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Waste Management using AI: Optimizing Sustainability through Innovation

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Abstract

There has been an increasing need for effective, sustainable, and scalable waste management systems due to the rapid increase in global waste generation. This comprehensive review intersects Artificial Intelligence (AI) with municipal solid waste management (MSWM) through the lens of 25 selected publications from the years 2018 to 2024. The review illustrates how AI has transformed waste forecasting, smart bin monitoring, route optimization, robotic waste sorting, and real-time decision making. In examining the core AI techniques machine learning, deep learning, computer vision, and hybrid models, the review places these techniques within the context of the waste life cycle—beginning with generation, through processing, to disposal. Moreover, it looks at integrated frameworks like SWM 4.0 where AI is combined with Industry 4.0 technologies, including the IoT, big data, and even blockchain. The results stress AI's ability to optimize operational activities, mitigate negative environmental effects, and facilitate concrete policy decisions. However, issues related to data quality, system incompatibility, and ethics pose challenges to realizing such opportunities. This review evaluates existing research on AI-based smart systems and sets forth a research agenda aimed at advancing circular economy objectives and fostering sustainable urban frameworks.

1. Introduction

1.1Background and Significance

The growing industrialization, population, and urbanization has resulted in an exponential increase in the municipal solid waste (MSW). An article from World Bank estimates a global projection of waste generation to reach 3.4 billion tonnes by 2050, an increase from 2.01 billion tonnes in 2016 [1]. This tremendous growth in waste poses severe health, economic, and environmental threats, in addition to overwhelming traditional waste management systems [2] [3]. Pollution and climate issues are further exacerbated with the inefficient collection systems, leasing recycling infrastructure, and lack of adequate waste segregation [4].

Our traditional Manual Intervention based strategies alongside disposal linear models just are not cutting it. Eco-centric and sustainable frameworks of predictive, data-driven automation aligned with circular economy principles are necessary to shift from reactive waste management to pro-active automation based systems [5] [6].

1.2 The Emergence of Artificial Intelligence in Waste Management

Every sector is witnessing a forceful transformation, and artificial intelligence (AI) is no exception, with waste management being poorly managed for the longest [6]. The vast capabilities of AI when it comes to processing massive amounts of data which is otherwise unstructured, spotting patterns, making forecasts or predictions, and optimizing processes helps pave the way for far more intelligent integrated systems for waste management [7].

From predicting waste creation and enhancing route planning to automated waste sorting with computer vision and robotics, AI technologies are transforming the entire waste lifecycle [8]. The combination of AI with IoT devices, blockchain, and big data analytics permits real-time decision-making and dynamic adaptation of systems, marking the evolution towards SWM 4.0 or Smart Waste Management 4.0 [6].

1.3 Scope and Objectives of the Review

This review analyzes 25 selected studies (2018-2024) focused on the application of AI in sustainable practices and the operational efficiency of waste management systems [9]. The key objectives of the review are:

- To identify and classify AI methodologies implemented in various stages of waste management—generation, collection, sorting, recycling, and disposal [10].
- To assess integrated models like SWM 4.0 that incorporate Industry 4.0 technologies [6].
- To analyze chosen studies for comparisons of methodologies, applications, and outcomes.
- To outline issues identified in AI-based solutions to waste management, highlight gaps in the current research, and suggest directions to be taken [5].

This paper aims to be a coherent point of reference by integrating disparate research across various fields to support educators, engineers, decision-makers, and urban engineers striving to advance the research and development of innovative solutions for waste management.

2. RESEARCH METHODOLOGY

2.1 Review Design and Approach

The review follows a systematic and thematic literature review strategy to assess the role of Artificial Intelligence (AI) in waste management. The process, based on frameworks for evidence-based reviews, is structured to capture comprehensiveness, relevance, and scholarly rigor. The approach involves qualitative synthesis and comparative analysis regarding the application and the technological depth of AI in municipal solid waste management (MSWM) [11].

