Clean Technologies and Environmental Policy (2026) 28:123
https://doi.org/10.1007/s10098-026-03476-x

REVIEW

Artificial intelligence application in municipal and port waste management: systematic literature review

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Received: 7 July 2025 / Accepted: 23 March 2026

Abstract

Effective waste management is critical for protecting human health and preserving environmental quality worldwide. Rapid urbanization and increasing waste generation have intensified the need for sustainable and efficient waste handling systems. In recent years, artificial intelligence (AI) has become a transformative technology, providing innovative solutions to improve waste collection, classification, routing, and disposal. These advancements contribute to greater resource recovery, lower operational costs, and reduced environmental impact. This study presents a systematic review of 50 scientific records published between 2014 and 2024, focusing on the waste management chain with a special concentration on AI applications. The review addresses a significant gap in the literature concerning AI-based waste management in port environments by thoroughly analyzing and classifying the waste management process into four key stages: classification, collection/vehicle routing, decision-making, and site selection. Our analysis reveals a diverse range of AI models employed across these stages, highlighting the superior accuracy and performance of many hybrid and advanced algorithms. The review further demonstrates the real-world optimization of waste management processes achieved through AI integration. Additionally, a comparative analysis between municipal and port waste management systems is conducted to explore the transferability and adaptation of successful AI approaches within port contexts. Building on these insights, the study proposes an AI-based framework for integrated port waste management, leveraging lessons learned from municipal systems to address the unique challenges of port environments. This framework aims to boost operational efficiency, sustainability, and resilience in port waste management.

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Graphical abstract

Keywords Port waste management · Solid waste management · Artificial intelligence · Machine learning · Hybrid AI models · Sustainable waste management

Introduction

Waste management has become an important challenge in the contemporary period, especially where environmental issues are amplified due to increasing population, globalization, and intensification of maritime activities. Ports are becoming important trade and transportation hubs that produce many types of waste such as solid, hazardous, along with marine waste. Efficiently managing this waste is crucial to decreasing environmental damage and satisfying local and international legislations such as the International Convention for the Prevention of Pollution from Ships (MARPOL convention) adopted by the International Maritime Organization (IMO) (International Maritime Organization 2022).

Although the role of AI in waste management has garnered much attention in recent years, most advancements have originated from work in the area of municipal solid waste (MSW). For instance, since October 2023, AI-driven tools, including machine learning algorithms for route optimization (Hossain et al. 2020) and computer vision systems for material sorting (Abdallah et al. 2020), have significantly improved operational efficiency and cost-effectiveness. That indicates potential for useful ideas to develop new pathways for AI integration in port waste management.

Generally, port waste processing flow, such as sorting, recycling, and disposal, may be similar to MSW's. However, port waste faces unique challenges, including dealing with international regulations and managing maritime-specific waste streams, such as bilge water, oil residues, and invasive species carried in ballast water (Argüello 2020). Regrettably, little academic research is directly focused on AI's role in port waste management.

Through this paper, we conducted a targeted search for studies specifically addressing the application of AI in port waste management as a systematic review. The search equation included keywords such as "Port Waste," "Artificial Intelligence," "Machine Learning," and "Port Waste Management Systems" to capture relevant studies. This search used the Scopus database, applying Boolean operators and word truncation to refine results.

The search initially yielded 12 articles; however, upon closer examination, it was evident that none of these studies directly addressed the subject of AI applications in port waste management. Instead, these articles focused tangentially on related topics, as shown in Table 1.

While these articles contribute valuable perspectives on environmental monitoring, digitalization, and technology adoption in port contexts, they do not explore AI-driven solutions for waste management. This highlights a significant gap in the literature, necessitating a broader approach that leverages insights from related fields, such as municipal waste management (MWM), where the application of AI is more established, and where the body of research is more robust.

Table 1 Summary of research findings on port waste management

Study	Objective	Key findings
Puig and Darbra (2024)	This review summarizes recent (2022–2024) advances in port environmental monitoring, detailing current techniques, key challenges, and future research paths	European ports are highly active in environmental management, with 92% using monitoring programs for water, waste, air, noise, and biodiversity. Recent innovations include low-cost sensors, mobile tools, eDNA, and smart tech. Efforts now aim to better integrate these tools for improved ecological assessment and impact reduction
Del Giudice et al. (2022)	This study explores how digital technologies can promote sustainable and innovative business models in shipping and ports, aligned with UN Goals 7 and 13. Leveraging business model innovation alongside resilience theory, it identifies models that balance environmental, economic, and social goals, and examines the needed technologies and research trends	Although digitalization is seen as essential for improving sustainability and performance at the ship-port interface, the specific impact of new technologies on sustainable business models is still poorly understood. Adoption remains limited due to regulatory gaps and the absence of industry-wide standards
Brunila et al. (2021)	This study highlights the initial challenges of port digitalization, emphasizing risks such as poor decision-making and system incompatibility, which can result in high costs and inefficiencies. It also investigates how these early issues may evolve into long-term disadvantages and discusses strategies to minimize their negative effects	Small ports encounter major obstacles to digitalization due to fragmented and outdated data, lack of system interoperability, and limited understanding of digital benefits. The continued use of closed systems and the absence of a strategic needs-based approach contribute to uneven progress, leaving these ports vulnerable to lagging in technological advancement
Argyriou and Tsoutsos (2024)	This research explores the key security risks and weaknesses associated with Internet of things (IoT) devices operating within port environments. It aims to assess the critical components involved in IoT deployment within ports, create an integrated approach to risk management customized for the unique challenges of these settings, and explore effective strategies and best practices for mitigating associated risks	This research introduces a framework within port settings of risk management for IoT devices, employing the Operational Risk Management (ORM) methodology. It identifies cyber risk as the most critical threat, with risks such as data breaches, system disruptions, and cyberterrorism scoring extremely high (10.1 on the ORM scale). Additionally, physical hazards from severe weather and environmental exposure contribute to operational delays and safety concerns. The analysis also highlights specific vulnerabilities, including phishing attacks, unsecured Wi-Fi access, and workforce shortages during the pandemic

Insights from MWM can serve as a critical reference point for understanding how AI can be applied to similar workflows in port waste management. Both sectors involve complex logistics, resource constraints, and a need for accurate decision-making, making the transferable potential of AI tools highly relevant. For instance, AI models designed to optimize municipal waste collection routes could be adapted to port environments to streamline waste transport from ships to treatment facilities. Similarly, machine learning algorithms for material recognition in municipal recycling centers could be tailored for port-specific waste streams.

This article aims to bridge this gap by systematically reviewing AI applications in MWM and extrapolating their relevance to port contexts. By identifying transferable methodologies and proposing tailored frameworks, it does not argue for the direct deployment of municipal AI models in ports; rather, it positions MSW as a mature reference domain from which port-specific AI systems can be systematically derived, adapted, and validated; moreover, it seeks to lay the groundwork for future studies and practical implementations of AI in port waste management.

Methodology

Search strategy

We developed a comprehensive search equation using Boolean operators, word truncation, and carefully selected keywords to identify relevant literature for this systematic review. The search was conducted in the Scopus database, focusing on publications from 2014 to 2024. The subject area was restricted to Environmental Science to ensure precision and relevance. And the following keyword combinations were used:

- *Waste Management and AI* ("Waste Management" AND "Artificial Intelligence")
- *Waste Management and IoT* ("Waste Management" AND "Internet of Things")
- *Solid Waste and AI* ("Solid Waste" AND "Artificial Intelligence")
- *Solid Waste Management*

The initial search yielded a total of 3,027 articles. Boolean operators and word truncation were employed to refine search queries, ensuring comprehensive coverage of relevant studies.

Inclusion and exclusion criteria

The following criteria were applied to ensure the relevance and quality of selected articles:

Inclusion Criteria

1. Articles published in English.
2. Studies explicitly focus on waste management processes and their integration with AI.
3. Articles categorized under the subject area Environmental Science in Scopus.

Exclusion Criteria

1. Publications unrelated to waste management or lacking a direct connection with AI or IoT applications.
2. Records focusing on waste treatment processes rather than waste management processes.
3. Records with no access to full-text articles.

Record selection process

After the initial search, a first filtration excluded articles unrelated to waste management, reducing the pool to 367 articles. A second filtration further excluded records that discuss water waste, resulting in 154 articles specifically addressing solid waste management. Additionally, two articles discussing petroleum waste management were identified, bringing the total to 156 articles.

Finally, records (petroleum waste management included) inaccessible due to lack of full-text availability were excluded, reducing the final database to 50 articles. These articles specifically address the use of AI in the waste management process, focusing on municipal systems.

Data from the selected articles were extracted using a standardized template. Key information included:

- Type of AI model used (e.g., machine learning, deep learning, etc.).
- Waste management processes targeted (e.g., collection, classification, etc.).

