Revolutionizing Urban Waste Systems: A Comprehensive Review of IoT, AI, and Optimization Techniques for Smart Waste Management

Lahcen GOUSKIR[1]*, Abdelmoula ABOUHILAL[2], Mohamed GOUSKIR[3],
Mohamed BASLAM[4], Soufiane BELHOUIDEG[5], Hanaa Hachimi[6]
Faculty of Science and Techniques, Sultan Moulay Slimane University, Beni Mellal, Morocco[1, 4]
National School of Applied Sciences, Sultan Moulay Slimane University, Beni Mellal, Morocco[3, 5]
Faculty of Sciences Semlalia, Cadi Ayyad University, Marrakech, Morocco[2]
National School of Applied Sciences, Ibn Tofail University, Kenitra, Morocco[6]

Abstract—**Urban waste management is shifting from fixed, reactive collection toward data-driven and adaptive service models. This review synthesizes 33 recent studies and technical contributions on Artificial Intelligence of Things (AIoT) for smart waste management. The synthesis is organized around six analytical dimensions: IoT sensing and communication, real-time monitoring performance, dynamic routing, AI-based classification and robotic sorting, edge/fog/cloud intelligence, and circular governance. Unlike a descriptive survey, the paper develops an AIoT-SWM taxonomy and an evaluation rubric for comparing smart waste systems according to interoperability, latency, energy profile, scalability, decision autonomy, circular-economy contribution, and social inclusion. Reported deployments show measurable operational gains, including 26-35% reductions in fuel consumption, more than 30% improvement in fleet utilization, 25% gains in collection efficiency, and up to 48% reduction in overflow incidents. AI sorting studies also report controlled classification accuracies above 90%, while recent techno-economic evidence indicates 95.1% material purity, 50 items/minute throughput, and payback periods of 4.3-4.9 years under specific emerging-economy conditions. The review concludes that AIoT can improve municipal waste services only when technical performance guarantees are combined with open data standards, cybersecurity safeguards, human oversight, and context-sensitive inclusion of informal waste actors.**

Keywords*—*Smart waste management; Internet of Things; Artificial Intelligence; AIoT; edge computing; dynamic routing; circular economy; robotic sorting

I. Introduction

A. Urban Waste Pressure and the Need for Intelligent Systems

Rapid urbanization and changes in consumption have increased the volume and heterogeneity of municipal solid waste (MSW). Many cities still depend on fixed schedules, manual reporting, and weakly integrated disposal chains. These models are costly and slow because they do not observe real-time waste generation, traffic conditions, or neighborhood-level variability [2], [4].

Smart waste management is therefore not only a matter of installing sensors. It requires a cyber-physical architecture that can sense the state of containers, transmit data reliably, transform data into operational decisions, and connect waste services with recycling, public health, mobility, and environmental governance [3], [13], [18], [24], [25].

The unresolved research problem is systems-level integration. Existing deployments often perform well as isolated pilots but remain limited by vendor lock-in, poor interoperability, uncertain latency guarantees, energy constraints, and weak governance of data and algorithms [10], [19], [21]. These gaps explain why many smart-bin pilots do not scale into citywide waste intelligence.

B. Scope and Contribution of the Review

This review examines how IoT, AI, optimization, robotic sorting, blockchain, and edge computing can support a transition from linear waste handling to adaptive and circular urban waste systems. The review focuses on municipal solid waste and closely related urban waste streams, including e-waste and recyclable fractions.

The main contribution is a structured synthesis artifact rather than a new experiment. The article proposes an AIoT-SWM taxonomy, a decision-oriented evaluation rubric, and a ranked research agenda. These instruments help compare systems across technical, economic, environmental, and social dimensions. They also clarify the trade-offs that municipalities face when moving from pilot projects to scalable infrastructure.

- Taxonomy: legacy, digitized, and AIoT-enabled waste systems are compared across sensing, connectivity, analytics, autonomy, and governance maturity.
- Evaluation rubric: smart waste systems are assessed using interoperability, latency, energy consumption, density, scalability, circularity, cybersecurity, and inclusion criteria.
- Research agenda: challenges are ranked by technical severity, deployment frequency, and urgency for future research and municipal policy.

*Corresponding author.

II. Review Methodology, Related Work, and Positioning

A. Review Design and Selection Criteria

The review follows a structured narrative approach. It prioritizes peer-reviewed studies and recent technical contributions published between 2020 and 2026 in the areas of smart waste management, IoT-enabled collection, AI sorting, routing optimization, edge/fog/cloud computing, blockchain traceability, and circular economy. Studies were retained when their primary domain was municipal or urban waste management, or when their method directly supported a waste-management function such as bin monitoring, vehicle routing, sorting, material recovery, or governance.

