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## Applications of artificial intelligence in urban solid waste management: A systematic literature review

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### Abstract

This research examines the application of artificial intelligence (AI) in urban solid waste management, focusing on innovative solutions that optimize processes and promote environmental sustainability. Through a systematic literature review, recent studies employing machine learning techniques, neural networks, and IoT sensors to transform traditional waste management systems are analyzed. The review covers research published between 2018 and 2025, selected from reputable databases such as Web of Science and Scopus, following PRISMA protocol guidelines to ensure the quality and relevance of the included works. The analysis highlights various areas of AI application, including waste collection route optimization, landfill site selection, supply chain improvement, and automated waste classification. These applications not only reduce operational costs and pollutant emissions but also foster the circular economy through more efficient recycling and material reuse. Additionally, real-time data integration facilitates strategic decision-making for infrastructure planning and resource allocation in complex urban environments. The study synthesizes current technological advances while identifying limitations such as dependence on data quality and availability and the need to expand access to diverse information sources. In conclusion, the incorporation of AI in solid waste management represents a transformative tool that can drive the development of smarter, more resilient, and sustainable cities.

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**Transparency:** The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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### 1. Introduction

Rapid urbanization and population growth have led to an exponential increase in urban solid waste production, representing one of the most critical environmental and public health challenges of our time. Inefficiencies in waste collection, treatment, and final disposal have become a pressing issue requiring innovative and sustainable solutions. In this context, artificial intelligence (AI) emerges as a disruptive tool capable of transforming traditional systems through process automation, predictive analysis, and operational optimization [1, 2].

The application of AI techniques in waste management spans multiple areas, from collection route optimization to automated material classification and landfill site selection. For example, studies have shown that implementing ant colony optimization (ACO) and evolutionary algorithms, such as genetic algorithms (GA), can significantly reduce travel distances, leading to lower fuel consumption and CO<sub>2</sub> emissions [1, 2]. Similarly, machine learning models have achieved high accuracy in identifying optimal landfill locations, minimizing pollution and operational costs [2, 3].

Furthermore, supply chain optimization in waste management has been explored using mathematical models and machine learning techniques, improving waste distribution and enabling more efficient resource planning, thereby reducing environmental impact [4, 5]. Another important research area focuses on waste conversion technology selection, where AI-based predictions have been used to compare various alternatives, identifying processes that reduce reliance on traditional landfills and promote the circular economy [6, 7].

Automated waste classification using computer vision techniques has replaced manual processes with high-precision systems. The use of convolutional neural networks (CNNs) has proven effective in segmenting and distinguishing between biodegradable and non-biodegradable waste, optimizing recycling processes and reducing cross-contamination [8, 9]. Additionally, the integration of IoT sensors and predictive models enables real-time waste generation monitoring, contributing to better infrastructure planning and proactive urban system management [10, 11].

This study is based on a comprehensive systematic literature review, using Web of Science and Scopus as primary sources and following the PRISMA protocol to ensure the quality and relevance of selected studies. The review not only compiles significant advancements in the field but also highlights existing challenges, such as dependence on data quality and the need to integrate diverse information sources [12, 13].

In summary, incorporating artificial intelligence into urban solid waste management offers transformative potential, optimizing processes, reducing operational costs, and minimizing environmental impact. This study establishes a reference framework that, in addition to synthesizing current advancements, encourages future research to overcome existing limitations and expand the application of these technologies in diverse urban contexts [14, 15].

## 2. Methodology

This research adopts a methodological approach based on a Systematic Literature Review (SLR) and a Bibliometric Analysis, following the guidelines established by the PRISMA protocol (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [16]. This combined approach enables a comprehensive analysis of scientific production on AI applications in waste management, facilitating the identification of trends, gaps, and future research opportunities.

**Search Design and Protocol:** The research question was formulated using the PICO model [17, 18]. Considering the following elements:

- P (Population): Urban solid waste management systems.
- I (Interest): AI applications for waste collection, classification, and recycling.
- Co (Context): Urban sustainability and circular economy.

The guiding research question is: *What is the impact of artificial intelligence on urban solid waste management?*

To achieve the study objective, the following research questions (Q) were formulated:

- Q1: What are the publication trends in this field, the most productive journals, and the countries with the highest concentration of studies?
- Q2: What are the main AI applications in waste collection, classification, and recycling, and how do they contribute to efficiency and sustainability?

**Databases and Search Strategy:** Scopus and Web of Science (WoS) were selected for their international recognition in scientific literature indexing [19, 20]. The search covered studies published between 2018 and 2025, considering the increasing adoption of AI-based solutions for waste management during this period.

The search strategy included Boolean operators, wildcards, truncation, and phrase searches, employing specific equations for each database:

- Web of Science: TS=("artificial intelligence" OR "machine learning" OR "deep learning") AND TS=("solid waste management" OR "urban waste" OR "municipal waste") AND TS=("optimization" OR "automation" OR "efficiency" OR "classification")
- Scopus: TITLE-ABS-KEY("artificial intelligence" OR "machine learning" OR "deep learning") AND TITLE-ABS-KEY("solid waste management" OR "urban waste" OR "municipal waste") AND TITLE-ABS-KEY("optimization" OR "automation" OR "efficiency" OR "classification")

**Inclusion and Exclusion Criteria:** To ensure relevance and quality, the following criteria were established:

- Peer-reviewed articles indexed in Scopus and WoS.
- Studies written in English or Spanish.
- Publications from 2018-2025.

