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Integrating artificial intelligence and internet of things for solid waste management: a review

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ABSTRACT

The increasing pace of urbanization and industrial growth has intensified the challenges of solid waste management, demanding intelligent, data-driven, and sustainable solutions. This review explores how the combined application of artificial intelligence (AI) and the internet of things (IoT) is revolutionizing conventional waste management practices into intelligent, automated, and responsive systems. Through a comprehensive review of 43 scholarly publications, case analyses, and technical studies, this paper emphasizes how AI-based methods—such as learning algorithms, image recognition, and data-driven prediction—improve waste sorting precision, recycling performance, and material recovery efficiency-enhance waste segregation accuracy, recycling efficiency, and resource recovery. Simultaneously, IoT-based systems employing sensors, cloud platforms, and smart bins enable real-time waste monitoring, dynamic routing, and optimized collection logistics. Emerging technologies like blockchain for waste traceability, robotics for automated sorting, and advanced analytics for decision-making are also examined. Despite these advancements, challenges related to scalability, interoperability, cost, and data privacy persist. This review identifies current research gaps, proposes future directions, and emphasizes the importance of integrating AI and IoT with circular economy principles under Industry 5.0 to achieve sustainable, efficient, and human-centric waste management solutions.

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1. INTRODUCTION

Municipal solid waste (MSW) generation has increased significantly due to rapid urbanization, industrialization, and population growth. According to the World Bank report, global waste generation is projected to increase substantially by 2050 if current management practices remain unchanged [1]. This rising waste volume poses serious environmental, economic, and public health challenges, particularly in developing and densely populated regions. Inefficient collection systems, lack of segregation at source, and limited monitoring mechanisms further aggravate the burden on municipal authorities.

Traditional waste management systems rely heavily on manual segregation and fixed collection schedules, which often result in overflow, inefficient routing, and increased operational costs. To address these challenges, the integration of internet of things (IoT) technologies has gained significant attention. IoT-based systems enable real-time monitoring of bin fill levels, route optimization, and data-driven waste collection planning [2], [3]. These systems improve operational efficiency while reducing fuel consumption and environmental impact. The global trend of increasing waste generation is illustrated in Figure 1. The specific trends regarding waste generation and recycling progress over the past decade are further detailed in Figure 2.

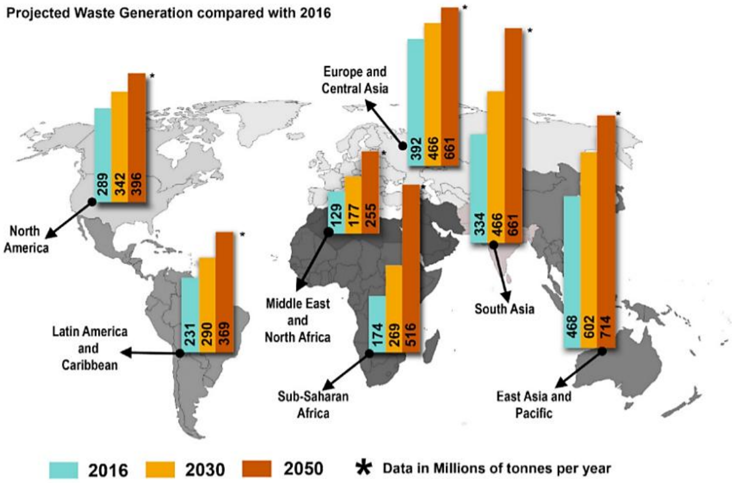

Figure 1. The amount of waste generated annually, along with projections for the near future, varies across different regions of the world [1]