Artificial intelligence models

Important information was collected, including details about the datasets, the areas where AI was used, the AI techniques used, and how the results were measured, which helped to organize and understand the data better. This review utilized key indicator parameters of AI, such as performance metrics and error measures, to assess and compare the outcomes reported in previous studies (Fig. 1).

The analysis of the selected studies showed that AI is applied across various processes in SWM as shown in Fig. 2. Geographic information systems (GIS), machine learning (ML) algorithms, genetic algorithms (GA) and artificial

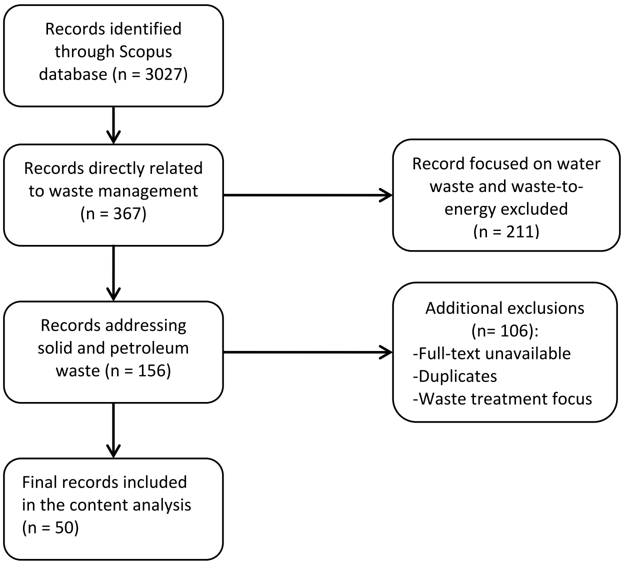

Fig. 1 Flowchart of the records–selection–process methodology according to PRISMA guidelines

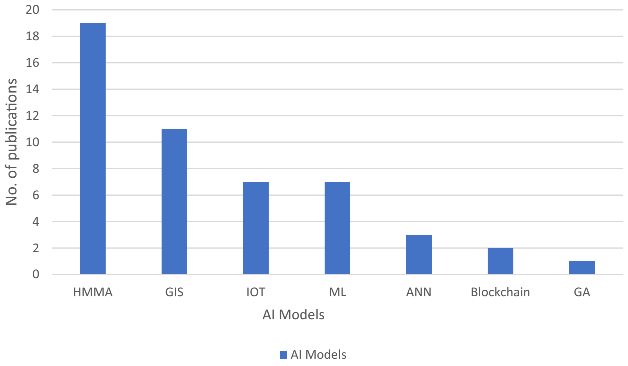

Fig. 2 Number of publications by AI model type

neural networks (ANNs) were among the most recurrent AI models.

ML approaches were employed across classification tasks, including supervised and unsupervised methods like k-means clustering. Regression approaches (RA), particularly linear and multivariate regressions and GA, were frequently used for classification, collection, and supporting decision-making frameworks. GIS-based systems emerged as a key integrative tool, especially in spatial decision-making, route optimization, and site selection processes. Additionally, hybrid and multi-method approaches (HMMA) that combine two or more AI models were increasingly adopted to tackle complex SWM challenges, such as integrated routing, classification, and facility planning. Techniques such as blockchain and IoT technologies have also appeared in multiple studies, contributing to data collection, traceability, and real-time system optimization. Those different methods show that SWM systems are moving toward smarter and more connected working methods.

AI applications in MSW management processes

In this review, 50 studies were analyzed, encompassing contributions from various countries worldwide. India led the research with 10 publications, followed by China with 8 studies. Turkey contributed 5 publications, while Brazil and Malaysia each had 3 studies. Australia, Nigeria, Thailand, and Spain each produced 2 publications. Other nations with single contributions include Iran, France, Greece, United Arab Emirates, USA, Germany, UK, Poland, Peru, Colombia, Saudi Arabia, Italy, and Morocco. This analysis highlights a global effort, with notable contributions from Asia, particularly China and India, alongside meaningful inputs from other regions such as North and South America, Europe, and Africa.

The analysis of the compiled studies identified five major fields of AI application in SWM: classification, collection/transportation, decision-making, and site selection as shown in Fig. 3. These fields illustrate the wide-ranging capabilities of AI in addressing various challenges within SWM systems, optimizing processes, and improving efficiency.

Classification methods were frequently applied to identify and categorize waste types, assess waste characteristics, and analyze waste generation patterns. Techniques such as convolutional neural networks (CNN), GIS, k-means clustering, ML, ANN, and RA were prominently used.

In the collection domain, advanced AI technologies such as blockchain, IoT devices, and GIS were utilized to monitor waste bin levels, optimize collection schedules, and allocate resources efficiently. IoT-enabled systems, in particular, provided real-time monitoring of bin capacities, allowing authorities to reduce unnecessary trips and improve operational efficiency. Blockchain was employed to ensure data security and transparency in the management of waste collection systems.

Transportation optimization, another significant focus area, relied on advanced AI methodologies such as blockchain, GIS, and IoT. They are used to design efficient vehicle routing systems, determine optimal collection frequencies, and minimize fuel consumption. IoT devices provided real-time updates on traffic conditions and waste levels, enabling dynamic route adjustments to reduce delays and costs.

Decision-making in SWM was enhanced by leveraging tools such as GIS, GA, and RA. These technologies were essential in resource allocation, prioritizing waste handling tasks, and optimizing overall waste management systems. For instance, GIS was utilized for spatial analysis and visualization, helping decision-makers assess the geographical distribution of waste and identify critical areas for intervention.

While site selection represents a vital aspect of waste management, also benefited from AI technologies, the GIS was extensively employed to identify the most suitable locations for waste treatment facilities and landfill.

Furthermore, several studies integrated multiple AI techniques to address complex problems within SWM. For example, the combination of different models demonstrated how interdisciplinary approaches could improve the efficiency of waste collection and processing systems. This integration highlighted the potential of AI to provide comprehensive solutions that cover various aspects of waste management; moreover, many studies address multiple stages of the waste management process through unified approaches. Combinations such as classification–collection or collection–transport–decision-making are common, reflecting a tend toward integrated, intelligent systems.

Results and discussion

Waste classification

AI has a progressively significant role in classifying solid waste, providing advanced solutions to enhance recycling efficiency, reduce reliance on landfills, and mitigate associated health risks. A wide range of AI and ML-based approaches are being developed and implemented to automate and optimize waste sorting processes (Table 2).

Results synthesis

The literature reflects a clear and sustained evolution in waste classification models, mirroring a broader paradigm shift in applied AI from conventional ML approaches toward increasingly sophisticated deep learning (DL) and hybrid architectures, driven by the escalating operational and environmental demands of municipal solid waste management (MSWM). Early ML techniques, including support vector machines, random forests, and K-nearest neighbor classifiers, established an essential baseline for automated waste recognition; however, their dependence on handcrafted feature extraction and limited representational depth significantly constrained their effectiveness when applied to high-dimensional and visually complex waste imagery. As waste streams diversified in composition, texture, and contamination levels, these models exhibited weak generalization capacity and high sensitivity to feature engineering choices, restricting their applicability largely to controlled experimental settings rather than operational environments.

The widespread adoption of CNN with architectures such as ResNet-50, MobileNetV2, InceptionV2/V3 (Chen et al. 2021; Hogan Itam et al. 2024; Mookkaiah et al. 2022), and You Only Look Once (YOLO) variants (YOLOv3, DSYOLO-Trash) (Al Duhayyim 2023; Ma et al. 2024) constituted a decisive methodological turning point by enabling end-to-end feature learning directly from raw image data. ResNet-50 gained prominence not solely due to increased depth, but because residual connections alleviated gradient vanishing issues, allowing stable training of deeper networks and facilitating finer visual discrimination across closely related waste categories. This architectural robustness supported the transition from isolated classification systems toward integrated object detection frameworks (Chen et al. 2021; Hogan Itam et al. 2024; Mookkaiah et al. 2022). Nevertheless, a persistent trade-off remains evident between detection accuracy and operational feasibility. Two-stage detectors, such as Faster R-CNN, deliver superior localization and classification precision but impose substantial computational burdens that limit real-time deployment (Ma et al. 2024), whereas one-stage detectors, including YOLO and Single Shot Detector (SSD) variants, prioritize inference speed and throughput at the expense of detailed localization accuracy (Chen et al. 2021; Ma et al. 2024). This contrast reveals an important insight: Algorithmic sophistication alone does not ensure industrial viability, as real-world waste sorting systems must balance accuracy with latency, hardware constraints, and processing scalability.

Recent advances increasingly emphasize optimization strategies and architectural augmentation rather than fundamental model redesign. Automated hyperparameter tuning via metaheuristic algorithms has emerged as a practical response to the inefficiencies of manual experimentation, enabling performance gains that would otherwise be impractical to achieve (Al Duhayyim 2023; Udayakumar et al. 2023). However, accuracy levels close to 99% raise valid concerns about whether these improvements represent real generalization or are mainly the result of increasingly fitting the model to limited datasets, with only marginal practical gains. Similarly, the integration of attention mechanisms and transformer-inspired modules enhances spatial and channel-wise feature prioritization, particularly for small, overlapping, or partially occluded waste objects (Ma et al. 2024). While these enhancements improve robustness, they also introduce increased architectural complexity, higher computational cost, and reduced interpretability, complicating deployment in resource-constrained environments.

