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Review Article

Artificial Intelligence and IoT for Smart Waste Management: Challenges, Opportunities, and Future Directions

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Abstract: Indonesia's waste management system faces significant challenges due to rapid urbanization, inefficient waste collection, and low recycling rates. The country's reliance on open dumping and landfilling has exacerbated environmental degradation, pollution, and greenhouse gas emissions. This study explores the transformative potential of Artificial Intelligence (AI) and the Internet of Things (IoT) in modernizing waste management through smart collection, automated sorting, real-time monitoring, and predictive analytics. AI-driven waste classification improves recycling efficiency, while IoT-enabled smart bins optimize collection routes, reducing operational costs and landfill dependency. However, widespread adoption is hindered by high implementation costs, digital infrastructure limitations, data accessibility issues, and privacy concerns. Addressing these barriers requires investment in AI-driven infrastructure, standardized data collection, and regulatory frameworks that ensure ethical and sustainable implementation. Collaborative partnerships between governments, technology firms, and research institutions are critical for scaling AI-based waste management. Pilot programs and feasibility studies will validate these technologies' effectiveness, driving large-scale adoption. With the right policies and investments, AI and IoT can revolutionize Indonesia's waste management, reducing environmental impact, promoting circular economy initiatives, and ensuring long-term sustainability in urban development.

Keywords: Artificial Intelligence; Indonesia; Internet of Things (IoT); Sustainable Waste Management; Waste Management.

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1. Introduction

Indonesia, the world's fourth most populous country, had an estimated population of 283.4 million in 2024[1]. The nation's economy has demonstrated resilience in the post-pandemic era, achieving a 5.05% growth rate in the second quarter of 2024. However, this rapid economic expansion and population growth have significantly increased waste generation, exceeding 175,000 tons per day in 2023[2]. Despite ongoing infrastructure development, the country's waste management systems remain insufficient to address the escalating waste crisis. Conventional waste disposal methods, including open dumping (57%) and sanitary landfilling (15%), remain dominant in urban areas[3], [4]. Although Law No. 18 of 2008 mandates the conversion of all landfills into sanitary facilities, compliance has been limited to a few cities. Ineffective waste management practices pose serious social, environmental, and public health concerns[5]. Open dumpsites are a major source of greenhouse gas emissions, particularly carbon dioxide (CO_2) and methane (CH_4), exacerbating global warming and intensifying climate change impacts[6].

Globally, waste generation has reached an alarming scale. A World Bank report estimates that approximately 2.01 billion tonnes of waste are produced annually, with projections indicating a potential increase to 3.40 billion annually by 2050[7]. In 2023, Indonesia alone generated approximately 68.5 million tons of waste, with this figure continuing to rise[2].

Indonesia's per capita waste generation stands at an estimated 0.68 kg per day [7]. As depicted in Figure 1, the composition of national waste is predominantly food waste (39.82%), followed by plastics (19.19%), wood and branches (11.77%), and paper and cartons (10.86%), with household sources contributing between 60% and 70% of the total waste, and markets accounting for approximately 20% to 25%. Artificial Intelligence (AI) has played an increasingly vital role in waste management, addressing key operational challenges and enhancing efficiency through data-driven solutions [8]–[11]. AI-driven innovations in waste management encompass sophisticated data analysis, pattern detection, and automated decision-making processes, all of which contribute to optimizing waste collection, resource utilization, and environmental sustainability[12], [13].

Advancements in AI-based waste management include the introduction of intelligent collection strategies, enhanced sorting mechanisms, and predictive analytics for improved planning [14]. AI-powered waste collection systems streamline route optimization and scheduling, effectively reducing inefficiencies and lowering operational costs[15]. Additionally, AI-integrated smart bins and real-time waste monitoring technologies facilitate efficient waste segregation, ultimately improving resource recovery and contributing to sustainable waste management practices[16].

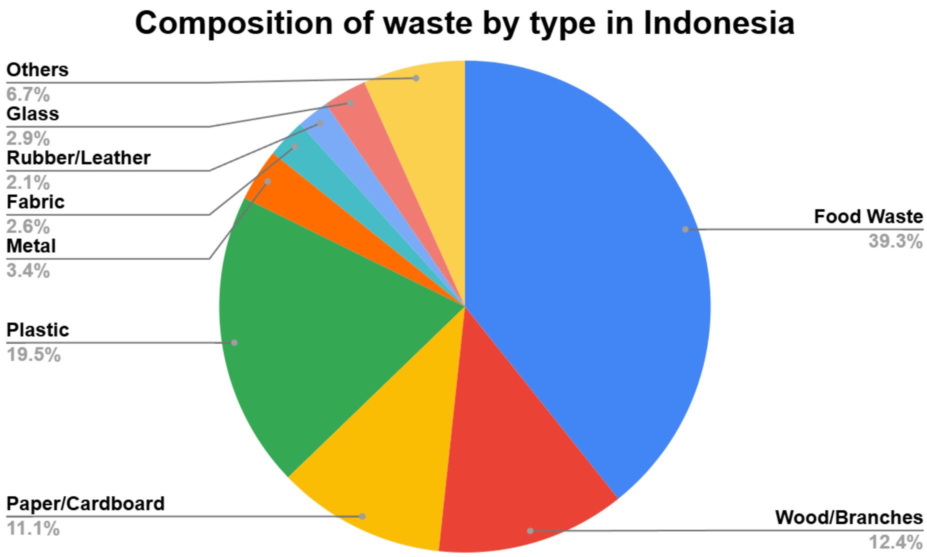

Figure 1. Composition of waste by type in Indonesia[17].

The field of waste sorting has undergone substantial advancements, transitioning from labor-intensive manual methods to AI-enhanced image recognition and machine vision technologies [18], [19]. These innovations have significantly increased sorting accuracy, enabling efficient separation of recyclable materials from non-recyclables, thus improving recycling rates [20]–[22]. Furthermore, robotics and automation have enhanced waste recycling efficiency by refining material identification processes and reducing contamination in recovered materials[23].

One of the notable advancements in technology is the improvement of waste monitoring systems. Using the Internet of Things (IoT) in waste management has made real-time tracking possible, allowing for better data analysis and informed decision-making regarding resource allocation [24]. By leveraging predictive analytics, waste management operations can enhance forecasting accuracy and streamline collection schedules to improve efficiency[25]–[28]. However, despite these innovations, several barriers still limit widespread implementation. Issues such as data reliability, privacy concerns, high costs of adoption, and ethical considerations present significant challenges[29]. Addressing these challenges requires collaboration between multiple parties to create effective solutions[30].

