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A Comprehensive Assessment to Harness Artificial Intelligence Technology in the Organic Waste Management of Urban India

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Abstract: India annually produces about 62 million tons of municipal solid waste, comprising 50–60% of organic matter. Accelerating urbanization and population growth in this country have intensified the challenges confronted by managing food, agricultural, and biodegradable waste, as the waste if handled improperly, would lead to groundwater contamination, soil degradation, and methane emission from landfills. This review provided a comprehensive assessment of the organic waste management (OWM) landscape in India, ranging from conventional methods like composting and vermicomposting to advanced approaches such as anaerobic digestion and biogas generation. It also evaluated the influence of policy frameworks and community-led initiatives on promoting sustainable practices. The focus of this study on the emerging role of artificial intelligence (AI) in the OWM highlighted its potential for improving waste segregation, process optimization, and real-time monitoring. While the application of AI in waste management has demonstrated over 90% of segregation accuracy in the pilot and global studies, its adoption remains minimal in India. By systematically comparing national practices with global benchmarks, this review identified critical gaps in technology adoption, scalability, and integration between policy and infrastructure; to fill a noticeable void in the existing literature, AI-driven innovations were adopted to deal with the unique challenge of waste management in India. The findings underscored the need for targeted support, capacity building, and technological deployment to transform organic waste from an environmental liability into a renewable and value-generating resource. Practical recommendations were offered to align technology, governance, and community participation with sustainable and resource-efficient OWM.

Keywords: Organic waste management (OWM); Processing methods; AI techniques; Urban sustainability; Municipal governance; Quantitative analysis; India

1. Introduction

The growing population and urban expansion have resulted in a dramatic increase in waste that could be categorized into wet and dry ones, thus highlighting the need for effective and sustainable waste management strategies. Authorities have initiated various programs including the Swachh Bharat Abhiyan, Clean India Mission, which enhanced the waste sector and demanded for waste management solutions. During the period of forecast from year 2021 to 2026, solid waste management in India is expected to rise at a compound annual growth rate of 7.5% due to growing urbanization, increased waste leading to sustainable and efficient waste management strategies, management awareness, and rising expenditures in the infrastructure of waste management. Over the last decade, the Indian government has launched initiatives in collaboration with state governments and union territories, including the commencement of Swachh Bharat Mission in year 2014, and has developed 100 smart cities throughout the nation in year 2015. In year 2016, the Ministry of Environment, Forest, and Climate Change updated Solid Waste Management regulations in India to reflect the three principles of circular economy: reduce, reuse, and recycle (R3). Along with the strict enforcement of the updated Solid Waste Management regulations by the Central Pollution Control Board (CPCB), these measures motivate all urban local bodies in India to establish a comprehensive waste management framework for segregating wet and dry waste, engage in source-specific collection, promote home composting or bio-methanation, and facilitate material and energy recovery from waste.

A flawed and inappropriate strategy for managing organic waste poses a severe menace to the environment and human health (Rao & Parsai, 2023). Sub-standard Solid Waste Management methods lead to several health and environmental hazards, including birth defects, childhood mortality, elevated cancer incidence, land degradation, and groundwater pollution. Accurately estimating the amount of municipal solid waste is crucial for efficient and successful operation of a waste management system; the projected figures could also help understand the current infrastructure construction for waste management, its further optimization, and sustainable growth. Large-scale issues such as insufficient or excessive waste management infrastructure for processing, landfilling, incineration, and collection could in turn result in imprecise estimations. The COVID-19 pandemic created a unique problem for organic waste management (OWM), but it prompted initiatives and actions about waste reduction, sustainable packaging, and local composting (Chowdhury et al., 2021). These initiatives helped raise awareness about the significance of responsible OWM for environmental sustainability; therefore, the advancement of waste management encompasses a range of actions and environmentally sustainable strategies designed to manage waste starting from its generation to ultimate disposal. The main goals are to reduce waste, encourage recycling, and minimize the environmental impact of waste disposal. Figure 1 shows a detailed overview of the waste management process. The systematic collection, transportation, processing, recycling, and environmentally responsible disposal of waste materials is known as waste management, which entails handling of different kinds of waste produced by homes, companies, industries, and other sources. Effective waste management strives to reduce the volume of waste, promote recycling and reuse, minimize environmental harm, and ensure public health (Kalauni et al., 2025).