To improve citation relevance, studies from unrelated application domains were excluded from the evidence base because they did not provide traceable evidence for urban waste management. As summarized in Table I, the revised bibliography prioritizes domain-specific references on LoRaWAN smart waste infrastructure, IoT smart bins, CNN-based smart waste classification, 5G-enabled smart waste systems, and robotic sorting feasibility [18], [22], [23], [28], [33].

TABLE I. Structured Review Criteria and Synthesis Outputs

Dimension	Inclusion Focus	Synthesis Output
Domain relevance	Municipal solid waste, smart bins, collection, sorting, recycling, e-waste, circular waste systems	Removal of non-waste references and strengthened citation base
Technology layer	Sensors, communication protocols, edge/fog/cloud, AI models, routing algorithms, robotic systems	AIoT-SWM architecture and technology taxonomy
Performance evidence	Latency, accuracy, throughput, energy, packet reliability, deployment density, fuel and route efficiency	Quantitative comparison tables and timing requirements
Decision and governance	MCDM, interoperability, cybersecurity, policy, inclusion, circular economy	Evaluation rubric and ranked research agenda
Practical feasibility	Cost, maintenance, calibration, integration complexity, human oversight	Balanced techno-economic assessment of robotic and AIoT systems

B. Related Work and Differentiation

Recent reviews and impact studies show that AI and IoT improve collection, sorting, recycling, and monitoring, but many remain broad and technology-centered [11], [29], [30]. Reviews on smart bins and circular resource recovery focus strongly on sensing and recovery infrastructure [13], whereas machine-learning reviews emphasize prediction, classification, and resource valorization [12], [15], [16].

The present review differs by connecting these strands into a systems-level framework. It does not treat IoT, AI, routing, edge computing, and circularity as separate themes. It maps their dependencies, identifies operational trade-offs, and proposes measurable criteria for deployment evaluation. As summarized in Table II, this positioning responds to the need for reviews that are useful for both researchers and municipal decision makers.

TABLE II. Positioning Against Existing Reviews

Review Stream	Dominant Focus	Gap Addressed in This Paper
AI/IoT review of collection, sorting, and recycling	General benefits of AI and IoT for waste operations [30]	Adds latency, interoperability, and deployment-readiness criteria
Smart bins for resource recovery	Smart-bin deployment and recovery outcomes [13]	Connects bin sensing to routing, edge intelligence, and circular governance
Machine learning for circular waste systems	Prediction, classification, and material recovery [12], [15]	Integrates ML with communication constraints, human oversight, and equity risks
IoT-enabled smart waste systematic reviews	Architectural components and city applications [29]	Adds a decision rubric and a ranked research agenda for scalable municipal adoption

III. Evolution of Waste Management Systems

A. From Linear Logistics to AIoT Ecosystems

Legacy MSW systems are built around collection, transport, and disposal. They offer limited visibility into fill levels, material composition, route status, or environmental risk. Their main advantage is operational simplicity, but their main weakness is that they respond after problems appear.

Digitized systems added GPS tracking, dashboards, GIS, and digital work orders. This improved transparency, but many systems remained descriptive rather than predictive. The major bottleneck was not data availability alone; it was the absence of interoperable architecture and decision intelligence [26].

AIoT-enabled systems combine sensor telemetry, edge analytics, cloud training, optimization algorithms, and decision dashboards. They can predict overflow, update routes, identify contamination, and support circular-economy reporting. As shown in Table III, their main risk is increased complexity: poor cybersecurity, weak standards, and insufficient maintenance can turn smart infrastructure into fragile infrastructure.

TABLE III. COMPARATIVE EVOLUTION OF URBAN WASTE SYSTEM ARCHITECTURES

Metric	Legacy Systems	Digitized Systems	AIoT-Enabled Systems
Main data source	Manual logs, fixed schedules, operator reports	GPS, GIS, digital dashboards	Real-time sensor telemetry, AI inference, multi-source data
Decision logic	Routine-based and reactive	Rule-based monitoring	Predictive and optimization-based
Latency profile	Hours to days	Minutes to hours	Seconds to minutes depending on protocol and edge layer
Scalability constraint	Labor, fleet, landfill capacity	Data silos and proprietary tools	Interoperability, cybersecurity, and maintenance capacity
Circular contribution	Low recovery and weak traceability	Improved reporting but limited automation	Material classification, recovery forecasting, traceability, and incentives
Main trade-off	Low complexity but low responsiveness	Visibility without autonomy	High performance but higher integration and governance burden

IV. IOT INFRASTRUCTURE IN WASTE MANAGEMENT

A. Sensor Modalities and Data Reliability

IoT infrastructure begins with the instrumentation of bins, vehicles, and facilities. Ultrasonic sensors estimate fill levels; load cells measure weight; gas sensors detect decomposition or hazardous emissions; temperature sensors support fire-risk monitoring; RFID and QR identifiers link bins, users, or assets to service records [18], [20], [22].