Integrating AI and IoT in waste management offers a promising opportunity to modernize traditional practices, making them more efficient, sustainable, and environmentally responsible [31]–[33]. Despite the vast potential of AI and IoT in improving waste management systems, there is still a lack of comprehensive studies that consolidate existing knowledge on their application in this sector. Many studies have explored AI and IoT technologies separately, but few have examined their combined impact on waste management efficiency, sustainability, and scalability. As waste management continues to be a global concern, a systematic review must assess how AI and IoT can optimize operations, reduce environmental impact, and overcome existing challenges. This study aims to bridge this knowledge gap by providing a structured understanding of these technologies, their benefits, and their challenges in waste management.

Several literature reviews have explored AI and IoT applications in waste management, as shown in Table 1. For instance, [34] focused on AI-driven waste management but lacked a detailed discussion on practical implementation challenges, such as financial and regulatory barriers. Similarly, [35] examined AI and IoT in waste collection and recycling but primarily addressed urban environments, overlooking developing countries' unique challenges. Another review by [36] provided insights into smart city waste management but did not analyze AI adoption's ethical and social implications.

Table 1. Summary of previous review studies and their limitations.

Ref.	Focus of the review	Shortcomings identified
[34]	AI applications in smart waste management	Limited discussion on practical implementation challenges and scalability
[35]	AI and IoT for waste collection, sorting, and recycling	Focused mainly on urban areas, lacking insights into developing countries
[36]	AI and IoT system architecture for smart city waste management	Lacks analysis of ethical concerns and social implications

Unlike previous studies, this review provides a broader perspective by addressing critical AI-driven waste management research gaps. It explores key adoption challenges, including financial, ethical, and regulatory barriers, and examines their impact on workforce dynamics and data privacy. Additionally, it highlights the specific challenges and opportunities associated with AI implementation in developing countries, particularly in Indonesia. This study contributes to a more informed and applicable understanding of AI-driven waste management strategies by identifying these limitations and offering insights into practical solutions.

The remainder of this paper is structured as follows: Section 2 examines the integration of AI in waste management, highlighting key technologies and their specific applications in waste collection, sorting, recycling, and monitoring. Section 3 explores the challenges and limitations of AI implementation, addressing issues such as data accessibility and reliability, privacy concerns, financial and infrastructure constraints, and moral and ethical implications. Section 4 discusses future directions and opportunities for AI-driven waste management, focusing on policy advancements and emerging technological innovations. Finally, Section 5 presents the conclusions and recommendations based on the findings of this review.

2. Waste Management and Artificial Intelligence

This section must contain a state-of-the-art explanation. It can be explained in several ways. First, you can discuss several related papers, both about objects, methods, and their results. From there, you can explain and emphasize gaps or differences between your research and previous research. The second way is to combine theory with related literature and explain each theory in one sub-chapter.

AI is increasingly crucial in enhancing the efficiency of waste management. AI's ability to process vast amounts of data enables accurate insights and automates various processes, leading to more effective waste management practices. AI-driven strategies have expanded within the sector, from waste collection to management planning[37], [38].

In recent years, there has been a notable rise in the adoption of AI within waste management as governments and organizations continue to invest in innovative solutions [39], [40]. The global AI market in this sector is expected to grow significantly, with projections indicating an increase from USD 428.00 billion in 2022 to approximately USD 2,025.12 billion by 2030[41]. Several AI techniques have been incorporated into waste management, such as Random Forests (RF), linear regression, support vector machines (SVMs), decision trees (DTs), K-Nearest Neighbors (KNN), Reinforcement Learning (RL), artificial neural networks

(ANNs), and genetic algorithms (GAs). The following sections explore these techniques and their applications in waste management.

2.1. Artificial Intelligence Techniques in Waste Management

AI is playing an increasingly vital role in improving waste management efficiency. By processing vast amounts of data, AI can provide accurate insights and automate various operations, making waste management more effective.

2.1.1. Random Forests (RF)

Recent studies highlight the success of Random Forests (RF) in waste classification, particularly for managing complex, multidimensional datasets. For instance, research has shown that RF improves the accuracy of waste sorting systems, leading to lower contamination rates in recycling streams[42]. This suggests that RF could significantly enhance the operational efficiency of material recovery facilities by accurately categorizing different waste types based on specific characteristics, which, in turn, optimizes sorting and contributes to better resource recovery and sustainability.

2.1.2. Linear Regression (LR)

Linear Regression (LR) is a supervised learning method that analyzes patterns and predicts outcomes based on linear relationships within data [43]. In solid waste management (SWM), LR is essential in examining waste-related factors. Models can be categorized into simple linear regression, which focuses on a single variable, and multiple linear regression (MLR), which incorporates several factors to address the complex interdependencies of waste forecasting and route optimization[44].

Linear regression is known for its efficiency, ease of use, and straightforward interpretation of results. However, it faces limitations when modeling nonlinear relationships, which may reduce accuracy in complex waste management scenarios [45], [46]. Despite this, LR has been applied to improve waste generation forecasting, waste collection route planning, and the optimization of treatment and disposal strategies [47], [48].

2.1.3. Support Vector Machine (SVM)

Support Vector Machine (SVM) has become a popular choice in waste prediction, waste detection at bin levels, and automated sorting for analyzing large datasets[49], [50]. These algorithms serve as non-parametric classifiers by finding hyperplanes that separate data points in multidimensional spaces. In addition to classification, SVMs excel in regression tasks, often outperforming other algorithms[51].

While SVMs are known for their efficiency and ability to handle well-separated data, they may struggle with large datasets due to their reliance on cross-validation techniques [52]–[54]. In waste management, SVMs are used for various tasks, such as predicting waste generation, detecting waste at the bin level, and sorting waste [55]–[59].

2.1.4. K-Nearest Neighbors (KNN)

K-Nearest Neighbors (KNN)is highly effective for waste classification, particularly in identifying waste types based on their physical attributes. One study demonstrated the use of KNN in classifying recyclable materials within urban settings, showing improved sorting accuracy [60]. This highlights KNN's potential to enhance recycling efficiency by precisely distinguishing between different types of waste, thereby reducing contamination and improving recovery rates in the process.

2.1.5. Decision Tree (DT)

Decision trees (DT) are a popular non-parametric supervised learning technique applicable to classification and regression tasks [19]. They are structured hierarchically with root, decision, and leaf nodes, illustrating various possible outcomes. DTs are robust, interpretable, and flexible, making them efficient for waste management applications [61], [62]. They have been effectively employed to improve waste generation predictions and optimize waste management planning [63], [64].

2.1.6. Artificial Neural Network (ANN)

Artificial neural networks (ANN) are designed to emulate the functioning of human brain nerve cells [65]. Composed of input, hidden, and output layers, ANNs excel at understanding complex patterns within large datasets, effectively simulating nonlinear relationships.