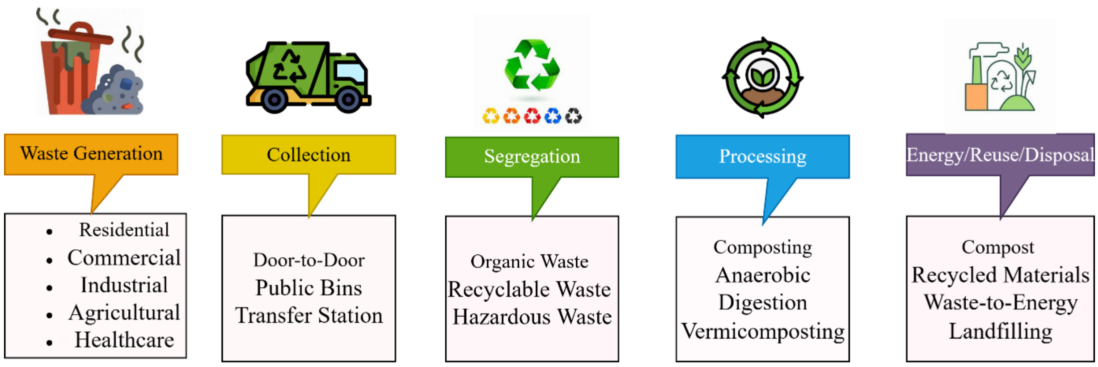


Figure 1. An overview of the waste management process

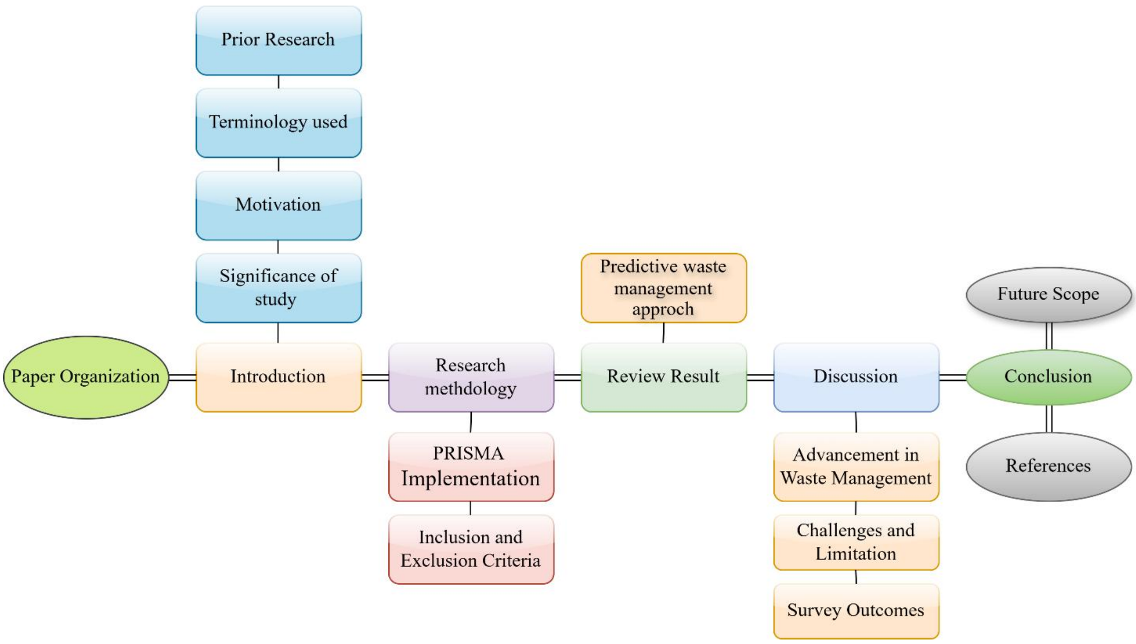


Figure 2. The organization of this study

To offer a thorough comprehension of the difficulties and solutions in the OWM, this article examined organic waste types, their impact on the environment, and primary challenges in the OWM, drawing findings from various studies and reports to provide up-to-date input about the steps taken for the OWM in India in terms of projects and patents. This review also offered information about the utilization and management of organic waste and its by-products in several states of India. Besides analyzing the current waste management strategies, such as recycling, waste-to-value resources, and waste reduction, this study discussed technical innovations and logistical barriers to effective OWM and highlighted existing gaps in research and policy. In view of the challenges from recycling organic waste and the related processing methods, this review inspired stakeholders of ongoing sustainable methods and technologies to manage organic waste, which might be helpful for environmental sustainability. Figure 2 illustrates the setup of this study, starting from an introduction and methodology, followed by a review of the results on predictive waste management. It then discussed advancement, challenges as well as survey outcomes, and ended with future scopes and references.

1.1 Significance of the Study

The management of organic waste in India presents a pressing environmental and public health challenge, driven by rapid urbanization, fast population growth, and increasing waste generation. Organic waste, including food scraps, agricultural residues, animal waste, paper, and biodegradable materials, accounts for approximately 50–60% of the 160 metric tons per day (MT/D) of municipal solid waste generated in the country (CPCB & World Resources Institute). Key sources include household kitchens, restaurants, food markets, agricultural processes, and religious gatherings.

Traditional waste handling methods, such as open dumping, incineration, and basic composting, often lack efficiency and pose environmental hazards (Kumar & Samadder, 2020). Despite various government initiatives like the Swachh Bharat Mission for promoting better waste management, significant gaps remain in waste segregation, treatment infrastructure, and public awareness. Moreover, most of the organic fraction still ends up untreated in landfills, releasing methane and leaching into groundwater. With cities facing intensified pressures from energy demand and land scarcity for waste disposal, there is an urgent need to adopt innovative and resource-efficient approaches. Despite the growing volumes of organic waste generated, waste management practices in urban India remain largely inefficient owing to limited segregation, treatment, and resource recovery. Although various technologies and policies exist to deal with the problem, their implementation remains fragmented and inconsistent, thus leading to increased environmental degradation, public health risks, and strain on landfill infrastructure. This study is significant in addressing this gap by analyzing current trends, assessing treatment effectiveness, and identifying policy and technological solutions to improve OWM. While global practices increasingly integrate artificial intelligence (AI) into waste collection, sorting, and processing, its application in India remains limited. This review assessed the adoption of AI and digital technologies to enhance the OWM in India, enabling them to become smarter, more efficient, and better aligned with sustainability goals. According to the National Restaurant Association of India (NRAI), the food service sector alone generates metric tons of food waste annually, resulting in the increasing waste volume.

Trends in Organic Waste Generation: The urbanization in India is progressing at an accelerated pace, with more than 35% of the population residing in urban centers (as of year 2021) and projections indicated a rise to 50% by year 2050. This urban proliferation has significant implications for the management of organic waste, creating both challenges and opportunities for progress.

Shifting Consumption Trends: As incomes grow, urban areas expand and the amount of organic waste increases along with changes in eating habits towards the rising consumption in packaged goods, processed items, and dining out. The quantity and makeup of waste are influenced by urban development and lifestyle shifts related to income levels.

The average waste generation and recovery figures are calculated by combining the data for each income group. Based on the percentage of a specific income category in the state population, the World Bank estimated that as of year 2021, approximately 22% of the total population in India (about 141 billion people) lived below the national poverty line.

1.2 Motivation

The motivation for this study stemmed from the global urgency to develop sustainable systems that not only manage waste efficiently but also contribute to environmental protection, public health, and the goals of circular economy. Organic waste, if not managed properly, becomes a lost resource and a cause of environmental degradation. However, when effectively treated, it can yield compost, renewable energy, and improved soil health.

In recent years, technological advancement in AI has begun to reshape waste management across the world. Although some progress has been made in India, the use of AI remains largely experimental and limited to isolated urban initiatives. The latest innovations in real-time waste tracking, automated sorting, and data-driven planning could offer significant improvements to face existing challenges of the OWM in India. Other technological innovations in waste segregation and control could make the OWM more scalable and effective (Fataniya et al., 2019).

Figure 3 depicts the trend of publications over the last decade to reflect the technological shift. From year 2014 to 2016, research largely focused on composting and biogas production. Between years 2017 and 2020, under the Swachh Bharat Mission, the focus shifted to waste-to-energy systems with strong government backing. Between years 2021 and 2024, studies began a new phase in the field via exploring pyrolysis and AI-based solutions. The current review therefore appears timely to consolidate and evaluate existing work, identify critical gaps, and guide future research on AI-enabled solutions tailored to the OWM in India.

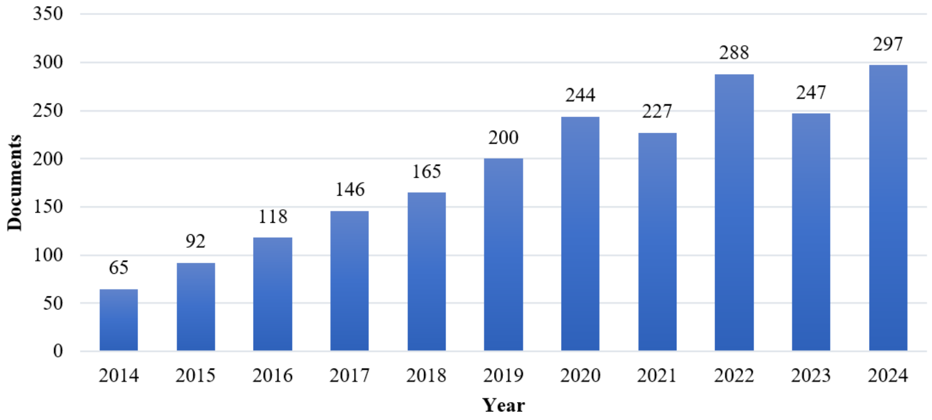


Figure 3. The trend of articles published on the OWM from 2014 to 2024

2. Literature Review

This section outlines key technologies and terminologies commonly associated with the processing of organic waste. Table 1 presents an overview of these methods, followed by a critical analysis of their relative performance, scalability, and applicability to the Indian urban context.

