapting to diverse operational conditions.

Implications for sustainable waste management

From a sustainability perspective, AI-driven waste management systems offer significant potential for improving resource efficiency, reducing environmental impacts, and supporting circular economy objectives. However, the effectiveness of these systems depends on their ability to integrate technological, environmental, and socio-economic factors. The proposed cyber-physical-environmental framework addresses these challenges by enabling real-time feedback, adaptive decision-making, and system-level optimization across the waste management lifecycle. These findings directly address the research gap identified in this study by demonstrating the necessity of integrating sensing, analytics, and environmental feedback within a unified framework, rather than relying on isolated AI applications.

Overall, the analysis indicates that the effectiveness of AI-driven waste management systems is not solely determined by algorithmic performance, but by the integration of data, infrastructure, and socio-environmental context.

Global Implementation Patterns of AI in Waste Management

The implementation of IoT and AI technologies in waste management demonstrates a clear geographic heterogeneity, which is fueled by differing levels of legislative maturity, economic capabilities, and digital infrastructure. As wealthy countries move toward fully integrated "Zero Waste" smart cities, emerging economies are using AI more and more to tackle fundamental issues like route optimization and unlawful dumping. Table 2 displays the AI and smart technology case studies in waste management from around the world. China and South Korea have been the front-runners in East Asia for extensive infrastructure integration. Research from Beijing and Shanghai shows that deep learning is heavily used for analyzing carbon emissions, and sophisticated logistics algorithms like Parallel Annealing are used to maximize collection times in crowded metropolitan settings. With its "Green New Deal," South Korea, in particular, is a prime example of a "Quadruple Helix" model in which the government, business, academics, and individuals work together to finance and deploy Internet of Things-based waste management systems. In a similar vein, Japan has turned its attention to human capital, leveraging industry-academia collaborations to close the skills gap needed to operate sophisticated recycling robots.

On the other hand, the Global South offers a range of focused, effective solutions. The main emphasis in Bangladesh and India is on policy development and surveillance. CNNs have been used in studies to detect unlawful dump sites with near-perfect accuracy. This is a crucial step for municipal enforcement. GIS and behavioral analysis are being used by countries in Africa, such as South Africa and Ethiopia, to manage the risks associated with liquid waste and comprehend the socioeconomic factors that contribute to careless dumping in informal settlements. The economic inefficiencies of conventional waste collection have been directly addressed by the Middle East and North Africa (MENA) region, especially Turkey and Tunisia, which have produced substantial research on genetic algorithms and ant colony optimization (ACO) to lower fuel consumption and logistics costs.

Table 2. **Global case studies of AI and smart technology in waste management.**

Country	City / Region	Focus Area	Methodology / Technology	Key Outcome / Finding	Referrence
Bangladesh	Dhaka	Waste Regime	Policy Analysis	Investigated the evolution of the waste regime and management practices in the capital city.	[16]
India	National	Forecasting	AI Models	Conducted a case study on forecasting municipal solid waste generation using various AI models.	[17]
Australia	National	Sustainable Management	Systematic Review	Analyzed AI adoption trends for sustainable solid waste management practices across the continent.	[18]
China	Chongqing	Effectiveness	Zero-Waste Index	Assessed solid waste management effectiveness using a "Zero-waste Index" to track exploration and practice.	[19]
Ethiopia	Bahir Dar	Liquid Waste	Risk Assessment	Assessed liquid waste management practices and risks in Bahir Dar.	[40]
Taiwan	University Labs	Liquid Waste	Risk Assessment	Focused on quality improvement and risk assessment of liquid waste management in chemical laboratories.	[41]
South Africa	National	Labor Market	Skills Gap Analysis	Discussed bridging the skills gap to tackle youth unemployment, relevant to green jobs in the waste sector.	[61]
UAE and Oman	National	Policy Integration	Climate Policy	Analyzed challenges in integrating climate policy with waste and resource management in oil-producing nations.	[62]
South Korea	National	Policy	Green New Deal	Examined the "Green New Deal" policy, which funds green skills training and IoT systems for waste management.	[64]
South Korea	National	Collaborative	Quadruple Helix	Investigated industry-academia-government-	[65]

		Model		citizen collaboration for environmentally sustainable cities.	
Japan	National	Human Capital	Industry-Academia Model	Reviewed challenges and achievements, highlighting cooperation between universities and local governments.	[66]
USA	NYC	Prediction	Gradient Boosting	Achieved 88% accuracy in short-term waste prediction using a Gradient Boosting model.	[89]
Bangladesh	National	Smart Systems	IoT & Robotics	Proposed a smart waste management system architecture specifically for the Bangladeshi context.	[99]
Egypt, Ghana, DRC, Nigeria, Zimbabwe	Multiple Cities	Informal Settlements	Review	Investigated waste challenges in informal settlements across Accra, Kinshasa, Lagos, Harare, and Cairo.	[108]
Ethiopia	Dejen Town	Site Selection	GIS & MCDM	Used GIS and Multi-Criteria Decision Making (MCDM) for optimal disposal site selection.	[136]
Indonesia	Banten	Policy Strategy	Urban Planning	Analyzed municipal government policy strategies for sustainable waste management in urban areas.	[144]
Australia	National	C&D Waste	Review & Policy Analysis	Evaluated practices and challenges in Construction and Demolition (C&D) waste management.	[145]
China	Beijing (Xuanwu)	Logistics	Parallel Annealing	Reduced waste collection time by 12% by optimizing vehicle routing in the Xuanwu District.	[146]
China	Shanghai	Carbon Emissions	Deep Learning	Analyzed carbon emissions under different domestic waste treatment modes and classification systems.	[147]
China	Hong Kong	Illegal Dumping	Big Data Analytics	Utilized big data analytics to identify illegal construction waste dumping patterns.	[148]
Denmark	Herning	Efficiency	Smart Sensors (IoT)	Implementation of 100 smart sensors reduced collection trips by 51% and costs by 71%.	[149]
India	National	Illegal Dumping	Multipath CNN	Achieved 98.33% accuracy in detecting illegal waste dumps using a multipath Convolutional Neural Network.	[150]
India	National	E-Waste	Artificial Intelligence	Developed an artificial intelligence-based system for the collection and management of household Waste Electrical and Electronic Equipment (WEEE), with the objective of reducing collection and operational costs by approximately 20% over a five-year period.	[151]
Iran	Large Scale (330 km^2)	Logistics	Simulated Annealing	Reduced total waste collection costs by 13.3% in a large-scale application using Simulated Annealing.	[152]
Poland	National	E-Waste	Harmony Search	Increased visited collection points by 5.4% using a Harmony Search algorithm for sustainable e-waste collection.	[153]
South Africa	Cape Town	Illegal Dumping	Behavioral Analysis	Analyzed the dynamics and drivers of indiscriminate/illegal dumping in Fisantekraal.	[154]
Togo	Lomé	Circular Economy	Sustainability Indicators	Implemented a circular economy model for waste management on the University of Lomé campus.	[155]
Tunisia	National	Logistics	Genetic Algorithm (SGA)	Reduced vehicle running time by 28.22% using a spatial GIS-based genetic algorithm for route optimization.	[156]
Turkey	Istanbul (Maltepe)	Logistics	Route Optimization	Optimized vehicle routing for solid waste management in the Maltepe district.	[157]
Turkey	Şanlıurfa	Logistics	Linear Programming / GIS	Optimized collection and transportation routes, reducing distances using Dijkstra and Tabu Search.	[158]
Turkey	Western Med.	Emissions	Machine Learning	Modeled energy and emissions from animal manure using machine learning methods.	[159]