This ability has led to their growing popularity across various fields, including waste generation prediction, sorting, and planning[66]–[68]. Despite their advantages, ANNs are susceptible to overfitting, require significant memory for storage, and demand considerable time for training [69]–[71]. ANNs have been successfully applied to optimize waste generation, sorting, and management planning [72], [73].

2.1.7. Reinforcement Learning (RL)

Reinforcement Learning (RL) has emerged as an effective tool for optimizing waste collection routes and resource allocation. One study used RL algorithms to dynamically adjust waste collection schedules based on real-time data, leading to better operational efficiency and cost savings[74]. This approach demonstrates RL's ability to develop adaptive systems that efficiently respond to changes in waste generation patterns, leading to more sustainable waste management practices.

2.1.8. Genetic Algorithm (GA)

Genetic Algorithms (GAs) are optimization techniques that improve waste management efficiency by identifying optimal solutions for complex problems, such as waste collection route planning and resource allocation[75]. A subset of evolutionary algorithms, GAs utilize selection, crossover, and mutation processes to solve complex optimization problems [76]. These algorithms are powerful tools for identifying optimal solutions in large search spaces [77]. Although GAs are highly effective for generating reliable results, they require careful design for efficiency and may not be suited for simpler problems[78]. Table 2 compares different AI techniques used in waste management, outlining their main functions, strengths, and limitations. This summary helps illustrate how each method contributes to tasks like waste classification, prediction, and route optimization. By understanding the advantages and challenges of each approach, waste management professionals can make more informed decisions about which AI techniques best suit their specific needs.

Table 2. Comparative Summary of AI Techniques in Waste Management.

AI Technique	Main Function	Advantages	Limitations
RF	Waste classification and sorting	High accuracy, handles large datasets	Computationally intensive
LR	Waste generation forecasting, route optimization	Easy to interpret, efficient for linear relationships	Poor performance in nonlinear scenarios
SVM	Waste classification, prediction, and detection	Strong classification ability, works well with small datasets	High computational cost for large datasets
KNN	Waste classification and sorting	Simple and effective for small datasets	Computationally expensive for large datasets
DT	Waste generation prediction, decision-making	Easy to interpret, flexible	Prone to overfitting
ANN	Waste generation prediction, sorting, and planning	Handles complex patterns with high accuracy	Requires large training data and computational power
RL	Route optimization, adaptive scheduling	Dynamic decision-making, cost-efficient	Requires extensive training data
GA	Route optimization, waste processing efficiency	Effective for complex optimization problems	Requires careful parameter tuning

2.2. AI in Waste Collection

AI has become increasingly instrumental in enhancing the efficiency of waste collection, contributing to a cleaner and more sustainable environment [79]–[82]. Recent technological innovations have significantly transformed traditional waste collection practices, incorporating systems like smart bins, intelligent route planning, dynamic scheduling, and demand-based prediction models [83].

AI-powered solutions are revolutionizing waste collection by improving operational efficiency, reducing costs, and mitigating environmental impact[84]. These technologies address scalability challenges using automation, predictive analytics, and data-driven decisions [85]. AI enhances waste sorting, collection, and recycling by optimizing resource management. Automating tasks like route planning and waste classification boosts operational efficiency and allows for handling larger volumes of waste without additional resources[86]. Additionally, AI-based predictive models assist in forecasting waste generation trends, facilitating proactive planning and more efficient resource distribution. This forward-thinking approach ensures that waste management systems remain adaptable and sustainable.

2.2.1. Pay-As-You-Throw (PAYT) Schemes

Pay-as-you-throw (PAYT) systems are increasingly vital in managing municipal solid waste flows. These schemes account for the waste produced by each entity (e.g., households, businesses) and assign corresponding economic responsibility[87]. Following the environmental principle "the polluter pays," PAYT systems are strongly supported by the European Union [88]. Figure 2 illustrates the traditional waste fee model based solely on weight.

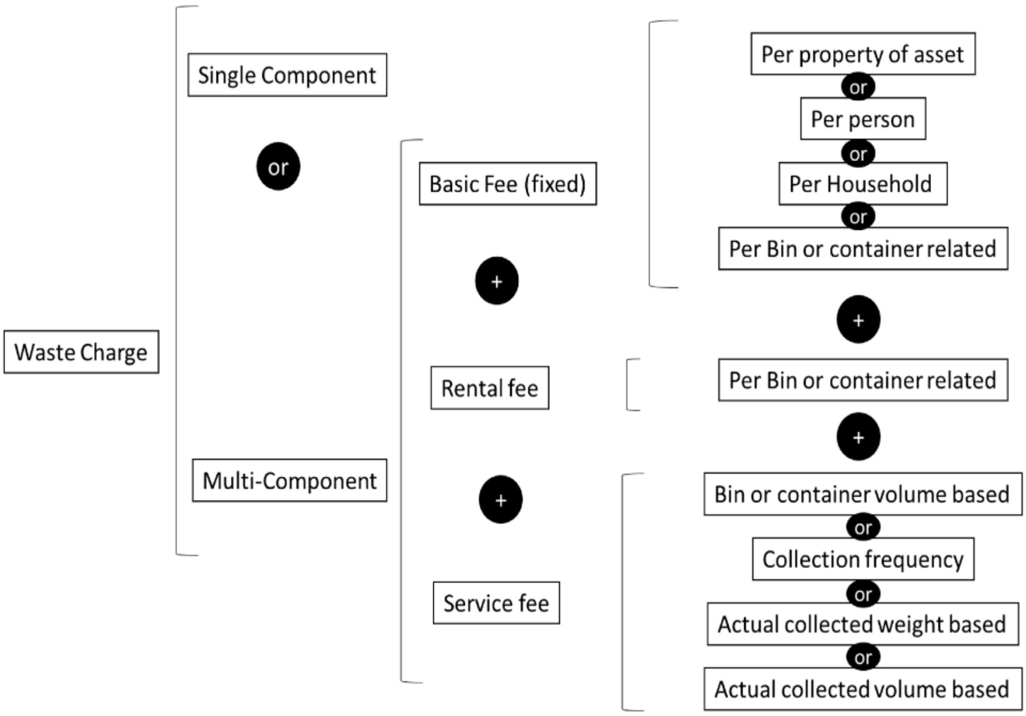

Figure 2. Possible waste fee components (adapted from [89]).

AI can enhance PAYT systems by integrating RFID tags or sensors to track the waste produced by each unit. This technology allows for accurate billing based on the actual amount of waste generated, encouraging waste reduction and increased recycling.

