*Journal of Harbin Engineering University*
*ISSN: 1006-7043*

Vol 47 No. 11
Nov 2026

# AI-Driven Circular Economy in Municipal Solid Waste Management: Evidence from Case Studies in Odisha, India

**Subhashree Pradhan, Prof. D.K. Mahalik,**

Research Scholar, Department of Business Administration, Sambalpur University,

Professor, Department of Business Administration, Sambalpur University,

**Abstract**- Rapid Urbanisation in different developing countries has leads to face more challenges in Municipal Solid Waste (MSW) Management and its impact in the environment. Circular economy frameworks which focus on recovering, reusing and regenerating resources are becoming more sustainable options rather than the traditional waste disposal methods. However, there are certain limitations due to data unavailability and limited technological integration. This paper examines the four documented waste management initiatives in Odisha, India through a multiple case study approach for assessing the current state of circular economy practices and how Artificial Intelligence (AI) could be used. The cases studied include Micro Composting Centre–Material Recovery Facility (MCC–MRF) model, the door-to-door collection system, the plastic waste management initiative, and the waste-to-energy (biogas) initiative. A comparison across all these cases shows that there is a robust foundation in policies and infrastructure base but there is a significant gap in data-driven decision making. Based on these findings, the study suggests an AI based circular waste management system that has four interoperating layers: data input, data processing, decision-making, and implementation. The frameworks offer a blueprint for operationally sound but analytically weak waste systems to intelligent, adaptive, and resource-efficient infrastructures. The findings provide implications for policy-makers, urban planners, and technology developers in Odisha and analogous emerging economies.

**Keywords:** municipal solid waste; circular economy; artificial intelligence; machine learning; waste management; Odisha; smart city; sustainability

## 1.Introduction

The Municipal Solid Waste (MSW) generation has become one of the pressing environmental challenges of the 21st century. In the year 2022 the world produced about 2.24 billions of waste every year and if the situation remains same then it is projected to reach 3.88 billions tons of waste by 2050(Kaza et al., 2018; World Bank, 2022).In India the challenge is intensified due to rapid urbanisation, an estimated 62 million tonnes of MSW is generated annually but only a small portion of it is treated properly or recycled through scientific process (MoEFCC, 2016; CPCB, 2021). Odisha, one of the fastest growing states of India is facing similar challenges producing a huge amount of Municipal waste putting pressure in the current waste management system for collecting, processing and recycling the waste.

Conventional linear methods of managing waste, like, collecting, transporting and disposing it away are becoming untenable for both ecological and economical standpoints (Ellen MacArthur Foundation, 2013; Kirchherr et al., 2017). The circular economy (CE) paradigm, which prioritise resource recovery, material-reuse, and closed-loop production systems act as a better way to handle waste (Geissdoerfer et al., 2017; Ghisellini et al., 2016).The ideas of circular economy match well with the sustainable development goals (SDG 11 and SDG 12) and India's Swachh Bharat mission which mandates the waste processing to 100 percent in urban local bodies (MoHUA, 2021).

Despite the CE Model shows a great performance in theoretical perspective but it is facing quite difficulties in practical implementation in low-and middle-income countries. It is hindered by various causes such as operational fragmentation, poor monitoring, poor data availability and not using digital technologies much (Wilson et al., 2015; Kalmykova et al., 2018). Artificial Intelligence (AI)

and Machine Learning (ML) have shown a great potential in areas like intelligent waste sorting, forecasting the waste generation, route optimization, and lifecycle tracking (Hannan et al., 2020; Gundupalli et al., 2017; Triantaphyllou & Mann, 2021). However, using AI in managing Municipal solid waste (MSW) in India, especially at the state and regional level is still in it's initial stage.

Despite the idea of the circular economy (CE) model being appealing, it's hard to put into practice in low- and middle-income countries (LMICs) because of things like fragmented operations, not enough monitoring, poor data, and not using digital tools much (Wilson et al., 2015; Kalmykova et al., 2018). Artificial intelligence (AI) and machine learning (ML) have shown great potential in areas like sorting waste more efficiently, planning better waste collection routes, predicting how much waste will be generated, and tracking the lifecycle of waste (Hannan et al., 2020; Gundupalli et al., 2017; Triantaphyllou & Mann, 2021). However, In India, using AI in managing Municipal solid waste (MSW) especially at the state level is still in its early stages.