There is still a digital divide in spite of these developments. The scalability of these technologies in developing places is nevertheless hampered by unique issues with data scarcity and infrastructure maintenance, even though Australian and European frameworks frequently concentrate on circular economy maximization and construction waste, as highlighted in recent thorough evaluations.

Artificial Intelligence-Based Chemical Analysis of Waste

The oxidation of micropollutants [160], municipal solid waste treatment [12], waste-to-energy conversion [161], and biochar for metal and organic compound adsorption [160, 162] are some of the areas where recent machine learning has attracted significant attention. Fig. 10 provides a schematic representation of the real-time data transmission pathways from ultrasonic bin sensors to centralized cloud-based management platforms.

***Figure 10*. Wireless Sensor Network (WSN) Architecture for Adaptive Urban Waste Collection and Logistics Optimization. Source: Author's own construction.**

Waste to Energy

Biogas generation represents a critical renewable energy source within a circular economy, utilizing organic waste from human and animal activities to produce electricity [155, 163]. As the International Energy Agency (IEA) predicts a two- to threefold increase in energy consumption this century, the transition toward sustainable power sources has become essential to manage resource depletion.

a) Global Energy Context (2020 Data): At over 620 Exajoules (EJ), the world's primary energy consumption in 2023 showed a slow recovery and rise in energy demand following the pandemic [164]. The global supply percentage and energy source are shown in Table 3. With a greater reliance on conventional fuels than on the newly emerging bioenergy, it is expected that urban waste generation will significantly contribute to the circular economy's resource pool, making AI-driven waste-to-energy frameworks more and more significant in this energy landscape.

***Table 3.* Source of energy and global supply percentage.**

Energy Source	Percentage of Global Supply [165]
Oil	29.47%
Coal	26.80%
Natural Gas	23.68%
Biofuels	9.84%
Other Renewable Sources	5.21%

b) The Strategic Importance of Biogas: Biogas is recognized as one of the most ecologically favorable and energy-efficient bioenergy technologies available. It is characterized by high utilization rates, particularly within circular economic frameworks [141]. This growth is notably visible in Europe, where biogas production has surpassed 6 million tonnes of oil equivalent, maintaining a robust annual growth rate of over 20% [166]. While biogas is a cornerstone of the circular economy, its production is often hindered by complex input requirements and slow reaction times. Researchers have found that traditional predictive models frequently fail to analyze key factors adequately, leading to inconsistent outputs. To address this, machine learning has been integrated to identify significant variables, effectively bypassing intricate manual computations and reducing the margin for error [159, 165].

c) Advanced Modeling and Fault Prediction: Data-driven tactics are being used in innovative ways to close the efficiency gaps in methane generation. By using deep learning models to drive predictive maintenance, biogas plants may anticipate problems in internal combustion engines that generate electricity, which simplifies troubleshooting and minimizes downtime [167]. At the same time, feedstock optimization has been improved by using ANNs, which accurately predict the best biogas yields from a variety of sources, including palm oil mill effluent, sugarcane bagasse, and bovine dung [168-169].

d) Time-Series Forecasting and LSTM: The failure to consider the effects of temporal dynamics on production capacity was a major weakness in previous studies. Due to their lack of temporal depth, conventional methods like SVM and k-nearest neighbors (k-NN) frequently proved inadequate in accounting for the time-varying nature of waste generation and energy output. To improve forecast accuracy, contemporary research uses a time-series technique. In particular, Long Short-Term Memory (LSTM) deep neural networks have become an excellent tool; they are perfect for modeling the long-term patterns of waste systems because of their special architecture, which enables them to handle high-dimensional variables and resolve the complex dependencies present in time-series forecasting [170]. Methane gas power generation remains a vital renewable energy source derived from organic human and animal waste. By leveraging machine learning and deep learning, specifically LSTM networks, researchers can now better identify key variables and predict both waste inputs and methane outputs with greater precision. Time-series forecasting is particularly important in waste management systems due to the dynamic and temporal nature of waste generation and energy production processes. Unlike static models, time-dependent approaches such as LSTM networks capture seasonal variations, population-driven fluctuations, and operational trends, leading to more accurate and reliable predictions for real-world applications.

Distinguishing Between Fossil and Modern Carbon

Precise quantification of emissions requires a clear distinction between carbon derived from modern biological processes and that originating from fossil sources. Within the context of solid waste analysis, carbon is functionally partitioned into three distinct reservoirs: the biogenic fraction, the fossil-based fraction, and the inert carbon group. This classification is essential for calculating the net greenhouse gas impact of waste-to-energy processes.

a) An important distinction is how these sources are treated in environmental policy, including environmental effects and the accuracy of estimates: Carbon accounting distinguishes between different kinds of waste according to their atmospheric lifespan in the context of environmental impact assessments. Because the carbon released during disposal was recently removed from the environment, emissions from organic materials like paper, food waste, and wood are typically classified as carbon neutral. On the other hand, human climate change is closely linked to emissions from industrial logistics and systems such as the Freight Classification Guide System [171]. The risk of overestimation is a crucial technical issue in waste-to-energy calculations; if carbon from biomass is not correctly separated from carbon from fossil fuels during the incineration of solid waste, the resulting findings on greenhouse gas (GHG) emissions could be greatly exaggerated, which would distort environmental policy data.

b) Challenges in Machine Learning Adoption: Three main obstacles prevent the widespread use of algorithms like Random Forests and SVM, despite the fact that they are effective at uncovering latent relationships in waste datasets [172]. First, model dependability is frequently hampered by data limitations, such as the small size and poor quality of accessible datasets [173]. Second, interpretability is still a problem since decision-makers find it hard to extract useful information from "black-box" models due to their lack of transparency [174]. Lastly, real-time deployment is made more difficult by lengthy timescales caused by high computational expenses and demanding processing needs [175].

c) Innovative Analytical Techniques: Researchers are increasingly employing hybrid spectroscopic techniques to increase forecast accuracy, which is sometimes constrained by studies that only look at one or two model types [176]. When Fourier-transform infrared (FTIR) spectroscopy and ML are combined, the mass-based biogenic and fossil carbon content may be precisely determined. This method produces findings quickly and with a large reduction in labor and chemical usage. Additionally, by enabling machine learning to detect and separate impurities like plastics and stones from organic feedstock, these bioprocessing innovations reduce environmental concerns and boost the overall profitability of anaerobic digestion and composting [177].