**Selection Process (PRISMA Model):** The study selection process followed the PRISMA framework, consisting of four phases:

1. Identification: Initial search results.
2. Screening: Removal of duplicates and studies unrelated to key terms.
3. Eligibility: Full-text evaluation to exclude irrelevant studies.
4. Inclusion: Quality assessment and selection by two experts.

**Bibliometric Analysis:** In addition to the systematic review, a bibliometric analysis was conducted using R software version 4.4.2 [21]. The variables considered included:

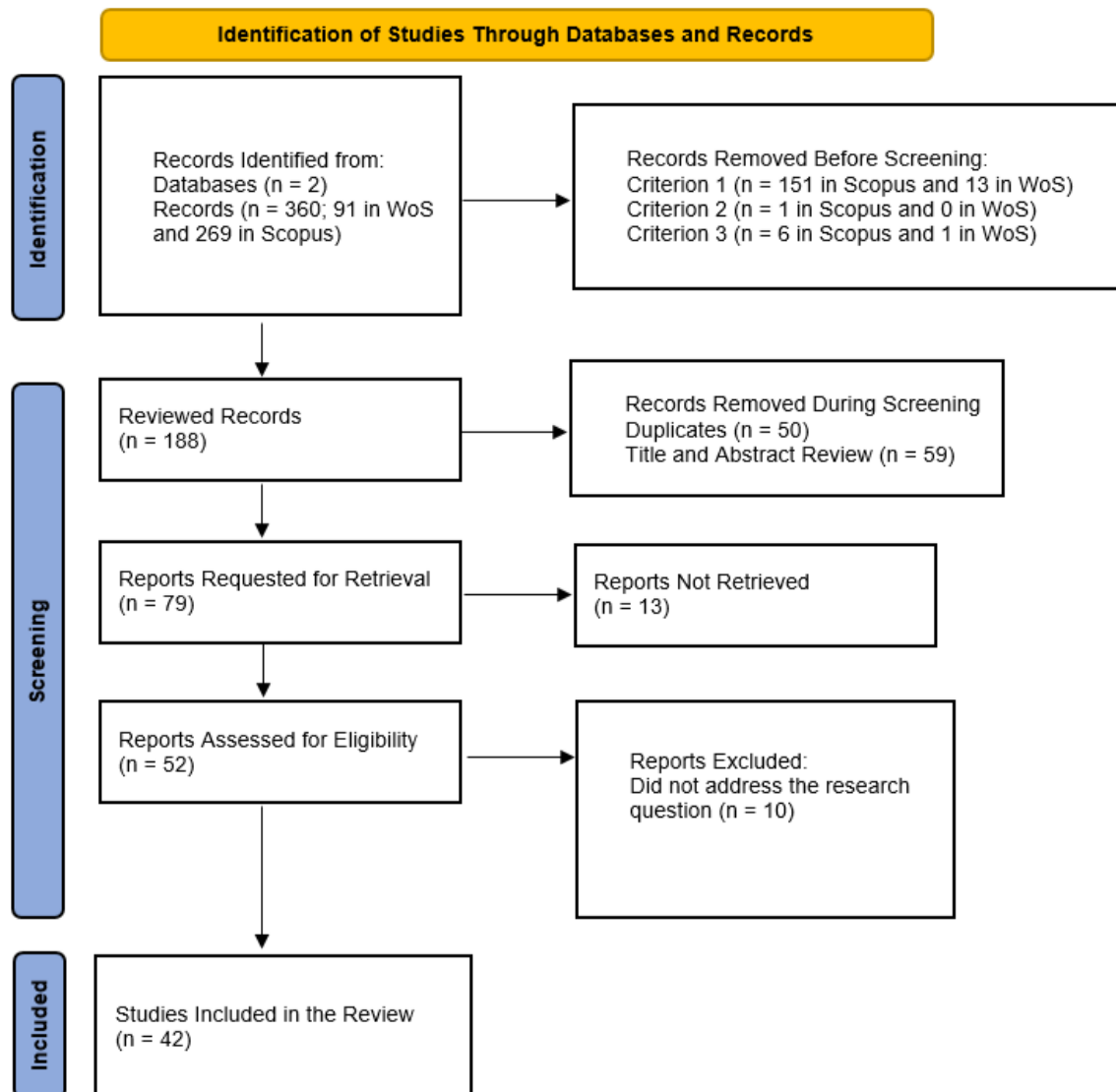
- Annual productivity.
- Most relevant journals.
- Geographical distribution.

Titles were normalized by converting them to lowercase and removing special characters. Duplicate record detection was performed using the `left_join()` function, which efficiently identified matches. Subsequently, title and abstract screening was conducted using the `grepl()` function, facilitating the search and selection of relevant documents.

This methodological approach ensures a robust and comprehensive analysis of the role of artificial intelligence in urban solid waste management, providing a foundation for identifying trends, challenges, and future research directions.

### 3. Results

The initial search was conducted on February 27, 2025, yielding a total of 360 records. During the identification process, 172 records were removed. In the screening phase, 109 documents were excluded. Additionally, full-text access was unavailable for 13 documents. Ultimately, 42 documents were included in this review (Figure 1).