Sensor fusion is necessary because no single sensor is robust in all waste environments. Ultrasonic readings can be affected by irregular waste surfaces, condensation, or acoustic noise. Weight sensors may be distorted by density variation across waste types. Gas sensors drift over time and require calibration. Combining fill level, weight, temperature, and gas signals increase confidence and allows edge-side anomaly detection.

B. Communication Protocols and Deployment Trade-Offs

Communication choices determine the practical scale of smart waste systems. Long-range protocols such as LoRaWAN are suitable for low-rate telemetry across large urban areas, while NB-IoT provides cellular-grade coverage and higher device density. ZigBee and BLE are useful for short-range clusters but require gateways. Wi-Fi or 5G may support cameras and higher data rates, but their energy and cost profiles are less suitable for small battery-powered bins [18], [28], [31].

TABLE IV. PRACTICAL PROTOCOL COMPARISON FOR SMART WASTE DEPLOYMENTS

Protocol	Typical Range	Latency Profile	Energy Profile	Deployment Density	Best Waste Use Case
LoRaWAN	Urban: hundreds of meters to several km; rural/peri-urban: longer	Seconds to minutes; not ideal for continuous video	Very low for small periodic packets	High, if duty-cycle and gateway planning are respected	Fill-level telemetry, temperature alerts, low-rate bin monitoring
NB-IoT	Cellular coverage with good indoor penetration	Usually seconds; operator dependent	Low to medium	Very high device density through licensed networks	Dense urban cores, underground bins, high-rise waste rooms
ZigBee/BLE Mesh	Short range, typically building/campus scale	Milliseconds to seconds inside mesh	Low	High locally but gateway dependent	Campus bins, indoor recycling rooms, industrial parks
Wi-Fi/5G	Access-point/cellular dependent	Low latency and higher throughput	Medium to high	Good where infrastructure exists	Camera-based sorting, dashboards, fleet depots, campus pilots

As summarized in Table IV, the choice of protocol must be driven by the required message size, alert urgency, node density, and power budget. For example, a fill-level packet can be transmitted every 15-60 minutes through LoRaWAN, while a fire or hazardous-gas alarm requires priority transmission and local edge triggering. Video-based sorting should not normally stream continuously from public bins; edge inference can transmit only events or metadata to preserve bandwidth and privacy [23].

C. Power Management and Sensor Longevity

Energy management is a primary condition for citywide feasibility. Battery-powered smart bins must minimize sensing, computation, and transmission time. Duty cycling, local aggregation, event-triggered messaging, and payload compression reduce energy consumption. Solar augmentation can extend the lifetime, but is site-dependent because shading, vandalism, dust, and seasonal variation reduce effective generation.

The revised framework, therefore treats energy as a design constraint rather than a peripheral issue. A technically successful pilot cannot be considered scalable if maintenance teams must frequently replace batteries, recalibrate sensors, or repair exposed electronics.

Fig. 1 summarizes the distributed architecture used in this review. Sensors collect local state information. Edge nodes filter and classify events close to the data source. Fog gateways aggregate neighborhood-level signals and support local coordination. Cloud services support long-term storage, model training, strategic dashboards, and cross-city comparison. This distribution improves resilience because the system can maintain partial service during network degradation or cloud outages.