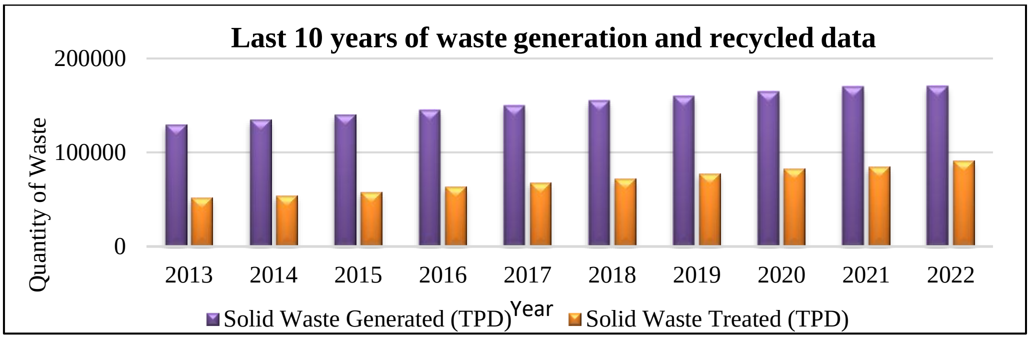

Figure 2. The last 10 years of waste generation and recycled data from India [1]

In parallel, artificial intelligence (AI) techniques have emerged as powerful tools for waste classification, sorting automation, and decision-making support. AI-driven waste management systems utilize machine learning, computer vision, and deep learning models to enhance segregation accuracy and resource recovery [3]–[5]. Such intelligent systems contribute toward circular economy objectives by improving recycling rates and reducing landfill dependency. Recent review studies emphasize that the combined integration of AI and IoT technologies offers greater potential compared to standalone implementations [5], [6]. The synergy between sensor-based monitoring and intelligent data processing enables predictive analytics, automated sorting, and optimized collection strategies. Despite significant technological advancements, challenges remain in scalability, cost-effectiveness, interoperability, and deployment in low-resource environments. To address these gaps, this review systematically analyzes recent advancements in AI- and IoT-enabled solid waste management systems, highlighting technological trends, implementation strategies, and research challenges.

2. METHODOLOGY

This review adopts a structured analytical framework to evaluate the integration of AI and IoT technologies in solid waste management (SWM). The methodology focuses on systematic literature filtering, technological classification, architectural comparison, and performance-based synthesis of selected studies.

2.1. Systematic review framework

A focused literature review was conducted using IEEE Xplore, SpringerLink, Elsevier, and MDPI databases. The search covered publications from 2018 to 2024 using keywords such as “AI-based waste segregation,” “IoT smart bin,” “machine learning waste classification,” “robotic sorting,” and “industry 5.0 waste systems.” After screening for relevance, duplication removal, and technical depth, approximately 30 high-quality studies were selected for detailed analysis. The systematic identification, screening, and inclusion process for the literature analyzed in this review followed the PRISMA framework, as shown in Figure 3. Only studies demonstrating experimental validation, prototype development, algorithmic modeling, or measurable performance metrics were included. Conceptual or purely policy-driven discussions without implementation details were excluded. Instead of treating each study independently, the selected literature was organized into five technological clusters:

a. Sensor-based detection systems
b. Microcontroller- and Arduino-driven architectures
c. Smart bin and IoT-enabled monitoring frameworks
d. Cloud and blockchain-integrated systems
e. Machine learning and deep learning classification models

This thematic structuring reduces redundancy and enables cross-comparison of performance indicators across system types.