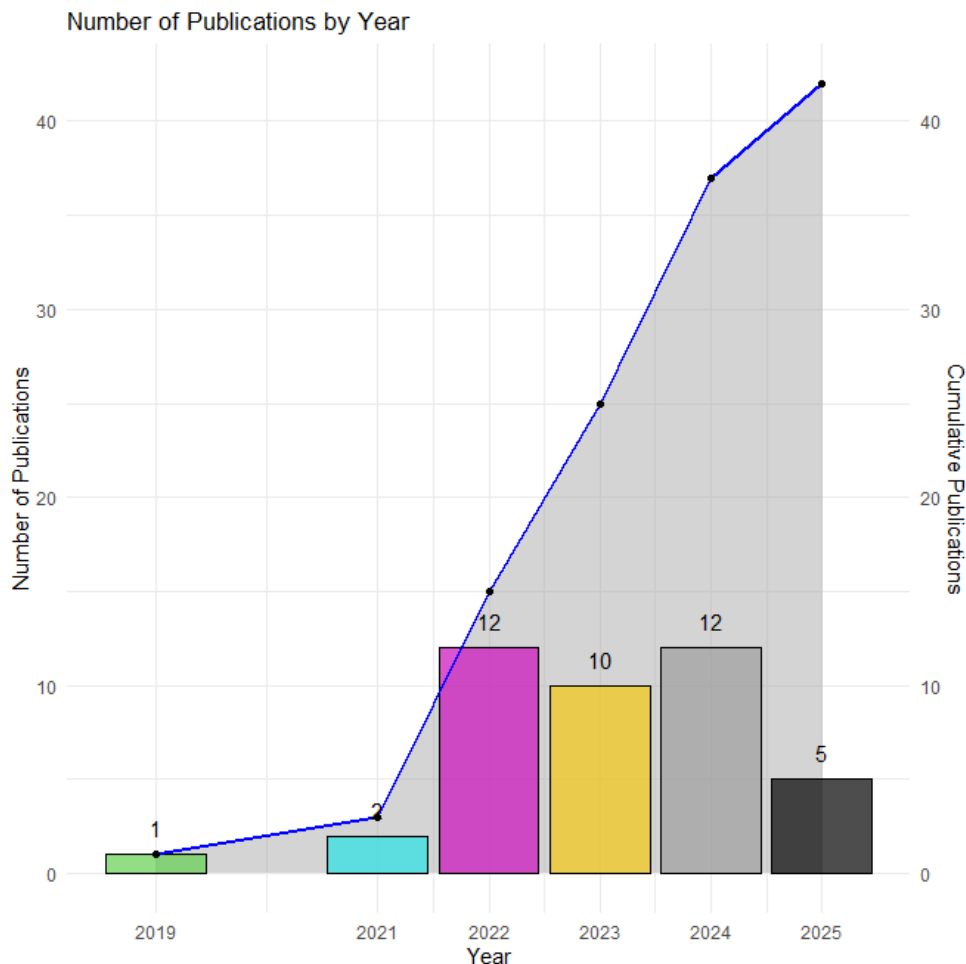
**Figure 1.**  
PRISMA Selection Process.

Table 1, Figures 2 and 3 were created to address research question Q1. Figure 2 shows a growing trend in the number of published studies, reflecting an increase in academic and scientific interest in this topic.

From 2019 to 2021, the number of publications was low, with only one article in 2019 and a slight increase in 2021. However, in 2022, there was a turning point with 12 publications, marking significant growth compared to previous years. This increase could be related to advances in artificial intelligence technologies and their adoption in the fields of sustainability and the circular economy.

In the following years, 2023 and 2024, the number of publications remained relatively stable, with 10 and 12 studies, respectively. This indicates that interest in the application of AI in waste management continues to be relevant and remains on the research agenda. However, in 2025, there is a decrease in the number of publications, with only five studies identified as of the search date (February 27, 2025). This decline may be explained by the fact that the year has not yet ended, so more studies may be published in the coming months.

Additionally, the blue curve represents the cumulative number of publications, showing growth that reaches a total of 42 studies in 2025. The acceleration in recent years suggests a growing interest in the use of artificial intelligence to optimize the collection, classification, and recycling of urban solid waste.



**Figure 2.**  
Evolution of Publications on AI in Urban Solid Waste Management (2019–2025).

The 42 studies selected in this review were published in 34 different journals. Table 1 presents the main journals in which the 42 documents selected for the systematic review on artificial intelligence applications in urban solid waste management were published. It details the number of documents published in each journal and their respective impact factor (IF), allowing for an analysis of the relevance of these sources within the scientific field.

In terms of publication distribution, *Sustainability (Switzerland)* is the journal with the highest number of studies in this field, with a total of three documents. This indicates that the topic of artificial intelligence applied to waste management is closely linked to sustainability. The other journals included in the table each contain two documents, suggesting an even distribution of studies across different academic sources, covering various areas of knowledge such as environmental technology, public health, and expert systems.

The impact factor of each journal is an indicator of its influence within the scientific community. In this case, *Environmental Science and Pollution Research* has the highest IF (1.006), indicating that the studies published in this journal have greater visibility and citations in the field of environmental science. *Scientific Reports*, with an IF of 0.9, is also a prominent source for disseminating applied scientific research. Other journals, such as *Expert Systems* (0.761) and the *International Journal of Environmental Research and Public Health* (0.808), show an intermediate impact, reflecting their importance in research on intelligent systems and environmental health. On the other hand, *Global Nest Journal* has the lowest IF (0.262), suggesting that its impact within the scientific community is lower compared to the other journals included in the review.