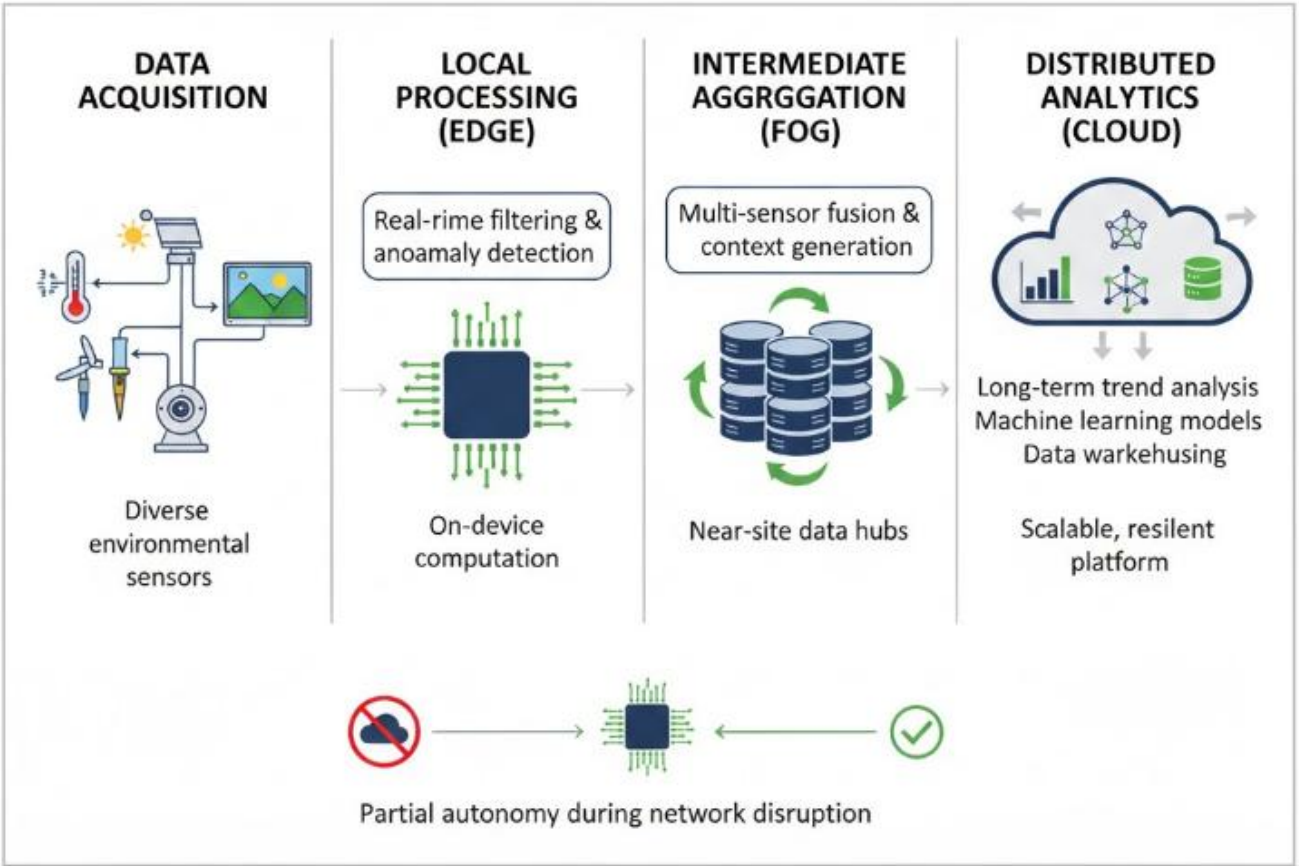

Fig. 1. Sensor-edge-fog-cloud architecture for smart bin management.

V. Real-Time Monitoring and Performance Requirements

A. Timing Model for Monitoring Architectures

Real-time monitoring should be evaluated through explicit timing assumptions. The end-to-end delay of a smart waste alert can be expressed as: L_total = L_sensing + L_edge_processing + L_queueing + L_radio + L_gateway + L_cloud_processing + L_decision. A system is operationally real time only when L_total is lower than the response requirement of the event being managed.

As summarized in Table V, different waste events require different timing classes. Fill-level monitoring can tolerate minutes because bin filling is usually slow. Fire, gas, or hazardous waste signals require faster edge-side response. Routing decisions require updates that are fast enough to influence vehicles before they leave a service zone.

TABLE V. Suggested Timing and Reliability Requirements by Waste Event

Event Type	Operational Requirement	Suggested Target	Critical Metrics
Routine fill-level update	Maintain collection visibility without excessive energy use	5-60 min update interval depending on bin dynamics	Packet delivery, battery life, sensor drift
Overflow risk alert	Trigger route adjustment before public overflow	Actionable alert within 5-15 min	End-to-end latency, false negatives, dashboard refresh
Gas/fire/hazard alert	Support safety response and local containment	Local edge detection within 30-60 s	Sensor confidence, local alarm, fail-safe behavior
Dynamic route refresh	Influence vehicle sequence during active collection	Route update within 5-10 min	Throughput, route stability, traffic integration
Sorting-line classification	Maintain conveyor throughput and material purity	Sub-second inference where robotic actuation is used	Accuracy, precision, purity, missed picks, processing FPS

B. Evidence from Deployed Monitoring Systems

Case evidence confirms that monitoring value emerges when telemetry is linked to operational action. In Greater Cairo, real-time telemetry and routing support were associated with 26% fuel-consumption reduction and more than 30% improvement in fleet utilization [4]. In Ghana, machine learning and GIS improved short-horizon waste generation and composition forecasting [14]. In South Korea, smart-bin allocation and vehicle routing connected bin state, location, and collection decisions [25].

These studies indicate that the decisive factor is not sensor presence alone. Gains appear when monitoring supports a closed loop: data capture, validation, prediction, decision, field action, and post-action learning.