This study addresses the gap by examining four waste management caste studies in Odisha, India. It seeks to: (i) documenting the existing CE practices (ii)Assessing the technology and data utilisation; and (iii)for suggesting a new AI-based circular waste management framework based on real-world evidence. This paper will contribute to the growing literature on smart waste management in developing country contexts and offers actionable insights for policymakers and urban planners.

## 2. Literature Review

### 2.1 Circular economy in Waste Management

The idea of the circular economy (CE) paradigm comes from foundational concepts such as industrial ecology and the cradle -to-cradle design (McDonough & Braungart, 2002), has witnessed increased scholarly and policy attention followed by the work done by Ellen MacArthur Foundation (2013). Basically, CE is conceptualized as an economic system where waste minimization is done by reducing, reusing, recycling, and recovering materials instead of disposing them simply at the end of their life (Kirchherr et al., 2017). In Municipal Solid waste management context, this paradigm shift translates into prioritization of materials and energy recovery by balancing the landfill disposal (Ghisellini et al., Korhonen et al., 2018). However, the CE implementation in developing regions presents a complex landscape. There are several studies from south and south Asia that highlights both opportunities and constraints in circular economy adoption. In Indian cities, informal recycling sectors plays a major role in enhancing the circularity (Chattopadhyay et al., 2009), many challenges such as poor segregation exists (Rajput et al., 2009). Recent research studies shows that a successful CE implementation requires integrated efforts which encompasses the infrastructure development, institutional alignment, public participation, and digital innovation (Rathi, 2021; Manoharan et al., 2021).

### 2.2 AI and Data-Driven Technologies in Waste Management

The integration of the AI and ML into the waste management systems has expanded across multiple operational areas. Hannan et al., (2020) presented a comprehensive review of smart waste management practices, highlighting the use of Internet of Things (IoT) sensors for real-time bin monitoring, computer vision techniques for waste classification, and deep learning models for contamination detection. Likewise, Gundupalli et al. (2017) demonstrated the high accuracy levels in controlled environments through machine vision systems, but their scalability in real-world conditions remains ongoing research subject. In addition, optimisation techniques such as genetic algorithms combined with ML-based traffic prediction have significantly improved the efficiency level in collection efficiency, reducing operational costs by approximately around 15 to 30 percentage in medium-sized urban localities (Vu et al., 2019; Chalkias & Lasaridi, 2009). Another emerging area having critical application is Predictive Analytics. Kannangara et al. (2018) has used regression-based ML models to forecast municipal solid waste (MSW) generation in different cities of Canada achieving high predictive accuracy ($R^2 > 0.85$). Likewise, Xu et al.(2018) utilized artificial neural networks to estimate organic waste availability for biogas production.

Despite many advancements in the technologies there is still a long way for the successful adoption of such innovations in low- and middle- income countries (LMICs) which depends on alignment with local, institutional, financial, and governance capacities which is highlighted in studies by Guerrero et al. (2013) and Wilson et al. (2015).

**2.3 Waste Management in India and Odisha**

The Solid Waste Management Rules, 2016 require all cities in India to follow different practices such as waste segregation, decentralized processing, and land fill management through scientific disposal methods. Many cities like Pune, Indore and Surat have performed very well, many smaller cities still face challenges in implementation (CPCB, 2021; NITI Aayog, 2022).

In Odisha, various steps have been taken by government to improve waste management through programs like the Odisha Solid Waste Management Project and the Smart City Mission. These efforts include recycling facilities, setting up composting centers, and door-to door waste collection systems (Government of Odisha, 2020; ODA, 2021).

Despite, ongoing improvements of the advanced technologies such as artificial intelligence (AI) and machine learning (ML) adoption remain limited within waste management systems. There is a noticeable shortage seen in the empirical studies that assess circular economy (CE) performance or examine the level of technological readiness in this domain (Panda et al., 2019; Mohanty, 2022). Furthermore, the existing literature study is largely focused on descriptive and policy-oriented analyses, with a little emphasis on systematic evaluation. To address this research gap, the present study employs a multi-case analytical framework to evaluate both CE outcomes and the potential for AI integration.