2.2.2. Smart Bin Systems

Smart bin systems have gained popularity for optimizing waste collection[90]. These systems use sensors to monitor bin fill levels in real-time, and AI algorithms analyze the data to optimize collection routes and schedules. New advancements, including ultrasonic and weight sensors, have improved the accuracy of waste accumulation measurements[91]. IoT integration allows smart bins to communicate with waste management authorities, ensuring real-time monitoring and proactive maintenance[92].

Machine Learning (ML) further enhances the accuracy of fill-level predictions, improving collection efficiency[93]. However, implementing this technology in regions like Indonesia presents challenges. Many rural and underserved areas lack the necessary infrastructure, such as stable internet access and reliable electricity, to support smart waste systems. Moreover, the high upfront costs and limited public awareness of these technologies hinder large-scale adoption. Addressing these challenges will require significant investment in infrastructure, public education, and collaboration between government and private sectors to ensure the long-term success of smart bin systems.

2.2.3. Demand Forecasting

AI-based demand forecasting models are essential for estimating waste generation rates across different regions [94], [95]. Recent advancements focus on combining data from various sources and applying sophisticated ML techniques[96]. Waste management companies now use information from IoT sensors, social media, and online platforms to track real-time waste generation trends[97].

ML methods like ensemble techniques and deep learning (DL) help produce accurate predictions by considering factors such as population density and historical waste data[98]–[100]. Accurate forecasting allows for better resource allocation, improved operational efficiency, and more proactive waste management strategies. However, successful implementation requires robust data collection systems, strong interagency collaboration, and seamless integration of IoT technologies. Real-time forecasting may be difficult in remote areas with limited internet connectivity or unreliable data access. Overcoming these barriers is essential to fully leveraging AI-powered waste forecasting.

2.2.4. Route Optimization

Optimizing waste collection routes is critical for minimizing travel time, fuel consumption, and vehicle emissions. Recent technological breakthroughs have introduced AI-powered optimization algorithms that improve route efficiency[101]. These systems use real-time data, such as GPS and traffic conditions, to dynamically adjust routes based on current operational needs [102].

Advanced techniques, like deep learning, enhance the ability to predict traffic patterns and optimize routes in real time[103]. Dynamic rerouting allows for immediate adjustments to collection routes, increasing operational flexibility and responsiveness to changing conditions[104]. By analyzing traffic congestion and the distribution of waste generation points, AI-driven route optimization reduces travel time and emissions, contributing to more sustainable and efficient waste collection. Figure 3 illustrates an example of real-time route planning based on waste bin status.

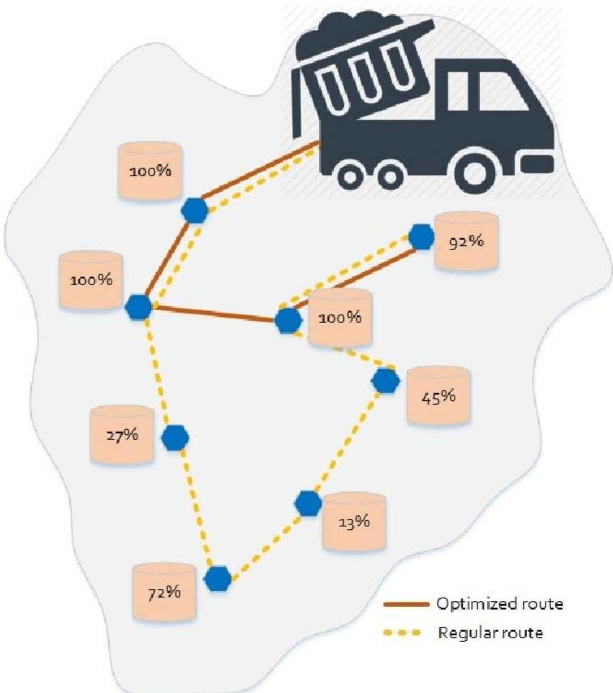

Figure 3. Route optimization and planning. (adapted from [105]).

2.2.5. Integration System

Effectively incorporating AI technologies into waste collection and management systems requires strategic planning to optimize performance while minimizing operational disruptions [106], [107]. Ensuring that AI solutions align with existing infrastructure is crucial for a seamless transition and to prevent inefficiencies. Additionally, AI-based waste management relies on accurate, well-structured data, making data consistency and integration essential for successful implementation[108].

Comprehensive training for waste management personnel enhances system performance and encourages technological innovation [109]. A thorough cost-benefit analysis can help justify AI investments by demonstrating long-term advantages, such as improved operational efficiency and cost reductions[110]. Furthermore, ensuring that AI-driven solutions remain scalable and adaptable will be vital as waste management needs evolve. Engaging diverse stakeholders—including government entities, private sector waste management firms, and local communities—helps align AI adoption with broader societal objectives and promotes inclusive decision-making.

2.3. AI in Waste Sorting

Accurate waste sorting is a fundamental aspect of effective waste management, enabling efficient material categorization for disposal and recycling [111]–[113]. Integrating AI into sorting processes has significantly improved speed, precision, and operational efficiency [114], [115]. The following sections explore key advancements in AI-powered sorting systems.

2.3.1. Image Recognition vs. Computer Vision

AI-powered image recognition and computer vision have revolutionized waste sorting by automating material identification and classification [116], [117]. These technologies employ AI-driven algorithms to analyze images or video footage, allowing for precise identification of waste composition[118].

Recent breakthroughs in this area include using high-resolution cameras, sophisticated image processing techniques, and DL models, which enable real-time waste detection and classification[119]. Advanced DL architectures, such as convolutional neural networks (CNNs), enhance sorting accuracy by identifying intricate material characteristics[120]. Additionally, machine vision systems integrated into conveyor-based sorting mechanisms allow for continuous and rapid waste processing, reducing the need for manual sorting[121].

2.3.2. Automated Robotic Sorting Systems

Integrating robotics with AI has led to fully automated sorting systems, significantly increasing efficiency and precision[122]. These robotic solutions leverage AI-powered sensors, high-resolution cameras, and robotic arms to classify accurately and sort waste materials based on their composition[123], [124].

Recent innovations in robotic waste sorting have focused on improving gripping mechanisms, enhancing sensor accuracy, and refining AI algorithms. Advanced robotic arms, with adaptable grippers and tactile sensors, can manipulate various materials with varying shapes, sizes, and textures[125]. AI-driven robotic sorting systems also utilize reinforcement learning techniques to improve sorting performance by adapting to changing waste compositions. The introduction of collaborative robots (cobots) further enhances sorting efficiency by enabling human-machine collaboration within waste management facilities [126].

Despite these advantages, job displacement and social equity concerns remain significant[127], [128]. The increased automation of waste management processes may disproportionately affect low-income workers, raising ethical concerns related to workforce displacement and environmental justice[129]. To mitigate these challenges, policymakers and industry leaders must implement responsible AI deployment strategies that balance automation benefits with economic and social considerations.