2.2 Literature Survey Strategy

Appropriate literature was collected from reputable sites which included peer-reviewed journals, conference proceedings, and cross-indexed websites like IEEE Xplore, ScienceDirect

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(Elsevier), SpringerLink, Scopus, and Google Scholar. The following keywords and Boolean combinations were used:

"Artificial Intelligence" AND "waste management"
"smart waste" AND "AI"
"waste sorting" AND "machine learning"
"AI in municipal solid waste"
"Industry 4.0" AND "smart cities" AND "waste"

The publications dated from 2018 to 2024 to incorporate recent technological advancements alongside practical applications within the field [12].

2.3 Inclusion and Exclusion Criteria

In the interest of maintaining relevance and adhering to quality control, the following criteria were put in place:

Inclusion Criteria:

- Publications available in the English language.
- Papers focusing explicitly on AI methods in waste generation, collection, sorting, recycling, or monitoring.
- Documents suggesting design ideas or models that utilize AI within smart or sustainable waste systems.

Exclusion Criteria:

- Ineligible articles not mentioning AI models or technologies.
- Editorials, opinion pieces, or other non-peer-reviewed blog posts.
- Incomplete publications or duplicates.

2.4 Dataset of Reviewed Papers

A number papers were identified through database searches. After doing a title and abstract filter, topic-specific articles were pulled and reviewed. Based on relevance and inclusion criteria core themes, 25 foundational papers were used for detailed synthesis and analysis [11]. The studies cover a range of subfields within intelligent waste management, such as:
•ML and DL applications for waste identification and categorization,
•AI for route planning accuracy,
•Smart bins with IoT integration,
•Recycling centers with AI, and SWM 4.0 frameworks with AI, IoT, big data, and blockchain [8].

2.5. Categorization of Framework

Every paper was assigned a code and placed into the following group criteria:
•AI Technique Used – e.g., ANN, CNN, SVM, GA, YOLOv3.
•Phase of Waste Management – generation, collection, sorting, recycling, monitoring.
•Integration of Technology – presence of IoT, cloud computing, industry 4.0 [9].
•Focus Result - sustainability, operational activity, efficiency, and cost decrease.
•Context and Region of Application - developed countries vs. developing countries and urban vs. semi-urban installations.
This enabled the literature to be compared across studies and provided an opportunity to identify research gaps and emerging trends [3].

3. AI Application In Waste Management Review

The applicability of Artificial Intelligence (AI) to waste management is evident throughout the entire system, from forecasting the generation of waste to its final disposal [5]. This chapter consolidates applications of AI as identified in a 25-study analysis into five overarching themes: forecasting, collection, sorting, recycling/resource recovery, and monitoring & decision making [13]. Each theme is detailed in consideration of the AI techniques used, the results achieved, the implementation challenges cited in the literature, and the results after the solutions were provided [8].

i. Waste Generation Forecasting

Citing specific literature, underscoring claims with evidence is best practice in academia—and for good reason. Strategic planning for waste management systems begins with an understanding of the pivotal facets, including the volume and composition of waste [14]. AI approaches such as Artificial Neural Networks (ANNs) along with machine learning techniques like Support Vector Machines (SVMs) Fuzzy Logic Systems are frequently implemented for this [15]. This is due to the fact the models outperform more classical statistical approaches by non-linear, multivariate inputs like population growth, urbanization, weather data, and consumption trends like the latter [16].

For example, El Jaouhari et al. created hybrid AI models to forecast the volume of municipal solid waste (MSW) in urban settings which permits better resource allocation [2]. Also, Ech-cheikh et al. demonstrated that AI is better in capturing seasonal aspects and spatial dynamics of waste generation patterns [5].

ii.Smart Collection of Waste and Route Organization

AI optimizes collection logistics by smart bins, GPS-tracked trucks, and cloud-based data systems [17]. To improve collection fuel use and overflow incidents, Genetic Algorithms (GA), Reinforcement Learning, and Dynamic Programming are utilized to create optimal routes for collection [18].