Hybrid temporal architectures, such as CNN–GLSTM models, attempt to overcome the limitations of static image-based classification by incorporating temporal dependencies and contextual continuity within waste streams, particularly in conveyor-belt or real-time sorting scenarios. This represents a conceptual advancement toward dynamic perception; however, temporal modeling introduces new sensitivities related to data continuity, sequence length, synchronization,

Table 2 Summary of AI models in the SWM classification literature

Method/Model	Types of waste classified	Dataset used	Key results	References
MCSOML-SWM (Modified Cuttlefish Swarm Optimization)	Glass, Paper, Plastic, Cardboard, Trash, Metal	TrashNet (2527 samples: Glass 501, Paper 594, Plastic 482, Cardboard 403, Trash 137, Metal 410)	Showed enhanced performance of the waste classifier across all training epochs (from 200 to 1000). Average analysis results are provided for 200 and 600 epochs, showing metrics like Accuracy, Precision, Recall, F-score, and Jaccard index Average performance at 200 epochs was: Accuracy 98.42%, Precision 94.85%, Recall 93.47%, F-score 94.09%, Jaccard index 89.07%. Average performance at 1000 epochs was: Accuracy 98.68%, Precision 95.96%, Recall 94.32%, F-score 95.05%, Jaccard index 90.75%	Al Duhayyim (2023)
(ResNet-50 + RPN, Mobilenet-v2 + RPN, SSD)	Recyclable waste (Metal, Paper, Fabric, Glass, Plastic)	Self-built dataset (2000 pictures of typical solid wastes, 500 from the network). Includes 300 pictures with random backgrounds for verification	Transfer learning improves performance ResNet-50 + RPN with transfer learning achieved mAP of 84.1%, AR 90.8%, and APAS and ARAS over 100%, demonstrating effective classification and recognition under non-ideal conditions such as different lighting, object occlusion, and complex backgrounds	Chen et al. (2021)

Table 2 (continued)

Method/Model	Types of waste classified	Dataset used	Key results	References
CNN, DRSN model (Deep Residual Super-resolution Network)	Recyclable waste (Cardboard, Glass, Metal, Paper, Plastic, Household waste)	TrashNet (2527 images)	Data enhancement strategies, with an emphasis on noise addition, greatly increase the accuracy of the model when tested on challenging image datasets. Noise augmentation strengthens the CNN model's capacity to generalize and plays a key role in reducing overfitting. The DRSN model showed remarkable resilience under these noise-enhanced scenarios CNN (no enhancement): test set accuracy 64.56%, CNN (normal enhancement): training set accuracy 98.43%, test set accuracy 74.26% CNN (noise enhancement): training set accuracy 89.57%, test set accuracy 81.78% DRSN (no enhancement): test set accuracy 70.30% DRSN (noise enhancement): training set accuracy 93.52%, test set accuracy 90.32% With noise enhancement, the CNN model's test set accuracy rose from 64.56% to 81.78%, while the DRSN model demonstrated an improvement from 70.30% to 90.32% in accuracy	Chen et al. (2024)
EBMOHDL-WC (Elitist Barnacles Mating Optimizer with Hybrid Deep Learning Model for waste classification), MobileNetv2	Cardboard, Glass, Metal, Paper, Plastic, and Trash	Garbage classification dataset from the Kaggle repository (2467 instances across 6 classes: Cardboard (393), Glass (491), Metal (400), Paper (584), Plastic (472), and Trash (127))	The EBMOHDL-WC technique achieved strong performance on the Kaggle garbage classification dataset, with an average accuracy of 98.04% over 2000 epochs. It recorded precision (93.89%), recall (93.33%), F-score (93.60%), MCC (92.41%), and JI (88.04%). It outperformed MLH-CNN, ResNet-50, VGG16, and AlexNet	Internet of Things Enabled Smart Solid Waste Management System. (2023)

Table 2 (continued)

Method/Model	Types of waste classified	Dataset used	Key results	References
PortiK (computer vision-based solution utilizing deep learning and deep neural networks)	Aluminum can stream	Data is acquired directly by the PortiK device in an operational MRF (Materials Recovery Facility). (7,404 objects, An independent test set of 99 images with 1,308 objects)	PortiK was validated in a real MRF setting, delivering real-time, non-intrusive monitoring. It achieved 91.2% precision and 90.3% recall for aluminum cans, with < 1% undercounting. Precision and recall were 80.2% and 78.4% for contaminants, with a 2.2% undercount. Mass purity estimates had ± 7% error after 5 min, improving to ± 5% after 8 h. Performance was influenced by appearance variability, object overlap, and training data quality, with notable accuracy drift after nine months, especially for contaminants	Cuingnet et al. (2022)
Thermal Imaging Classification	Dry recyclables (Iron, Aluminum, Paper, Stainless steel, Plastic, Wood)	Training dataset (9000 thermograms). Test dataset (1000 mixed thermograms)	Classification relies on the mean and standard deviation of thermogram intensities, identifying four distinct groups (s1–s4) Classification accuracy is in the range of 85–96%. Useful for robotic sorting	Gundupalli et al. (2017)
Hough gradient and FFNN (Feedforward Neural Network)	Bin fill level (empty, medium, full, overflow)	250 images of waste bins captured with a webcam	Waste classification system combining image acquisition, Hough transform-based feature extraction, and neural network classification Useful for resource planning (trucks, bins) and waste management policies	Hannan et al. (2014)
Enhanced CNN	Organic and Recyclable classes	Original dataset (16,378 images) and augmented dataset (33,222 images). Images resized to 150 × 150	The Enhanced CNN model achieved an accuracy of 94.40%, precision of 96.00%, recall of 95.00%, and F1-score of 96.00% It surpasses other tested models (Old CNN, ResNet-50, Inception-V3, VGG-19)	Hogan Itam et al. (2024)

Table 2 (continued)

Method/Model	Types of waste classified	Dataset used	Key results	References
K-means Clustering (Community Behavior)	Related to MSW accumulation patterns based on community behavior. Not a direct material classification	148 observations 24. Based on social indicators: Age, Land use, Population density, Average monthly income, and Consumption patterns	It emphasis that K-means clustering is suitable for the district scale Relevant social indicators include age, land use, population density, average monthly income, and consumption patterns Recommend increasing the number of observations for better results	Izquierdo-Horna et al. (2021)
CNN-GLSTM (Graph Long Short-Term Memory)	Biodegradable (BD) and Non-Biodegradable (NBD). Six categories (Cardboard, Glass, Metal, Paper, Plastic, Organic waste)	Dataset (6437 labeled images). 80% training, 20% test. Images 1280×960	Achieved an average precision of 95.46%, recall of 94.91%, accuracy of 97.55%, mAP of 95.92%, and IoU of 83.13% for the six classes. Evaluated over 500 iterations The training accuracy of the proposed model increased from 94.093% in the first epoch to 96.91% in the last epoch	Li and Chen (2023)
MSWNet (ResNet-50 with transfer learning)	MSW. Four categories (hazardous, recyclables, organic, residual)	58,060 waste images, 11,614 test images	Provide a reference framework for building deep learning models, optimizing learning rates, and reducing high-dimensional datasets to two dimensions The MSWNet model demonstrated superior performance in MSW classification, achieving a sensitivity of 93.50%, a precision of 93.40%, an F1-score of 93.40%, an accuracy of 93.50%, and an AUC of 92.00%	Lin et al. (2023)
DSYOLO-Trash (YOLOv5 + CBAM + CotNet)	Recyclable waste (glass, paper, cardboard, plastic, metal, household waste)	TrashNet (2528 images). MMTrash (self-created, 2332 images, 11,026 labels). Datasets are split 7:3 for training/testing	DSYOLO-Trash achieved state-of-the-art performance compared to other models (SSD, Faster-R-CNN, EfficientDet, YOLO variants) on TrashNet (mAP 97.3%, Recall 93.7%) and MMTrash (mAP 98.5%, Recall 97.3%) A robust solution for superimposed/occluded objects. Integrates attention mechanisms	Ma et al. (2024)

Table 2 (continued)