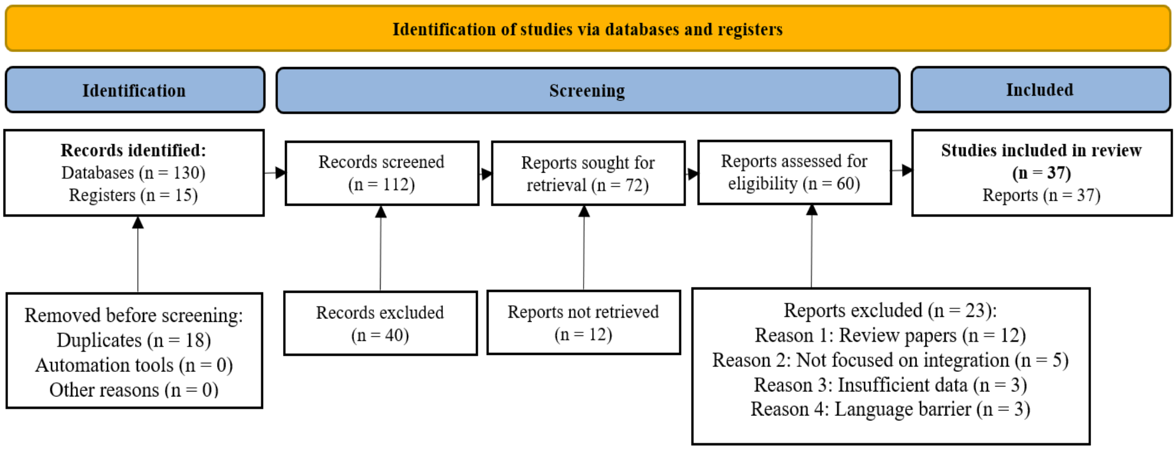

Figure 3. PRISMA flow diagram of study selection process

2.2. AI and IoT design methodologies

Two dominant architectural approaches were identified in the reviewed literature:

a. Rule-based control systems

These systems use predefined logical conditions embedded in microcontrollers to trigger sorting mechanisms. Although cost-efficient, they are limited in handling mixed or unpredictable waste streams.

b. AI-driven adaptive systems

AI-based systems integrate machine learning algorithms and computer vision models with real-time IoT sensor inputs. These frameworks dynamically classify waste, optimize collection intervals, and improve operational intelligence. Studies report that AI–IoT integration can reduce manual intervention by nearly 60% while increasing sorting consistency [7].

2.3. Integration of sensors

Sensors form the foundation of AI- and IoT-based waste segregation systems. Capacitive, inductive, and infrared (IR) sensors are commonly used to detect and differentiate materials. The capacitive sensor identifies solid-colored materials such as plastic or paper (excluding transparent materials), the inductive sensor detects metals, and the infrared sensor identifies the presence of any solid object. Waste is classified based on the combination of sensor responses:

a. Organic waste → (IR=1, Inductive=0, Capacitive=1)
b. Inorganic waste → (IR=1, Inductive=0, Capacitive=0)
c. Metallic waste → (IR=1, Inductive=1, Capacitive=1) [7].

Table 1 summarizes the results of the capacitive proximity sensor trial, showing successful and unsuccessful detections for various object types and materials. This combination of sensors enables classification accuracy of over 90% under laboratory testing, demonstrating the potential of low-cost sensing modules in automated segregation systems.

Table 1. Evaluation of capacitive proximity sensor performance for material detection [7]

Object criteria	Results
Opaque plastic and paper objects in multiple colors (green, red, blue, brown)	Successfully identified
Transparent plastic samples of assorted geometries	Not detected reliably
Transparent glass specimens of different sizes	Not detected reliably
Colored glass articles (non-transparent)	Successfully identified
White, non-transparent objects (plastic/paper)	Successfully identified
Metallic samples of varying dimensions	Successfully identified

2.4. Microcontroller and IoT-enabled implementations

Arduino and ESP-based microcontroller systems form the operational backbone of many reviewed architectures. An ESP32-based system integrating IR and ultrasonic sensors enabled real-time monitoring and mobile dashboard updates [8]. Another Arduino Mega 2560-based implementation achieved classification accuracies above 92% for metallic and glass waste [9].

IoT-enabled smart bin systems integrate ultrasonic fill-level detection, GSM communication modules, and cloud interfaces to reduce overflow and optimize collection scheduling [10]–[12]. Hybrid implementations combining microcontrollers with AI-based detection models (e.g., YOLO frameworks) demonstrated up to 25% improvement in collection efficiency [13]–[15]. The physical architecture for these processes, specifically the arrangement of organic and inorganic waste sorting modules, is illustrated in Figure 4.

Figure 4. Diagram of organic and inorganic waste sorting systems [9]

2.5. Mechanical and cloud-integrated sorting systems

Advanced automated sorting systems integrate sterilization units, conveyor-based separation, and optical detection. Systems operating under controlled temperature and pressure conditions achieved segregation efficiencies between 94% and 96%, with approximately 15% reduction in energy consumption compared to manual methods [16], [17].