Table 1. Terms and terminologies frequently used in organic waste

Methods	Explanation
Anaerobic Digestion	A proven method for treating organic waste, producing biogas and digestate as byproducts (Prasanna Kumar et al., 2024).
Composting	A biological decomposition method, suitable for forecasting compost quality through indicators like the Germination Index (GI).
Biogas/Incineration	Converts organic substrates into energy and bioproducts; incineration is suitable for high-calorific waste (Rodrigues et al., 2025).
Vermicomposting	Uses earthworms to convert waste into nutrient-rich compost; predictive models like the Medical Loss Ratio (MLR) and Artificial Neural Network (ANN) are used for nutrient recovery (Patwa et al., 2024).
Landfilling	A traditional method; emerging techniques now recover bioenergy using microbial fuel cells (Al-Hazmi et al., 2024).
Waste-to-Energy	Extracts energy from waste; applicable to both organic and inorganic streams (Khan et al., 2022).
Pyrolysis	Thermochemical decomposition method with high energy return potential (AlNouss et al., 2024).
Biodegradable	Refers to waste capable of decomposing naturally; potential to yield biofuels and other value-added products (Ashokkumar et al., 2022).

2.1 Comparative Evaluation of the Processing Methods of Organic Waste

While several processing technologies exist for organic waste, their performance and scalability vary widely, especially in the Indian urban context.

Anaerobic digestion offers high biogas yields and nutrient-rich digestate. It performs well in decentralized and semi-urban areas. However, consistent feedstock quality and skilled operation limits its widespread scalability in slum-dense or informal zones lacking source segregation.

Composting, particularly aerobic composting remains to be a low-cost and widely adopted method. Its performance is modest in terms of energy recovery but favorable for soil improvement. However, its dependency on segregated input waste and open-air processing makes it less viable in densely populated cities due to space and odor issues.

Vermicomposting is suitable for household or community-level operations. It offers high nutrient recovery but is labor-intensive and sensitive to climatic variations, which limit its adaptability for large-scale urban applications.

Waste-to-Energy (WTE) and incineration provide high energy output, especially for mixed or high-calorific value waste. However, these technologies are capital-intensive and have to face public resistance in India due to emissions and previously poor implementation records.

Landfilling is the least preferred environmental method but still dominates urban waste disposal due to infrastructure gaps. Modern enhancements like microbial fuel cells remain largely experimental and untested at scale in Indian cities.

Pyrolysis, while promising high energy recovery, requires dry feedstock and is best suited to industrial applications. Its operational complexity and energy input limit its current use in Indian municipal setups.

The integration of AI into methods like smart sorting, process optimization, or real-time monitoring has been globally adopted, yet is still at a nascent stage in India as the combined methods are mostly confined to pilot projects or trials in the private sector.

2.2 Applicability of the Methods Used in Indian Urban Settings

The urban centers in India are diverse in terms of population density, waste composition, and municipal capacity. Therefore, a one-size-fits-all solution is impractical. Table 2 summarizes the critical evaluation of technology used to deal with organic waste on the basis of scalability and suitability.

Table 2. Comparative analysis of technology used in the OWM in urban India

Methods	Performance	Scalability	Urban Suitability
Anaerobic Digestion	High (biogas + digestate)	Medium (requires controlled input)	Suitable for decentralized plants
Composting	Medium (compost quality)	High (low cost)	Good in peri-urban settings
Vermicomposting	High (nutrient recovery)	Low (labor/climate dependent)	Ideal for residential societies
WTE/Incineration	High (energy output)	Medium (high cost)	Limited by pollution concern
Landfilling	Low (high emissions)	High (still widespread)	Not sustainable in the long term
Pyrolysis	High (energy return)	Low (technical demands)	More suited to industrial zones
AI Applications	Varied (data-driven efficiency)	Low (limited use)	High potential if integrated

2.3 Prior Research

The increasing complexity of the OWM has led to a growing body of review literature focused on evaluating treatment strategies, valorization opportunities, and potential of advanced tools such as artificial intelligence (AI). However, many of these reviews remain largely descriptive, with limited integration of technological, infrastructural, and policy considerations necessary for practical implementation.

As summarized in Table 3, several previous studies such as those by Dhar et al. (2017), Marzbali et al. (2021), and Rakkini et al. (2017) examined processing methods and valorization pathways, often from a technical or environmental perspective. More recent contributions by Ahmad et al. (2021), Chen et al. (2024), and Gupta et al. (2024), respectively highlighted the roles of machine learning, thermochemical modelling, and blockchain in optimizing organic waste systems. However, these studies often treated technological innovations in isolation, without adequately addressing the broader infrastructural challenges or regulatory frameworks required to support their real-world application.

Studies such as Fang et al. (2023), Mishra et al. (2021), William et al. (2024), and Zhang et al. (2022) made significant strides in applying AI to waste management, yet they fell short of providing critical insights into the integration of these technologies with policy measures, readiness of urban infrastructure, or data governance. Additionally, the methods for data acquisition, validation, and real-time deployment remain underexplored across much of the existing literature.

To bridge these gaps, the present review adopted a broader and more integrated approach. In addition to synthesizing six key dimensions commonly found in earlier works, including the processing methods, environmental and health risks, valorization, AI applications, operational challenges, and future trends, this study introduced two dimensions frequently overlooked, i.e., policy and infrastructure alignment, and unresolved research gaps. The additions provided a more actionable framework for translating AI-based insights into deployable systems that are both technologically sound and contextually feasible. By mapping the neglected areas and highlighting inadequacies of prior reviews, this study offered a comprehensive foundation to guide future research and decision-making in the OWM. It aimed not just to summarize existing knowledge, but to chart a forward-looking path that connects innovation with implementation.

Table 3. Comparative evaluation of review papers on the OWM

Features	Manea et al. (2024)	Rakkini et al. (2017)	Marzbali et al. (2021)	Dhar et al. (2017)	Gupta et al. (2024)	Chen et al. (2024)	Ahmad et al. (2021)	This Review (2025)
Processing Methods	√	√		√				√
Environmental & Health Risks	√	√						√
Opportunities for Valorization	√	√	√					√
AI Techniques	√	√	√	√	√	√	√	√
Challenges	√	√	√	√	√	√	√	√
Future Scope	√	√	√	√	√	√	√	√
Policy & Infrastructure					√		√	√
Research Gaps Addressed								√
Overview	Sustainable organic waste treatment	Segregation and collection	Technology for valorization	Digital integration & advancement	Thermochemical technology modeling and optimization based on data	Machine learning algorithm for the prediction of waste generation	Blockchain for extended producer responsibility (EPR) compliance	Integrated AI + policy-based OWM

3. Research Methodology

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021) to ensure transparency, reproducibility, and rigor. The methodology was structured into multiple stages: formulation of research questions, systematic database search, screening, eligibility checks, full-text review, and final inclusion. The flow of article selection is illustrated whereas justifications for all methodological decisions, including search strategy, inclusion/exclusion criteria, and quality assessment, were provided below. This research included neither a synthesis nor meta-analysis; no data pooling or cross-study integration was conducted. Instead, the focus is on identifying common thematic directions and documenting the coverage of existing literature.

3.1 Research Questions

The review was guided by structured research questions focusing on:

- Barriers to effective OWM and strategies to address these difficulties
- Suitability of decentralized systems and AI integration in the Indian context
- Integration of AI with traditional OWM brings forth new and improved solutions
- Smart and efficient methods to handle organic waste, and the way in which AI can help achieve more accurate predictions and decisions in this area

These research questions were used to inform the selection of keywords, screening filters, and thematic synthesis.