Method/Model	Types of waste classified	Dataset used	Key results	References
CNN and CNN by the inception of ResNet V2	Classification and waste level measurement. Types include Household, Construction waste, Dry/Wet/Recyclables, and Organic	Various datasets were mentioned, including Kaggle and self-built. It uses a data-driven iterative approach. (23,000 images for training, 1000 images for testing)	Developed and trained a basic CNN and a CNN with the inception of ResNet V2 using transfer learning. Models were trained and tested using the same datasets as the comparison algorithms (ANN, SVM, KNN, DT, NB) CNN with ResNet showed the best accuracy (Average 94.44%) and the lowest loss of 9.26%	Mookkaiah et al. (2022)
IPSODL-MSWM (Improved PSO with Deep Learning) (SDD/deep CNN/IPSO)	Various solid waste types: Household waste, Glass, Paper, Wood, Plastic, and Metal	TrashNet (2527 images)	Achieved optimal precision. Significantly surpasses other compared models (SVM-SWM, BN-CNN, MSWNet (Lin et al. 2023), MCSOML-SWM (Al Duhayyim 2023)) Proposed IPSODL-MSWM framework: Accuracy 99.45%, Precision 96.52%, Recall 98.27%, F1-score 97.62%	Udayakumar et al. (2023)
Street Waste Detection (Imagery)/GIS	Waste on the street	Data from Medellín, Colombia (23.04 km^2 study area). It uses ortho tiles and building footprint data	Evaluates the impact of using building footprint data. Reports OA, PA, and UA for different categories Grouped OA reached 87.08% Focus on detecting waste accumulation, which is correlated with urban poverty	Ulloa-Torrealba et al. (2023)

Table 2 (continued)

Method/Model	Types of waste classified	Dataset used	Key results	References
Smart Ecological Points (Random Forests, Logistic Regression, Neural Network, MLP Classifier, KNN (K = 4))	Recyclable and Organic waste. Sampled types: Plastic, Glass, Metal, Organic	Data collected via sampling campaigns with the MNT (Non-Traditional Model Sensor Prototype sensor) (100 records) Measures capacity and weight	An experimental capacitive sensor (MNT) and load cells are used to measure capacity and weight Different ML models were tested (RF, LR, NN, MLP Classifier, KNN). Capacity and weight are relevant variables. Classifies waste into "White" (recyclable) and "Green" (organic) containers based on Colombian regulations Random Forests: Score: 1.0, Accuracy: 1.0, Recall: 1.0, F1: 1.01 Logistic Regression: Score: 1.0, Accuracy: 0.99/1.0, Recall: 0.96, F1: 0.981 Neural Network MLP Classifier: Score: 1.0, Accuracy: 1.0, Recall: 1.0, F1: 1.01 KNN (K = 4): Score: 1.0, Accuracy: 0.99/1.0, Recall: 0.96, F1: 0.981	Vesga Ferreira et al. (2024)

and training stability. As a result, temporal intelligence remains an emerging capability rather than a fully mature solution in operational waste classification systems (Internet of Things Enabled Smart Solid Waste Management System. 2023; Li and Chen 2023; Udayakumar et al. 2023).

Data availability and quality persist as the most structurally limiting factors across all model families. Transfer learning has become a near-universal strategy to compensate for small and imbalanced datasets, significantly improving convergence speed and baseline accuracy by leveraging knowledge from large-scale natural image repositories. Nevertheless, this approach assumes that features learned from generic imagery are transferable to the highly domain-specific visual characteristics of waste, an assumption that does not always hold in practice. Data augmentation and noise-assisted enhancement techniques further expand dataset diversity and improve robustness under industrial conditions characterized by dust, lens contamination, illumination variability, and motion blur. The demonstrated effectiveness of noise-aware architectures underscores the importance of explicitly modeling environmental disturbances rather than treating them as incidental artifacts (Chen et al. 2021; Lin et al. 2023; Mookkaiah et al. 2022).

The growing adoption of specialized sensing and multimodal systems reflects recognition of the intrinsic limitations of Image-based models (that use only red, green, and blue (RGB) visual information). Thermal imaging and capacitive sensing provide complementary information grounded in physical material properties rather than visual appearance, offering greater resilience under degraded optical conditions. However, these modalities are constrained in classification granularity and operational scope, often necessitating simplified material groupings or controlled deployment conditions. Remote sensing approaches using very high resolution aerial imagery further extend the spatial scale of analysis, shifting emphasis from object-level classification toward urban-scale diagnostics. While valuable for strategic planning and policy assessment, such systems introduce additional challenges related to spectral ambiguity, temporal inconsistency, and contextual misinterpretation (Gundupalli et al. 2017; Vesga Ferreira et al. 2024).

Despite increasing methodological sophistication and impressive experimental metrics, several fundamental challenges remain unresolved. Visual similarity among waste categories continues to confound classifiers, particularly for materials with overlapping textures, shapes, or reflective properties (Al Duhayyim 2023; Chen et al. 2021, 2024; Hogan Itam et al. 2024; Ma et al. 2024; Ulloa-Torrealba et al. 2023). Environmental sensitivity remains a major source of performance instability, as background clutter, occlusion, and contextual noise disproportionately influence model predictions. Moreover, although detection accuracy has advanced rapidly, reliable real-time tracking of waste objects under motion and occlusion remains an open problem (Gundupalli et al. 2017; Ma et al. 2024; Ulloa-Torrealba et al. 2023). The integration of tracking algorithms represents a step toward operational realism, yet it simultaneously exposes the fragility of end-to-end systems when individual components degrade.

Overall, the current generation of waste classification models reflects a field that has reached methodological maturity but has not yet achieved operational closure. Accuracy-focused benchmarks frequently obscure deeper issues related to robustness, adaptability, and scalability, suggesting that future progress will depend less on incremental performance gains and more on systemic integration, realistic data pipelines, and cross-modal intelligence. Addressing these structural challenges is essential for transitioning AI-driven waste classification from laboratory success to sustainable real-world deployment.

Methodological challenges, overfitting, and translational relevance

The reviewed literature consistently exposes persistent and structural methodological limitations, many of which are closely intertwined with overfitting risks stemming from small, imbalanced, or overly simplified datasets. These challenges span across algorithmic architectures, sensing modalities, and application scales, indicating that high reported accuracy alone is insufficient to ensure robustness, generalization, or real-world applicability. A recurring issue concerns the trade-off between accuracy, inference speed, and computational complexity. One-stage detection frameworks, such as SSD and YOLO, are frequently preferred for real-time scenarios, due to their streamlined architectures that bypass region proposal networks, enabling faster inference (Al Duhayyim 2023; Udayakumar et al. 2023). However, this efficiency is often achieved at the expense of mean average precision (mAP), particularly when detecting small, partially occluded, or densely clustered waste objects. In contrast, two-stage detectors, notably Faster R-CNN combined with deep backbones such as ResNet-50, deliver superior accuracy and generalization but remain computationally demanding, limiting their suitability for low-latency or resource-constrained environments (Chen et al. 2021). Deep CNN architectures introduce additional constraints: While models such as ResNet and Inception enhance feature abstraction, they are susceptible to vanishing gradients, loss of spatial detail due to pooling operations, and excessive parameterization (Hogan Itam et al. 2024). In several studies, models appear to rely on specious correlations, such as object orientation, scale, or proximity rather than learning semantically meaningful waste characteristics, raising concerns regarding interpretability and reliability. Highly optimized architectures such as MixNet and DSYOLO-Trash achieve strong performance but require significant computational resources because of large kernels or deep layers, limiting their use on edge devices or low-cost municipal systems (Al Duhayyim 2023; Ma et al. 2024).

Traditional machine learning approaches, such as support vector machines (SVMs), K-nearest neighbors (KNN), and random forests (RF), remain constrained by their dependence on hand crafted features and limited capacity to model high-dimensional visual data, resulting in weak generalization and poor robustness in heterogeneous waste environments (Chen et al. 2024; Lin et al. 2023). Similarly, parametric image-processing techniques, including the Hough transform, are inherently limited to predefined geometric patterns, reducing their effectiveness when confronted with irregular or highly diverse waste shapes (Hannan et al. 2014).

Overfitting emerges as one of the most significant challenges, as many studies rely on small-scale benchmark datasets, most notably TrashNet, with approximately 2,500 images, characterized by clean backgrounds, centered objects, and limited inter-category variability. Models trained on such datasets frequently achieve training accuracies exceeding 95%, yet experience marked performance degradation during testing, reflecting memorization rather than robust feature learning (Chen et al. 2024; Ma et al. 2024). This issue is further intensified by category imbalance, where underrepresented categories, including hazardous or mixed waste, exhibit significantly lower recall and higher misclassification rates (Udayakumar et al. 2023). To address these limitations, transfer learning is widely adopted to compensate for data scarcity and accelerate convergence, although it imposes architectural rigidity and constrains model customization (Chen et al. 2021). Moreover data augmentation techniques, such as rotation, cropping, noise injection, and brightness variation, improve generalization but often remain simplistic and fail to capture the full complexity of real industrial or urban waste scenes (Chen et al. 2024). Advanced regularization strategies, such as noise-assisted learning and Deep Residual Shrinkage Networks, enhance robustness by promoting the learning of invariant features rather than superficial patterns, thereby reducing the gap between training and testing performance. Metaheuristic optimization methods further help mitigate overfitting by automating hyperparameter selection and avoiding local optima, although they introduce greater algorithmic complexity and higher computational demands. Consistently, non-vision-based sensing modalities (thermal imaging and capacitive sensing) naturally reduce overfitting by operating in lower-dimensional feature spaces (Gundupalli et al. 2017; Vesga Ferreira et al. 2024), though this robustness is achieved at the expense of fine-grained material discrimination.