2.3.3. Automated Sorting Machines and Systems

Automated waste sorting technologies use AI algorithms to classify materials based on their physical and chemical properties [130]. These systems integrate advanced sensing technologies such as near-infrared (NIR) spectroscopy, X-ray fluorescence (XRF), and hyperspectral imaging to analyze and categorize waste with high precision [131], [132]. AI algorithms process this data to classify materials and efficiently separate them into appropriate categories accurately.

Recent advancements in automated sorting have led to the incorporation of DL models and neural networks, enabling AI systems to process and differentiate a broader range of materials with increased accuracy [133]. Well-trained AI models can distinguish between plastics, metals, glass, paper, and organic waste, leading to more efficient sorting and reduced contamination [134].

While AI-driven sorting solutions improve recycling efficiency and sustainability, challenges such as mixed waste streams, contamination, and scalability remain significant[135]. Addressing these issues will require further investment in research, technological advancements, and workforce training to optimize AI integration in waste sorting.

2.3.4. Sensor-Based Sorting Systems

AI-powered sensor-driven sorting systems have revolutionized waste classification by significantly enhancing precision and operational efficiency. These systems employ a variety of sensors, such as near-infrared (NIR), X-ray transmission, and optical sensors, to analyze physical characteristics such as color, size, and material density, ensuring precise waste categorization [136].

AI algorithms process real-time data from these sensors to enable accurate and efficient sorting of plastics, metals, paper, glass, and other materials. AI-powered sorting technologies continuously refine their ML classification methods, improving accuracy and minimizing errors over time [137].

By reducing contamination in recycling streams and optimizing material recovery, AI improves sorting efficiency and enhances the performance of waste management equipment, including conveyor belts and robotic arms [138], [139]. Recent innovations in sensor-based sorting integrate multiple sensing modalities, such as optical, infrared, and electromagnetic sensors, to provide more detailed material analysis, ensuring high sorting accuracy even in complex waste environments [140].

The continuous evolution of AI-driven sorting solutions focuses on improving speed, precision, and adaptability. By leveraging a combination of advanced sensors, computer vision, robotics, and ML, modern waste sorting technologies play a pivotal role in reducing waste contamination and improving recycling outcomes[141]. As these innovations advance, they will contribute significantly to circular economy initiatives and the broader goals of sustainable waste management [142], [143]. Figure 4 illustrates a real-time sorting robot system for Panax notoginseng, showcasing the system's key components.

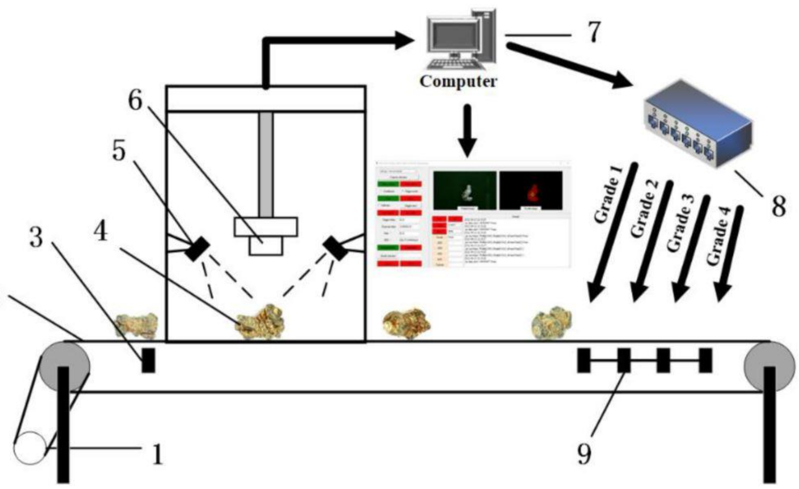

Figure 4. Panax notoginseng real-time sorting robot system(adapted from [144]). Note: 1—actuation system; 2—conveyor belt; 3—photoelectric sensor; 4—taproots of Panax notoginseng; 5—bar light source; 6—industrial camera; 7—computer; 8—low-level controller; 9—jet mouth.

2.4. AI in Waste Recycling

AI is significantly transforming the recycling industry by improving efficiency, precision, and automation in multiple phases of waste processing [145]. From identifying and categorizing materials to optimizing procedures and ensuring quality control, AI-driven innovations are enhancing recycling performance and contributing to sustainability initiatives.

2.4.1. Smart Material Identification and Sorting

Accurate identification and proper sorting of waste materials are critical to an effective recycling system [146], [147]. Advanced AI technologies, including ML, computer vision, and spectroscopic techniques, provide high-precision classification for various types of waste. A notable development in this field is the combination of AI with high-resolution cameras, hyperspectral imaging, and sophisticated sensors, significantly improving the detection and separation of complex and mixed waste streams.

DL models, particularly CNNs, are widely employed to analyze visual characteristics and classify different materials with exceptional accuracy [148]–[150]. By integrating AI-based sorting techniques, recycling facilities can streamline processes, enhance material purity, and increase overall operational effectiveness[151].

2.4.2. Waste Optimization Models

Enhancing the recycling process requires optimizing every stage to improve resource recovery and minimize operational costs. AI is key in leveraging predictive analytics and data-driven decision-making [152] and continuously analyzing real-time operational data, such as equipment performance, energy consumption, and material movement. AI systems can identify inefficiencies and optimize key parameters. These models learn from historical and live data, enabling adaptive process optimization and improved predictive accuracy[153]. Adjustments in temperature, pressure, and processing time contribute to higher recovery rates, improved material quality, and greater sustainability in recycling operations.

2.5. AI in Waste Monitoring

AI is increasingly vital in waste monitoring, significantly improving efficiency, precision, and automation across different recycling and waste management phases [145]. By leveraging AI-driven technologies, waste monitoring has evolved to include intelligent material classification, real-time tracking, and enhanced decision-making, all contributing to sustainability efforts.

2.5.1. Predictive Analytics

Accurate material classification and sorting are fundamental to efficient waste monitoring and recycling[146], [147]. AI-powered solutions, including advanced ML models, image recognition, and spectral analysis, enable precise identification and categorization of waste materials. A key advancement in this domain involves the integration of AI with high-resolution imaging, hyperspectral sensing, and state-of-the-art sensors, significantly improving the detection of complex and heterogeneous waste compositions.

DL architectures, particularly CNNs, have demonstrated remarkable proficiency in analyzing visual patterns and accurately categorizing materials [148]–[150]. By incorporating AI-driven predictive analytics into the waste sorting process, recycling facilities can enhance processing speeds, improve the quality of sorted materials, and boost overall operational efficiency [151].