Cloud-connected systems transmit sensor data—including waste type, weight, and timestamp—to remote servers via API interfaces [18]. Reported performance metrics include:

a. Metal detection accuracy: 93.7%
b. Organic/inorganic classification: 91.5%
c. Data latency below 2 seconds [19]

Cloud-based analytics and route optimization algorithms reduce operational delays by nearly 20% [20].

2.6. Machine learning and deep learning frameworks

Image-based waste classification significantly enhances sorting precision. A dataset of 2,400 labeled waste images was used to train an artificial neural network (ANN) model with 50 epochs and a learning rate of 0.001, achieving 92% accuracy—outperforming k-NN (85%) and support vector machine (SVM) (88%) classifiers [21]. Real-time validation demonstrated robustness above 90% under varying environmental conditions [22]. The relationship between data inputs and processing stages for AI, IoT, and automated reporting is summarized in Figure 5.

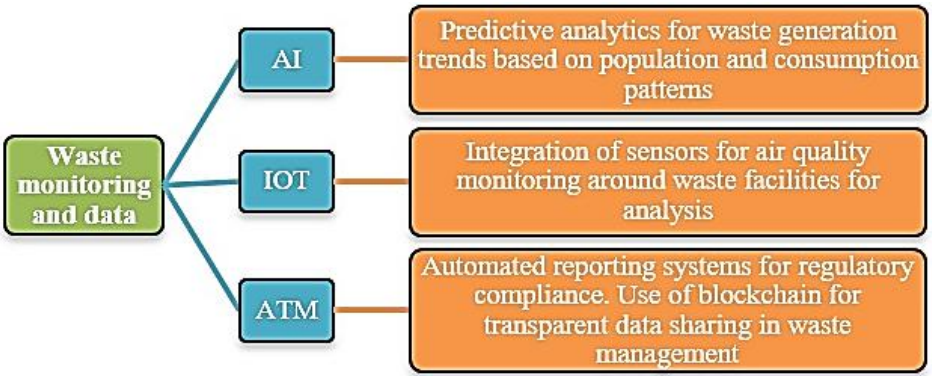

Figure 5. Waste processing and data

3. RESULTS AND DISCUSSION

The reviewed literature demonstrates that the integration of AI, IoT, automation, and emerging digital technologies significantly enhances the operational efficiency, classification accuracy, and sustainability of solid waste management (SWM). The results are synthesized across four major domains: cloud-enabled intelligence, blockchain transparency, AI-driven automation, and large-scale municipal implementation.

3.1. Cloud-based intelligence and data optimization

Cloud computing plays a critical role in enabling real-time monitoring, analytics, and predictive waste collection. IoT devices such as programmable interface controller (PIC) controllers and Node-MCU modules transmit waste parameters-type, weight, timestamp, and fill level to centralized cloud platforms for storage and analysis [22].

Cloud-based product-service system (PSS) architectures integrate physical waste infrastructure with analytics layers and user applications, allowing dynamic route optimization and predictive scheduling [23]. Experimental evaluations report:

a. 20%–25% reduction in collection time
b. 15%–18% reduction in fuel consumption
c. Improved resource allocation efficiency [23], [24].

These improvements demonstrate that cloud integration transitions waste management from reactive collection models to predictive, data-driven frameworks.

3.2. Blockchain for transparency and incentive systems

Blockchain-based waste management frameworks enhance traceability, transparency, and accountability. By recording each transaction-collection, transfer, and disposal on decentralized ledgers, blockchain ensures immutable data verification [25]. Smart contract mechanisms automate recycling rewards and operational permissions. Route optimization models demonstrated a 15% reduction in fleet size and up to 22% reduction in travel distance [26]. Token-based incentive systems encourage citizen participation in recycling programs, supporting circular economy objectives [27].