Beyond model architecture, a fundamental gap persists between laboratory validation and real-world deployment; many systems are evaluated under controlled conditions with stable lighting and clean backgrounds, whereas operational MSW environments are characterized by dust, moisture, lens contamination, variable illumination, and continuous motion, leading to unstable performance outside benchmark settings (Hogan Itam et al. 2024; Ulloa-Torrealba et al. 2023). Temporal dynamics are also largely overlooked, as most studies focus on single-frame analysis; while integrations of tracking algorithms such as DeepSORT with YOLO represent progress, they remain computationally intensive and insufficiently explored.

Real-world effectiveness also depends on system-level integration within smart city ecosystems, where waste classification functions as part of a broader decision-support pipeline connected to geographic information systems, global positioning systems, cloud platforms, and communication networks to enable route optimization, demand-driven collection, and policy enforcement (Hannan et al. 2014; Vesga Ferreira et al. 2024). Spatial and temporal generalization remains uneven; aerial and remote sensing approaches provide valuable macroscale diagnostics for illegal dumping and infrastructure gaps but suffer from low temporal resolution, whereas conveyor-based and smart-bin systems deliver continuous data streams with limited spatial coverage (Ulloa-Torrealba et al. 2023). This complementarity underscores that no single model or sensing modality is sufficient for scalable MSWM, necessitating hybrid, multi-scale solutions. Finally, societal, health, and regulatory drivers strongly motivate deployment, as automated classification reduces reliance on hazardous manual sorting and supports compliance with waste separation policies and sustainability objectives. However, misclassification in real-world settings carries tangible economic and environmental consequences, reinforcing the need for deployment-aware designs that prioritize reliability and robustness over marginal accuracy gains.

Waste collection/Vehicle routing

An effective solid waste collection process is a fundamental element of integrated SWM strategies (Islam et al. 2012; Wu et al. 2020). Collection accounts for a majority of SWM costs (Singh and Satija 2018). Poorly coordinated collection schedules and inefficient truck allocation often lead to delays, traffic congestion, and increased operational costs. To address these issues, AI-based smart waste collection solutions are being explored, although the technology remains in development (Abdallah et al. 2020; Król et al. 2016; Popa et al. 2017).

Current studies primarily focus on different stages of waste collection (Table 3), emphasizing the optimization of logistical processes such as vehicle routing, fleet management, and the strategic location of collection points or transfer stations (Amal et al. 2018; Malinowski et al. 2022; Asefi et al. 2019; Vecchi et al. 2016). The use of modern technologies and methods, such as GIS for mapping and analysis (Amal et al. 2018), GA and DL for optimization (Fasano et al. 2021), IoT sensors to track bin levels (Ramson et al. 2021), and blockchain to improve transparency and cost control (França et al. 2020), aims to make waste management more efficient, economical, and environmentally sustainable (Malinowski et al. 2022; Asefi et al. 2019; Fasano et al. 2021).

The strategic objectives of MSWM emphasize resource recovery, landfill reduction, and environmental protection. However, traditional collection practices are increasingly insufficient due to bin overflow, unsanitary conditions, extended collection routes, reliance on driver experience, and escalating operational costs, especially under the expanding requirements for waste stream separation. Effectively, collection/transportation on its own, it may constitute up to 70% of the total costs in waste management systems (Fasano et al. 2021; Ramson et al. 2021; Franco-González et al. 2023; Chaudhari and Bhole 2018; Hu et al. 2024).

To address these inefficiencies, smart collection systems integrating IoT technologies have emerged as promising solutions (Franco-González et al. 2023; Chaudhari and Bhole 2018; Sureshkumar and Pavithran 2019). These systems typically involve deploying sensors designed to track waste bin fill levels, weight, temperature, humidity, and gas emissions, with data transmitted wirelessly to centralized platforms. This real-time monitoring enables dynamic route adjustments compared to static collection schedules, thereby reducing operational time, conserving resources, and lowering overall costs (Fasano et al. 2021; Sureshkumar and Pavithran 2019). Additionally, IoT-based systems (gas sensor) contribute to early hazard detection such as fires inside bins for further safety (Ramson et al. 2021; Franco-González et al. 2023; Prakash et al. 2022; Chaudhari and Bhole 2018; Sureshkumar and Pavithran 2019).

AI can also facilitate multivariate analyses by identifying key infrastructural, social, economic, and demographic factors affecting per capita waste generation, collection efficiency, and cost structure (Fasano et al. 2021; Sureshkumar and Pavithran 2019). The routing optimization has benefited from advanced algorithms like the Improved Ant Colony-Shuffled Frog Leaping Algorithm (IAC-SFLA), which reduces collection distances while improving loading efficiency (Hu et al. 2024).

Algorithms for shortest path routing have also been deployed to assist vehicle drivers (Chaudhari and Bhole 2018), and knowledge-based decision systems utilize historical data to prioritize bin collection (Franco-González et al. 2023). Furthermore, the planning of Municipal Solid

Table 3 Overview of reviewed studies categorized by different AI models and application sub-processes

AI Models/Methods	Stages of waste collection	
	Vehicle routing	Collection
Genetic Algorithm (GA)/SGA/Dijkstra	Amal et al. (2018), Karabulut et al.(2024)	
Spatial Geographic Information System (GIS)	Amal et al. (2018), Karabulut et al. (2024), Rızvanoğlu et al. (2020)	Malinowski et al. (2022)
Linear programming	Rızvanoğlu et al. (2020)	
Mixed Integer Linear Programming (MILP)	Vecchi et al. (2016), Asefi et al. (2019), Mahdavi et al. (2022)	
Lexicographic Optimization (SLO, HLO)/Goal Programming (GP)	Asefi et al. (2019);	
Deep learning		Fasano et al. (2021)
IoT		Franco-González et al. (2023), Prakash et al. (2022), Ramson et al. (2021), Chaudhari and Bhole (2018), Sureshkumar and Pavithran (2019)
Blockchain technology		França et al. (2020)
Optimization Models (Binary Integer Linear Programming (BILP), p-median, CARP, Hierholzer—adapted)	Vecchi et al. (2016)	
Particle swarm optimization and tabu search algorithm (PSO-TS)	Qiao et al. (2020)	
Analytical Hierarchy Process (AHP)		Malinowski et al. (2022), Popa et al. (2017)
Predictive bin distribution algorithm		Prakash et al. (2022)
IoT Platforms/Protocols/Databases (Web platform, MQTT, etc.)		Franco-González et al. (2023), Prakash et al. (2022), Ramson et al. (2021), Chaudhari and Bhole (2018), Sureshkumar and Pavithran (2019)
Basic Ant Colony Algorithm	Karabulut et al. (2024)	
IAC-SFLA (Improved Ant Colony-Shuffled Frog Leaping Algorithm)	Hu et al. (2024)	Hu et al. (2024)
IMMAS (Improved Max–Min Ant System: hybrid augmented ant colony)	Babaee Tirkolaee et al. (2020)	

Waste Collection Points (MSWCPs) has been supported by integrating GIS tools and the AHP, providing robust multi-criteria site selection frameworks that consider social and environmental constraints (Malinowski et al. 2022).

The methodologies employed across the reviewed literature include prototyping of IoT-enabled sensors connected to visualization platforms (Franco-González et al. 2023), application of DL on large datasets to extract insights about influencing factors (Fasano et al. 2021; Ramson et al. 2021; Chaudhari and Bhole 2018), and performance evaluations of routing algorithms such as IAC-SFLA via real-world case studies. Additionally, GIS-AHP frameworks have been utilized for spatial analysis and site selection, and sensor-based pilot programs have been conducted to study waste accumulation patterns and frequency requirements (Malinowski et al. 2022; Franco-González et al. 2023; Hu et al. 2024).

Empirical findings from these efforts demonstrate significant advantages. IoT systems have been shown to enhance operational visibility and reduce both pollution and collection delays relative to conventional systems (Prakash et al. 2022; Chaudhari and Bhole 2018). DL models have successfully identified predictors of waste management efficiency, such as residential building characteristics, service types, and the organic content of collected waste (Fasano et al. 2021). Routing strategies utilizing IAC-SFLA report improvements in collection distance and loading rate compared to baseline ant colony and single-vehicle approaches (Hu et al. 2024). Similarly, GIS-AHP models have proven valuable for site suitability analysis by accommodating various weighted decision factors (Malinowski et al. 2022). Sensor trials revealed consistent fill patterns in high-frequency collection zones and further highlighted waste settlement effects on fill level accuracy (Franco-González et al. 2023).