The diversity of journals in which these studies have been published indicates that research on artificial intelligence in solid waste management is not yet centralized in a single source but is distributed across different disciplines. The presence of

publications in specialized journals on sustainability, environmental science, and expert systems demonstrates that this is a multidisciplinary field that combines process optimization with sustainability and automation objectives. In conclusion, the publication of these studies in medium-impact journals within the environmental and technological fields reflects that artificial intelligence applied to urban solid waste management is a growing area. The concentration in sustainability and environmental science journals suggests that this line of research aligns with global efforts to improve efficiency and reduce environmental impact through the use of advanced technologies.

**Table 1.**

Most Relevant Journals.

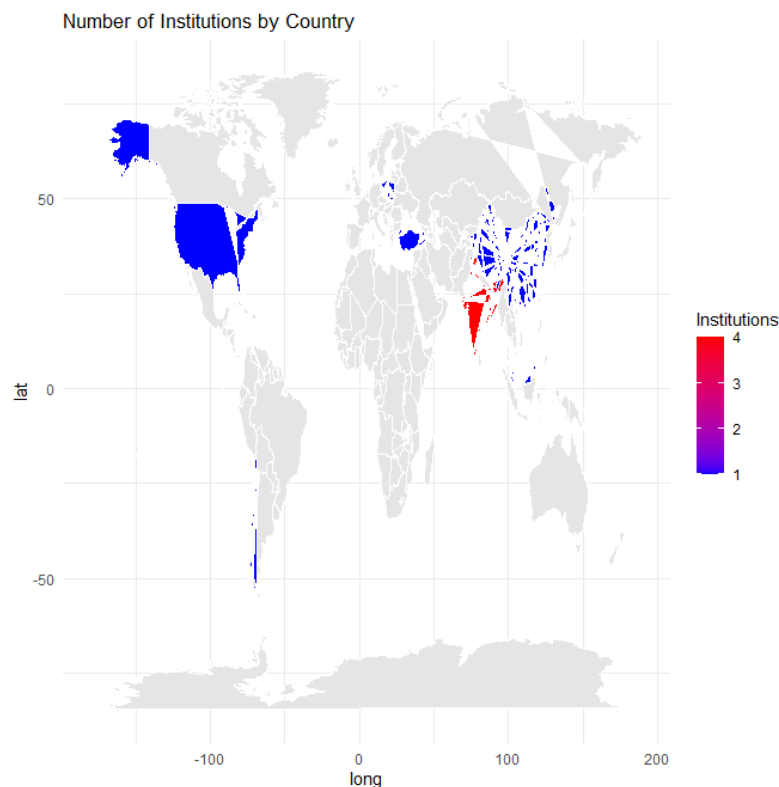
| Source title  | Documents | Impact Factor (SJR) |
|---|-----------|---------------------|
| Sustainability (Switzerland)                                      | 3         | 0.672               |
| Environmental Science and Pollution Research                      | 2         | 1.006               |
| Expert Systems  | 2         | 0.761               |
| Global Nest Journal   | 2         | 0.262               |
| International journal of environmental science and technology     | 2         | 0.598               |
| International Journal of Environmental Research and Public Health | 2         | 0.808               |
| Scientific Reports  | 2         | 0.9                 |

The distribution of studies on artificial intelligence applications in urban solid waste management (Figure 3) shows a significant concentration in India, which leads with four studies. This indicates a high level of interest in AI for optimizing waste management in the country, possibly due to the challenges it faces in urban waste handling, population growth, and the need for innovative technological solutions.

The other countries on the list—Turkey, the United States, Malaysia, the Kingdom of Bahrain, Poland, China, and Chile—each have one study. This suggests that research in this field is being conducted in various regions worldwide, although in a less concentrated manner than in India.

The presence of studies in countries with different economic and environmental conditions indicates that the issue of urban solid waste and the interest in applying artificial intelligence to its management is global. However, the uneven distribution suggests that some countries may be investing more resources in this type of research or facing more urgent challenges in waste management.

In terms of regions, Asia is the most represented in the set of studies, with India, China, Malaysia, and Bahrain contributing to the research. This may be due to the rapid urban growth in these countries and the need for advanced technologies to address the increasing waste generation. America, represented by the United States and Chile, and Europe, represented by Turkey and Poland, also have a presence, indicating an international interest in developing more efficient and sustainable solutions.



**Figure 3.**  
Geographical Distribution of the Reviewed Studies.

Q2: What are the main applications of artificial intelligence in waste collection, classification, and recycling, and how do they contribute to efficiency and sustainability?

Artificial intelligence (AI) has proven to be a key tool in improving efficiency and sustainability in urban solid waste management, with notable applications in waste collection, classification, and recycling. First, optimizing collection routes using advanced algorithms such as Ant Colony System (ACS) and Genetic Algorithm (GA) has allowed for up to a 40.52% reduction in the distance traveled and significantly decreased fuel consumption, contributing to lower CO<sub>2</sub> emissions and operational costs [1]. Similarly, the use of machine learning models has enabled more precise site selection for landfills, achieving up to 91% accuracy in identifying optimal areas for their location, minimizing pollution and optimizing the use of urban land [2].