AI in route optimization has been noted to reduce operational cost by 20% while increasing collection frequency, as noted by Olawade et al. and Idrissi et al [6] [7]. The inclusion of IoT-based fill-level sensors and AI prediction models enable dynamic scheduling due to real-time updates driven by the need to service bins only as necessary [19].

iii.Classification Automation

Sorting continues to be one of the most labor-intensive processes in waste management [20]. The development of AI, specifically Deep Learning (DL) models has automated this process with Convolutional Neural Networks (CNNs) and YOLOv3 Object Detection [21].

With the help of computer vision, Fang et al. and Sahu & Prusty subdivided waste images into recyclables, organics, and hazardous materials with high accuracy of up to 98% which aids in automating the process [3] [22]. These technologies not only alleviate the burden of manual work but also improve the quality of recyclable materials extracted which increases recovery efficiency overall [23].

The invention of robotic sorting technologies paired with real-time artificial intelligence (AI) models continues to drive the change toward zero-landfill smart facilities [24].

3.1Recycling and Resource Recovery Optimization

AI enhances recycling optimization through the prediction of process parameters, material flow, and lifecycle assessment [25]. Random Forest, Decision Trees, and Bayesian Networks are used to determine optimal treatment routes for various waste streams [26].

The models reviewed Huang Li-ting and Gupta et.al. highlight the ability of AI to predict contamination level, versatile recyclable yield, and the optimization of pyrolysis or composting conditions for organic wastes [27] [28]. Such models are critical in waste-to-energy systems, where control

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over the streams fed into the system significantly impacts the overall energy conversion efficiency [29].

3.2 Precision Waste Monitoring and Tactical Planning

AI-powered dashboards and decision-support systems (DSS) have enabled real-time monitoring of waste flows and evaluation of policy impacts at the municipal level using urban AI [30]. System performance alongside other factors like automated and citizen engagement monitoring captured using Big Data, Natural Language Processing (NLP), and multi-objective optimization algorithms give insight into the system's environmental as well as citizen engagement impact [31].

Smart Waste Management 4.0 (SWM 4.0) frameworks, like the one developed by Kannan et al. [8], merges AI with IoT, blockchain, and cyber-physical systems to form a holistic waste ecosystem [32]. These holistic platforms enhance transparency, operational precision, and collaboration across different stakeholders, allowing governance to be based on factual information [2].

3.3 Summary of Techniques and Trends

Waste Management Function	AI Techniques Used	Common Outcomes
Forecasting	ANN, SVM, Fuzzy Logic	Improved accuracy in planning
Collection & Routing	GA, RL, DP	Reduced fuel and overflow
Sorting	CNN, YOLO, Tensorflow	High classification accuracy
Recycling Optimizing	RF, DT, Bayesian Net.	Enhanced yield, reduced contamination
Monitoring & Policy	NLP, Big Data, DSS	Real-time alerts, citizen analytics

This analysis of the thematic areas highlights the diverse scope of AI application impact on waste management for sustainability [33]. Every individual effort is aimed towards contributing not only towards operational excellence but augmenting environmental sustainability and it's the circular economy ecosystem [34].

4 SMART WASTE MANAGEMENT 4.0 FRAMEWORK

The intersection between Artificial Intelligence (AI) and Industry 4.0 (I4.0) technologies has led to the evolution of one of the newest fields in environmental engineering, which is called Smart Waste Management 4.0 (SWM 4.0) [8]. This model transforms waste ecosystems strategically and systemically by integrating AI, IoT, blockchain, big data, cyber-physical systems (CPS), and mobile/cloud technologies to allow real time, decentralized, self-regulating, and sustainable processes [11].

4.1 Evolution Toward SWM 4.0

The traditional approaches to waste management are best described as 'collect–transport–dispose' systems—subsisting as a
linear sequence lacking data collaboration and responsiveness [35]. SWM 4.0 transforms this approach by incorporating intelligence across all layers of the waste management cycle, including policy enforcement, generation, and recycling [3].
The following provide the basis for the advancement:

•Collection and GPS-enabled smart bins equipped with IoT sensors for data decentralization [36].
•Recognition, forecasting, and optimization driven by AI analytics [9].
•Infrastructure scalability via Cloud and edge computing [37].
•Citizens' trust in data exchange enabled by blockchain transparency and needs traceability [38].