3.2 Process of Systematic Review

3.2.1 Selection of database and search strategy

A comprehensive search was conducted across the databases in Web of Science (n = 1520), Scopus (n = 117), and IEEE Xplore (n = 50). These databases were chosen due to their strong coverage of interdisciplinary research in environmental engineering, sustainability, and computer science. The search period was set from year 2014 to 2024 in order to capture the most recent developments, particularly research on AI-driven waste management over the last decade. Limiting the scope to English-language peer-reviewed articles was necessary to ensure consistency in evaluation and interpretation.

3.2.2 Keywords and search string

Search strings were designed using a combination of general and domain-specific terms. The main search terms are shown in Table 4. Databases such as Scopus and Web of Science (WoS) were used to retrieve relevant literature. The queries were designed to capture studies focusing on processing approaches and data-driven methods in waste management. This approach yielded 117 results in Scopus and 1,520 in WoS to form the basis for further screening and analysis.

Table 4. Search on Scopus and WoS with parameters

Dataset	Exact Queries	Results
Scopus	("Waste management" OR "India") AND ("Municipal Solid Waste Management" OR "Organic" OR	117
WoS	"Processing Technique") AND ("AI" OR "machine learning" OR "data-driven")	1520

3.2.3 Inclusion and exclusion criteria

To ensure methodological transparency and maintain the relevance and quality of the included studies, the following inclusion and exclusion criteria were applied during the screening process.

Inclusion Criteria

Articles were selected for inclusion based on the following conditions:

Publication Period: Studies published between years 2014 and 2024 were included to capture a decade of research progress, particularly the evolution of AI applications in OWM.

Language: Only English-language publications were considered to maintain consistency in interpretation and evaluation.

Types of Sources: The review included both peer-reviewed journal articles and conference papers to maintain a high standard of reliability and academic quality. Alongside these, selected grey literature such as government publications and publicly available data from recognized institutions was reviewed when offered meaningful contributions to the topic of OWM.

Accessibility: Only studies with full-text availability were included to allow complete quality assessment and data extraction.

Exclusion Criteria

Articles were excluded if they met any of the following:

Non-peer-reviewed: Preprints without peer review were excluded.

Language Restriction: Articles written in languages other than English were not considered due to limitations in accurate content assessment.

Lack of Focus: Studies that focused broadly on the municipal solid waste without a dedicated discussion of organic waste were excluded.

Insufficient Details: Articles lacking methodological clarity, poorly defined objectives, or irrelevant conclusions were excluded during the quality assessment phase.

Duplicate Publications: Redundant or duplicate records across the databases were identified and removed.

3.2.4 Screening and selection for the study

The initial search yielded 1,687 articles; 564 articles remained after screening and removing 99 duplicates. The articles were screened further based on titles and abstracts, resulting in 254 full texts to be considered for eligibility. Among these, 192 articles were excluded due to a lack of relevancy or access, leaving 62 articles included in the final synthesis. The PRISMA-based literature selection flow can be visualized in Figure 4.

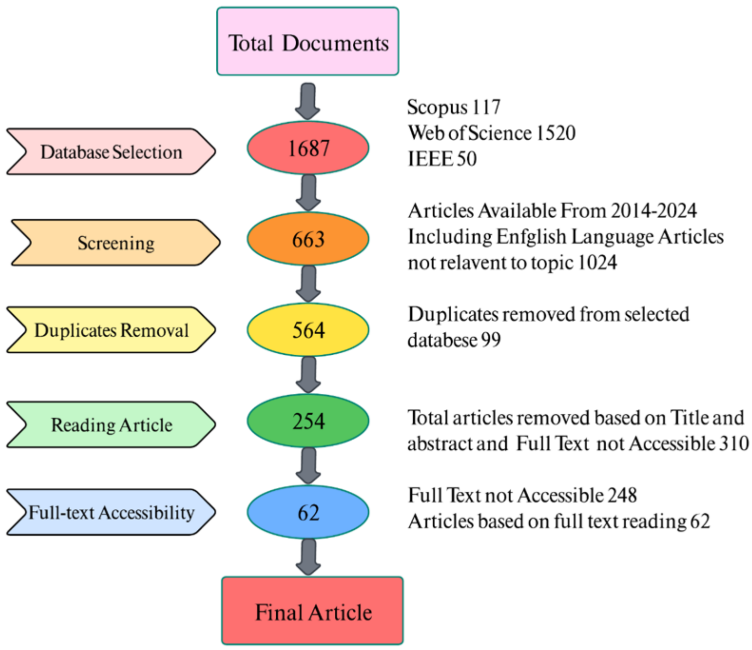


Figure 4. Flowchart of PRISMA-based literature selection

3.2.5 Quality assessment

To ensure the reliability and relevance of the studies included in this review, a structured quality assessment was performed. Table 5 represents the core criteria for quality assessment. Each article was evaluated based on the following five core criteria, adapted from the established systematic review practices (Page et al., 2021).

Table 5. Criteria for quality assessment

Criteria	Descriptions
1. Clarity of Objectives	Clear statement of research aims or questions
2. Methodological Transparency	Detailed description of data collection and analysis procedures
3. Relevance to the Focus of Review	Direct applicability to topics of AI integration, organic waste treatment, or sustainability
4. Quality of Data and Findings	Evidence-backed conclusions and sound research design

3.3 Predictive Waste Management Approach in India

Data-driven technologies (Zhang et al., 2019) and AI (Fang et al., 2023) are used in India to manage, monitor, and forecast the generation and disposal of organic waste efficiently and sustainably. India, having a large population and growing urbanization, faces significant challenges in managing organic waste. Empirical data are used to establish the pattern for better prediction via technology applied with the predictive approach (Intharathirat et al., 2015; Mishra et al., 2021). Many cities use sensors to track levels in real time, waste conditions, and trends of waste generation based on population density, festivals, and seasons. AI and machine learning models (Zhang et al., 2022) examine past statistics on waste production, climate patterns, and demographic trends to forecast upcoming waste quantities. The predictive model could optimize waste collection for better efficiency and reduce transportation costs (William et al., 2024). As regards waste sorting and recycling, an AI-based system will be used to identify materials which are compostable, recycled, or requiring another processing method. By identifying regions with significant levels of organic waste, predictive analytics, beneficial for environmental sustainability, enables the production of biogas or compost (Ganesh et al., 2024). AI is significantly changing the management of organic waste by providing innovative solutions to enhance operational efficiency, minimize contamination, promote sustainable practices, and support a circular economy by transforming organic waste into useful resources.

4. Results and Discussion

The OWM in India confronts significant challenges and substantial opportunities, while the country deals with issues like waste segregation, infrastructure inadequacy, and behavioral issues. Many technological innovations are required to manage system performance. Table 6 present successful case studies about machine learning algorithms implemented in specific cities, and this section discusses the research questions arising from previous research.