On the other hand, the optimization of the waste supply chain using machine learning techniques has improved the distribution and collection of waste, reducing costs and enhancing strategic planning [4]. A key aspect of this optimization is the implementation of IoT sensors in monitoring systems, which allow for real-time analysis of waste generation and anticipate collection needs, preventing the accumulation of waste in urban areas and improving service efficiency [4].

Regarding waste classification, the use of Convolutional Neural Networks (CNNs) has proven to be highly effective in differentiating between biodegradable and non-biodegradable materials, improving recycling processes and reducing cross-contamination in waste processing centers [8]. In this regard, computer vision and deep learning have enabled the development of automated classification systems with accuracy above 97%, reducing the need for human intervention and speeding up the segregation of recyclable materials [22].

Another significant advancement has been waste-to-energy conversion, where AI models have facilitated the selection of more efficient conversion technologies. Research has shown that analyzing over 160 technological structures through AI has enabled the identification of optimal processes to reduce landfill dependency and promote the circular economy [23]. Additionally, predicting waste generation through machine learning models and neural networks has improved infrastructure planning, allowing authorities to anticipate waste production and allocate resources efficiently [24].

**Table 2.**

Applications of Artificial Intelligence in Urban Solid Waste Management.

| Author                     | AI Application  | Key Results   | Impact on Efficiency and Sustainability   |
|----------------------------|---|---|---|
| Karabulut, et al. [1]      | Collection route optimization   | 40.52% reduction in travel distance with ACS and 29.81% with GA   | Lower fuel consumption and CO <sub>2</sub> reduction  |
| Mohsin, et al. [2]         | Site selection for landfills  | 91% accuracy with FAHP-RF in identifying suitable sites   | Minimization of pollution and operational costs   |
| Ochoa-Barragán, et al. [4] | Waste supply chain optimization   | Cost reduction and improvement in waste distribution  | Better planning and lower environmental impact  |
| Ali, et al. [23]           | Waste conversion technology selection   | Comparison of 160 technological structures with optimal prediction via AI   | Reduction in landfill dependency  |
| Kodmelwar [8]              | Waste classification with AI  | CNN models identify biodegradable and non-biodegradable waste with high accuracy  | Increased efficiency in recycling and collection  |
| Arthur, et al. [9]         | Intelligent waste monitoring  | Implementation of IoT sensors to optimize collection  | Reduction of CO <sub>2</sub> emissions, reduction of waste accumulation, and improved recycling   |
| Giel, et al. [25]          | Decision-making automation  | Use of AI to predict waste generation patterns  | Route optimization and emission reduction   |
| Wu, et al. [24]            | Waste generation prediction   | Use of ML and neural networks for accurate estimation   | Better infrastructure planning and collection   |
| Belsare, et al. [22]       | Automatic waste classification with computer vision   | Neural networks for segmentation and real-time classification   | Reduction of cross-contamination in recycling   |
| Xia, et al. [26]           | Site selection for waste treatment centers  | Optimized framework using remote sensing data and machine learning algorithms, achieving 92% prediction accuracy  | Improved waste prediction accuracy, optimized site selection, and reduced operational and environmental costs   |
| Sala-Garrido, et al. [3]   | Eco-efficiency assessment in municipal solid waste management using the Efficiency Tree Analysis (EAT) method | Applied EAT to improve eco-efficiency evaluation in waste management in 98 Chilean municipalities, estimating optimal levels of operational costs and unclassified waste, with a potential 43.6% reduction in unclassified waste and an estimated economic saving of 105,973 USD annually | Improved eco-efficiency assessment, reduction of operational costs, and optimization of waste management, promoting circular economy and environmental sustainability                           |
| Wilts, et al. [5]          | Automated municipal waste classification using robotics and AI  | Implemented a robotic system with AI in a municipal waste sorting plant in Barcelona, achieving an average purity of 97% across 13 recyclable materials. AI improved detection and classification efficiency through deep learning  | Increased recyclable material recovery, reduced landfill waste, and improved worker safety and ergonomics by reducing manual waste handling   |
| Cheng, et al. [7]          | Automatic construction waste recognition via aerial images and deep learning                                  | Used the YOLO model to detect construction waste in drone-captured images, achieving 80% accuracy in classifying five types of construction waste (concrete, brick, wood, tile, and steel) with a high recall level (around 0.8)  | Improved identification and classification of construction waste at demolition sites, optimized recycling management, and reduced environmental impact through dynamic and efficient monitoring |
| Banerjee [27]              | Modeling and optimization of biomass conversion processes to bioenergy using AI and machine learning          | Analyzed biomass conversion technologies, including combustion, torrefaction, and dark fermentation. The integration of AI and ML improved efficiency and productivity forecasting in the biomass supply chain  | Optimized biomass conversion process design, increased prediction efficiency, and reduced operational costs in biorefineries  |