Measuring carbon emissions requires the precise identification of biogenic and fossil sources. Utilizing ML (Random Forests, SVM) alongside FTIR spectroscopy allows for the efficient extraction of data and quantification of carbon types, ultimately leading to more sustainable and fiscally beneficial waste management strategies.

Pyrolysis Conditions Prediction for Recycling Plastic

Current global waste management systems lack the capacity to securely dispose of or recycle the vast amounts of waste plastic produced, leading to significant environmental accumulation, including millions of tonnes of microplastics entering the seas annually [30, 178]. Pyrolysis has emerged as a vital conversion technique to address these ecological obstacles by transforming waste polymers into useful products.

a) Machine Learning in Pyrolysis Simulation: According to Ascher et al. [160], ML greatly aids in the comprehension of intricate mathematical relationships in pyrolysis processes by linking feedstock inputs to certain chemical reactions. Since they can frequently estimate tar, coke, and permanent gas yields better than traditional gas balance models, ANNs have become the most widely used method for modeling biomass gasification [179]. Furthermore, life cycle assessments and economic studies have been effectively combined with tree-based algorithms such as Random Forests and Decision Trees to analyze the feasibility of different pyrolysis feedstocks [179]. SVMs have outperformed ANNs in certain prediction tasks, such as biochar yield, by obtaining smaller root mean squared errors and higher R2 values [180]. Many advanced AI models, particularly deep learning architectures, are often referred to as “black-box” systems because their internal decision-making processes are not easily interpretable. This lack of transparency can limit their adoption in policy-sensitive and safety-critical applications. To address this issue, explainable AI techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) are increasingly used to provide insights into model predictions and improve trust in AI-driven systems.

b) Input Factors and Variable Selection: The correct classification of polymers, including polyethylene (PE), polypropylene (PP), polystyrene (PS), polyvinyl chloride (PVC), and polyethylene terephthalate (PET), is necessary for accurate modeling of plastic waste management. The evaluation of essential chemical components, mainly carbon, hydrogen, oxygen, nitrogen, and chlorine, supports this classification, but sulfur is usually left out because of its insignificant influence [30]. Additionally, some operating parameters, such as particle size, feed capacity, pyrolysis temperature, and steam residence duration, are essential for simulating effective waste-to-energy conversion and are dependent on the optimization of these models [181].

c) Catalyst Selection and Hydrogen Production: ML is essential for maximizing the production of hydrogen from the hydrothermal gasification of biomass, especially when Principal Component Analysis is used to screen alkali and transition metal catalysts [182]. Catalyst integration is essential to improving hydrogen generation, according to technology decision support systems [183]. Nevertheless, a crucial trade-off is shown by environmental modeling employing Levenberg-Marquardt and Bayesian regularization algorithms: although catalysts such as sodium hydroxide optimize gas composition, they may also raise the process's potential for global warming [184].

Table 4. **Artificial intelligence applications in waste chemistry.**

Field	Key information	Reference
Calculate the emissions of carbon	When determining greenhouse gas emissions from burning solid waste, the composition of the carbon source (biochar, fossil, and inert) is crucial. The features of solid refuse groups can be predicted, and latent connections can be found using machine learning approaches like support vector machines and random forests. By utilizing infrared spectroscopy and machine learning to quantify the carbon content of biological sources and fossils in terms of mass, researchers can assess how burning solid waste can reduce carbon emissions while saving a significant amount of time and reagents.	[171, 176, 185, 186]
Bioenergy from waste	A complicated substance widely utilized in carbon capture and sustainable waste management is porous carbon made from biomass waste. A sustainable energy source, biogas power generation is fueled by biological waste generated by humans and animals. It is considered one of the most environmentally friendly and energy-efficient bioenergy production methods and is a component of the circular economy. However, the production of biogas power requires a complex input and a long response time, and there is no way to combine deep learning and machine learning models.	[26, 166, 167, 169, 187, 188]
Pyrolysis of waste	By comprehending the mathematical connections between intricate procedures and algorithms, machine learning can be enhanced by connecting inputs to appropriate outputs. The study's input variables include steam residence time (s), pyrolysis temperature (°C), and feed capacity (kg/h). Particle size (mm), final analysis, and the composition of various plastic kinds are examples of raw material characteristics that are taken into account as input parameters in the study. Catalysts that maximize hydrogen production while reducing carbon dioxide yield can be found and assessed using these models. These models may also be used to reproduce the sodium hydroxide-catalyzed hydrothermal gasification of waste biomass and optimize hetero-catalyst loading during hydrothermal gasification in order to examine the process's environmental effects.	[160, 179, 189, 190]

d) Future Directions and Research Gaps: Future research must move toward more visible and integrated approaches in order to solve the "black-box" constraints of ML, which frequently obfuscate particular reaction pathways. In order to give a better understanding of the underlying reaction mechanisms, one main tactic is to combine ML with conventional kinetic research [160]. Improving model interpretability is also crucial for elucidating the connections between input variables and desired outcomes, which will help academics and decision-makers better understand these intricate algorithms. In order to guarantee accuracy and scientific clarity, the ultimate objective is to create thorough, integrated predictive models that take into account all important operational and environmental factors.

Waste pyrolysis, carbon emission prediction, and energy conversion are the three primary areas where AI is applied in waste chemistry, according to Table 4, which summarizes 14 articles. Significant details are also condensed.