VI. Routing and Collection Optimization

A. From Fixed Routes to Demand-Responsive Logistics

Fixed collection routes simplify planning but ignore spatiotemporal variation. They can cause premature emptying, fuel waste, missed overflow events, and inefficient vehicle loading [4]. IoT-enabled routing changes the problem by turning bins into dynamic demand points. Vehicles can be dispatched according to fill level, predicted overflow, capacity, distance, time windows, and traffic conditions.

Optimization methods include ant colony optimization, genetic algorithms, mixed-integer formulations, fuzzy decision-making, and reinforcement learning. Multi-objective formulations are more realistic than shortest-path optimization because municipal routing must balance fuel, labor time, overflow risk, emissions, noise restrictions, and citizen complaints [5], [6], [9].

B. Quantified Gains and Limits

Reported gains include 35% reduction in fleet fuel consumption and 48% reduction in overflow incidents in an AI-optimized Cairo case [4]. In Taiwan, technology-barrier analysis and route modernization evidence point to improvements in collection efficiency and service stability when digital infrastructure is combined with organizational readiness [10].

However, dynamic routing is not automatically superior. It may increase driver uncertainty, increase dispatch complexity, or create unstable routes if thresholds are noisy. Municipalities should therefore use route-change limits, confidence thresholds, and human oversight during transition phases.

VII. AI-Based Waste Classification and Robotic Sorting

A. Computer Vision and Sensor Fusion

AI-based classification supports recycling by detecting material categories, contamination, and high-value recyclable fractions. CNN and lightweight edge models can classify plastics, paper, metal, glass, organic waste, and hazardous objects in controlled settings [6], [23], [32]. Sensor fusion improves reliability when images are degraded by dirt, occlusion, lighting variation, or deformation.

Computer vision should therefore be combined with weight, near-infrared, moisture, temperature, or gas data where possible. The objective is not only classification accuracy; it is useful material recovery. A model with high laboratory accuracy may fail if it cannot maintain throughput, purity, and calibration under real waste-stream conditions.

B. Robotic Sorting: Feasibility and Constraints

Robotic sorting can improve consistency and reduce worker exposure to hazardous materials, but it should be assessed realistically. Main constraints include capital cost, conveyor integration, gripper wear, lighting conditions, object overlap, contamination, calibration drift, maintenance skills, and dependence on stable recyclable markets.

Recent techno-economic evidence from urban Indonesia reports 90% average sorting accuracy, 95.1% material purity, 50 items/minute throughput, and a payback period of 4.3-4.9 years under local assumptions [33]. Table VI summarizes the associated feasibility checklist. These figures are promising, but they should not be generalized without considering labor costs, electricity prices, waste composition, maintenance contracts, and commodity-price volatility.

TABLE VI. Techno-Economic Feasibility Checklist for AI Robotic Sorting

Factor	Benefit	Main Constraint	Recommended Assessment
Accuracy and purity	Improves recyclable quality and downstream value	Soiled or overlapping items reduce detection confidence	Validate on local waste composition, not only benchmark datasets
Throughput	Supports continuous MRF operation	Conveyor speed must match detection and actuation	Measure items/minute and missed-pick rate under field conditions
Cost and payback	Potential labor savings and higher recovery revenue	High capital cost and market-price volatility	Use local wage, electricity, maintenance, and recyclable-price scenarios
Maintenance	Reduces repetitive manual sorting	Gripper wear, calibration, dust, and spare parts	Include preventive maintenance and local technician capacity
Social integration	Can reduce hazardous exposure	May displace informal workers if unmanaged	Use hybrid human-AI roles and worker transition plans

VIII. Edge Computing and Decentralized Intelligence

A. Limits of Cloud-Only Architectures

Cloud computing supports large-scale storage, historical analytics, and model training, but cloud-only architectures are weak in latency-sensitive and connectivity-constrained contexts. Network congestion, high video bandwidth, cellular outages, and privacy concerns can reduce reliability. These risks are especially important in cities where waste service is a public-health function rather than a convenience application [19], [27].

Edge computing reduces this dependency by processing sensor signals or images near the source. Fog gateways provide a neighborhood layer that aggregates bins, detects local anomalies, and coordinates vehicles. Cloud platforms then perform strategic analytics and long-term learning. This hierarchy enables partial autonomy during network disruption.

B. TinyML and Local Decision Loops

TinyML allows compact models to run on microcontrollers or small embedded boards. In smart waste systems, it can support anomaly detection, fill-rate prediction, and lightweight classification without continuous connectivity. The main advantage is lower latency and reduced bandwidth. The main limitation is that models must be compressed, monitored for drift, and updated securely.

For hazardous events, local loops are necessary. A gas or fire alert should not wait for cloud inference if the device can trigger a local alarm and send a high-priority message. This is the operational meaning of decentralized intelligence in waste systems.