Table 6. Case studies that applied machine learning in the OWM

Case Studies	Application	Performance Metrics	Uses
Ludhiana	Understanding of studies about agricultural sustainability helps affect farmer behaviour.	DNN-MSE 0.036 and Validation 0.137	Singh et al. (2023)
Bengaluru	Employing a time series forecasting model to estimate the volume of waste produced in the upcoming years.	ARIMA RMSE (753.5742), MAD (577.4601), and MAPE (11.6484) R2 (0.9788)	G. & S. K. (2022)
Delhi	Anaerobic Sludge Specific Methanogenic Activity (SMA) Prediction	SVR model R2 0.97	Priyadarshi et al. (2025)
Nashik	A model was developed to predict the compost generation.	NNM MSE less than 1% R2 0.8788	Mohod et al. (2023)

4.1 Barriers to Effective OWM and Strategies to Tackle the Problems

Efficient OWM in urban areas, particularly in countries like India, is challenged by a complex interplay of infrastructural limitations, behavioral norms, and policy gaps. Nevertheless, a lack of public awareness about waste segregation remains a fundamental issue. In many Indian cities, household waste is routinely mixed, despite municipal directives encouraging source separation. This results in contamination of organic waste, rendering composting or anaerobic digestion inefficient or even unfeasible (Kumar et al., 2017). In contrast, countries like Sweden and Japan demonstrated success in nationwide source-segregation education campaigns, thus indicating that public awareness and behavioral change form the foundation of any effective waste management strategy.

Segregation at source is therefore not just a technical necessity but a behavioral challenge, demanding investment in community education, municipal outreach, and school curricula. In India, studies like Kharola et al. (2022) highlighted the use of fuzzy-DEMATEL techniques to model public behavior as a decision-making network, an AI-driven approach that could help policymakers identify the most influential behavioral barriers and design targeted interventions. Infrastructure constraints further exacerbate the problem of segregation. Many Indian municipalities lack dedicated composting or biogas units, and even where facilities exist, they are often underutilized due to poor maintenance or logistical bottlenecks (Meena et al., 2023). Unchecked methane emissions, coupled with the rapid urban expansion of Indian cities, pose the threat of long-term sustainability crises. Moreover, landfilling occupies valuable land in urban zones, competing with critical needs like housing, green spaces, and water recharge zones. Other strategies to facilitate the OWM involve increasing public awareness through educational efforts, encouraging recycling through monetary incentives, and enhancing infrastructure like waste collection and recycling facilities (Arena et al., 2021).

Figure 5 shows that more than half of the waste, about 53%, we generated is organic and comes from things like garden trimmings, leftover food, and other biodegradable materials. This large share of organic waste is a real challenge because it decomposes quickly, causes unpleasant odors, and releases harmful gases like methane if not managed in time. In comparison, construction debris and silt constitute 29% of the waste, while smaller portions come from clothes, plastic, and paper. The sheer volume of organic waste implies our waste systems need smarter solutions, such as composting, biogas production, and AI-assisted sorting, to turn this problem into a resource.

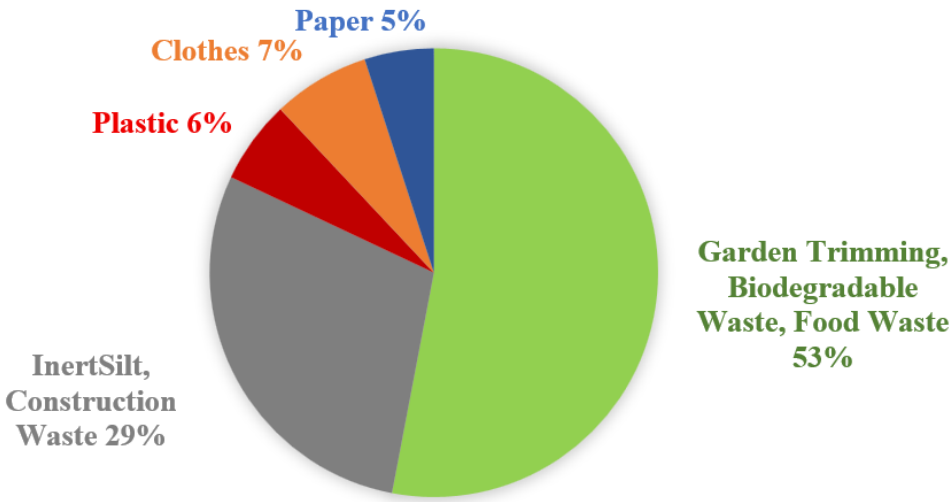


Figure 5. The composition of waste highlighting organic waste as the major challenge

To address these multi-layered challenges, India is recommended to embrace a systems-thinking approach that includes:

- Incorporating life cycle assessment (LCA) to compare waste treatment technologies (Miao & Zeller, 2025);
- Designing incentive-based schemes for households and housing societies. e.g., compost credit systems;
- Empowering local bodies with both technical tools and financial autonomy to manage waste at the ward level;
- Developing a central data repository of waste composition; and
- Processing outcomes to improve the accuracy of AI model.

4.2 Decentralized Systems and Integration of AI in the Indian Context

Decentralized OWM systems offer a pragmatic solution tailored to the socio-economic realities of India. With an expanding population and increasing urban sprawl, the volume of municipal solid waste is expected to rise steeply in the coming decades (Dutta & Jinsart, 2020). Centralized systems, which transport all waste to a single yet often distant processing facility, are logistically inefficient and environmentally taxing. By contrast, decentralized systems establish multiple small-scale composting or biogas units within city zones, managed either by municipal bodies or empowered community groups. This model reduces the transportation burden and ensures that organic waste is processed close to its generation point. Studies from Lavergne et al. (2020) and Rao & Parsai (2023) demonstrated that decentralized systems not only reduced operational costs but also enhanced community engagement, particularly when supplemented by user-pay systems or civic incentives. The integration of AI, while promising, should be critically contextualized for India as high-performing AI models often require large and high-quality datasets, which many current Indian municipalities lack due to poor digitization of waste records and informal handling practices. Furthermore, the cost and technical expertise for deploying predictive models, robotics, and smart sensors might not be viable for smaller towns unless centrally subsidized. However, simpler AI methods like fuzzy logic, decision trees, and classification models trained on local datasets could contine to offer meaningful insights for route optimization, waste forecasting, and behavior analysis (Kharola et al., 2022).

The novelty of this review lies in its focus on synergizing AI with decentralized OWM system, a hybrid model not extensively explored in previous literature. While existing reviews focused on the application of AI in centralized systems or industrial contexts, this study advocated localized integration of AI, such as ward-level waste prediction, anomaly detection in compost quality, or citizen reporting via mobile platforms.

4.3 Novelty of Combining AI with Traditional OWM

While existing literature often treated the applications of AI in waste management separately from grassroots or traditional practices, this review bridged that gap by examining the assistance of AI to enhance and localize the conventional OWM systems, particularly in the developing countries like India. The novelty of this approach lies in integrating AI not as a standalone innovation, but as a complementary tool to strengthen the decentralized and community-based models that are already culturally and logistically embedded in many Indian urban and semi-urban contexts.

This review contributed beyond previous works by:

Contextualizing AI tools within the decentralized systems—Most reviews focused on centralized and industrial-scale waste processing units. In contrast, this study explored the methods of lightweight AI, such as fuzzy logic and decision trees, deployed at ward or community levels to support composting, waste sorting, and behavioral analysis.

Focusing on feasibility and accessibility—Unlike reviews that highlighted cutting-edge but resource-intensive AI techniques, this review highlighted cost-effective and scalable solutions suitable for the fragmented infrastructure and varying digital literacy in India.