Despite these advancements, several challenges persist. The widespread deployment of IoT sensors involves significant capital investment, especially for municipal authorities. Technical limitations such as limited battery life, vulnerability to environmental factors, and cybersecurity concerns remain key obstacles (Ramson et al. 2021; Franco-González et al. 2023). Findings suggest that continuous monitoring may be redundant in areas with predictable collection patterns typically associated with high-frequency services. Instead, temporary sensor deployment can be a cost-effective strategy for system calibration and pattern recognition (Franco-González et al. 2023). Moreover, routing optimization frameworks often lack comprehensive integration of cost and constraint factors (Hu et al. 2024).

IoT-enabled solutions demonstrate clear operational benefits when contrasted with conventional systems, especially in scenarios requiring real-time adaptability (Fasano et al. 2021; Prakash et al. 2022; Hu et al. 2024). The GIS-AHP combination further offers a flexible, multi-criteria method for strategic site planning adaptable to local context and stakeholder concerns (Malinowski et al. 2022) (Table 4).

The optimization of vehicle routing for MSW collection is a critical problem in urban logistics, widely addressed as a variant of the Vehicle Routing Problem (VRP), including the Capacitated VRP (CVRP) and the Capacitated Arc Routing Problem (CARP), aiming to reduce operational expenses, time, distance, fuel consumption, and environmental emissions while maximizing efficiency, including loading rates and the number of visited service points. The complexity of these problems, often classified as NP-hard (Vecchi et al. 2016; Rızvanoğlu et al. 2020; Hu et al. 2024), necessitates the application of diverse AI models and optimization methodologies. Metaheuristic algorithms are prominent, such as GA and ant colony optimization (ACO) or ant colony systems (ACS), sometimes employed in improved or hybrid forms, like IAC-SFLA (Hu et al. 2024). GIS-based approaches are also extensively used, particularly utilizing Network Analysis tools, which often incorporate algorithms like Dijkstra for route determination. GIS serves as a powerful tool for data modeling, visualization, and network analysis in waste management (Amal et al. 2018; Karabulut et al. 2024; Rızvanoğlu et al. 2020). Additionally, Mathematical Programming models, including BILP and MILP, are formulated to solve the VRP variants (Asefi et al. 2019; Vecchi et al. 2016; Rızvanoğlu et al. 2020). Some studies adopt sequential or multi-phase approaches combining different models or algorithms; for example, one method proposes three phases using a p-median model for grouping, followed by a CARP-adapted MILP for route optimization, and finally an adapted Hierholzer algorithm for sequencing arcs (Vecchi et al. 2016). The Fleet Size and Mix VRP variant is addressed using multi-objective optimization approaches like Lexicographic and Goal Programming to concurrently minimize transportation cost and optimize load allocation to transfer stations, even though methods like Lexicographic may require higher computation (Asefi et al. 2019).

Comparative studies across the sources demonstrate the significant benefits of these optimized methods over traditional or less sophisticated approaches. Comparisons to real-life routes show notable improvements: ArcGIS Network Analysis achieved distance reductions compared to practical routes (Amal et al. 2018) and reduced travel distance for a 10-point problem from 1377 to 791m (Rızvanoğlu et al. 2020). ACO specifically resulted in a total distance of 16.0262 km, outperforming GIS (22.9616 km) and real-life routes (22.8488 km) in one study (Karabulut et al. 2024). A genetic algorithm (SGA) was shown to be better than practical routes and ArcGIS with Dijkstra in terms of total traveling time, distance, fuel consumption, and truck release, with SGA's traveling distance with a length of 13 km less than practical routes and 1.5 km less than ArcGIS routes (Amal et al. 2018). The superiority of using multiple vehicle types over single types is highlighted, leading to reduced total distance and fewer collection trips, along with increased average loading rates and stops per route; hybrid algorithms also appear promising, with an improved ant colony-hybrid frog-jumping algorithm reducing distance by 34.3 km and increasing average loading rate by 2.33% points compared to a single-vehicle ant colony model in one case (Hu et al. 2024). Overall, despite variations in methodologies and problem formulations (e.g., considering heterogeneous fleets (Asefi et al. 2019; Hu et al. 2024) or multiple depots (Amal et al. 2018; Asefi et al. 2019; Vecchi et al. 2016; Mahdavi et al. 2022)), computational optimization techniques consistently demonstrate substantial environmental and economic benefits in MSW collection routing.

Results synthesis

The reviewed literature indicates a clear methodological shift from experience-based and static planning toward data-driven, algorithmic optimization of MSW collection and routing. Rather than reiterating the NP-hard nature of routing problems, recent studies emphasize the practical implication of this complexity; exact optimization is infeasible at urban scale, making metaheuristic and hybrid frameworks the dominant paradigm. Comparative evaluations consistently demonstrate that hybridized strategies, which combine global search mechanisms with localized path refinement or adaptive heuristics, yield superior performance relative to single-algorithm or purely GIS-based approaches. These gains are manifested in measurable reductions in travel distance, fuel consumption, and collection time, suggesting that routing efficiency is primarily driven by algorithmic integration and problem specific tailoring rather than by the choice of any single optimization technique.

Beyond static optimization, the literature highlights the added value of dynamic, sensor informed routing when operational conditions are highly variable. Integrating real-time bin status information enables demand-responsive collection policies that selectively service bins exceeding defined thresholds, thereby reducing redundant trips and improving resource utilization. However, critical evidence

Table 4 AI model analyses within SW collection studies

Study	Location of the study	Methodology/approach	Technology/tools used	Key results	Specific data/metrics	Specific information
Chaudhari and Bhole (2018)		Development of an Internet of Things (IoT)-enabled system designed to facilitate real-time waste monitoring and provide intelligent route guidance for collection operations	IoT, ThingSpeak IoT Platform	The proposed system provides facilities for monitoring bin status and location and guiding garbage trucks		
Fasano et al. (2021)	Apulia Region, Italy	Deep learning analysis (2008–2018) of 102 factors using cleaned, coded data; model performance assessed (RMSE, MAE) and key factors validated statistically	Deep learning models built in R (Keras); variable importance (vip), ICE plots used for visualization, and results validated with inferential statistics	Deep learning accurately predicted MSW generation, separate collection, and management costs, with key influencing factors varying by region	Apulia's 2018 MSW production was 467 kg/inhabitant (− 24.3% since 2008), with separate collection rising to 51.4% by 2019 and costs increasing by 39.7%. Deep learning models achieved 86.2–94.8% accuracy using robust datasets, with only 1.7% inconsistencies	
Franco-González et al. (2023)	Valencia, Spain (medium-sized city with 800,180 inhabitants in 2021)	The pilot project monitored six waste bins across routes using commercial sensors and an open-access platform, with detailed system setup, experimentation, and results analysis	The system used ultrasonic sensors for bin levels and GPS tracking based on historical data, integrated with a commercial-grade, open-access platform	Bins showed consistent medium-to-high fill levels with linear trends. Sensors were best suited for service calibration in well-managed areas, leading to selective deployment for route optimization	In 2021, Valencia collected 323.7 kg/inhabitant of mixed waste and operated 20,552 bins. Sensor data showed average bin fill levels of 60% at 21:20, peaking at 92% on one day	Citizens often ignored recommended bin-filling schedules. Sensor challenges included battery life, humidity and chemical resistance, and theft or vandalism protection
França et al. (2020)		Design Science Research (DSR)	Blockchain, DSR framework	Blockchain is proposed to improve information integrity and quality assurance in solid waste management		

Table 4 (continued)

Study	Location of the study	Methodology/approach	Technology/tools used	Key results	Specific data/metrics	Specific information
Hu et al. (2024)	Baohe District, Hefei City, China	The study developed an Improved Ant Colony-Shuffled Frog Leaping Algorithm (IAC-SFLA) to optimize municipal waste collection using an extended CVRP model in MATLAB, tested on single- and multi-vehicle cases with population-based waste estimates and multiple runs for reliability	The IAC-SFLA algorithm was implemented in MATLAB using GIS road network data from OpenStreetMap, statistical data from Hefei City Yearbook, and information from online housing websites	Multi-model collection systems reduce MSW costs; using high-capacity vehicles lowers travel distance and trips. IAC-SFLA outperformed the basic Ant Colony algorithm, achieving a 96.83% loading rate and a 995.81 km total route in the Baohe District	Multi-model waste collection cuts costs (50% of waste management expenses). IAC-SFLA improved routes by reducing the distance by 19.76 km and increasing loading rates by 4.15%. In Baohe District, 995.81 km were covered with a 96.83% loading rate over 28 collections. Larger vehicles boosted efficiency; China's average daily waste removal is 1.12 kg/person	Population density was used as the primary factor for estimating waste generation
Sureshkumar and Pavithran (2019)		An IoT prototype monitors bin waste levels and sends data to a central server, which processes it to optimize collection routes	IoT sensing prototype, Internet, Server for storage and processing	The system tracks waste levels and sends data to a server for route optimization. Analysis showed a high organic waste content, indicating biogas production potential		
Malinowski et al. (2022)	Liszki commune is a rural area in Poland	The methodology combines GIS and AHP to identify suitable MSWCPs by mapping zones and evaluating site factors through pairwise comparisons for optimal location selection	GIS (ArcView GIS. 10.2 software), AHP	GIS identified potential MSWCPs sites across buffer zones; larger buffers yielded fewer, larger plots. AHP prioritized sites based on land use, population, and proximity, selecting twelve top sites with over 50% suitability, reflecting flexible criteria due to low environmental impact	Three buffer zones identified 247, 167, and 88 potential MSWCPs sites with larger average plot sizes. Suitable areas covered 37% of the commune; potential sites ranged from 7.1% to 3.8%. AHP prioritized land use, distance to the center, and population density with strong consistency (CI = 0.016, CR = 0.014)	The Not In My Backyard (NIMBY) phenomenon limits the availability of suitable sites close to residential areas