3.3. AI-driven sorting, robotics, and circular economy

Artificial intelligence significantly enhances sorting precision and automation efficiency. convolutional neural networks (CNNs) such as Inception-ResNet V2 and VGG-16 achieve classification accuracies exceeding 95% on large datasets of 10,000–13,000 images [28]. Compared to traditional machine learning models, CNN-based systems:

a. Improve accuracy by 10%–12%
b. Reduce misclassification rates by up to 15% [29]

Industrial robotic platforms integrating multi-sensor fusion (RGB, NIR, VIS, and metal detection) enable high-accuracy classification at industrial-scale throughput, reducing manual sorting dependency and improving material recovery. Material recovery facilities (MRFs) integrating programmable logic controller (PLC)-controlled sorting systems demonstrate classification precision above 98%, surpassing manual methods in consistency and operational safety [30], [31]. Together, AI-driven robotics and automated control systems significantly contribute to circular economy performance indicators by increasing recovery efficiency and reducing landfill dependency.

3.4. Emerging waste-to-energy and conversion technologies

Beyond sorting and monitoring, emerging waste conversion technologies improve sustainability outcomes. Physicochemical and biological conversion methods, including transesterification and fermentation, achieve conversion efficiencies between 85% and 90% under optimized conditions [32]. Advanced energy recovery technologies such as triboelectric nanogenerators (TENGs) and microbial fuel cells (MFCs) utilize waste's electrochemical potential for renewable energy generation [33]. These approaches support waste-to-resource transitions and reduce environmental burden.

3.5. Municipal-scale smart waste systems

City-level smart waste management integrates AI, IoT, and cloud analytics to optimize municipal operations. Smart garbage bins (SGBs) equipped with embedded sensors reduce overflow incidents by approximately 40% [34]. Municipal-scale implementations demonstrate:

a. 18%–22% reduction in fuel consumption
b. 15% reduction in collection frequency
c. Improved emission monitoring [35]

Communication protocols such as radio frequency identification (RFID), ZigBee, Bluetooth, and LTE enable real-time responsiveness between bins and control centers.

3.6. Technological, economic, and social barriers

Despite measurable improvements, large-scale deployment remains constrained by multiple factors. Technological barriers include sensor calibration costs, system interoperability issues, and cybersecurity concerns. Economic constraints in developing regions limit investment in advanced hardware and cloud infrastructure [36]. Social resistance-often described as the "not in my backyard" (NIMBY) effect-continues to delay infrastructure projects and recycling facility expansion [37]. Additionally, limited digital literacy and public awareness reduce adoption rates of smart systems. Overcoming these barriers requires policy reform, financial incentives, public–private partnerships, and standardization of waste management protocols.

3.7. Synthesis of performance improvements

Across the reviewed literature, integrated AI - IoT systems consistently demonstrate:

a. Classification accuracy up to 95%
b. 20% - 25% operational efficiency improvement
c. 15% - 22% fuel consumption reduction
d. 30% - 40% improvement in worker safety
e. Enhanced traceability and circular economy compliance

The integration of AI, IoT, cloud computing, and blockchain transforms waste management from a labor-intensive process into an intelligent cyber-physical system aligned with Industry 5.0 principles.

4. CONCLUSION AND FUTURE SCOPE

This review systematically examined recent advancements in Artificial Intelligence (AI) and IoT technologies across the solid waste management lifecycle, from segregation and monitoring to automated processing and resource recovery. The analysis reveals that AI-driven classification and IoT-enabled monitoring significantly enhance sorting accuracy, operational efficiency, and data-driven decision-making compared to conventional waste management practices.

However, a clear gap persists between laboratory-scale prototypes and large-scale industrial deployment. While high-performance results are frequently reported under controlled conditions, standardized benchmarking, long-term reliability assessment, and economic feasibility analyses remain limited. In particular, the integration of industrial-grade automation and robotics into municipal systems is comparatively underexplored despite its strong potential for scalability and safety.

Bridging this research–implementation divide will be critical for translating intelligent waste management systems from experimental frameworks into resilient, economically viable, and circular economy–oriented infrastructure. Future progress must therefore emphasize real-world validation, system interoperability, and alignment with sustainable urban development strategies.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest regarding the publication of this paper.

DATA AVAILABILITY

No new data were created or analyzed in this study. All data supporting the findings are available from the cited literature and sources referenced within this article.

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