Waste Disposal and Illegal Dumping

Illegal dumping poses significant ecological and health risks [154, 191]. While traditional surveillance is resource-heavy and often ineffective [192], several AI frameworks have been developed to automate detection:

a) Computer Vision and Street Surveillance: Computer vision is used in street surveillance as a tool for spatial monitoring and as a potent deterrent against unlawful dumping. Multipath architectures have demonstrated up to 98.33% accuracy in identifying waste zones, demonstrating the great efficacy of CNN [150]. Additionally, it has been demonstrated that adding Residual Networks (ResNet) to convolutional layers greatly improves target location and detection accuracy [193]. In addition to this, the YOLO (You Only Look Once) algorithm is frequently used to locate cars and people who dispose of rubbish. Advanced versions of these systems use the OpenPose algorithm to track the spatial separation between waste bags and dumpers with 93% accuracy, while others examine the precise form and motion of waste-carrying trucks to guarantee legal compliance [192, 194].

b) Aerial and Satellite Monitoring: The scope of waste management has increased from street-level surveillance to regional environmental protection thanks to aerial and satellite monitoring. Nowadays, waste is autonomously located in river channels and crowded urban corridors using Unmanned Aerial Vehicles (UAVs) fitted with Faster R-CNN and Single Shot Detector Algorithms (SSDA) [195-196]. More broadly, high-resolution satellite data is analyzed by Random Forest algorithms and Feature Pyramid Networks to identify illicit dump sites with an accuracy of up to 88% [197-198]. Significant limitations still exist, though; low-resolution data or persistent cloud cover most of the time make it difficult for existing aerial approaches to identify waste pieces smaller than 64 cm^2 [197, 199]. Notwithstanding these obstacles, the use of AI keeps improving the effectiveness of the four main disposal pillars: landfilling, incineration, composting, and recycling [130].

c) Waste Recycling and Reuse: AI makes it easier to physically sort materials and evaluate the structural integrity of recycled goods in the recycling and reuse space. While transfer learning techniques have been successfully adapted to identify complex electronic waste, such as smartphones [200], CNNs have shown remarkable precision, classifying waste into five distinct categories with 96.57% accuracy [201]. AI improves material reuse in engineering beyond sorting; models that use

Particle Swarm Optimization and Boosted Regression Trees can precisely forecast the mechanical strength of recycled composites. By drastically reducing the need for conventional, time-consuming mechanical testing, our computational method speeds up the circular economy's adoption of materials derived from waste [202].

d) Waste Composting: AI is a vital tool in the waste composting industry for maximizing quality and reducing environmental risk. In order to produce high-quality, nutrient-rich fertilizers, ANNs are used to fine-tune maturity factors during the composting process [203-204]. By combining ML and genetic algorithms, heavy metal concentrations in livestock manure can be predicted and reduced, reducing the possibility of soil contamination and allaying safety concerns [177]. Additionally, Random Forest algorithms offer an advanced way to track atmospheric impact, with 88% accuracy in predicting CO_2 emissions from green waste composting cycles in particular [205].

e) Waste Landfilling: AI improves logistical planning and environmental safety in the field of landfill management by using high-precision modeling. For better containment and treatment planning, double-hidden-layer ANNs are the best design for predicting leachate production rates [206]. In order to find places with the least amount of ecological damage, researchers use integrated models that combine the Fuzzy Analytic Hierarchy Process (FAHP) with Random Forests within GIS frameworks for the crucial task of site selection [207]. Additionally, landfill operations have a significant difficulty in odor control, which can be handled by integrating ANN models with genetic algorithms to predict emission rates of volatile compounds such as methyl sulfide with a sufficient level of accuracy [208].

f) Waste Incineration: AI is turning heat treatment in the waste incineration industry from a completely mechanical procedure into a highly efficient digital system. In order to replicate the intricate, nonlinear dynamics of incineration power plants and enable more stable energy recovery, deep learning models are being used more and more [119, 209]. Additionally, these computational tools are essential for environmental compliance; for example, it has been demonstrated that using ANNs to optimize combustion conditions reduces nitrogenous gas emissions by 34%, indicating a significant improvement in pollution control over manual monitoring [210]. The comparative overview of AI models in waste management is displayed in Table 5.

Table 5. **Comparative summary of AI models in waste management.**

AI Model/Algorithm	Primary Application	Specific Performance/Accuracy	Reference
Multipath CNN	Illegal Dumping Detection	98.33% Accuracy	[150]
LSTM Deep Neural Networks	Time Series Forecasting	Handles numerous variables	[170]
YOLO + OpenPose	Monitoring Humans (Dumping)	93.00% Accuracy	[192]
ResNet 50 + FPN	Illegal Dump Identification	88.00% Accuracy	[198]
CNN	Waste Classification (5 types)	96.57% Accuracy	[201, 202]
Random Forest	CO_2 Prediction (Composting)	88.00% Accuracy	[205]
ANN (Double Layer)	Leachate Forecasting	Identified as Optimal	[206]
Fuzzy AHP + Random Forest	Landfill Site Selection	GIS-integrated selection	[207]
Genetic Algorithms	Odor Emission Prediction	Satisfactory Accuracy	[208]
ANN	Incinerator Optimization	34% Reduction in N-gas	[210]

g) Synthesis of AI-Driven Waste Management Pathways:

i. Monitoring and Detection of Mismanagement: Governments are moving away from manual patrols toward automated surveillance. High-resolution imagery combined with Faster R-CNN and SSDA allows for the identification of waste via drones, though challenges remain in wooded or low-resolution areas [195, 196, 211].

ii. Optimization of Disposal and Recycling: The circular economy is being greatly advanced by AI technologies, which optimize recycling and disposal routes. Transfer learning is used in recycling to accurately classify complex electronic waste, like smartphones, and particle swarm optimization is used to predict the structural strength of repurposed materials, which eliminates the need for destructive testing [202, 212]. A strong foundation for reducing the hazards of heavy metals in livestock manure is provided by Support Vector Regression, and ANNs are used for biological treatment to increase the maturity of compost [177, 203]. Moreover, deep learning models and Ant Optimization Algorithms are being used to improve incineration efficiency by simulating the nonlinear dynamics of power plants to maximize energy recovery and operational stability [119, 213].

h) Advanced Environmental Modeling: The integration of FTIR spectroscopy with ML provides a rapid, chemical-free method for distinguishing between biogenic and fossil carbon, which is crucial for accurate GHG emission reporting [171, 185]. Furthermore, in the realm of bioenergy, LSTM networks are becoming the standard for resolving time-series issues in biogas input and output forecasting [170].

Transportation, Recycling, and Logistics

The logistics and transportation phase represents a critical "hub" in waste management, connecting sources to treatment facilities [214]. However, this sector faces significant challenges: collection costs often account for 70-80% of total waste management budgets, exacerbated by disorganized planning and personnel constraints [18, 215]. AI solutions have been implemented to optimize these processes across four primary metrics: distance, cost, time, and efficiency [10]. The summary of AI-driven logistics improvements is displayed in Table 6.