2.5.2. Real-Time Waste Monitoring Systems

Enhancing waste monitoring efficiency involves optimizing each process step to maximize resource recovery while reducing operational expenses. AI is integral to this effort, utilizing predictive modeling and data analysis to support informed decision-making[152].

AI-powered systems continuously evaluate real-time operational metrics, such as equipment functionality, energy consumption levels, and material distribution, to detect inefficiencies and recommend corrective measures. These models dynamically refine operational processes using historical and live data, resulting in adaptive optimization and improved predictive accuracy[153]. Adjustments in critical parameters, such as temperature, pressure, and processing time—enhance resource recovery rates, elevate material quality, and promote sustainable waste management practices.

2.5.3. Data-Driven Decision Making (DDDM)

AI-driven analytics significantly enhance decision-making capabilities by processing vast datasets collected from waste monitoring infrastructure[154]. This data analysis provides crucial insights into waste generation trends, recycling efficiencies, and cost factors, enabling stakeholders to formulate well-informed policies, allocate resources strategically, and make sound investment decisions[155].

AI fosters more effective and sustainable waste management approaches by identifying complex patterns and emerging trends that may not be apparent through traditional methods [156]. This shift towards data-centric decision-making enhances operational efficiency while aligning waste management strategies with broader environmental objectives.

2.5.4. IoT and Sensor Integration

Integrating AI with the IoT and sensor networks transforms waste monitoring by facilitating real-time data collection and analysis. IoT-enabled sensors continuously track waste-related factors such as fill levels, temperature fluctuations, and air quality, transmitting this information to centralized platforms for AI-based evaluation and interpretation [157], [158].

This continuous data flow enables swift responses to emerging waste management issues, enhancing overall system efficiency [159]. The fusion of AI and IoT further streamlines data exchange, ensuring seamless communication between different waste monitoring components and improving operational effectiveness[160].

Recent advancements in AI-powered waste monitoring focus on refining sensor accuracy, expanding predictive analytics capabilities, and leveraging IoT-based automation to drive sustainable waste management solutions[161]. Achieving these advancements requires strong collaboration among technology developers, researchers, and waste management organizations [162]. Figure 5 depicts a conventional wireless sensor network for solid waste management utilizes temperature and humidity sensors to facilitate comprehensive and precise monitoring.

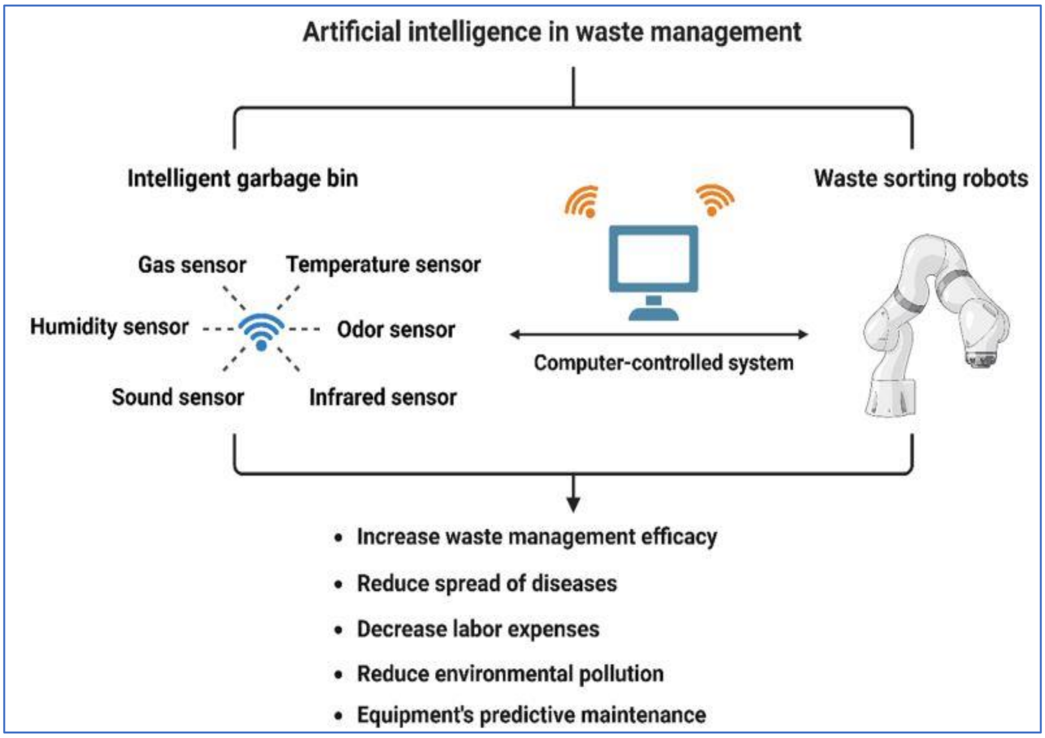

Figure 5. Uses of artificial intelligence in the garbage bin and waste robotic sorting [163].

Integrating AI in waste management has significantly enhanced waste sorting, recycling, and monitoring processes by improving efficiency, accuracy, and automation. AI technologies, such as image recognition, robotic sorting, predictive analytics, and IoT-based monitoring, have optimized material classification, streamlined recycling operations, and enabled real-time waste tracking. These advancements contribute to a more sustainable waste management system by reducing contamination, increasing resource recovery, and supporting data-driven decision-making. However, challenges such as handling mixed waste streams, ensuring scalability, and addressing workforce displacement remain critical. Table 3 comprehensively summarizes key recommendations for improving AI applications in waste sorting, recycling, and monitoring. These recommendations include enhancing AI algorithms for complex waste streams, integrating advanced sensing modalities, investing in AI-driven spectroscopic techniques, and improving the accuracy of waste monitoring systems. Addressing workforce displacement through reskilling programs and ensuring regulatory frameworks for ethical AI deployment are essential for balancing technological advancements with social and environmental responsibilities.

Table 3. Summary of Recommendations for Enhancing AI Applications in Waste Management.

Area	Recommendations
Waste Sorting	• Enhance AI algorithms to handle complex and mixed waste streams more effectively. • Integrate multiple sensing modalities (optical, infrared, electromagnetic) to improve sorting accuracy. • Address workforce displacement concerns through reskilling programs and job transition strategies. • Establish regulatory frameworks for ethical AI deployment in waste sorting.
Waste Recycling	• Develop adaptive AI models to classify and process complex waste compositions better. • Invest in AI-powered spectroscopic techniques (e.g., hyperspectral imaging) to improve material differentiation and reduce contamination. • Implement AI-driven predictive analytics to enhance resource recovery and recycling efficiency. • Promote industry collaboration with policymakers to ensure economic feasibility and alignment with circular economy initiatives.
Waste Monitoring	• Improve the accuracy and reliability of AI-powered waste monitoring systems. • Standardize AI and IoT integration protocols to ensure seamless interoperability. • Increase investment in cost-effective AI-driven waste monitoring solutions. • Expand AI-driven decision-making models to support data-driven policy formulation in waste management.