Table 4 (continued)

Study	Location of the study	Methodology/approach	Technology/tools used	Key results	Specific data/metrics	Specific information
Prakash et al. (2022)		The system uses sensor nodes in smart bins to monitor waste level, temperature, humidity, gas, and fire, gathering data from both IoT-enabled and conventional bins	IoT, Smart Dustbins, Sensing sensor nodes, Sensors (waste level, temperature, humidity, CO2, CO, Methane, Fire Detection), LoRa Low Power Wide Area Network (LPWAN)	The study compares IoT-enabled bins with conventional ones, using various waste-related data to ensure effective monitoring of bin conditions	The study compares waste levels in 15 bins, showing lower levels in IoT bins and detailed sensor data (temperature, humidity, CO_2, CO, methane, fire detection) for IoT bins, e.g., Bin 2 with 77.63% fill and specific environmental readings	Emphasizing the importance of low power consumption and extended battery life by configuring the sensing sensor nodes
Ramson et al. (2021)		An IoT-based solid waste management system was developed and tested for bin monitoring, sensor lifespan, wireless range, and system cost	IoT solution, Bin Level Monitoring Unit (BLMU—sensor node), Wireless Access Point Unit (WAPU), Central server, Smart graphical user interface, Self-powered design	The IoT system allows accurate remote monitoring of trash bin levels from a central station and performs reliably in rainy conditions	The Battery Life Monitoring Unit (BLMU) lasts about 434 days and transmits up to 119 m, and the smart-bin prototype costs $107—much cheaper than commercial alternatives. Data is sent every 5 min and tested on an 82.5 cm height bin	

shows that these benefits are strongly context-dependent. In high-frequency service areas characterized by stable and predictable fill patterns, predictive models calibrated on historical data can approximate sensor-driven decisions with comparable accuracy, raising questions regarding the cost-effectiveness and scalability of continuous sensing infrastructures. Importantly, empirical deployments reveal that technical optimization alone does not guarantee operational robustness. Field studies expose vulnerabilities that are often absent from simulation-based assessments, including sensor degradation, maintenance overhead, and data reliability issues, which can undermine long-term system performance. Furthermore, uncertainty in waste generation necessitates a balance between efficiency and resilience; highly optimized routing increases sensitivity to demand fluctuations, whereas conservative strategies inflate operational costs. Social and spatial factors remain underrepresented in many models, despite growing evidence that behavioral resistance, demographic heterogeneity, and land-use constraints materially influence both routing feasibility and system acceptance.

Overall, the synthesized evidence suggests that AI-based collection and routing systems deliver the greatest value when deployed selectively and in alignment with local operational realities. Hybrid optimization frameworks and dynamic routing mechanisms offer clear efficiency gains, but their sustainable impact depends on economic justification, infrastructural reliability, and integration of social considerations. The strongest contributions therefore advocate for balanced operational strategies that combine advanced routing algorithms with predictive analytics and targeted sensing, ensuring that technological sophistication translates into durable, real-world improvements rather than theoretical optimality alone.

Methodological challenges, overfitting, and translational relevance

A cross-study synthesis reveals that methodological limitations and overfitting risks in MSW collection and routing research are structural rather than incidental, arising from persistent tensions between computational tractability, data availability, and operational realism. Although reported performance gains over conventional practices are often substantial, they are frequently contingent on restrictive assumptions, localized datasets, and context-specific calibration choices, thereby limiting transferability across municipalities.

A dominant limitation lies in the widespread use of deterministic formulations that assume fixed waste generation rates, vehicle capacities, and travel times (Amal et al. 2018; Asefi et al. 2019; Vecchi et al. 2016; Mahdavi et al. 2022). While such assumptions facilitate solvability, they systematically underrepresent the stochastic nature of real-world waste systems, where demand variability, traffic uncertainty, and operational disruptions are intrinsic. Even when uncertainty is incorporated, as in fuzzy credibility-based approaches (Babaee Tirkolaee et al. 2020). These approaches introduce additional dependencies through subjective parameterization, notably decision-maker risk preferences and expert-specified membership functions, thereby increasing human bias and reducing reproducibility across institutional and managerial settings.

Hybrid and sequential optimization frameworks further exhibit sensitivity to initial conditions and parameter design. In (Amal et al. 2018), routing outcomes remain bounded by the quality of the initial Smart Routing (modified Dijkstra) solution pool, allowing sub-optimal early solutions to propagate through subsequent GA stages. Similarly, in Vecchi et al. (2016), the final CARP solution is fundamentally constrained by the preceding p-median grouping, with early-stage inaccuracies persisting downstream. Although advanced hybrid metaheuristics such as hybrid ant colony optimization (HA-ACO) (Babaee Tirkolaee et al. 2020) and IAC-SFLA (Hu et al. 2024) attempt to mitigate premature convergence through simulated annealing, multi-operator local search, or parameter design techniques (e.g., Taguchi methods), these enhancements substantially increase algorithmic complexity and calibration sensitivity, shifting the methodological burden from optimization to parameter tuning.

Overfitting manifests in domain-specific forms that extend beyond conventional machine learning contexts. First, many models are validated on spatially constrained or small-scale instances, including 39 collection sites in Sfax (Amal et al. 2018), 105 containers within a single neighborhood (Karabulut et al. 2024), or aggregated node representations (Mahdavi et al. 2022). Performance improvements reported under these conditions, often exceeding 30 to 40%, are likely inflated, as reduced problem sizes fail to capture congestion effects, workforce constraints, and coordination complexities inherent to city scale systems. Exact solvers, demonstrate limited scalability: MILP-based formulations (Asefi et al. 2019; Mahdavi et al. 2022) achieve optimality only after substantial simplification, restricting their applicability to larger, heterogeneous networks.

A second overfitting mechanism arises from case-specific economic and operational parameterization. Inputs such as fuel costs, labor wages, and vehicle acquisition prices (Asefi et al. 2019; Mahdavi et al. 2022) are often derived from local administrative records or interviews, embedding municipal specific economic structures into the optimization logic. While appropriate for localized evaluation, such parameterization necessitates extensive recalibration for deployment in regions with differing cost regimes. Metaheuristic studies similarly rely on finely tuned algorithmic coefficients, including pheromone decay rates and neighborhood search parameters (Karabulut et al. 2024; Hu et al. 2024), whose effectiveness may degrade under alternative urban morphologies, waste generation patterns, or fleet compositions.

IoT-enabled routing systems introduce a distinct form of operational overfitting. Studies such as (Ramson et al. 2021; Franco-González et al. 2023; Prakash et al. 2022; Chaudhari and Bhole 2018; Sureshkumar and Pavithran 2019) frequently validate sensing strategies over short monitoring horizons or limited bin deployments. Behavioral and environmental regularities inferred from these constrained settings such as linear fill rates or stable threshold exceedance, often fail to persist under real-world disturbances, including weather variability, vandalism, sensor drift, compaction effects, and heterogeneous disposal behaviors. This study (Franco-González et al. 2023) explicitly demonstrates this limitation, showing that monitoring strategies effective in residential contexts deteriorate in commercial zones characterized by irregular disposal patterns.