Table 6. **Summary of AI-driven logistics improvements.**

Objective	AI Algorithm	Key Impact / Improvement	Reference
Time	Parallel Annealing	12% Time Saving	[146]
Efficiency	Harmony Search	5.4% More Points Visited	[153]
Time	Genetic Algorithm	28.22% Time Saving	[156]
Distance	Dijkstra-Tabu Search	28% Reduction	[158]
Distance	Ant Colony Optimization	13% Reduction	[216]
Cost	Simulated Annealing	13.3% Cost Saving	[217]
Efficiency	Backtracking Search	36.78% Efficiency Gain	[218]

a) Optimization of Transportation Distance: Spatial navigation algorithms have proven to significantly reduce journey distance, which immediately lowers emissions and operating costs. Iterations of ACO have demonstrated a 13% reduction in the overall transit distance, demonstrating its effectiveness in identifying the shortest routes from localized data points [216]. Even more successful has been the combination of the Dijkstra algorithm for shortest-path calculation and Tabu search for finding the fastest routes; in tests with up to 200 collection points, this hybrid approach reduced the transport distance by 28% [158].

b) Optimization of Transportation Cost: The optimization of intricate distribution networks is made possible by randomized heuristic models, which are increasingly being used to target financial efficiency in waste logistics. In order to discover a global optimum, the Simulated Annealing Algorithm iteratively refines initial values generated by random processes. This is a prime example. In particular, this approach was used to successfully reduce overall operating costs by 13.3% in a network of 43 recycling nodes in Iran [217].

c) Optimization of Transportation Time: Dynamic scheduling methods immediately address operational inefficiencies by drastically lowering the number of hours that cars spend on the road. In Tunisia, genetic algorithms, which are frequently combined with GIS and Python-based visualization, have shown promise in reducing vehicle running times by 28.22%, according to experiments [156]. Similarly, a 12% reduction in collecting time was attained by the Parallel Annealing Algorithm when it was successfully implemented in Beijing's Xuanwu District [146]. These models' assumption of unchanging vehicle speeds, which does not yet adequately account for real-time traffic variations, is a current drawback.

d) Optimization of Efficiency and Accessibility: The amount of waste collected every trip is greatly increased via smart bin integration and search algorithms, improving accessibility and operating efficiency. It has been demonstrated that the Backtracking Search Algorithm can increase overall collection efficiency by 36.78% while lowering the total number of bins needed when combined with real-time data from smart waste cans [218]. The Harmony Search Algorithm has also been used in specialized logistics, such as the collection of electronic waste in Poland, where it was able to improve the number of collection places visited by 5.4%, guaranteeing a more comprehensive recovery of hazardous goods [153].

Recovering and Identifying Important Resources

The rapid expansion of the global economy has led to a surge in waste production, overwhelming traditional management methods like landfilling and incineration, which often result in environmental degradation [147, 219]. While recycling offers a sustainable alternative, manual classification is inefficient. Consequently, researchers are turning to AI and deep learning to provide reliable, automated identification and classification systems [220]. The classification models' comparative performance is displayed in Table 7.

Table 7. **Comparative performance of classification models.**

Model Approach	Classification Goal	Accuracy	Reference
CNN (Standard)	4 Categories	92.43%	[202]
ResNet + Self-Monitor	6 Material Types	95.87%	[220]
Deep CNN	5 Municipal Categories	97.63%	[222]
CNN (Textiles)	13 Textile Types	95.40%	[224]
Two-Stage Retrieval	13/4 Categories	N/A	[228]
Multilayer Hybrid CNN	6 Material Types	92.60%	[230]
CNN (Organic/Inorganic)	10 Sub-classes	90.00%	[231]
Binary CNN	Recyclable/Non-recyclable	99.50%	[232]

a) Deep Learning and CNN Architectures for Waste Sorting: CNNs and their variations have become the industry standard for classifying waste according to its form and substance. For example, two-stage recognition-retrieval algorithms can classify waste into thirteen initial categories and four larger categories [204, 220]. Multi-stage and hierarchical models have been very useful. In a similar vein, hierarchical techniques employing Faster R-CNN have been effectively used to differentiate waste from food trays according to intricate physical characteristics [221]. In municipal settings, Deep CNNs employing single-shot detectors have reached impressive accuracy rates of 97.63% across five major waste categories [222]. While models incorporating self-monitoring modules in ResNet have achieved 95.87% accuracy, researchers note a common limitation: these models often rely on idealized datasets that may not fully reflect the unpredictable conditions of real-world waste streams [223]. Furthermore, specialized CNN systems are now tailored for material-specific streams, achieving 95.4% accuracy for textile waste and providing high-precision sorting for complex plastic polymers [224-227].

b) Transfer Learning and Data Augmentation
Researchers use sophisticated training methods like Transfer Learning and Data Augmentation to get over the typical problem of data scarcity in waste management modeling. Although the quality and complexity of the original training imagery frequently limit the efficiency of transfer learning, which uses pre-trained CNN architectures to correctly classify waste into five material classes with 82% accuracy [228]. Classifying building waste has also benefited greatly from data augmentation, which is the process of artificially growing databases through transformations. However, during the primary image collection phase, environmental factors like lighting conditions and the overall volume of data still have an impact on how reliable these models are [229].

c) Real-World Application and Mobile Integration: Beyond industrial settings, AI is moving into the consumer space. Real-time mobile applications now use image recognition and CNNs to help users classify waste into six categories and determine recyclability on the go [233]. However, challenges such as high hardware costs, energy consumption, and the "reality gap" between lab datasets and actual waste remain a focus for future development [202, 228].

Enhancing Quality of Life and Public Health

Implementing AI in waste management is a transformative strategy to enhance sustainability, protect public health, and transition toward a circular economy [48, 234]. By automating complex tasks such as sorting, monitoring, and logistics, AI helps reduce the reliance on natural resources while maintaining high living standards [235-237]. The comparison between AI-powered and conventional waste management is displayed in Table 8.

Table 8. **Comparison of AI-powered vs. traditional waste management.**

Features	Traditional Management	AI-Enhanced Management	Reference
Sorting Speed	30-60 items per minute	Up to 160 items per minute	[18]
Logistics	Static routes/Fixed schedules	Dynamic route optimization	[156, 218]
Accuracy	Prone to fatigue and error	95-99% Precision	[222]
Health Risk	High (Manual handling)	Low (Automated/Remote)	[243-244]
Operation	Limited by shifts/Labor laws	Continuous 24/7 operation	[245]

a) The Role of AI in Municipal Solid Waste (MSW): The growing amount of solid waste in the world, which currently usually surpasses existing recycling capabilities, can be managed strategically with AI [145]. Intelligent sorting, where traditional manual labor is being replaced by autonomous machines, is at the center of this change. Compared to the 30-40 materials that human workers normally manage, these AI-driven systems can process up to 160 items per minute, which is a huge improvement [18]. In order to accomplish this, computer vision systems use deep learning to scan objects on fast conveyor belts, accurately and consistently differentiating between organic waste, metals, and plastics [238-239].