3. Challenges and Limitations of AI in Waste Management

Despite the transformative potential of AI in waste management, several challenges must be addressed to ensure its effective implementation [164]–[167]. These challenges include issues related to data reliability, privacy and security risks, financial constraints, and infrastructure limitations. Table 4 outlines key obstacles and potential solutions for AI-driven waste management systems.

3.1. Accessibility and Reliability of Data

One of the major hurdles in utilizing AI for waste management is the inconsistency and poor quality of available data [168], [169]. AI models depend on extensive and diverse datasets to generate precise predictions; however, waste management data is often incomplete, disorganized, or lacks standardization[170], [171]. Moreover, the lack of seamless data integration between stakeholders complicates the development and implementation of effective AI-powered solutions [172].

Data accuracy and consistency are essential for AI's success in this sector. This can be achieved by improving data collection methodologies, establishing standardized data formats, and integrating IoT technologies to enhance monitoring and real-time data acquisition.

3.2. Privacy Concerns

AI applications in waste management involve processing sensitive information, including waste disposal patterns and user-specific behaviors, which raises privacy and security concerns [173], [174]. Protecting this data is crucial to maintaining public confidence and ensuring compliance with regulatory standards[175].

Privacy-preserving methods such as data anonymization and encryption are increasingly being adopted to mitigate these risks. However, concerns regarding data ownership and potential cyber threats highlight the need for more stringent security measures. Effective solutions include the implementation of robust encryption protocols, controlled access mechanisms, and well-defined data governance frameworks[176]. Additionally, IoT devices in AI-driven waste management systems remain susceptible to cybersecurity threats, which could disrupt operations if not adequately protected.

3.3. Financial and Infrastructure Requirements

The deployment of AI in waste management demands substantial initial investments in specialized software, hardware, and supporting infrastructure. One of the main challenges is ensuring cost-effectiveness and compatibility with pre-existing waste management systems [177].

To make AI solutions more accessible, there is a growing need to develop cost-efficient technologies that seamlessly integrate with current infrastructures. Cloud-based and edge computing solutions offer a scalable approach to AI implementation, reducing computational costs and improving processing efficiency[178], [179]. Additionally, emerging advancements such as Quantum AI (QAI) provide revolutionary benefits in project management by addressing high-dimensional complexities. However, challenges like qubit stability and infrastructure costs must be resolved for broader adoption[180].

Nevertheless, certain regions struggle with inadequate digital infrastructure, such as unreliable internet connectivity, which restricts the broad adoption of AI and IoT-based waste management solutions. For small and medium-sized enterprises (SMEs), the financial burden of acquiring AI-powered technologies, including hardware, software, and infrastructure, poses an additional barrier to widespread adoption[181].

Table 4. Summarizing the challenges and limitations of AI in waste management.

Challenges	Description	Key Considerations
Accessibility and Reliability of Data	AI requires large, high-quality datasets, but waste management data is often inconsistent, scattered, or lacks standardization.	Improving data collection, standardizing formats, and incorporating IoT technologies can enhance data reliability.
Privacy Concerns	AI relies on sensitive data, such as waste generation habits, raising privacy and security risks.	Implementing data anonymization, encryption, and strong governance policies is essential to prevent breaches and ensure compliance.
Financial and Infrastructure Requirements	High initial investments in AI hardware, software, and infrastructure pose challenges, especially for SMEs.	Developing cost-effective AI solutions, leveraging cloud and edge computing, and ensuring widespread digital infrastructure is crucial.
Moral and Ethical Implications	AI algorithms may introduce biases, leading to ethical concerns in decision-making processes.	Ensuring algorithm transparency, fairness, and inclusivity through ethical guidelines and frameworks can mitigate biases and improve trust.

3.4. Moral and Ethical Implications

Integrating AI into waste management introduces significant ethical and moral concerns, particularly regarding the potential biases embedded within AI algorithms[182]. Ensuring that AI-driven systems operate fairly, inclusively, and equitably requires the development of well-defined ethical frameworks and guidelines[183].

Enhancing the transparency and interpretability of AI models can assist stakeholders in recognizing and mitigating biases, thereby maintaining ethical standards throughout decision-making processes. Establishing robust ethical principles prevents discrimination and ensures transparency in AI-powered waste management solutions.

Next, substantial opportunities exist to strengthen the synergy between AI and the IoT, refine ML and DL methodologies, and foster increased collaboration among key stakeholders [184], [185]. AI-driven platforms can enable secure data-sharing mechanisms, promoting technological advancements while adhering to privacy regulations[186], [187]. Furthermore, establishing comprehensive policies and regulatory measures will be crucial in facilitating AI's responsible and sustainable implementation in waste management, particularly concerning data security, privacy, and ethical accountability [188].

4. Future Directions and Opportunities for AI-enhanced Waste Management

Integrating AI in waste management presents significant opportunities to enhance efficiency, sustainability, and resource utilization. As AI continues to evolve, innovative approaches are emerging to address persistent challenges in Indonesia's waste management sector.

The combination of AI and the IoT offers transformative solutions by addressing inefficiencies and optimizing waste collection, processing, and disposal [184], [185]. IoT-enabled smart bins with sensors generate real-time data on waste disposal trends, which AI-powered analytics can process to improve decision-making. Predictive models help forecast waste generation patterns, allowing municipalities to refine collection schedules, optimize resource allocation, and minimize operational costs while reducing environmental impact [189]. Additionally, ML-driven automation enhances waste sorting, leveraging advanced image recognition technologies to identify and categorize materials accurately, thereby increasing recycling efficiency and reducing contamination [190].

Real-time monitoring through IoT provides key performance insights, enabling greater transparency in waste management. This allows government agencies, policymakers, and local communities to track sustainability progress and improve waste-handling efficiency. AI-driven smart bins, which transmit data on fill levels, help optimize collection routes, reduce unnecessary pickups, and lower emissions from transportation. AI-powered mobile applications support public engagement by sending collection reminders and promoting recycling initiatives through incentive-based programs.

ML and DL are increasingly crucial in advancing waste management solutions in Indonesia. Sophisticated ML algorithms, including decision trees and support vector machines, have improved waste classification accuracy, reducing contamination in recyclable materials and refining sorting processes. DL techniques, such as CNNs and recurrent neural networks (RNNs), enhance waste identification and classification through image-based analysis [191], [192]. These automated systems reduce reliance on manual labor while increasing efficiency in waste processing facilities. Moreover, ML-based predictive models analyze historical waste generation data to forecast future trends[193]. This allows municipalities to optimize waste collection strategies, allocate resources effectively, and enhance operational efficiency. With waste streams becoming increasingly complex, the ability of AI models to adapt and refine their predictions will be essential in ensuring effective waste management and sustainability initiatives.