IX. Data Integration and Decision-Making Frameworks

A. From Data Silos to Interoperable Decision Systems

Smart waste systems often fail at the integration layer. Bin data, vehicle GPS, citizen complaints, MRF records, weather data, and traffic feeds may exist in separate proprietary systems. Without open APIs, common data models, and semantic consistency, dashboards become isolated monitoring tools rather than decision systems.

Interoperability must therefore be treated as a core performance metric. A smart waste platform should expose standardized data interfaces, support integration with municipal GIS, and preserve auditable decision records. Blockchain can support traceability for high-value or sensitive waste streams, but it should not replace practical data-governance rules [1], [7].

B. AIoT-SWM Evaluation Rubric

The proposed AIoT-SWM rubric helps municipalities and researchers compare systems before procurement or deployment. As presented in Table VII, each criterion can be scored from 1 (weak or absent) to 5 (mature and validated). The rubric is intentionally multi-dimensional because a system with excellent AI accuracy may still be unsuitable if it lacks interoperability, cybersecurity, maintenance feasibility, or social safeguards.

TABLE VII. AIoT-SWM Evaluation Rubric

Criterion	Low Maturity (1-2)	Medium Maturity (3)	High Maturity (4-5)
Interoperability	Closed vendor system; manual export	Partial API or limited GIS integration	Open interfaces, semantic model, multi-system integration
Latency and reliability	No formal timing targets	Basic uptime reporting	Measured end-to-end latency, packet delivery, fallback logic
Energy and maintenance	Frequent battery replacement; no calibration plan	Duty cycling but limited maintenance data	Lifecycle energy plan, calibration schedule, ruggedized devices
AI and optimization	Static rules or laboratory-only model	Pilot model with partial validation	Field-validated model with explainability and retraining plan
Circular economy impact	Collection-focused only	Some recycling indicators	Material recovery, traceability, contamination, and emissions metrics
Cybersecurity and governance	Unsecured devices and unclear ownership	Basic authentication	Encryption, audit logs, access control, data governance policy
Inclusion and human oversight	No social assessment	Limited citizen or worker feedback	Human-in-the-loop decisions and informal-sector integration

X. Sustainability, Circular Economy, and Social Inclusion

A. Waste as a Measurable Resource Stream

The circular value of smart waste systems depends on their ability to improve recovery, reduce contamination, and generate trustworthy material-flow data. RFID, QR codes, blockchain logs, and AI classification can support traceability from generation to collection, sorting, and recycling. However, traceability is useful only when it improves recovery decisions or accountability [1], [7], [17].

Environmental benefits also depend on routing and treatment choices. Dynamic routing reduces unnecessary collection mileage and fuel use. Early organic-waste identification can support composting or anaerobic digestion. Material-recovery forecasting can help plan MRF capacity and avoid over-investment in poorly located infrastructure [13], [15].

B. Inclusion of Informal Waste Actors

In many cities, informal waste workers recover a significant share of recyclable material but remain outside formal data and payment systems. Smart waste initiatives can either improve their position or make them invisible. Inclusion requires digital tools that support fair payment, route access, safety information, and cooperative organization rather than simply replacing human labor [2], [8].

Human-in-the-loop governance is therefore necessary. Municipalities should allow operators, community representatives, and waste-worker organizations to question algorithmic priorities, report service gaps, and correct data errors. Technical intelligence must remain accountable to public-service objectives.

XI. Challenges, Limitations, and Ranked Research Agenda

A. Prioritized Challenge Taxonomy

The main challenges are not equally severe. Some affect basic system operation, while others influence long-term legitimacy. Table VIII organizes limitations by technical severity, deployment frequency, and research urgency. It is intended to guide both future research and municipal procurement.

TABLE VIII. RANKED CHALLENGES AND RESEARCH AGENDA

Rank	Challenge	Severity	Research/Policy Priority
1	Interoperability and vendor lock-in	Very high	Open APIs, common data models, procurement standards, municipal data governance
2	Energy and maintenance burden	Very high	Low-power design, ruggedization, lifecycle-cost studies, calibration protocols
3	Latency and reliability guarantees	High	End-to-end timing models, packet delivery benchmarks, edge/fog fallback mechanisms
4	AI model drift and field robustness	High	Local datasets, explainable models, retraining pipelines, contamination-aware evaluation
5	Cybersecurity and privacy	High	Encryption, secure updates, device authentication, privacy-preserving edge analytics
6	Economic feasibility of robotics	Medium-high	Local techno-economic models, modular robots, hybrid human-AI sorting
7	Equity and informal-sector inclusion	Medium-high	Human-in-the-loop governance, fair payment platforms, participatory indicators

B. Limitations of this Review

This paper is a structured review and synthesis, not an experimental evaluation. The reported performance values come from cited studies whose assumptions, local costs, sensor choices, and deployment environments differ. Therefore, comparative tables should be interpreted as decision-support tools rather than universal benchmarks.