3. Methodology

3.1 Research Design and Data Collection

This research uses an exploratory multiple-case study approach to examine the complex and content-specific nature of waste management systems. It is quite appropriate for investigating real-world phenomena and identifying common patterns across various cases (Yin, 2018). The analysis focuses on individual waste management initiatives as the unit of study. Analytical techniques include pattern matching and building explanation, as recommended by Yin (2018) and Eisenhardt (1989).To enhance the reliability of the results, data were gathered through three main sources: (i) official documents like government reports and municipal records; (ii) secondary literature including peer- reviewed journal articles and institutional reports; and (iii) structured comparison of selected case studies on the cross-case synthesis method outlined by Miles et al. (2014). This triangulation of data sources strengthens both the reliability and validity of the study outcomes.

**3.2 Case Selection**

A purposive sampling strategy was used to ensure the selection of suitable cases for analysis. Selection criteria included engagement with municipal solid waste management, adoption of circular economy practices (e.g., recycling or energy recovery), degree of institutional support, digital or technological integration opportunities, and diversity in operational characteristics. Based on these parameters mentioned above, four cases from Odisha were selected: the MCC-MRF decentralised system, the door-to-door waste collection model, plastic waste management initiatives, and biogas-based waste-to-energy systems. Together, all these cases represent different stages of the waste management value chain and provide a basis for cross-case comparative analysis.

**3.3 Analytical Framework**

The analytical process was conducted in two stages. The first stage involved within-case analysis which is conducted to examine the internal dynamics of each initiative. This is followed by cross-case comparison to identify patterns, differences, and relationships across different cases. This analysis focuses on the key dimensions such as operational efficiency, technological adoption, CE outcomes, and AI readiness. The findings are synthesised for developing a conceptual framework that captures the interplay between the circular economy practices and digital transformation.

**4. Case Studies: Waste Management Initiatives in Odisha**

**4.1 Case 1: Decentralised Waste Management (MCC–MRF Model)**

4.1.1 Description and context

The Government of Odisha has developed a network of Micro Composting Centres (MCCs) and Material Recovery Facilities (MRFs), commonly referred to as "Waste to Wealth Centres" as part of it's decentralised waste management strategy (Government of Odisha, 2020; ODA, 2021). The implementation of these facilities is done at ward level in cities such as Bhubaneswar, Cuttack, and Berhampur, thereby reducing transportation requirements which also follows the guidelines of the solid waste management rules, 2016, which recommend treating waste near its source (MoEFCC, 2016).

4.1.2 Operational Mechanism

The model is structured around a bifurcated waste stream approach. The System works by separating waste into two types. Organic waste is sent to MCCs for composting, while dry waste is manually sorted at MRFs to extract recyclable materials. Household-level segregation is a critical prerequisite, supported by behavioural interventions and infrastructure provision. The resulting compost is reintegrated into urban and peri-urban ecosystems, reinforcing circular resource flows (ODA, 2021).

4.1.3 Circular Economy Outcomes and Limitations

While the MCC-MRF system demonstrates clear alignment helps to reduce landfill waste and promotes recycling, which supports circular economy goals with CE principles by enabling the material recovery and landfill diversion. However, most of the monitoring is done manually, and there is little use of digital technology. Also, planning is based on the past data rather than predictions, which can lead to many issues like overloading or underuse of facilities (Panda et al., 2019; Mohanty, 2022).

4.1.4 AI Potential

The integration of AI-based forecasting models could enhance system performance by predicting waste generation patterns based on demographic and seasonal variables (Kannangara et al., 2018). Additionally, the deployment of IoT-enabled sensors and real-time monitoring systems would support performance tracking and such interventions would enable a transition from reactive to proactive waste management, improvising both efficiency and scalability (Kannangara et al., 2018; Hannan et al., 2020).

**4.2 Case 2: Door-to-Door Waste Collection System**

**4.2.1 Description and Context**

The scaling up of door-to-door waste collection services across Odisha reflects a significant institutional initiative aimed at enhancing primary waste collection efficiency. This system uses battery-operated vehicles (BOVs) and is supported by government programs like the Swachh Bharat Mission- Urban and the Smart City Mission (MoHUA, 2021). At the household level, people are encouraged for source-level separation of wet and dry waste, the model seeks to enhance the effectiveness of subsequent waste processing stages, although its success depends on consistent household participation.