Collaboration between stakeholders is vital to overcoming AI adoption challenges in Indonesia's waste management sector. Data inconsistencies, system incompatibilities, and technological fragmentation hinder the seamless exchange of information between government agencies, industries, and researchers [186]. Additionally, concerns regarding data privacy, cybersecurity, and intellectual property rights often discourage sharing critical insights[194]. AI-driven platforms can address these barriers by providing secure and regulated data-sharing frameworks, fostering collaboration, and accelerating technological advancements. Open-source initiatives and digital knowledge-sharing platforms allow industry players to co-develop AI tools customized for Indonesia's unique waste management challenges [186]. Strengthening partnerships among waste management firms, technology developers, and policymakers will facilitate AI adoption tailored to local infrastructure and socio-economic conditions, fostering transparency and building public trust in AI-driven waste management solutions[39].

Advancements in AI-related technologies, such as natural language processing (NLP), offer new capabilities for analyzing large volumes of waste-related data. These innovations support decision-making by identifying waste generation trends, sustainability patterns, and policy impacts. AI-powered robotics also transform waste sorting and recycling processes by enhancing speed and precision in material separation[195]. Additionally, optimization algorithms are being developed to improve waste transportation logistics, reduce costs, and minimize environmental harm.

Despite these technological advancements, ethics, regulatory compliance, and technical feasibility challenges must be addressed to ensure the successful implementation of AI in waste management. Data privacy protection, AI-driven decision-making transparency, and mitigating automated system biases are key concerns. Policymakers must proactively develop regulations that govern AI applications in waste management, establish data security standards, and promote cross-sector collaboration to enhance system interoperability[196].

Establishing clear regulatory frameworks and industry standards is crucial for AI's responsible and ethical deployment in waste management. Policies should address critical aspects such as data protection, fairness, transparency, and accountability to prevent unintended risks such as biased decision-making or violations of individual rights. Indonesian policymakers should develop regulatory guidelines encouraging AI adoption while ensuring data sharing and interoperability across waste management systems. Standardized frameworks will enhance operational efficiency and foster stakeholder collaboration, including government agencies, technology developers, and researchers.

Additionally, AI-driven waste management initiatives must align with sustainability and social equity objectives [107]. This includes assessing AI technologies' environmental impact and ensuring that AI innovations' benefits reach underserved communities disproportionately affected by waste management challenges. Engaging industry experts, waste management enterprises, and community representatives will help policymakers develop well-balanced regulations that promote innovation while safeguarding public and environmental interests [58]. A robust regulatory framework will ensure that AI integration supports Indonesia's broader sustainability goals, leading to a more efficient, transparent, and equitable waste management system. Table 5 outlines the major future directions for integrating AI into Indonesia's waste management sector. It highlights opportunities in smart waste collection, automated sorting, policy-driven decision-making, data sharing, advanced AI technologies, and ethical considerations. These advancements aim to improve efficiency, sustainability, and collaboration while ensuring responsible AI deployment.

Table 5. Key Future Directions for AI-Enhanced Waste Management in Indonesia.

Focus Area	Key Future Directions
Smart Waste Collection	• Use AI-powered predictive models to optimize waste collection schedules and reduce costs. • Implement IoT-enabled smart bins to track waste levels and optimize pickup routes. • Reduce emissions by minimizing unnecessary waste transportation.
Automated Waste Sorting	• Develop AI-driven image recognition for accurate waste classification. • Use DL models, e.g., CNNs, to enhance sorting efficiency. • Reduce contamination in recyclables to improve recycling rates.
AI-Driven Policy and Decision Making	• Utilize AI analytics to identify waste trends and improve sustainability policies. • Enhance transparency in waste management through real-time monitoring. • Implement AI-based decision-support systems for resource allocation.
Data Sharing and Collaboration	• Develop secure AI platforms to facilitate data exchange among stakeholders. • Encourage open-source AI tools tailored to Indonesia's waste management challenges. • Strengthen partnerships between government, industry, and technology developers.
Advanced AI Technologies	• Apply NLP to analyze waste-related policies and trends. • Deploy AI-powered robotics for faster and more efficient material separation. • Optimize waste transportation logistics using AI-based route planning.
Ethical and Regulatory Considerations	• Establish clear guidelines for AI deployment in waste management. • Ensure data privacy, transparency, and accountability in AI-driven decisions. • Align AI adoption with sustainability and social equity goals.

5. Conclusions and Recommendations

Integrating AI and the IoT in waste management presents a transformative opportunity to enhance efficiency, optimize resource utilization, and promote sustainability. AI-driven solutions, such as predictive analytics, smart waste collection, and automated sorting, can significantly improve waste classification, reduce landfill dependency, and advance circular economy practices. Despite these benefits, challenges remain, including data accessibility, privacy concerns, financial constraints, infrastructure limitations, and ethical considerations.

A structured approach is necessary to harness the potential of AI in waste management effectively. First, improving data accessibility and standardizing collection methods are critical for ensuring accurate AI-driven decision-making. Establishing centralized waste management databases and implementing robust data privacy frameworks will enhance predictive modeling and real-time monitoring while addressing security and public trust concerns. Moreover, investment in AI-driven infrastructure, such as IoT-enabled monitoring tools and real-time waste tracking mechanisms, should be prioritized to optimize waste collection efficiency and resource allocation. Collaborative partnerships between governments, technology firms, waste management companies, and research institutions are essential to overcoming barriers and ensuring the scalability of AI solutions.

On a broader scale, AI applications in waste management require continuous advancements in ML algorithms, deep learning-based waste classification, and robotic automation. These innovations can further improve sorting accuracy, recycling efficiency, and cost-effectiveness. Encouraging pilot programs and feasibility studies will provide empirical validation of AI-driven waste management strategies, supporting their large-scale implementation. Beyond technology, ethical and social considerations must be addressed. AI adoption should accompany workforce training programs to enhance professional expertise while mitigating employment displacement risks. Additionally, government policies should ensure equitable AI benefits, particularly for communities facing significant waste management challenges.

A comprehensive, multi-stakeholder approach is essential to fully realize the benefits of AI and IoT integration in waste management. Strengthening regulatory frameworks, investing in digital infrastructure, fostering public awareness, and ensuring cross-sector collaboration will be fundamental for long-term improvements. By adopting smart waste management solutions, global waste management systems can become more sustainable, efficient, and aligned with circular economy principles, benefiting local and international stakeholders.

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