A second limitation is that many smart waste studies still report pilot results without long-term maintenance data. Future research should report lifecycle cost, seasonal reliability, calibration frequency, failure rates, and social effects after deployment.

XII. CONCLUSION

This review shows that smart waste management is a systems-integration challenge. IoT sensing improves visibility, but visibility becomes useful only when communication protocols, edge/fog/cloud computing, AI analytics, routing algorithms, and municipal decision processes operate as a closed loop. The revised synthesis therefore moves beyond a descriptive overview and proposes an AIoT-SWM taxonomy, evaluation rubric, and ranked research agenda.

The technical sections demonstrate complementary strengths and unresolved tensions. LoRaWAN and NB-IoT support low-power telemetry, but they cannot replace local edge logic for urgent alerts or high-bandwidth classification. AI routing can reduce fuel and overflow, but it must manage route stability, driver usability, and uncertain sensor data. Robotic sorting can improve purity and throughput, but its feasibility depends on local waste composition, maintenance capacity, labor economics, and recycling-market volatility.

The main implication is that future smart waste systems should be designed as resilient public infrastructures, not as isolated smart-bin pilots. Strong systems will combine measurable latency and reliability targets, open interoperability, cybersecurity, human oversight, circular-economy metrics, and inclusive governance. Only under these conditions can AIoT contribute to waste systems that are efficient, scalable, transparent, and socially responsible.

STATEMENTS AND DECLARATIONS

Funding: The authors received no specific funding for this work.

Competing interests: The authors declare that they have no competing interests.

Data availability: No new datasets were generated or analyzed during the preparation of this review.

Declaration on Generative AI-Assisted Editing: Software-assisted language refinement and formatting support were used during manuscript preparation. The authors reviewed, revised, and validated the final content and remain fully responsible for the scientific accuracy, originality, and integrity of the manuscript.

REFERENCES

[1] A. Castiglione, L. Cimmino, M. Di Nardo, and T. Murino, "A framework for achieving a circular economy using the blockchain technology in a sustainable waste management system," Comput. Ind. Eng., vol. 180, p. 109263, 2023.

[2] M. Batista et al., "A framework for sustainable and integrated municipal solid waste management: Barriers and critical factors to developing countries," J. Clean. Prod., vol. 312, p. 127516, 2021.

[3] I. Papamichael et al., "A metaverse framework for sustainable waste management considering circular economy," Chem. Eng. J., vol. 512, p. 162283, 2025.

[4] A. Alsobky, M. Ahmed, S. Al Agroudy, and K. El Araby, "A smart framework for municipal solid waste collection management: A case study in Greater Cairo Region," Ain Shams Eng. J., vol. 14, p. 102183, 2023.

[5] M. Dharmalingam and D. Kang, "A study on sustainable system for managing municipal solid waste through a multi-criteria group decision-making technique," Eng. Appl. Artif. Intell., vol. 150, p. 109393, 2025.

[6] N. B. M. Ishaque and S. M. Florence, "An intelligent deep learning based classification with vehicle routing technique for municipal solid waste management," J. Hazard. Mater. Adv., vol. 18, p. 100655, 2025.

[7] P. Jiang et al., "Blockchain technology applications in waste management: Overview, challenges and opportunities," J. Clean. Prod., vol. 421, p. 138466, 2023.

[8] M. J. Alam et al., "Determinants of adopting web-based systems for e-waste management and ensuring sustainable environment: Evidence from Bangladesh," Cleaner Waste Syst., vol. 11, p. 100282, 2025.

[9] P. Chatterjee and M. R. Seikh, "Evaluating municipal solid waste management with a confidence level-based decision-making approach in q-rung orthopair picture fuzzy environment," J. Ind. Inf. Integr., vol. 42, p. 100708, 2024.

[10] T.-D. Bui et al., "Municipal solid waste management technological barriers: A hierarchical structure approach in Taiwan," Resour. Conserv. Recycl., vol. 190, p. 106842, 2023.

[11] R. Alsabt et al., "Optimizing waste management strategies through artificial intelligence and machine learning - An economic and environmental impact study," Cleaner Waste Syst., vol. 8, p. 100158, 2024.

[12] M. T. Munir, B. Li, and M. Naqvi, "Revolutionizing municipal solid waste management (MSWM) with machine learning as a clean resource: Opportunities, challenges and solutions," Fuel, vol. 348, p. 128548, 2023.