**4.2.2 Operational Mechanism**

Operationally, the system is based on fixed collection routes, with BOV operators servicing designated areas. Community participation is encouraged through awareness campaigns and supervisory oversight. Proper segregation at the source is a must need which enhances the quality of recycle materials and reduces contamination in composting streams, thereby supporting the circular economy objectives (Government of Odisha, 2020).

**4.2.3 Circular Economy Outcomes and Limitations**

Although the system has contributed to improved segregation rates and increased the recovery of recyclable materials directed to Material Recovery Facilities (MRFs) (ODA, 2021). However, by the use of static routing systems operational efficiency remains limited that causes in failing to account for spatial land temporal variations in waste generation, as well as real-time traffic conditions (Vu et al., 2019). Furthermore, there exists some lacuna which includes lack of GPS tracking and IoT-based monitoring restricts real-time oversight,

which results in delayed identification of service gaps such as missed collections or vehicle malfunctions (Chalkias & Lasaridi, 2009; Hannan et al., 2020).

#### 4.2.4 AI Potential

The integration of machine learning- based route optimisation models could significantly enhance operational efficiency by incorporating real-time traffic data, bin fill- level information, and historical waste generation patterns. This approach has the potential to reduce fuel consumption by 15-25% while improving service coverage (Vu et al., 2019; Chalkias & Lasaridi, 2009). It can also help in monitoring vehicles and waste bins using sensors which will improve the service quality and reduce the fuel use (Vu et al., 2019; Hannan et al., 2020).

### 4.3 Case 3: Plastic Waste Management Initiative

#### 4.3.1 Description and Context

In selected urban areas of Odisha, biogas plants have been established to convert organic fractions of municipal solid waste (MSW) into renewable energy, in alignment with national bioenergy policies and the National Bioenergy Programme (MNRE, 2021). This has been supported by national bioenergy initiatives, these systems utilize anaerobic digestion with circular economy principles (MNRE, 2021).

#### 4.3.2 Operational Mechanism

The system involves the process of segregation and collection of organic waste, followed by its controlled decomposition within AD reactors. The resulting biogas is used for energy applications, while the residual digestate is repurposed as organic fertilizer. This approach enables the recovery of both energy and nutrients from waste streams (Xu et al., 2018).

#### 4.3.3 Circular Economy Outcomes and Limitations

Biogas plants help to reduce landfill wastage and to produce renewable energy and fertilizer. However, there exist some challenges i.e. the supply of organic waste is not always consistent because of poor segregation and seasonal changes. Also, the unavailability of proper tools for predicting how much waste will be available, so the plants often don't work at full capacity (MNRE, 2021).

#### 4.3.4 AI Potential

AI can enhance biogas systems and aid in improved process management by forecasting the amount of trash that will be accessible through Predictive ML models. In order to boost biogas output and boost efficiency, it can also modify different variables which includes temperature settings and feedstock mixing ratios (Kannangara et al., 2018). Additionally, by dynamically controlling operational factors like temperature, feedstock composition, and retention time, process optimization algorithms can maximize biogas output and boost overall system efficiency.

## 5. Cross-Case Analysis

### 5.1 Comparative Summary

**Table 1. Cross-Case Comparison of Waste Management Initiatives in Odisha**

| Case | Technology Level | Operational Efficiency | Circular Economy Output | Primary AI Potential |
|---|---|---|---|---|
| MCC–MRF Model | Low–Moderate | High | Compost & recycling | Waste forecasting; smart monitoring |
| Collection System | Moderate | Moderate | Segregation | Route optimisation; real-time tracking |
| Plastic Management | Low | Moderate | Recycling | Lifecycle tracking; EPR enforcement |

| | | | | |
|---|---|---|---|---|
| Biogas Initiative | Moderate | High (when feed is stable) | Energy recovery | Feedstock forecasting; process optimisation |

**5.2 Cross-Case Insights**

According to the cross-case analysis, the four initiatives exhibit several recurring trends. First, each scenario demonstrates measurable contributions to circular economy (CE) results, suggesting that Odisha has built a fairly solid infrastructure and policy foundation for circular waste management. This result is consistent with the assessments carried out by the Government of Odisha (2020) and the CPCB (2021), which emphasize on boosting compliance with the Solid Waste Management Rules, 2016. Second, there is still a reasonable degree of technology integration in all circumstances. Even while MRFs have some digital tools, such GPS-enabled collection vehicles and weighbridge systems, their data is not adequately integrated in a consistent manner, which is useless for decision-making.