4.2.Core Pillars of SWM 4.0 Frameworks

In accordance to the integrated framework proposed by Kannan et al. [8], SWM 4.0 has four foundational pillars:
Smart People
Engaged citizens equipped with mobile reporting applications, waste separation instructions, and rewards for participating in recycling campaigns [6]. AI facilitates behaviour monitoring and encourages participation through gamification models [39].
Smart Cities
Real-time data is utilized in urban centers to automate waste collection, regulate air and water quality, and assist in zoning or infrastructure building [11]. Advanced urban planners employ waste scenario simulation aided by digital twins and AI integrated with GIS [5].
Smart Enterprises
AI adoption is evident in the enhancement of internal waste audit processes, supply chain traceability, and standards compliance at the organizational level [36]. AI technologies assist in transforming industrial processes from waste generation to resource circularity [40].
Smart Factories
Material waste is minimized through vending equipment that employs robotic sortation, AI driven excess production forecasting, predictive maintenance, and by-product recycling loop routing [41].

The combination of all these components enables the development of collaborative intelligence that encompasses humans, machines, and platforms toward building an ecosystem designed for achieving operational and environmental objectives [21].

4.3Advantages of Integrating SWM 4.0

•Impact Area Contribution of SWM 4.0 Operational Efficiency Optimization of routes, automation, bin fill prediction, and task execution [7].
•Environmental Impact Emission reduction, minimization of dump site activity, leak detection [42].
•Economic Viability Expense reduction, resource reclamation, asset depreciation [43].
•Citizen Engagement Campaigns directed toward educated, mobile interfaces, participation through feedback loops [3].
•Governance Supervision of policy enactment in real-time and recording data in an open registry. [28]
SWM 4.0 adoption has shown measurable improvements in waste diversion, collection efficiency, and citizen participation in European and Asian cities [11].

4.4. Current Limitations and Considerations

Although promising, issues with implementing SWM 4.0 at scale include the following:
•Interagency and cross technological platform data incompatibility [44].
•Insufficient funding due to capital expenditure's excessive operational costs [30].
•Cyber security risks posed by IoT and AI systems [21] [27].
•Lack of workforce skills apt to integrate AI into waste systems [5].

•The ethics and privacy issues involving behavioural monitoring and tracking [32].
Consequently, future frameworks must abide to inclusive design approaches, open source methodologies, and multi stakeholder governance to guarantee that technology is responsive, responsible and fair.

4.5.Conceptual Representation of SWM 4.0

Smart Waste Management 4.0
AI is not just a tool but a lever for transforming a passive view of waste management into an integrated, proactive system designed around synergy and sustainability [6]. SWM 4.0 illustrates the case for how digital evolution is a solution to constructive realignment of environmental imperatives with socio-economic development [45].

5.COMPARATIVE ANALYSIS OF REVIEWED STUDIES

The swift progress of AI technologies in waste management has resulted in multiple applications in different regions, technologies, and stages of waste processing [11]. Although the analyzed literature focuses on the same concept of intelligent, automated, and integrated waste management systems in their futuristic cities, they differ a lot in approach, state of application, scope, and impact measurement [33]. This part offers a cross-section comparison analysis to illustrate these differences and find underlying patterns [15].

5.1 Summary Table of Reviewed Studies

Out of the comprehensive AI waste management studies, a multitude of AI techniques were incorporated into different stages of the waste management cycle [6]. For example, El Jaouhari et al. [2] incorporated ANN and hybrid forecasting and planning models which were frequently combined with GIS and machine learning for more accurate predictions of MSW generation with pyrometric models [20]. Fang et al. [3] used CNN and object detection for smart city waste sorting and classification using IoT and image recognition, achieving classification accuracy of 98%. Ech-cheikh et al. [5] worked on forecasting and collection planning using SVM and fuzzy logic which improved adaptive planning through advanced data analytics. Monitoring and optimization of routes were the focus of Olawade et al. [6], who applied genetic algorithms and heuristic models which, in combination with IoT and cloud, resulted in savings of 20% using real time systems. Using an AI + ICT framework, real collection and routing was done with rule based AI systems and ANN by Idrissi et al. [7]. Kannan et al. [8] developed a model, SWM 4.0, integrating AI, blockchain, and cyber-physical systems into a single comprehensive urban solid waste management system offering decision support throughout the entire process [42].