b) Smart Bins and Urban Monitoring: Smart bins are a crucial real-world example of AI in action, enabling local governments to maximize resource distribution through data-driven logistics. Fill-Level Monitoring, which uses integrated sensors to track bin capacity in real-time, is a fundamental component of these systems. By doing this, waste management firms can drastically cut down on labor intensity and fuel usage by dynamically optimizing collection routes and timetables [240-241]. Beyond logistics, Automated Classification at the Point of Disposal ensures higher purity in segregated streams from the start of the waste lifecycle by using machine learning to identify and sort waste as it is disposed of [13].

c) Medical Waste and Pandemic Response (COVID-19): The COVID-19 pandemic highlighted the urgent need for AI in the handling of hazardous medical waste, which poses serious hazards of infection to the air, water, and soil [242]. In order to reduce human interaction with contaminated goods and break the viral transmission chain, AI-driven picture classification and item recognition systems have been implemented to lessen these risks [243]. Furthermore, hospitals and clinical settings can be remotely monitored thanks to Intelligent Surveillance frameworks, which employ an "Internet + video surveillance" strategy. These technologies ensure stringent regulatory compliance without exposing staff to high-risk regions by automatically detecting abnormal disposal behaviors and setting off real-time alarms for law enforcement [244].

AI waste management integration is now essential for sustainable development, not just a fad. AI improves everyone's quality of life and the environment by optimizing the waste lifecycle from generation to final disposal [246-247]. While laboratory-scale studies demonstrate the effectiveness of AI-assisted waste chemistry processes such as FTIR-based carbon analysis and pyrolysis optimization, large-scale implementation remains challenging. Issues such as data variability, feedstock heterogeneity, and process scalability must be addressed to ensure practical deployment. Future research should focus on integrating these models with industrial systems and validating their performance under real-world operational conditions.

Developing Smart City Waste Management Systems

In the architecture of smart cities, waste management is no longer a passive utility but a dynamic, data-driven ecosystem [200, 248]. Leveraging the IoT and AI, these cities transition from static, schedule-based collection to "event-driven" systems that respond to real-time urban needs [249]. The integration of AI-assisted chemical analysis for optimizing waste-to-energy pathways and resource recovery is comprehensively modeled in Fig. 11.

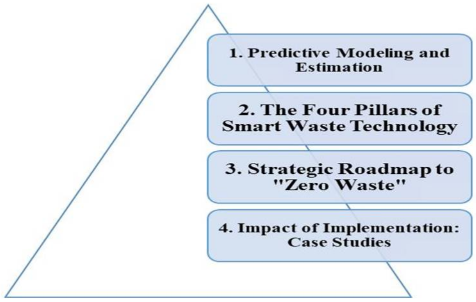

Figure 11. **Process flow for AI-assisted thermochemical and biological conversion of solid waste into sustainable bioenergy resources. Source: Author's own construction.**

Predictive Modeling and Estimation: Smart cities are moving from historical observation to proactive future estimation to develop sustainable urban infrastructures. By classifying forecast durations into three different temporal scopes, short-term (daily to monthly), medium-term (3-5 years), and long-term (reaching decades), AI models enable this transition. More accurate resource allocation is made possible by these models, which combine intricate sociodemographic and economic data to forecast particular waste surges, such as those involving plastic and household packaging [250-251]. A strong algorithm stack, mainly using ANN, SVM, and ANFIS, maintains high predicted accuracy. In order to guarantee that municipal infrastructure develops in step with urban growth, these methods are excellent at spotting non-linear patterns in waste generation [250].

The Four Pillars of Smart Waste Technology: A strong, smart waste ecosystem is characterized by four fundamental technical pillars that connect digital and physical waste management [252]. The fundamental spatial intelligence is provided by space technology, which uses GPS and GIS to track collection vehicles in real time and strategically manage disposal locations [29]. Identification techniques like barcodes and RFID tags, which enable accurate tracking of individual waste units over the course of their lifecycle, are used in conjunction with this. Advanced data acquisition tools are used by the system's "senses"; ultrasonic and infrared sensors, when paired with high-resolution photography, offer vital information on waste composition and bin fill levels [68]. Data Communications infrastructure, which uses 5G, Wi-Fi, and LoRaWAN to connect these elements, guarantees smooth, low-latency data transfer between smart bins, transport fleets, and central command hubs, allowing for the real-time responsiveness needed in contemporary urban settings [249].

Strategic Roadmap to Zero Waste: A systematic, modular framework that combines advanced physical processing, human behavior, and industrial data is required to realize the "Zero Waste" concept in urban settings [249, 253]. Three main functional components characterize this roadmap: Product Life Cycle Collating is the main focus of Module I, which creates a strong data framework to track products from manufacturing to final disposal; Citizen Engagement is the main focus of Module II, which uses cutting-edge mobile applications to encourage and reward responsible waste reduction behaviors; and Intelligent Infrastructure, including automated conveyor belts and AI-vision-guided systems, is deployed in Module III to maximize the recovery of high-value materials [254]. Municipalities can go from conventional linear waste disposal to a fully optimized circular economy that guarantees resource efficiency and environmental sustainability by coordinating these modules.

Impact of Implementation: Case Studies: Pilot projects conducted in the real world offer strong proof of the effectiveness of AI and IoT-driven waste designs. By installing 100 smart sensors, the city of Herning, Denmark, was able to cut collection trips by 51%, which resulted in a significant 71% reduction in waste management expenses annually [121, 143, 204]. Songdo, South Korea, has adopted a more systemic approach by putting in place a pneumatic waste collection system throughout the entire city. This system demonstrates the potential for fully automated urban waste logistics by transporting waste through a network of subterranean pipes straight to processing facilities, doing away with the need for conventional waste trucks [255-256].

The smart city design modules summary is displayed in Table 9. The machine learning algorithms and AI models for solid waste prediction, reduction, and recycling are displayed in Table 10. The amount of information that each algorithm needs for machine learning varies, as do their sizes. Every algorithm has a different set of benefits [255, 257-259].