This supports the findings of Hannan et al. (2020), who contend that waste management systems in LMICs often suffer from fragmented and non-integrated technological adoption. Third, there also exists some of the significant untapped potential for AI implementation across all the four cases. While there is availability of relevant data sets such as operational records, sensor data, and spatial information but they are neither systematically captured nor effectively digitised. This finding aligns with Wilson et al., (2015), who identified weak data governance as a major barrier to digital transformation in developing-country waste management systems. Finally, operational performance is generally higher in systems with relatively advanced physical infrastructure, such as MCC-MRF facilities and biogas plants. However, all cases have shown that there exist some inefficiencies due to the lack of predictive and optimisation tools. This suggests that integrating AI technologies could lead to adequate improvements required for the existing infrastructure base.

**6. Proposed AI-Driven Circular Waste Management Framework**

6.1 Framework Overview

This study suggests an AI-Driven Circular Waste Management Framework (AI-CWMF) specific to Odisha based on the cross-case results and body of existing literature. The framework's four interrelated layers data input, data processing, decision-making, and implementation all work together to serve the goals of the circular economy. The design is based on the well-established concepts of AI-enabled resource optimization (Triantaphyllou & Mann, 2021) and smart waste systems (Hannan et al., 2020), modified to take into account regional institutional and infrastructural constraints.

6.2 Layer 1: Data Input

The aggregation of various data streams needed for AI applications is the main goal of this layer. These include operating metrics from MCC-MRF facilities, demographic and spatial statistics from municipal records, fleet-related data like GPS routes and collection logs, and real-time trash generation data from IoT-enabled bins. Weather information, market activity data, and EPR compliance records are all included in the input. In line with national digital initiatives like the National Urban Digital Mission, the establishment of this layer necessitates a central repository and compatible data standards (MoHUA, 2022).

6.3 Layer 2: Data Processing

The data processing layer uses machine learning and statistical methods to transform unprocessed data into insights that can be put to use. Waste generation forecasting, anomaly detection in facility operations, computer vision-based automated waste sorting, and natural language processing-based sentiment analysis of public comments are some of the important uses. Additionally, effective data handling and real-time decision-making can be supported by cloud-based platforms and edge computing systems (Hannan et al., 2020).

6.4 Layer 3: Decision-Making

Route optimization, resource allocation, and waste segregation are the three main domains that

convert the analytical results into practical strategies. Routing systems based on machine learning can save travel times and increase coverage effectiveness. Automated sorting logic improves material recovery, while predictive models help allocate resources like cars and processing power. GIS-enabled dashboards are used to visualize the decision-outputs, enabling human monitoring and intervention (Triantaphyllou & Mann, 2021).

6.5 Layer 4: Implementation

The implementation layer uses physical systems, such as well-functioning biogas plants, AI-assisted sorting facilities, and optimized collecting fleets, to make AI-driven judgments. Performance metrics such as waste diversion rates and energy output are linked to the data layer through an ongoing feedback loop. As a result, the system can get better over time (Hannan et al., 2020; Xu et al., 2018).

**6.6 Results of the Circular Economy**

The framework's goal is to achieve results in three areas: Material recovery: better recycling rates and better use of resources increasing the volume of secondary materials re-entering the economy (Ellen MacArthur Foundation, 2013).

Energy generation: more biogas production, data-managed feedstock supplies help to meet Odisha's renewable energy goals (MNRE, 2021)

Less landfill: less leftover waste and less damage to the environment reducing greenhouse gas emmissions (Kaza et al., 2018, Ghisellini et al., 2016).

**6.7 Steps to Implementation and Enabling conditions**

Four enabling factors must be taken into consideration in order to translate the AI-CWMF from idea to operation. First, data governance: the Odisha state government should create explicit procedures for data ownership, quality control, and interagency sharing. This might be done by creating a special urban waste data authority (MoHUA, 2022). Second, capacity building: in accordance with current Smart City Mission capacity-building regulations, municipal employees must receive training in data interpretation and AI-assisted decision tools. Third, public-private partnerships: Private sector collaborations, organized through open procurement procedures, will probably be necessary for the creation of AI models and the implementation of IoT infrastructure. Fourth, community engagement: ongoing investment in social communication, incentive programs, and community mobilization is necessary to maintain home segregation compliance, which is essential to information and materials quality (Rathi, 2021).