Addressing socio-behavioral and infrastructural barriers—This paper framed AI not just as a technological solution but as a decision-support system that could model complex human behaviors, improve awareness campaigns, and optimize small-scale logistics.

Proposing a hybrid model for future waste systems—By combining traditional OWM methods, such as composting, biogas, and community participation with predictive AI tools, the review proposed a novel hybrid framework that balances sustainability, affordability, and technological advancement so as to fill a notable gap in the current literature.

Considering policy relevance and practical deployment—The study outlined the alignment of AI-supported OWM with the Smart Cities Mission and decentralized governance structures in India, thus offering a roadmap for real-world implementation in policy and municipal planning.

This integration of AI with traditional and people-centric systems represents a unique contribution and offers a grounded and practical path forward, which was rarely discussed in the same depth by earlier reviews.

4.4 Efficient Approaches to Managing Organic Waste

As per the literature survey, the OWM provided several effective methods like composting, anaerobic digestion, vermiculture, and landfill to process the organic waste. The processing method should be selected based on the type of organic waste. For instance, Black Soldier Fly (BSF) larvae can transform the food waste from hospitals into feed for animals and fertilizer (Siddiqui et al., 2022). Besides, decentralized systems are the predominant method advocated by many cities (Morais & Ishida, 2025). Table 7 shows the comparative analysis of the most commonly used processing methods (Dutta & Jinsart, 2020; Ibarra-Esparza et al., 2023; Kumar & Samadder, 2020; Peng et al., 2023; Prasanna Kumar et al., 2024; Soni et al., 2023).

The data were collected from an open-access platform, covering only the highly populated cities such as Delhi, Mumbai, Pune, Surat, Ahmadabad, Bengaluru, Chennai, Kolkata, Hyderabad, and Jaipur. Figure 6 presents a comparative boxplot illustrating the cost distribution in ₹/ton for four major waste disposal methods, i.e., composting, incineration, recycling, and landfill. Recycling shows the least cost variability with a narrow interquartile range and minimal outliers, hence suggesting a financially stable and predictable method. Composting and landfills both show a wide cost range to indicate variability, due to factors like the scale and location of infrastructure as well as operational efficiency. The median cost of composting is lower than landfill, implying its potentially more affordable application in decentralized setups. Incineration, often effective in reducing the volume of waste and enabling energy recovery, exhibits a high median cost and large variation, likely due to complex setup and requirements of emission control. These cost profiles could help decision-makers identify cost-effective and scalable waste management strategies, depending on local economic and environmental priorities.

Table 7. Comparisons of methods used in the OWM

Parameters	Anaerobic Digestion	Composting	Vermiculture	Incineration	Landfill (with Gas Recovery)
Waste Reduction	Reduced by 90%	Reduced up to 30–50%	Reduced by 50–70%	Reduced by 90%	Limited reduction
Energy Recovery	Biogas (renewable energy)	No energy recovery	No energy recovery	Generate energy (heat/electricity)	Methane for energy recovery
Environmental Impact	Low to moderate (with proper management)	Low, but odor and pests	Low (natural process)	High (pollutants, dioxins)	High (methane, leachate issues)
Operational Costs	Moderate to high	Low to moderate	Low to moderate	High (fuel, operation, emissions control)	Low (long-term)
Capacity	High (suitable for large-scale operations)	Medium (best for small to medium scale)	Low (small-scale)	High (large-scale)	Low (land use constraints)
Valuable Product	Biogas, digestate (fertilizer)	Compost (fertilizer)	Vermicompost (fertilizer)	Ash (often Landfill)	Methane/ Composting material
Public Acceptance	Moderate	High	High	Low (emission concerns)	Low (because of pollution concerns)
Key Performance Indicators (KPIs)	Biogas yield (m^3/ton); Volatile solids reduction; Retention time	Compost quality (C: N ratio); Decomposition rate; Odor levels	Compost maturity Worm biomass growth; Moisture & pH control	Calorific value of waste; Energy output (kWh/ton); Emissions (dioxins, particulate matter)	Methane recovery (m^3/ton); Leachate generation rate Landfill gas efficiency

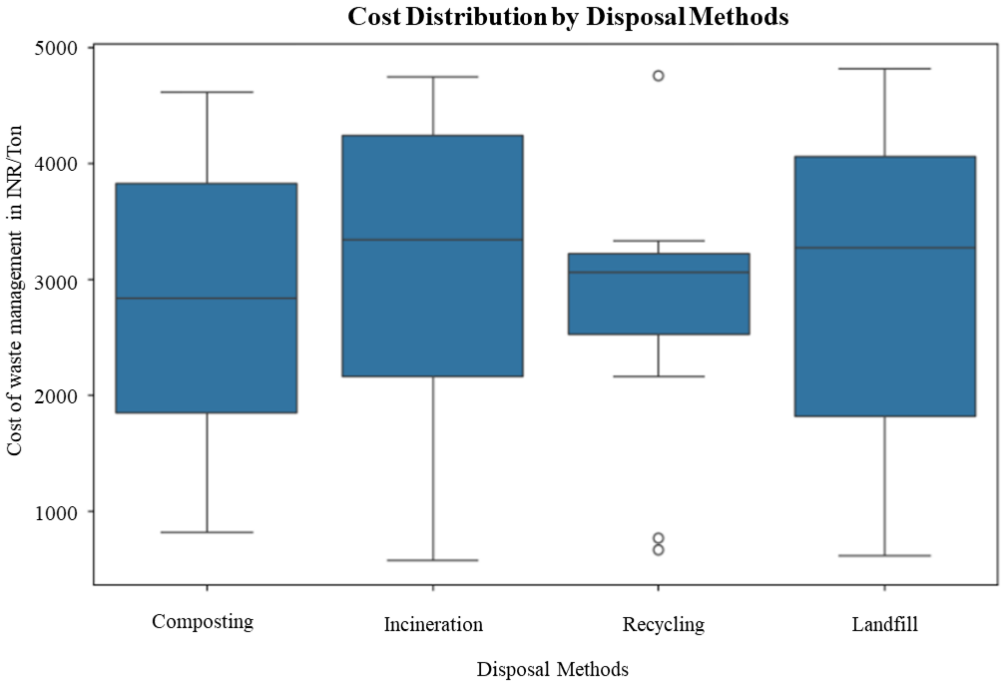


Figure 6. The cost distribution of waste management by disposal method (in ₹/Ton)

Several government programs in India and around the world aim to tackle organic waste through better policies and infrastructure:

Swachh Bharat Mission (SBM): The SBM of India was launched in 2014, focused on improving sanitation and waste management across urban and rural areas. It encourages source segregation, composting, and setting up of waste-to-energy plants.

The Organization for Economic Cooperation and Development (OECD) Extended Producer Responsibility (EPR) in 2024: Many governments are introducing the EPR policies so as to hold manufacturers and producers responsible for the waste their products generated, and encourage them to design packaging that could be reused or composted. Government entities promote decentralised waste management by formulating policies, establishing regulations, and providing financial support. Local governments manage the planning, infrastructure development, and involvement of the community. They facilitate appropriate waste separation, recycling, and composting within the community. Training, awareness initiatives, and oversight are crucial responsibilities in maintaining sustainability.