|                           |   |   |   |
|---------------------------|---|---|---|
| Canzaniello, et al. [10]  | Urban waste generation prediction using graph neural networks (GNN) and deep learning   | Implemented a model based on graph neural networks to analyze spatial and temporal patterns of municipal waste generation, integrating heterogeneous data such as demographic and geospatial information for accurate waste generation prediction   | Optimized resource allocation for waste management, reduced operational costs, and improved infrastructure planning, contributing to more sustainable urban waste management strategies                           |
| Solano Meza, et al. [11]  | Comparison of support vector machines (SVM) and long short-term memory (LSTM) networks in predicting and managing urban solid waste | Implemented SVM and LSTM models to predict waste generation in a megacity (Bogotá). Results showed SVM offered better fits to training data, with lower error and more consistent regression curves than LSTM   | Improved waste generation prediction accuracy, optimized collection and disposal costs, and better infrastructure planning for urban waste management   |
| Bobulski and Kubanek [12] | Automatic plastic waste classification using convolutional neural networks (CNN)  | Implemented a CNN-based system to classify plastic waste into four categories: PS, PP, PE-HD, and PET, achieving 97.43% accuracy with 120x120 pixel images after 4 epochs of training   | Improved plastic waste segregation to optimize recycling, reduced cross-contamination in sorting plants, and potential application in portable devices for waste separation at the domestic and industrial levels |
| Ali, et al. [6]           | Estimation of benefits and recommendation of waste conversion technologies using the DeMI tool                                      | Developed an interface based on the Decision-Making Integration (DeMI) framework using WEKA software and P-graph to analyze the profitability of municipal solid waste conversion. The tool used the M5P algorithm for benefits estimation and the J48 algorithm for recommending waste conversion technologies | Improved decision-making on waste conversion technologies based on economic benefits potential, optimized resource use, and reduced landfill dependency   |
| Mookkaiah, et al. [28]    | Intelligent municipal solid waste management based on IoT and computer vision   | Developed an automatic waste classification system using convolutional neural networks (CNN) with ResNet V2 architecture, achieving a 19.08% improvement in accuracy and a 34.97% reduction in error rate compared to existing models   | Optimized waste classification, reduced errors in separating biodegradable and non-biodegradable materials, and improved efficiency in recycling and disposal of urban solid waste                                |
| Akkad, et al. [29]        | Cyber-physical systems design for solid waste management focusing on energy efficiency and sustainability                           | Developed a waste management system based on Industry 4.0, incorporating IoT, heuristic optimization models, and digital twins. Two cases in Budapest with 30 and 20 smart containers optimized collection routes using genetic algorithms, particle swarm optimization, and simulated annealing                | Optimized collection routes, reduced pollutant emissions and energy consumption, integrated IoT sensors to improve collection planning and operational efficiency   |
| Ahmed Khan, et al. [30]   | Waste classification in smart cities using federated deep learning  | Compared ten convolutional neural network (CNN) models for automatic waste classification in urban environments. The ResNeXt-101 model achieved the highest classification accuracy (89.62%) on the TrashBox dataset  | Improved waste segregation in smart cities, optimized identification and classification of recyclable materials, and reduced operational costs through decentralized deep learning models                         |
| Lazzari, et al. [31]      | Distribution of urban sludge on agricultural lands through interpolation and machine learning                                       | Used spatial interpolation methods (spline, cubic spline, IDW) with machine learning models (kNN, random forest, neural networks) to analyze sludge distribution in agricultural fields, with the neural network model combined with IDW achieving the highest precision  | Optimized sludge application on agricultural lands, reduced environmental impact, and improved soil nutrient management through predictive distribution models  |



|                              |   |  |  |
|------------------------------|---|--|--|
| Henao-Rodríguez, et al. [32] | Analysis of factors influencing environmental awareness and waste management practices in Bogotá using LASSO regularized logistic regression          | The LASSO algorithm achieved a precision coefficient of 70%. A direct correlation was identified between the number of years individuals have lived in Bogotá and their likelihood to separate waste by 3.2%. Trust in the recycling process increases the probability of waste separation by 62.7%. Availability of recycling containers significantly influences waste separation likelihood, with 81.2% probability that households with a single container rarely separate waste | Improved public policy planning and environmental strategies to promote sustainable waste management practices. Provides scientific evidence to develop environmental education and awareness programs in Bogotá |
| Jassim, et al. [33]          | Municipal solid waste generation prediction   | Used linear regression, time series, neural networks, and SVM algorithms to predict waste generation   | Improved infrastructure planning for waste management with more accurate estimates   |
| Bień [34]                    | Prediction of municipal waste accumulation rate and personal consumption expenditures using the autoregressive vector model (VAR)                     | Used a VAR model to analyze the relationship between waste generation and personal consumption in Poland, achieving 97.7% accuracy with an RMSE of 2.3%. Confirmed that personal consumption expenditures have a direct impact on urban waste generation   | Improved waste management infrastructure planning with more accurate predictions. Allows policymakers to design data-driven strategies for optimizing waste collection and treatment                             |
| Ahmed, et al. [13]           | Prediction of smart bin filling status using deep learning models   | Applied deep learning models (1D CNN, LSTM, GRU, and Bi-LSTM) to smart bin sensor data; LSTM showed the best accuracy with a MAPE of 1.855 and RMSE of 1.579   | Improved waste collection planning, reduced overflow in bins, optimized routes, and better management of municipal infrastructures   |
| Udayakumar, et al. [14]      | Optimization of urban solid waste management through an enhanced particle swarm optimization (IPSO) model combined with deep learning in smart cities | Implemented the IPSODL-MSWM model using SSD object detector and MobileNetV2 based on deep convolutional neural network (CNN). The model achieved 99.45% accuracy in municipal waste classification, showing a significant improvement over previous models   | Allows more accurate categorization of waste in smart cities, optimizes waste collection and separation, and enhances sustainability of urban waste management systems   |
| Gabbar and Ahmad [35]        | Optimization of waste-to-energy conversion process  | Developed an integrated model based on thermodynamic analysis, machine learning, and simulations to optimize bio-oil, biocarbon, and gas production from municipal solid waste   | Improved efficiency in the waste-to-energy conversion process, reduced operational costs, and assessed environmental impact through life cycle analysis  |
| Taweesan, et al. [36]        | Use of clustering algorithms and machine learning in waste collection optimization  | Improved identification of waste generation patterns and optimized collection routes   | Reduced emissions and operational costs in waste management  |
| Joshi, et al. [37]           | Implementation of an intelligent waste management system based on IoT and machine learning  | Developed a real-time monitoring system with IoT sensors and cellular networks for managing smart bin filling in urban areas. Automatic notifications were sent to municipal services when bins reached capacity, optimizing collection  | Improved waste collection efficiency, reduced resource waste, and optimized waste transport. Contributes to sustainability by reducing pollution and improving waste management in urban environments            |
| Vijayalakshmi, et al. [38]   | Optimization of waste management using IoT and deep learning  | Developed a model based on the Elitist Barnacles Mating Optimizer with a Hybrid Deep Learning Model (EBMOHDL-WC) for waste classification in a sustainable IoT environment   | Improved automated waste classification, optimized use of IoT sensors in urban solid waste management, reduced collection costs, and enhanced sustainability of the waste management system                      |