**7. Discussion**

With energy recovery, recycling, and composting all operating at considerable scale, the analysis's findings validate that Odisha's MSW system has a stronger CE foundation than is commonly acknowledged in the policy literature. However, the system operates far below its potential due to a lack of data-driven management. This trend of CE practice without CE intelligence is seen in waste systems in many rapidly developing cities (Wilson et al.,2015; Kalmykovaetal.,2018)

The proposed AI-CWMF responds to this gap. The approach enables incremental, evidence-based improvement while mitigating the risk of technology-led disruption by layering AI-based decision intelligence on top of the current operational infrastructure. This methodology avoids the risk of technology-led disruption while enabling progressive, evidence-based improvement.

This strategy is consistent with the suggestion made by Guerrero et al. (2013) that technology adoption in waste systems in developing countries be incremental and contextually tailored. The framework's focus on a closed-loop feedback architecture also addresses a significant shortcoming in earlier AI-in-waste literature: the majority of current systems are constructed as one-directional (input-to-output) pipelines without the self-correcting mechanisms needed for continuous performance in dynamic urban environments. The AI-CWMF is positioned as an adaptive management solution rather than a static instrument by employing continuous model retraining on operational feedback data. It is critical to acknowledge the limitations of this research.

It is important to recognize the limitations of this study. The empirical foundation for framework calibration would be strengthened by primary quantitative data on waste generating quantities, collection efficiencies, and processing rates; the research currently depends on secondary data and document interpretation. Furthermore, future research should concentrate on proof-of-concept deployment in one or more Odisha municipalities to assess feasibility and identify implementation challenges, as the suggested framework has not been piloted or validated in practice.

**8. Conclusion**

Using a multiple-case research design, this paper evaluated four waste management case studies in Odisha, India, and found that although circular economy principles are applied in a meaningful way, AI and data-driven decision systems are noticeably lacking. Strong physical infrastructure and policy congruence are limited by the lack of digital intelligence, according to cross-case analysis. By combining IoT-enabled data collecting, ML-based processing, AI-informed decision-making, and implementation feedback loops into a single, cohesive architecture, the proposed AI-Driven Circular Waste Management Framework (AI-CWMF) fills this gap.

The approach may be useful outside of Odisha because many Tier-2 and Tier-3 Indian cities, as well as comparable municipalities in other South Asian and sub-Saharan African countries, have inadequate data systems and emerging CE infrastructure. The AI-CWMF provides a replicable, scalable, and context-sensitive route to intelligent circular waste management by showing how AI integration may be stacked onto current operational foundations rather than necessitating the development of new systems.

Future research should focus on funding and governance models for public AI infrastructure in municipal trash systems, mathematical modelling of CE and efficiency advantages under AI-managed scenarios, and empirical validation of the framework through pilot implementation. These contributions will be essential to realizing the enormous potential of AI-driven circular waste management in India and other developing countries.

**Conflict of interest:** The authors declare no conflict of interest.

**Funding:** No fundings.

**Data availability:** The data supporting the findings of this study are derived from publicly available government reports and institutional publications cited in the references.

**References**

1. Chalkias, C., & Lasaridi, K. (2009). A GIS based model for the optimisation of municipal solid waste collection: The case study of Nikea, Athens, Greece. *WSEAS Transactions on Environment and Development*, 5(10), 640–650.
2. Chattopadhyay, S., Dutta, A., & Ray, S. (2009). Municipal solid waste management in Kolkata, India – A review. *Waste Management*, 29(4), 1449–1458.
3. CPCB (2021). *Annual Report on Solid Waste Management.* Central Pollution Control Board, Government of India.
4. Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review*, 14(4), 532–550.
5. Ellen MacArthur Foundation (2013). *Towards the Circular Economy: Economic and Business Rationale for an Accelerated Transition.* Ellen MacArthur Foundation.
6. Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The Circular Economy – A new sustainability paradigm? *Journal of Cleaner Production*, 143, 757–768.
7. Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production*, 114, 11–32.
8. Government of Odisha (2020). *Odisha Solid Waste Management Project: Progress Report.* Housing and Urban Development Department, Government of Odisha.
9. Guerrero, L. A., Maas, G., & Hogland, W. (2013). Solid waste management challenges for cities in developing countries. *Waste Management*, 33(1), 220–232.
10. Gundupalli, S. P., Hait, S., & Thakur, A. (2017). A review on automated sorting of source-

separated municipal solid waste for recycling. *Waste Management*, 60, 56–74.