At the same time, Sahu and Prusty [22] classified waste images using edge AI deployment with high precision and low latency. Economic policy and public governance gaps regarding waste governance AI frameworks were identified by Kumar [44] as lacking in the domain of simulation analytic expert systems for policy and planning workflows. Last, the review by Abdallah offered an overarching conceptual structure using ANNs, SVMs, and genetic algorithm frameworks, aiming at diverse lifecycle stages while outlining strategic uncertainties in automated systems research [15].

5.2 Analytical Results from Multiple Sources

•Application and AI Domain
The creation of algorithms for estimating the volume of waste produced leans heavily on ANN, SVM, and fuzzy logic frameworks [15].
Classification and sorting incorporate various deep learning algorithms alongside robotic systems with vision interfaces or robotic eyes using YOLO and CNN frameworks [21].
Heuristic optimization and genetic algorithms along with neural network reinforcement learning systems are
employed in routing and logistic activities [46].
•Integration with Other Technologies
The combination of cloud computing and Internet of Things (IoT)—which is integrated in [6], [7]—produced enhanced responsiveness and real-time capabilities to the system designed for the study.
For decentralized detail governance and traceability, blockchain, as illustrated in [8], is gaining popularity alongside cyber-physical systems (CPS).
•Performance Assessment
Cost operational benchmarks: reduced operational cost by 30%, reduced collection time, improved fuel efficiency [20].
Environmentally: improved rate for recycling, reduced landfill usage, reduced carbon emissions [7].
Social metrics: increased civic participation, diminished grievances, and improved compliance with segregation policies and social norms [33].

5.3 Research Maturity and Scalability

When analyzing the research development level and scalability, some trends are clear. The most mature are forecasting models based on ANN, SVM, and hybrid systems; the newest approaches, like federated AI and temporal ensemble models, are still experimental [5]. Smart bins equipped with IoT devices and optimized with genetic algorithms or reinforcement learning are mature in urban areas, while edge-AI applications in rural areas are still maturing [47]. Waste classification using deep CNNs and YOLOv3—especially with sufficient large-scale training data—is highly mature, while using transfer learning for uncommon or obscure waste types is relatively unexplored [21]. Governance integration is found in works that apply AI to IoT dashboards; however, automated public transparency via blockchain has not been addressed beyond the conceptual stage [9]. As a point of note, only a handful of end-to-end SWM 4.0 frameworks have been implemented in smart cities, as most studies are simulations or conceptual due to funding, infrastructure, or regulatory alignment constraints [47].

5.4. Cross-Cutting Challenges From Studies

Data Issues: Absence of labelled datasets, diversity of data sources, lack of interoperability [7].
Scaling Gaps: Most proposed solutions are at the prototype or pilot phase due to infrastructural limitations [4].
Governance and Ethics: Issues of surveillance, consent, and transparency of algorithms on public systems [10].
Cost and Accessibility: Adoption is limited within resource-strapped municipalities due to the high initial investment [22].

5.5.Key Takeaways

AI now influences strategic decision making and policy setting for sustainable waste management beyond merely automating processes [6].

Integration as a Differentiator: Multi-Technology Solutions (AI + IoT + Blockchain) offer competitive advantages over single Technology solutions [33].

There is no universal model—solutions need to be context specific and respond to local social and infrastructural systems.

Looking through this lens of comparison reveals that although AI is accelerating in academic and pilot applications, the true transformation potential rests in systemic integration design with integrated inclusive framework or Smart Waste Management 4.0 [25].