|                              |   |   |   |
|------------------------------|---|---|---|
| Ulloa-Torrealba, et al. [39] | Detection of waste in streets using high-resolution satellite imagery   | Implemented machine learning models for urban waste identification  | Facilitates waste management in urban areas with accurate detection   |
| Singh and Uppaluri [40]      | Prediction and forecasting of urban solid waste generation rate using machine learning models like Decision Tree (DT), Random Forest (RF), and Gradient Boosting (GB) | GB performed best with an $R^2 = 0.99$ and RMSE = 3.01, outperforming DT and RF. Validated correlation between socio-economic factors and waste generation  | Improved waste prediction accuracy, facilitating better planning in urban solid waste management and reducing negative environmental impacts  |
| Al Duhayyim [41]             | Modified cuttlefish swarm optimization (MCSO) with machine learning for sustainable solid waste management in IoT   | The MCSOML-SWM model uses object detection with SSD, feature extraction with MixNet, hyperparameter tuning with MCSO, and classification with SVM, achieving 99.34% accuracy  | Improved waste classification in smart city environments, reducing errors and enabling more efficient and automated urban waste management  |
| Jansi Rani, et al. [42]      | Object detection and classification in solid waste management using Region Proposal Networks (RPN) and the YOLOv5 model   | Implemented Faster R-CNN with ResNet50 and YOLOv5 for multi-object classification in solid waste. YOLOv5 achieved the best mean average precision (mAP) of 0.98 with an IoU threshold of 0.5  | Reduces processing time and improves waste classification compared to previous models, facilitating automation and optimization of solid waste management   |
| Kaya, et al. [43]            | Optimization of deep CNN models for waste classification  | Tested architectures like VGG19, DenseNet169, ResNet101, Xception, InceptionV3  | DenseNet169 with hyperparameter tuning achieved 96.42% accuracy and an F1-score of 96%, improving automatic waste classification  |
| Pitakaso, et al. [44]        | Municipal waste classification system based on AI for waste management in disaster scenarios  | The proposed model outperformed algorithms like VGG19, YOLOv5, and InceptionV3 in classifying urban solid waste, improving by 11.18%. For disaster waste, it achieved 96.48% and 96.49% accuracy, surpassing ResNet-101, DenseNet-121, and InceptionV3 by 3.47% | Significantly improves waste management in disaster contexts, enabling more efficient and rapid classification. Reduces hazardous waste accumulation and enhances sustainability by integrating AI into municipal waste management policies |
| Oyebode and Abdulazeez [45]  | Supply chain optimization in solid waste management using a hybrid Genetic Algorithm and Fuzzy Logic approach   | Optimizes collection frequency and the number of waste containers in Lagos, improving collection efficiency   | Enables more efficient waste flow management, optimizing stakeholder involvement in the supply chain, reducing waste accumulation, and promoting sustainability   |
| Vesga Ferreira, et al. [15]  | Smart Ecological Points for waste classification in Colombia using capacitive sensors and machine learning algorithms   | Developed a Smart Ecological Point prototype with low-cost sensors and machine learning algorithms, achieving efficient classification of recyclable and non-recyclable waste   | Optimizes waste classification at the source, reducing contamination, improving recycling rates, and reducing health risks for workers in the sector  |
| Borzdynski, et al. [46]      | Solid waste analysis using open-access socioeconomic data and machine learning models   | Applied regression and clustering models to predict waste generation in OECD countries  | The Random Forest Regressor (RFR) model showed the highest accuracy in predicting solid waste, achieving an $R^2 = 1$ for municipal and household waste. Identified key correlations between socioeconomic variables and waste generation   |

|                              |   |  |   |
|------------------------------|---|--|---|
| Li and Zhang [47]            | Multi-scale Context Fusion Network for detecting urban solid waste in remote sensing images | Implemented a deep learning detection architecture with spatial attention mechanisms | The model outperformed other approaches in detecting waste in satellite images, achieving 81.8% mAP50 and 65.7% mAP75. Optimized multi-scale feature extraction and fusion, improving waste localization accuracy |
| Rajamanikam and Solihin [48] | Waste classification with AI  | CNN models identify biodegradable and non-biodegradable waste with high accuracy     | Increased efficiency in recycling and collection  |

#### 4. Discussion

The incorporation of artificial intelligence (AI) in urban solid waste management has proven to be a key tool in addressing contemporary challenges related to increasing urbanization and uncontrolled waste generation. In this systematic review, several AI applications were identified that not only optimize traditional collection and classification processes but also promote environmental sustainability and operational efficiency in waste management.