11. Hannan, M. A., Lipu, M. S. H., Akhtar, M., Begum, R. A., Al Mamun, M. A., Hussain, A., Mia, M. S., & Basri, H. (2020). Solid waste collection optimisation: Systematic review and roadmap for sustainable development. *Journal of Cleaner Production*, 244, 118682.
12. Kalmykova, Y., Sadagopan, M., & Rosado, L. (2018). Circular economy – From review of theories and practices to development of implementation tools. *Resources, Conservation and Recycling*, 135, 190–201.
13. Kannangara, M., Dua, R., Ahmadi, L., & Bensebaa, F. (2018). Modeling and prediction of regional municipal solid waste generation and diversion in Canada using machine learning approaches. *Waste Management*, 74, 3–15.
14. Kaza, S., Yao, L., Bhada-Tata, P., & Van Woerden, F. (2018). *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050.* World Bank Publications.
15. Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling*, 127, 221–232.
16. Korhonen, J., Honkasalo, A., & Seppälä, J. (2018). Circular economy: The concept and its limitations. *Ecological Economics*, 143, 37–46.
17. Manoharan, K., Kavin, T., & Krishnamoorthy, S. (2021). A critical review of smart waste management in Indian cities: Challenges and opportunities. *Environmental Science and Pollution Research*, 28, 47890–47905.
18. McDonough, W., & Braungart, M. (2002). *Cradle to Cradle: Remaking the Way We Make Things.* North Point Press.
19. Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative Data Analysis: A Methods Sourcebook* (3rd ed.). SAGE Publications.
20. MNRE (2021). *National Bioenergy Programme.* Ministry of New and Renewable Energy, Government of India.
21. MoEFCC (2016). *Solid Waste Management Rules, 2016.* Ministry of Environment, Forest and Climate Change, Government of India.
22. Mohanty, S. (2022). Digital readiness in Odisha's urban solid waste management: Gaps and pathways. *Urban India*, 42(1), 88–104.
23. MoHUA (2021). *Swachh Bharat Mission–Urban 2.0: Guidelines and Framework.* Ministry of Housing and Urban Affairs, Government of India.
24. MoHUA (2022). *National Urban Digital Mission: Implementation Guidelines.* Ministry of Housing and Urban Affairs, Government of India.
25. NITI Aayog (2022). *Urban Solid Waste Management in India: Status and Recommendations.* NITI Aayog, Government of India.
26. ODA (2021). *Odisha Development Authority Annual Report 2020–21.* Odisha Development Authority.
27. Panda, R., Mishra, B., & Nayak, A. (2019). Challenges in municipal solid waste management in Odisha: A study of selected urban local bodies. *International Journal of Environmental Studies*, 76(4), 612–628.
28. Rajput, R., Bhave, P., & Bhave, A. (2009). Municipal solid waste management in developing countries. *Environmental Monitoring and Assessment*, 151(1–4), 441–449.
29. Rathi, S. (2021). Optimization of integrated solid waste management to minimize costs. *Waste Management & Research*, 28(5), 412–421.
30. Triantaphyllou, E., & Mann, S. H. (2021). Using the analytic hierarchy process for decision making in engineering applications: Some challenges. *International Journal of Industrial Engineering*, 2(1), 35–44.
31. Vu, H. L., Ng, K. T. W., & Fallah, B. (2019). Analysis of input set characteristics and variances on k-fold cross-validation for a Recurrent Neural Network model on waste disposal rate estimation. *Journal of Environmental Management*, 236, 95–103.
32. Wilson, D. C., Rodic, L., Modak, P., Soos, R., Carpintero, A., Velis, K., Iyer, M., & Simonett, O. (2015). *Global Waste Management Outlook.* United Nations Environment Programme (UNEP).
33. World Bank (2022). *Solid Waste Management Overview.* World Bank Group.

34. Xu, F., Li, Y., Ge, X., Yang, L., & Li, Y. (2018). Anaerobic digestion of food waste – Challenges and opportunities. *Bioresource Technology*, 247, 1047–1058.
35. Yin, R. K. (2018). *Case Study Research and Applications: Design and Methods* (6th ed.). SAGE Publications.