Table 7 exemplifies that anaerobic digestion and incineration are the most effective methods, cutting waste by around 90% and producing usable energy at the same time. Composting and vermiculture, which do not generate energy but create nutrient-rich fertilizers, are well accepted by the public with a lower environmental impact. Composting works well for small to medium operations, while anaerobic digestion and incineration fit large-scale needs. Landfilling with gas recovery is the least favored option, used mainly where other solutions are deemed impractical.

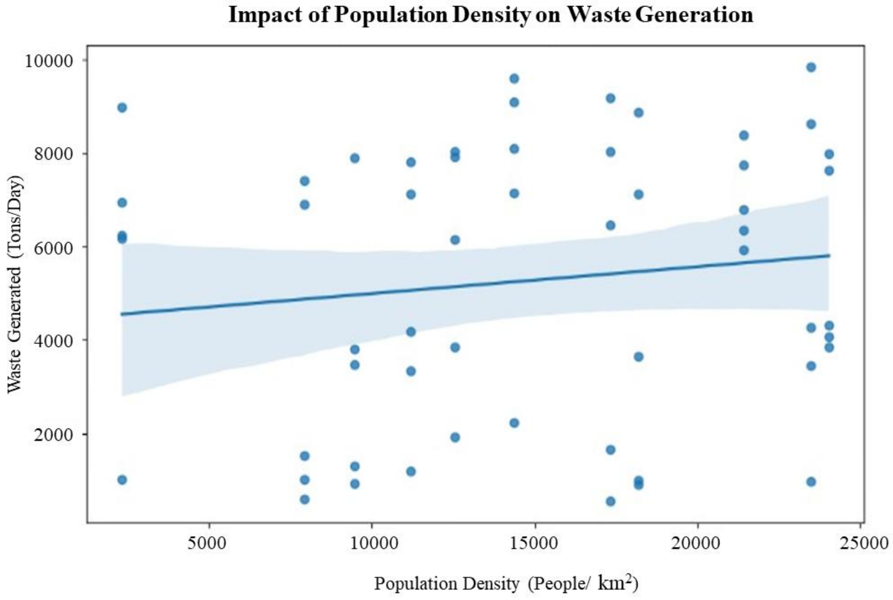
4.5 Integration of AI into OWM, Forecasting, and Decision-Making

Difficulties found in the OWM are addressed by AI (Nawaz & Kasote, 2025), which play a crucial role in automotive sorting, transportation routing, and energy production to develop a more effective and environmentally friendly method for managing waste (Gupta et al., 2019). Based on the complication of model architectures, methods powered by AI can be divided into two primary categories, which are Machine Learning and Deep Learning. Machine learning (ML) is an organized method of data processing, in which information from the data is absorbed and then judgments are made from the gained knowledge. Among the broader category of machine learning methods, techniques like K-Means and Neural Networks (NN) represent the field of unsupervised machine learning and deep learning is considered to be a specialized subset. Based on the particular goals to be met, two separate forms of supervised machine learning are distinguished, i.e., regression and classification. Many different kinds of garbage are categorized using classification algorithms (Gupta et al., 2019; Gupta et al., 2024). Regression algorithms, on the other hand, facilitate the anticipation of waste using previous data. There are two types of classification algorithms: K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). Occasionally, hybrids of these methodologies comprising multiple data-driven algorithms result in enhanced efficacy. The OWM research community has explored a variety of ML models (Gupta et al., 2024). To address persistent challenges in the OWM, powerful AI-driven tools for waste management offer more intelligent, efficient, and sustainable solutions through important technology like robots, Internet of Things (IoT), computer vision, machine learning, data-driven and hybrid methodologies. While traditional methods often struggle with inefficiencies in sorting, transportation, and processing, AI provides targeted improvements ranging from automated waste classification to optimized routing for collection vehicles. For instance, ML and deep learning models could analyze large datasets from sensors, images, and historical waste generation patterns to produce accurate predictions and operational decisions.

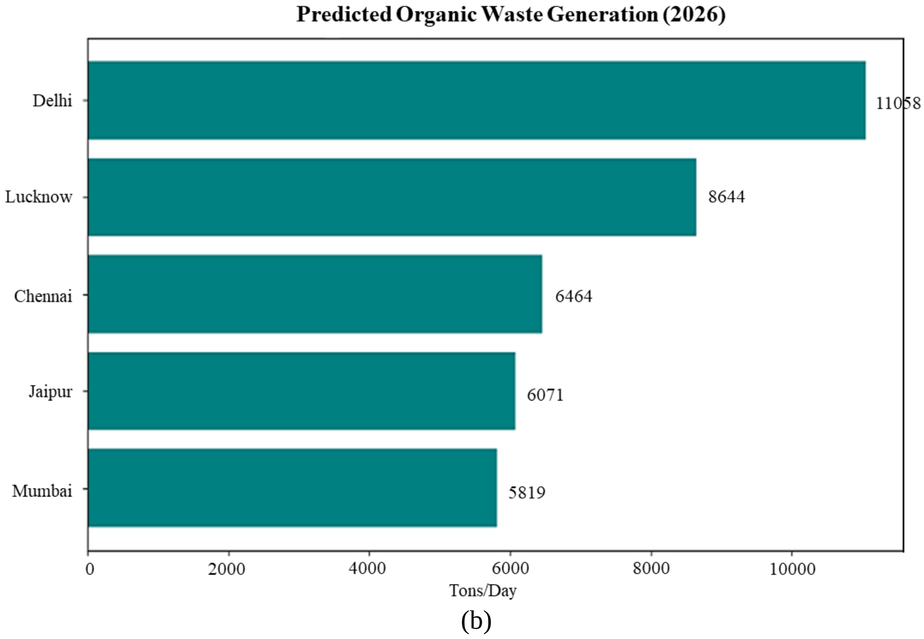
In the Indian context, these technologies hold particular promise. High population densities, diverse waste compositions, and infrastructure gaps create a complex management environment. Predictive analytics help municipalities anticipate surges in waste generation, while computer vision-based systems reduce contamination in composting streams. Robotic process automation could address labor shortages and improve safety for waste workers. However, adoption of AI is hindered by barriers such as high implementation costs, limited availability of high-quality training data, and a lack of AI literacy in municipal agencies.

Every method helps improve the overall effectiveness, reduce costs, and enhance sustainability (Alsabt et al., 2024) according to the studies on the highly populated cities in India. Figure 7a shows a scatter plot representing the relationship between population density and waste generation. While the trend line indicated a moderately positive correlation, the data exhibited substantial variance, thus implying that population density could influence waste generation, regardless of the significant role played by other local factors such as income levels, urban infrastructure, and lifestyle. The shaded confidence interval reflected the uncertainty in prediction, reinforcing the requisite for city-specific waste strategies rather than a one-size-fits-all approach.

Figure 7b shows the predicted organic waste generation (in tons/day) by year 2026 for major Indian cities. Delhi was projected to generate the highest organic waste of 11,099 tons/day, likely due to its dense population and high urban activity. Lucknow and Chennai also showed significant increases, reflecting the trend in urban expansion. Jaipur and Mumbai, being traditionally large waste producers, were slightly lower in rank possibly due to effective interventions or projections of slower population growth. These findings highlighted the need for forward-looking waste management infrastructure in rapidly growing urban centers and suggested the value of predictive modelling in guiding the efforts for sustainable waste planning. Globally speaking, AI is being integrated into circular economy frameworks, linking waste reduction with resource recovery and renewable energy production. India adapts these lessons by developing open-access waste datasets, incentivizing AI start-ups in the environmental sector, and integrating AI tools into policy-driven initiatives like the Swachh Bharat Mission.