[13] P. Zoumpoulis et al., "Smart bins for enhanced resource recovery and sustainable urban waste practices in smart cities: A systematic literature review," Cities, vol. 152, p. 105150, 2024.

[14] J. N. Sackey et al., "Forecasting municipal solid waste generation and composition using machine learning and GIS techniques: A case study of Cape Coast, Ghana," Cleaner Waste Syst., vol. 7, p. 100140, 2024.

[15] L. A. Rodriguez-Padilla, A. G. Carrillo-Ramos, and F. R. Gomez, "Improving circularity in municipal solid waste management through machine learning in Latin America and the Caribbean," Cleaner Waste Syst., vol. 7, p. 100144, 2024.

[16] Y. Zhang, X. Zhang, and Y. Wang, "Integrating clustering algorithms and machine learning to optimize regional snapshot municipal solid waste management for achieving sustainable development goals," Cleaner Waste Syst., vol. 8, p. 100149, 2024.

[17] P. Rawat, R. Kumar, and S. Jain, "Strategic approach towards sustainability by promoting circular economy-based municipal solid waste management system: A review," Cleaner Waste Syst., vol. 9, p. 100166, 2024.

[18] D. Baldo, A. Mecocci, S. Parrino, G. Peruzzi, and A. Pozzebon, "A multi-layer LoRaWAN infrastructure for smart waste management," Sensors, vol. 21, no. 8, p. 2600, 2021.

[19] J. Ali et al., "A deep dive into cybersecurity solutions for AI-driven IoT-enabled smart cities in advanced communication networks," Comput. Commun., vol. 229, p. 108000, 2025.

[20] R. K. Kodali, B. Sahu, and M. R. Rajeev, "Advances in real time smart monitoring of environmental parameters using IoT and sensors," Mater. Today Proc., vol. 80, pp. 3885-3892, 2024.

[21] F. Ferrari et al., "An innovative IoT-oriented prototype platform for the management and valorisation of the organic fraction of municipal solid waste," J. Clean. Prod., vol. 247, p. 119618, 2020.

[22] T. Ali, M. Irfan, A. S. Alwadie, and A. Glowacz, "IoT-based smart waste bin monitoring and municipal solid waste management system for smart cities," Arab. J. Sci. Eng., vol. 45, pp. 10185-10198, 2020.

[23] N. C. A. Sallang, M. T. Islam, M. S. Islam, and H. Arshad, "A CNN-based smart waste management system using TensorFlow Lite and LoRa-GPS shield in Internet of Things environment," IEEE Access, vol. 9, pp. 153560-153574, 2021.

[24] S. Saha and R. Chak, "IoT based smart waste management system in aspect of COVID-19," J. Open Innov. Technol. Mark. Complex., vol. 9, p. 100048, 2023.

[25] A. Roy, A. Manna, J. Kim, and I. Moon, "IoT-based smart bin allocation and vehicle routing in solid waste management: A case study in South Korea," Comput. Ind. Eng., vol. 171, p. 108457, 2022.

[26] A. A. Kapitanov, A. N. Lavrova, and V. V. Nikiforov, "Smart city solutions: Comparative analysis of waste management models in IoT-enabled environments using multiagent simulation," Simul. Model. Pract. Theory, vol. 139, p. 102788, 2023.

[27] S. Safa et al., "Optimizing waste management with integrated AIoT edge computing and LoRaWAN communication technologies," Cleaner Eng. Technol., vol. 24, p. 100917, 2024.

[28] E. Longo, F. A. Sahin, A. E. C. Redondi, P. Bolzan, M. Bianchini, and S. Maffei, "A 5G-enabled smart waste management system for university campus," Sensors, vol. 21, no. 24, p. 8278, 2021.

[29] I. Sosunova and J. Porras, "IoT-enabled smart waste management systems for smart cities: A systematic review," IEEE Access, vol. 10, pp. 73326-73363, 2022.

[30] A. Lakhouit, "Revolutionizing urban solid waste management with AI and IoT: A review of smart solutions for waste collection, sorting, and recycling," Results Eng., vol. 26, p. 104018, 2025.

[31] N. Cruz, N. Cota, and J. Tremoceiro, "LoRaWAN and urban waste management - A trial," Sensors, vol. 21, no. 6, p. 2142, 2021.

[32] C. Wang, J. Qin, C. Qu, X. Ran, C. Liu, and B. Chen, "A smart municipal waste management system based on deep-learning and Internet of Things," Waste Manag., vol. 135, pp. 20-29, 2021.

[33] I. Nurhaida, M. Nasucha, and H. Nugraha, "AI-driven robotic waste sorting for techno-economic assessment in urban Indonesia," Int. J. Adv. Comput. Sci. Appl., vol. 17, no. 2, 2026.