6 Challenges And Research Gaps

While the reviewed literature does highlight some advancements of Artificial Intelligence (AI) applications in municipality solid waste management (MSWM), there are still persistent challenges and gaps which make it impossible to achieve fully smart, scalable, sustainable, and AI-integrable systems [4]. These problems include technological, infrastructural, socio-economic, and political factors, which highlights the need for a more holistic approach to these issues [15].

6.1 Infrastructure And Data Governance Gaps

The lack of high-quality structured datasets and annotation data for quantitative AI training is a major hindrance [5]. Many smart waste systems reliant on vision-based predictive/optimization algorithms require vast contextualized data [1]. This includes data pertaining to waste generation patterns, image databases for sorting, and real-time bin-level data [33]. In developing and resource-constrained settings, data is either non-existent, siloed among stakeholders, or non-digitized, rendering AI devoid of unbiased data or unreliable data streams for training [19]. Furthermore, proprietary software and closed-loop hardware ecosystems stagnate progress towards integration, with cross-platform interoperability being virtually non-existent [28].

The more critical issues relate to the infrastructure such as computing and IoT reliability, consistent power supply, and access to cloud infrastructure which might not be easily accessible in rural or semi-urban municipalities [5]. The absence of stable digital infrastructure prohibits the functionality of optimally trained AI which stifles their operational impact at the ground level [7].

6.2.Technical and Algorithmic Problems

While many AI approaches tend to work well in a controlled environment or a pilot project, scalability remains a persistent problem [15]. A model that works very well on small datasets or local trials tends to perform poorly when AI is deployed at a larger geographic or demographic scale. Furthermore, many solutions are tailored to specific types of waste or certain types of conditions, rendering those myriad environments transferable only after extensive retraining or customization [33].

Lack of real-time responsiveness and adjustability is another technical shortcoming. As is shown with the work of Sahu & Prusty [22], edge computing can be used for low-latency sorting, but most AI systems still rely on a centralized architecture with monitoring and feedback loops that introduce latencies to the operational and decision loops [36]. This is particularly troublesome for more robotic subprocesses such as routing of collection vehicles for waste collection or handling overflow in emergency situations, wherein slow reactions can seriously impact operational efficiency [18].

6.3 Financial and Resource Constraints

There is a significant financial burden when integrating AI into waste management, particularly with the installation of sensors, smart bins, robotic arms, and the associated data storage frameworks [19]. Most cities, especially those which are low-income or in the process of rapid urban development, find it difficult to shift their focus from fulfilling basic civic requirements to even considering investing in these systems. Additionally, the ROI of AI-powered waste management systems is typically medium to long-term, posing a challenge to investment from public and private sectors [25].

Available funding for multidisciplinary research that combines environmental science with AI and urban governance is virtually zero, constraining most AI innovations to academic or pilot research settings without transitioning into public policy or commercial waste management frameworks [33].

6.4.Policy, Ethical and Governance Issues

The application of AI in public utilities like waste management raises ethical issues concerning data privacy, surveillance, and the use of opaque algorithms [38]. While automating the analysis of household waste, predicting recycling participation, or citizen reporting, the systems have the potential to profile identifying constituents unless adequate privacy-preserving strategies are employed.

Simultaneously, the provided guidelines have not had enough attention. There is a lack of guidelines on the governance of AI technologies in public waste management systems, and the governance frameworks are often vague about responsibility, risk, and consent of the citizens. The lack of uniformity makes it impossible to define success metrics and makes it difficult to establish interoperable systems across cities or regions [40].

6.5Gaps in Adoption and Design Focused on the Citizens

Most of the AI-supported waste solutions talk about some aspects of citizen participation, and few provide strong user-friendly designs that encourage participation or behavioural change [39]. The mobile applications and gamified approaches are still at an early stage and out-of-the-loop with the municipal feedback cycles. There is a gap in the design that is responsive to the needs of those who are directly affected for populations like the marginalized citizens strongly informal waste workers and small-scale recyclers who operate informally within entrenched waste systems [20].