Table 9. **Summary of smart city design modules.**

Design Component	Primary Technology	Impact on Sustainability	Reference
Bin Monitoring	Ultrasonic Sensors (IoT)	Prevents overflow & unhygienic conditions.	[68]
Route Optimization	GIS and Dynamic Routing	Reduces fuel/CO_2 by up to 50%.	[121, 143, 204]
Predictive Analysis	SVM and Neural Networks	Forecasts plastic/packaging trends.	[251]
Automated Sorting	Multilayer CNNs	Replaces manual, error-prone labor.	[254]

Table 10. **Machine learning algorithms and artificial intelligence models for solid waste reduction, recycling, and prediction.**

Parameters for input	Parameters for output	Artificial intelligence technology types	Scale	Benefit	Reference
Weather, household waste collection, and tonnage information from the past.	Tonnage of municipal solid waste generated each week.	Decision trees with gradient boosting.	Short-term	It works well for prediction problems and may be applied to big data sets.	[89]
Monthly time series of the production of municipal solid waste.	Production of solid waste from municipalities.	Assist with vector machines.	Short-term	When there is a maximum marginal splitting of groups, the system performs well.	[91]
Temperature, heating rate, and biomass sludge ratio.	Percentage of significant losses.	Perceptron network with many layers.	Short-term	-	[209]
Data is gathered on specific building qualities, weather, neighborhood socioeconomic indicators, and chosen route levels.	Construction-grade production of municipal solid waste.	Decision trees with gradient boosting.	Medium-term	Compared to other models, the linear regression function showed a higher correlation coefficient for the training data set.	[260]
Transportation, gas, electricity, water, and human power.	Recycled materials, bio-depletion potential, acidification potential, and eight more environmental impact categories.	Perceptron network with many layers.	Short-term	-	[261]
Amount of waste tea, pH, concentration of polyacrylonitrile, flow of sample and eluate, volume of eluate, and concentration of lotion.	Manganese and cobalt extraction percentage.	Inverse of a particle swarm neural network.	Short-term	It is possible to do a sensitivity analysis.	[261]
The weight bridge's monthly solid waste volume and vehicle travels.	The size of the landfill is estimated using the amount of solid waste that is produced and collected.	Neural network with feed-forward back-propagation.	Medium-term	Learning techniques for artificial neural networks are very resilient to noise in training data.	[262]
Temperature, pH, stirring, and duration of pretreatment for municipal waste-activated sludge.	The activity of enzymes.	Perceptron network with many layers.	Short-term	-	[263]

Efficiency Gains and Cost Savings in Waste Systems

The integration of advanced algorithms has demonstrated a dual impact: reducing the time required for waste collection and significantly lowering operational expenditures.

Enhanced Detection and Collection Efficacy: Waste recovery systems are now much more effective because of developments in automated identification and logistics, especially in complex or dynamic contexts. Despite the additional processing load, the usage of Faster R-CNN in a Few-shot waste detection framework has proven useful in identifying rubbish in natural situations, with an accuracy 1.68% higher than traditional detectors [264]. In terms of logistics, the use of the Cuckoo Search Algorithm, which considers both waste categories and truck capacity, has simplified processes to the extent that collection may now take place within a constrained 15-minute timeframe [256]. To illustrate the effectiveness of synchronized hardware and software in urban management, an improved Backtracking Search Algorithm combined with real-time smart bin data has increased overall collection efficacy by 36.78% [218].

Economic Benefits of Automation: AI-driven systems are demonstrating superior cost-effectiveness compared to traditional manual labor by minimizing operational overhead and maximizing material recovery. For specialized streams, a CNN-based system for electronic waste classification achieved 96% accuracy across eight categories, projecting a 20% reduction in costs over five years [265]. In terms of logistics, the integration of IoT software with ACO for route planning has led to a reported 30% reduction in direct collection expenses [266]. These financial gains are further validated in large-scale urban applications, such as a 330 km^2 area in Iran, where the Simulated Annealing algorithm successfully reduced total system costs by 13.3% [217].

Critical Challenges in AI Implementation

Despite these successes, the "black box" nature of AI and data-related hurdles remain significant obstacles to further progress.

The "Black Box" Problem: The internal complexity and independent operation of AI models make it difficult to estimate the significance of individual variables. This lack of transparency limits manual intervention and creates uncertainty in real-world environmental applications [185, 250].

Data Scarcity and Quality: AI has great potential for waste management, but the sector confronts major challenges with regard to data quality and scarcity, especially in poor countries. Incomplete records and data gaps are still common, even though deep learning and machine learning models need large, high-quality datasets for efficient training [10]. Overfitting, in which a model performs well on training sets but is unable to generalize in uncertain real-world situations, is frequently the result of relying on inadequate or out-of-date data. Additionally, low-quality data lowers overall training efficiency, which in turn lowers deep neural network reliability in crucial municipal applications [185, 250].

Lack of Tailored Models: Current research often relies on "off-the-shelf" models (like standard CNNs or Faster R-CNN) rather than systems designed specifically for the unique variables of waste streams. There is an urgent need for collaboration between waste management experts and computational scientists to develop customized AI models [10]. The impact vs. barriers summary of AI is displayed in Table 11.

Table 11. **Summary of artificial intelligence impact vs. obstacles.**

Benefit Category	Impact Level	Key Obstacle	Reference
Collection Efficacy	+36.78%	Computational Complexity	[218]
Direct Cost	-30.00%	Data Scarcity	[266]
E-Waste Accuracy	96.00%	Lack of Customization	[265]
General Cost	-13.30%	Black Box Uncertainty	[217]

Limitations in Current AI Applications and Future Pathways

The transition from lab-controlled environments to real-world waste management reveals several systemic weaknesses:

Logistics and Surveillance Constraints: Even though AI has made significant strides in logistics and surveillance, a number of practical limitations prevent extensive real-world deployment. Operational idealization is a major drawback; many path optimization algorithms make the assumption that vehicle speeds are set, which is very difficult to do given the unpredictability of actual traffic situations [146]. Additionally, existing models for detecting unlawful dumping, including those that use Faster R-CNN, are sometimes limited in their applicability, excelling in particular terrains like riverbeds but falling short in the visually complex metropolitan environments [195]. Detection via drones also faces visibility barriers, as these systems cannot identify waste hidden beneath tree canopies or within forested areas [196]. Finally, model sensitivity to image resolution remains a significant bottleneck, where high-resolution aerial models frequently produce errors when processing lower-resolution imagery, leading to critical identification failures [211].

The "Reality Gap" in Sorting and Classification: There is a notable "reality gap" in automated waste sorting when comparing laboratory achievement to field deployment. One of the main challenges is the simplicity of the dataset; CNN and transfer learning model training images are usually clean and well-lit, but they don't capture the filthy, distorted, and overlapping waste that is present in real-world situations, which invariably leads to lower practical accuracy [220]. Furthermore, as many high-precision systems require costly GPU infrastructure and high-power consumption, the hardware and energy requirements of many deep learning architectures present a hurdle to scalability [202]. Trade-offs associated with data augmentation make it more difficult to refine models; in the classification of construction waste, for example, increasing the volume of data without accounting for environmental factors can actually worsen performance, especially when training sets contain imagery taken at different times of day, like sunrise or sunset [229].