(a)



(b)

Figure 7. Waste generation and prediction analysis. (a) The relationship between population density and waste generation, and (b) Top 5 cities by predicted organic waste generation

Table 8 shows different modern technologies being applied to waste management and explains their application, usage and benefits. It covers tools like machine learning, neural networks, robotics, computer vision, and other smart systems that help sorting waste, improving processes, monitoring operations, and automating routine tasks. Each method is linked to practical outcomes such as faster and more accurate waste classification, reduced manual work, better resource recovery, and overall improved efficiency. The novelty of this review lay in the combination of AI-centered technical analysis with considerations of policy and infrastructure, thus bridging a gap left by prior reviews that primarily focused on either technology or policy in isolation. Future research should test AI-enabled systems in rural and peri-urban areas, explore hybrid models that combine machine intelligence with community-led initiatives, and evaluate the impacts of sustainability in the long term.

Table 8. AI used in OWM

AI Technology	Definition	Application in the OWM	Advantages
Machine Learning (ML)	ML is a subset of AI that uses statistical techniques. It allows systems to gain knowledge from data and enhance their functionality.	- Predictive analytics for waste generation - Optimization - Sorting waste via sensor data	Improved efficiency in sorting and processing (Dehghan et al., 2025; Guo et al., 2021; Gupta et al., 2024)
Neural Networks	A type of ML model that simulates how biological neural networks in the human brain process information.	- Classification of organic waste material - Image recognition for waste sorting	High accuracy in waste classification (Vadivel et al., 2024)
Robotic Process Automation (RPA)	Automation of repetitive tasks with robots, frequently augmented by AI for decision-making capabilities.	- Autonomous robots for sorting and handling organic waste - Waste collection optimization	Reduced human error and labour costs (Leffler et al., 2023)
Computer Vision	AI that enables machines to understand and make choices based on visual information.	- Visual inspection for contamination detection - Sorting organic waste using cameras and sensors	Reduces contamination in composting and recycling (Mookkaiah et al., 2022)
Natural Language Processing (NLP)	A subfield of AI that gives robots the ability to comprehend and interpret human languages.	-Analyzing and categorizing textual data on OWM policies and reports	Helps in understanding trends and public feedback (Hernández-Romero et al., 2024)
Internet of Things (IoT with AI)	AI-powered IoT devices to collect and analyze real-time data for optimization.	- Sensors for compost temperature and moisture monitoring - Smart waste bins that detect organic waste levels	Improves monitoring and control of composting processes (Gavilanes et al., 2024)
Reinforcements Learning (RL)	An ML-type agent learns to make decisions by receiving rewards or penalties.	- Improving energy use in composting facilities - Optimizing waste management routes and schedules	High accuracy in waste classification (Vadivel et al., 2024)
Genetic Algorithms	Optimization algorithm	- Optimizing waste-to-energy conversion processes - Optimizing composting methods and parameters	Identifies the most efficient solutions and helps to reduce waste and maximize resource recovery (Buenrostro-Delgado et al., 2015)
Fuzzy Logic	AI deals with reasoning, i.e., fixed and exact	- Monitoring and controlling waste processing conditions - Decision-making in uncertain waste management scenarios	Improved control in complex systems like composting (Gavilanes et al., 2024)

5. Outcomes of the Survey

The survey shown in Table 9 depicts the intelligence and efficiency enabled by modern technology in the OWM, as maintenance tools for tracking methane production and compost maturity help keep plants running smoothly and equipment extended their lifecycles. IoT sensors and publicly available datasets provide the key information required for better decision-making. By combining data from thermal cameras, gas sensors, moisture probes, and drones, operators could monitor processes more accurately. Reliable connections such as 4G/5G and Long Range Wide Area Network (LoRaWAN) allow the equipment to work in both cities and remote areas. Advanced AI models, ranging from Convolutional Neural Networks and Long Short-Term Memory networks (CNN-LSTM) for waste segregation to reinforcement learning for dynamic pickup routes, facilitate the efficiency and effectiveness of the entire process. The survey results showed a steady move in OWM from manual and labor-intensive methods toward systems that are more connected, automated, and efficient. While many respondents still rely on traditional segregation and monitoring, there is a noticeable rise in the use of technologies such as moisture and gas sensors, along with image-based sorting units in collection points and processing facilities. These tools are increasingly supported by both publicly and privately maintained datasets, helping to improve the accuracy of monitoring, support timely decision-making, and reduce operational delays.

Figure 8 presents a framework developed from the findings of the survey. It shows the incorporation of different sources of information sensor readings, public records, and image data, and their processing to improve waste sorting, recycling at the source, and planning for waste treatment. By combining multiple streams of information, the approach addressed common challenges such as inconsistent data, limited manpower, and unpredictable waste composition. Overall, the responses highlighted a clear trend: the sector is moving toward integrated and responsive waste management systems that wisely utilize available technology to improve reliability, efficiency, and long-term sustainability.

Table 9. Outcomes of the survey

Topics of the Survey	Outcomes (Adapted for the OWM)
Maintenance approach	Combining cost-effective resource allocation with predictive maintenance such as tracking methane production and compost maturity to maximize the efficiency of biogas plants and composting facilities. The life of the assets can be increased by using predictive models for equipment failure like digester leaks and mixer blades.
Data collection	Primary: IoT sensors for moisture and gas in processing plants. Secondary: Public datasets (i.e., CPCB).
Sensor fusion	Thermal cameras, moisture probes, and gas sensors for CH_4 and CO_2 are used to enhance anaerobic digestion and composting processes. Drones to track organic waste in landfills.
Data procurement	Compatibility (e.g., 4G/5G for urban smart bins, LoRaWAN for rural locations). Scalability of decentralized units with modular topologies.
AI techniques	CNN-LSTM for images of waste segregation with time-series of biogas production; data fusion is an example of a hybrid model. Reinforcement learning for routing waste pickup in a dynamic manner.

Figure 8. The ways to improve waste sorting, source-level recycling, and treatment planning

6. Conclusions

This comprehensive review elucidated and highlighted the substantial advancement and obstacles found in the field of waste management. Much research about the OWM focused on innovative approaches to enhance productivity, sustainability, and environmental results. As cities become smarter, the implementation of real-time data monitoring, coupled with AI-facilitated optimization, has the potential to transform the methodologies employed in the processing of organic waste. Prominent improvements transforming the methods of waste management featured the adoption of innovative technologies, particularly those driven by the IoT and AI to elevate efficiency, accountability, and transparency.

Although challenges of public awareness and infrastructure development remained to be overcome, there is a bright future ahead for converting organic waste into a useful resource. Future studies should prioritize the assessment of the scalability and adaptability of innovative technologies in rural and peri-urban contexts, where infrastructure and resource availability differ significantly. Addressing these gaps would be critical to developing inclusive and effective solutions to OWM for the benefits of diverse communities.

Author Contributions

Conceptualization, Methodology, Writing-Original draft preparation, and Software, P.B.; Visualization, Investigation, Writing, and Editing, M.D.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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