One of the most relevant findings is the impact of collection route optimization, which has been addressed through advanced algorithms such as Ant Colony System (ACS) and Genetic Algorithm (GA). These models allow for a significant reduction in traveled distances, leading to savings in fuel and lower CO<sub>2</sub> emissions, which has been documented in several studies. For example, Karabulut, et al. [1] reported a 40.52% reduction in traveled distance with ACS, implying not only an improvement in operational costs but also a reduction in the carbon footprint associated with waste management. However, despite these advances, it remains essential to consider the geographical and demographic context of cities to maximize the impact of these solutions, as collection routes may vary significantly across urban regions [28].

Automated waste classification through computer vision techniques and convolutional neural networks (CNNs) has also been a significant advancement. These systems allow for precise identification of recyclable materials, which not only reduces human labor but also improves recycling quality by minimizing cross-contamination in processing plants [8]. However, the implementation of these technologies faces challenges, such as the variability in waste types and environmental conditions, which can affect the models' accuracy. While promising, AI models still require further training and adaptation to improve their performance in real-world scenarios, where conditions can vary widely. In this regard, Arthur, et al. [9] highlight the need for constant model adjustment to adapt to the evolving types of waste generated at different times and locations.

Moreover, the use of IoT sensors and predictive models to monitor and predict waste generation in real time has opened up new opportunities for proactive management of urban systems. The integration of real-time data has allowed for better resource allocation and more precise infrastructure planning for collection [10, 11]. However, one of the main challenges lies in the quality and availability of data. As noted by Mohsin, et al. [2] the accuracy of predictive models largely depends on the reliability and quality of the input data. The successful implementation of these systems requires ensuring that IoT sensors are correctly installed and calibrated, and that the data collected is consistent and representative of the urban environment in which they are applied.

The application of AI in waste conversion technology selection has also been highlighted as an important step toward a circular economy. AI models have enabled the evaluation and selection of more efficient waste conversion technologies, such as combustion and fermentation, reducing dependence on traditional landfills and promoting material reuse [23]. This approach contributes to more sustainable resource management; however, as noted by Banerjee [27] and Cheng, et al. [7], the diversity of available technologies and processes still poses a challenge in terms of comparison and standardization. Selecting the right technology must consider not only efficiency and economic costs but also its environmental impact and adaptability to different waste types and local contexts.

Although AI applications in urban solid waste management are promising, limitations and challenges remain that need to be overcome to ensure their successful implementation. The main barrier continues to be the dependence on data quality, as well as the need to integrate heterogeneous data sources to improve the accuracy of predictive models [12]. Furthermore, the adaptability of models to diverse geographical and socio-economic realities remains a challenge, as the diversity of urban environments means that a solution that works in one city may not be effective in another. Therefore, future research should focus on improving data quality and accessibility, as well as developing adaptive models that can adjust to different urban conditions.

Finally, despite technological advances, the large-scale adoption of AI-based solutions also faces economic and social challenges. According to Wilts, et al. [5] initial investments in technological infrastructure and staff training are essential but may represent barriers for many cities, especially in developing countries. Social acceptance also plays a crucial role, as the implementation of AI technologies in waste management may raise concerns about privacy, data security, and employment impact. It is crucial that public policies and regulatory frameworks evolve to facilitate the inclusive and equitable adoption of these technologies, ensuring their accessibility and long-term sustainability.

#### 5. Conclusion

This systematic review demonstrates that artificial intelligence offers transformative potential in urban solid waste management. The identified solutions, based on route optimization, automated classification, and smart monitoring, show significant improvements in operational efficiency and environmental sustainability. These advances suggest that integrating

advanced technologies can contribute to the implementation of more efficient systems and the promotion of the circular economy, adapting to the specific characteristics of each urban context. In general terms, the application of AI in urban solid waste management presents a series of transformative opportunities, but its large-scale implementation faces significant challenges. Data availability, investment in technological infrastructure, social acceptance, and regulatory frameworks are key factors in the consolidation of these solutions. As research in this area progresses, it will be essential not only to improve AI models but also to design strategies to ensure their accessibility, sustainability, and equity in application.

## 6. Limitations

One of the main limitations of this study is the restriction in the bibliographic search, as only the Web of Science and Scopus databases were used. This may have limited the inclusion of relevant studies published in other repositories or in different languages. Additionally, the methodological diversity and the varied approaches of the reviewed studies make direct comparison of results difficult, limiting the generalizability of the conclusions. Finally, the available information on economic aspects and energy consumption associated with the implementation of AI-based solutions is limited, highlighting the need for future research to explore these aspects in greater depth.

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