Future Prospects and Research Directions: The scientific community is turning toward three crucial evolutionary phases that define the future of smart waste management in order to overcome present constraints. In order to deconstruct the "black box" nature of deep learning, Explainable AI (XAI) must be integrated. Class Activation Mapping (CAM) offers preliminary visual cues, but more reliable interpretative frameworks are needed to guarantee accountability and trust for humans in the loop [185, 267, 268]. Second, a move toward responsive, real-time data flows is being facilitated by the smooth technological integration of data science and IoT. In addition to improving operational dynamism, this synergy mitigates overfitting and increases overall model dependability by using strict data-cleaning rules [185, 268, 269]. Lastly, multi-model hybrid systems are becoming more popular. These systems incorporate many architectures, including CNNs, residual networks, and gradient boosting regression, to provide a level of accuracy and resilience that single-model approaches are unable to match [185]. The summary of limitations compared to future pathways is displayed in Table 12.

Table 12. **Summary of limitations vs. future pathways.**

Research Area	Key Limitation	Future Prospect	Reference
Logistics	Fixed-speed assumptions	Real-time traffic data integration	[146]
Surveillance	Poor visibility in covered areas	Multi-sensor fusion (IR/Lidar)	[196]
Transparency	"Black box" nature	Explainable AI (XAI)/CAM	[185, 267]
Accuracy	Simple training datasets	Data science and multi-model hybrids	[228, 268, 270, 271]

Research Gaps and Future Agenda

Despite rapid progress in AI-driven waste management, several critical gaps remain unresolved.

Unresolved Challenges

a) Data scarcity and heterogeneity: High-quality, labeled, and standardized waste datasets remain limited, especially in low- and middle-income regions.

b) Model generalizability: Many AI models perform well in controlled environments but fail when applied to different cities, climates, or waste compositions.

c) Integration of environmental impact metrics: Most studies optimize operational efficiency but do not fully integrate life-cycle emissions, toxicity, or ecological impacts.

d) Economic feasibility and cost-benefit uncertainty: There is limited long-term economic validation of AI systems in real municipal budgets.

e) Infrastructure and interoperability limitations: Fragmented systems and incompatible hardware/software platforms limit scalability.

f) Policy and governance barriers: Lack of regulatory frameworks and standards slows the adoption of AI-based waste systems.

g) The social acceptance and behavioral factors: Public participation, waste segregation behavior, and trust in AI systems remain uncertain.

h) Energy footprint of AI systems: Training and operating AI models themselves consume energy and can offset environmental gains.

Future Research Directions

a) Development of open, standardized waste datasets: Global collaborative data platforms are needed for benchmarking and model transferability.

b) Hybrid AI-physical modeling approaches: Combining machine learning with process-based environmental models will improve reliability and interpretability.

c) Life-cycle integrated optimization frameworks: Future systems should jointly optimize cost, emissions, and material recovery.

d) Real-world pilot and longitudinal studies: Long-term field deployments are required to validate economic and environmental performance.

e) Integration with circular economy digital platforms: Blockchain, material passports, and traceability systems can enhance resource circularity.

f) Low-energy and edge AI systems: Energy-efficient AI architectures should be developed for sustainable deployment in smart cities.
Addressing these gaps will enable the transition from experimental AI applications to scalable, resilient, and sustainable waste management systems worldwide.

Conclusion

This systematic review demonstrates that AI-driven waste management systems offer substantial improvements over conventional approaches in terms of operational efficiency, classification accuracy, and resource recovery. The integration of IoT-based sensing technologies, ML and deep learning models, and automated decision-making systems enables real-time monitoring and optimization across the entire waste management lifecycle. However, the analysis also reveals that system performance is highly dependent on data quality, infrastructure readiness, and the ability to integrate heterogeneous data sources within complex urban environments.

From a practical perspective, AI-enabled waste management systems present significant opportunities for enhancing sustainability in rapidly urbanizing regions. These systems can reduce collection inefficiencies, lower operational costs, and improve recycling outcomes through data-driven optimization. In developing urban contexts such as Dhaka, the adoption of such technologies has the potential to transform existing waste management practices. Nevertheless, implementation remains constrained by infrastructural limitations, limited data availability, and the need to integrate technological solutions with existing socio-economic structures, including informal waste management sectors.

A key contribution of this study is the development of a cyber-physical-environmental framework that integrates sensing systems, data processing layers, intelligent analytics, and environmental feedback mechanisms within a unified architecture. Unlike conventional approaches that treat AI applications in isolation, this framework emphasizes system-level interaction and adaptive optimization. By incorporating continuous feedback loops and real-time decision-making, the proposed framework addresses critical gaps in current literature related to fragmentation, scalability, and environmental integration.

Despite these advancements, several challenges remain. The transition from pilot-scale implementations to large-scale deployment requires robust data infrastructures, interoperability across systems, and sustainable economic models. In addition, the widespread use of complex AI models introduces concerns related to interpretability, reliability, and long-term maintenance, particularly in resource-constrained environments.

Future research should therefore focus on improving the scalability and robustness of AI-driven waste management systems under real-world conditions. Key priorities include the development of standardized and high-quality datasets, the integration of explainable AI techniques to enhance transparency and trust, and the design of hybrid models that combine data-driven intelligence with domain-specific knowledge. Furthermore, techno-economic evaluations and long-term performance assessments are essential to ensure practical feasibility. Particular attention should also be given to adapting these systems to diverse socio-economic contexts, especially in developing regions where infrastructure and governance conditions differ significantly from those in developed countries.

Overall, the findings of this review highlight that the effectiveness of AI-driven waste management systems is not solely determined by algorithmic performance, but by the successful integration of technological, environmental, and socio-economic factors. Achieving sustainable and scalable implementation will require coordinated efforts across policy, infrastructure development, and stakeholder engagement, ensuring that intelligent waste management systems can be effectively deployed in real-world urban environments. From an implementation perspective, cities should prioritize the development of integrated data infrastructures, invest in scalable sensor networks, and adopt hybrid AI models that balance performance with interpretability. Policymakers should focus on aligning technological deployment with local socio-economic conditions, particularly by incorporating informal waste sectors into smart waste management frameworks. Additionally, standardization of data collection protocols and cross-sector collaboration will be critical to enable large-scale, sustainable deployment of AI-driven waste management systems.

Conflicts of Interest

No conflicts of interest have been disclosed by the paper's author.

AI-Assisted Language Statement

The author utilized artificial intelligence-based tools solely for English language editing, grammatical correction, and enhancing the technical clarity of the text. These AI tools were not employed for data generation, the synthesis of the systematic review results, the development of the conceptual frameworks, or any scientific decision-making regarding the comparative performance of the AI-based waste management systems discussed. The author takes full responsibility for the integrity and final content of the manuscript.

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