Without citizens' backing, even the most sophisticated AI infrastructure is likely to fail because of resistance, withdrawal, and lack of useful feedback. Therefore, future systems need to focus on human-machine cooperation that emphasizes function, ease of use, and cultural respect.

6.6.Refined Focus on Opportunities

The review suggests the following areas need more refined focus:

- Flexibility of AI frameworks oversimplified for low data sets including those from emerging markets [11].
- Uniform performance appraisal systems of AI in various waste contexts.
- Move privacy, latency, and local decision-making closer to the edge with decentralized and federated AI architectures [36].
- AI allows for lifecycle assessment in the context of zero-waste strategies and alignment with circular economy principles [40].
- Combining behavioural science with AI technologies to increase citizen participation with regard to recycling and civic engagement impacts citizens' engagement with civic participation and recycling [30].

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These problems need s multi-stakeholder collaboration: technologists, urban designers, policy makers, environmental advocates, and citizens. Together they comprehensively resolve how AI can be sustainably, inclusively, and intelligently transform waste management systems [14].

7.Future Research Opportunities

The latest advancements in artificial intelligence (AI) can be integrated into Municipal Solid Waste Management (MSWM) Technology on several strategic levels to enhance its penetrating depth for future studies. A paramount focus includes the shift to edge AI and federated AI systems which are capable of real-time data processing. For example, Edge AI can facilitate the functioning of smart bins and sensor based routing while federated AI permits the training of models at different localities without sharing sensitive information or compromising security [36].

Advancing AI development frameworks to integrate principles of the closed-loop economy is inviting another bold next step [47]. In the perspective of future systems, instead of focusing solely on identifying disposal of the item, more emphasis should also be placed on exploring the item's potential to be reused or recycled. With the help of AI, the material recovery process can be enhanced by predicting recyclability and contaminant detection to aid in the waste-to-resource transformation through lifecycle assessments [40].

Empowerment of informal and decentralized waste networks with disregard to the development regions is an increasing need. Simple to use, affordable mobile devices along with image classification technology can assist informal waste workers, providing better safety and tracking and closing the gap between formal and informal sectors [20].

Human participation can be increased with the combination of AI and behavioural science. Better segregation of waste and participation from local community members in maintaining them as active members of their local community is possible through personally tailored prompts, gamification and chatbot-based help. The leap towards participative and functional waste systems comes with human and AI systems working together [39].

Another focus area is standardization. Further research can be done on the benchmarking frameworks, open-access databases, and their interoperable nature to improve model comparability and cross-regional usage [32]. At the same time, the policy-level implementation of AI in smart city and sustainability initiatives is crucial for responsible integration and long-term sustainability [40].

As for the advancement of AI in waste management, it requires multidisciplinary collaboration from technology experts, urban designers, environmental scientists, and community members. They are able to collaboratively design frameworks that change the perception and experience of waste management toward smarter, greener, and equitable systems [34].

8.Conclusion

This review paper is based on 25 peer-reviewed articles published between 2018 to 2024 and assesses the impacts AI has had towards transforming waste management systems. The review outcome shows AI is applied in almost all processes within the waste management cycle such as forecasting, collecting, sorting, recycling, decision making, and others. The combination of IoT, cloud computing, and smart infrastructures with deep learning, neural networks, computer vision, and heuristic optimization is making 4th industrial revolution Smart Waste Management (SWM 4.0) a reality [8].

Although there is no doubt the advancement in technology brings with it reduced costs, efficient operations, and environmental benefits, challenges arise from data quality, scalability, ethical use, citizen engagement, and participatory governance [33]. Also, there remains a considerable gap in the optimization of academic innovations into practical and adaptable frameworks that are policy-attached and nationwide scope [25].

Alongside the gaps identified, the AI application gaps in waste management are targeting the circular economy, edge computing, decentralized intelligence, and behavioural integration. Building smart sustainable just waste ecosystems requires change policies and collaborative multidisciplinary effort for enduring conversion [34].

This paper seeks to metabolize interdisciplinary fragmented research in order to promote innovative processes for waste management by advancing stakeholders through the innovation, inclusivity, and intelligence framework detailed in this review.

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