Taken together, these limitations indicate that reported performance gains are often conditional on localized assumptions, short-term observations, and tightly controlled settings. This sensitivity highlights a persistent gap between experimental validation and the complex, disturbance-driven conditions of real municipal waste systems. Nonetheless, when models are grounded in realistic data, operational constraints, and municipal practices, they demonstrate clear potential to move beyond analytical prototypes toward deployable decision-support tools. Accordingly, the reviewed studies indicate that AI, metaheuristic optimization, and IoT-enabled systems are increasingly applicable to real-world MSWM operations. Their practical relevance extends beyond route optimization performance to include the integration of heterogeneous fleets, real road networks, operational constraints, and institutional realities faced by municipalities.

a. Operational Feasibility

A key strength of routing-oriented studies is their grounding in actual road networks and municipal fleets. GIS-integrated models (Amal et al. 2018; Asefi et al. 2019; Karabulut et al. 2024) replace Euclidean distance assumptions with network-based travel distances derived from ArcGIS or Google Maps APIs, accounting for road connectivity, one-way streets, and realistic travel distances. This enhances operational realism and allows generated routes to be directly executable by municipal drivers. Reported reductions in travel time, route length, fuel consumption, and total operational costs demonstrate measurable efficiency gains over experience-based or GIS-only planning. Given that collection and transportation typically constitute 50–80% of MSWM budgets, even modest improvements translate into significant financial savings.

b. *Fleet Heterogeneity and Operational Constraints*

Many approaches explicitly incorporate heterogeneous fleets to reflect real municipal conditions. Studies including (Amal et al. 2018; Asefi et al. 2019; Hu et al. 2024; Babaee Tirkolaee et al. 2020) integrate multiple vehicle types with varying capacities, costs, speeds, and operational zones, essential for cities using mixed fleets such as compactors, tractors, semi-trailers, and residue trucks. Advanced models also consider operational constraints including maximum working hours, landfill distances, multi-trip routing, waste compatibility, and safety regulations, moving AI applications closer to deployable decision-support systems.

c. *IoT-Enabled Dynamic Collection*

IoT-based studies demonstrate a shift from fixed collection schedules to demand-responsive operations. Sensor-equipped bins monitor fill levels, gas emissions, temperature, and humidity, enabling dynamic routing based on actual demand. Benefits include preventing bin overflow and public health risks, reducing unnecessary trips to partially filled bins, supporting driver decision-making via mobile interfaces, and enhancing safety through early detection of fires or hazardous gas accumulation. Importantly, evidence suggests that IoT systems are most effective when deployed strategically, for example, to calibrate predictive models rather than for continuous full-scale monitoring, which aligns well with budget-limited municipalities.

d. *Scalability*

Real-world applicability is reinforced by demonstrated scalability. While exact solvers (e.g., MILP) remain suitable for small instances, urban-scale complexity is effectively addressed using metaheuristic algorithms (GA, ACO, SFLA, hybrid models), providing high-quality solutions within acceptable computation times for networks of dozens to hundreds of collection points. IoT systems scale via cloud platforms, lightweight communication protocols (e.g., MQTT), and modular sensor deployment, allowing city monitoring without requiring sensors on every bin.

e. *Institutional and Socioeconomic Relevance*

Several studies highlight applicability in developing or resource-constrained contexts, where formal waste management is often fragmented. Low-cost hardware, mobile interfaces, and incremental deployment make AI-based systems accessible to municipalities with limited infrastructure. Socially oriented models (França et al. 2020) further demonstrate the potential of these systems to support inclusion, public health, transparency, and sustainability, extending their impact beyond operational logistics.

Decision-making

Effective MSWM requires robust classification systems, optimized collection and routing strategies, and informed, data-driven decision-making. As waste systems grow increasingly complex, integrating environmental, economic, technical, and legislative factors, traditional approaches often fall short in supporting strategic planning. This complexity necessitates using advanced decision-support tools to process large volumes of heterogeneous data, account for uncertainty, and simultaneously evaluate multiple objectives.

In addressing the increasing complexity of MSWM, recent research emphasizes the integration of advanced optimization tools to support data-driven decision-making. This study (Roberts et al. 2018) introduces the Solid Waste Infrastructure Modeling System (SWIMS), a dynamic, nonlinear life cycle-based optimization tool that integrates environmental and economic criteria to guide infrastructure planning. Using a GA and depth-first search within a life cycle assessment framework, SWIMS simulates treatment scenarios over time and space, identifying infrastructure needs while optimizing environmental and financial performance. The results of a UK case study demonstrate that existing and planned infrastructure may meet future demands with limited additional investment, making it an effective decision-support tool for national policy planning. Similarly, this study (Ali et al. 2022) proposes a hybrid framework combining Process Network Synthesis (PNS) and ML to optimize MSW conversion technologies in Malaysia. The P-graph model generates over 100 feasible waste-to-energy pathways, while ML (particularly the multilayer perceptron) is used to identify optimal strategies with high correlation performance ($R^2 = 0.7169$). This approach demonstrates flexibility and accuracy in generating adaptive solutions even with minimal data, supporting strategic planning under uncertainty. Further this research (Sornil 2014) contributes by applying a graph-based multi-objective GA (NSGA-II) to optimize MSWM in Thailand, minimizing cost and landfill volume. The model accommodates diverse scenarios and constraints, and its case application in Saraburi province outperformed current practices. Moreover, this study (Oyebode and Abdulazeez 2023) employs a hybrid fuzzy logic–GA approach to improve Lagos, Nigeria's waste management supply chain. Based on real-world data from four Local Government Areas (LGAs), collected through field observations and stakeholder interviews, their model incorporates variables such as collection frequency, number of bins, disposal method, and price sensitivity. The fuzzy inference system calculates solution fitness, which the GA optimizes to deliver area-specific recommendations. This approach improves logistics efficiency and reflects behavioral and economic drivers of waste management in dense urban contexts.

Additionally, this study (Batur et al. 2020) by the ALOMWASTE, a novel mixed integer linear programming model, introduces a robust MILP-based framework for long-term MSWM planning by addressing one of the field's most persistent modeling barriers: the nonlinear formulation of mass balances involving multiple waste inputs. By designing each processing node with hypothetical sub-nodes, ALOMWASTE eliminates the need for nonlinear constraints and allows unrestricted mass flow modeling across six interrelated decision layers: collection, process selection, waste allocation, transportation, site selection, and capacity assessment. Applied to a 25-year case study in the Umraniye district of Istanbul, the model generated an optimized infrastructure plan comprising transfer stations, Materials Recovery Facilities (MRFs), composting units, incinerators, and landfills, with a projected profit of over €1.35 billion. It further integrates technical constraints (e.g., calorific thresholds for incineration, landfill capacity limits) and delivers comprehensive outputs, including facility locations, sizing, and material flow routing. Beyond its optimization performance, ALOMWASTE reduces structural uncertainty in decision-support tools and strengthens the modeling basis for future life cycle assessments.

Collectively, these models illustrate how integrating AI, optimization algorithms, and real-world data can support decision-making across multiple scales, from national infrastructure forecasting (SWIMS), adaptive technology planning (PNS-ML), and trade-off optimization (NSGA-II), to localized operational strategies (fuzzy-GA) and full-system, multilayer integration (ALOMWASTE) (Fig. 4).

Results synthesis

Building on the need for advanced decision-support tools highlighted above, the synthesized literature demonstrates that AI-driven decision-making frameworks significantly extend the strategic scope of MSWM beyond static and single-objective planning paradigms. Rather than seeking a single optimal configuration, contemporary models increasingly frame MSWM as a multi-objective problem characterized by structural balancing between economic efficiency, environmental performance, and system resilience. In this context, evolutionary optimization techniques, particularly GA and their multi-objective extensions, play a central role by generating Pareto-optimal solution spaces that explicitly expose these trade-offs. Such representations support informed strategic judgment and consistently outperform conventional planning approaches by achieving simultaneous reductions in cost and environmental burden.

Complementing optimization-based planning, ML predictive models enhance upstream decision reliability by improving waste generation, cost, and performance forecasting. The reviewed studies indicate that nonlinear learners, especially neural network architectures, are more effective than linear models in capturing the complex and heterogeneous drivers of waste generation. This predictive advantage is critical, as forecasting errors propagate through planning decisions, directly affecting infrastructure sizing, investment sequencing, and technology selection. As such, improved predictive accuracy strengthens the overall robustness of long-term MSWM strategies.

The literature further highlights the importance of hybrid and qualitative modeling frameworks in addressing decision contexts where uncertainty and subjectivity are unavoidable. Fuzzy logic-based systems enable the structured integration of expert judgment, social considerations, and regulatory ambiguity into formal optimization processes, while graph-based formulations expand decision support by systematically exploring feasible system configurations across interconnected treatment pathways. These approaches shift MSWM analysis from isolated technology assessment toward holistic system design, revealing solution structures that may remain inaccessible under conventional modeling assumptions.

From a strategic perspective, AI-driven decision-support tools are increasingly positioned as instruments for policy exploration rather than purely technical optimizers. Dynamic planning platforms enable scenario analysis, phased investment evaluation, and assessment of policy interventions, supporting governance in MSWM. Nonetheless, their strategic value ultimately depends on the realism of model assumptions and the transparency of their outputs. Without adequate representation of operational disruptions, behavioral responses, and contextual constraints, analytically optimal solutions may lack practical resilience.

Methodological challenges, overfitting, and translational relevance

Despite the growing analytical sophistication of AI-based decision-support frameworks, the reviewed studies consistently reveal methodological limitations that constrain their transferability and operational robustness. A central limitation concerns strong context dependency. Optimization models such as P-graph-based frameworks demonstrate high sensitivity to regional characteristics, including waste composition, population density, economic conditions, and technological feasibility. As shown by Ali et al. (2022), models calibrated for European systems proved unsuitable for Malaysian conditions without extensive recalibration, a pattern similarly observed by Sornil (2014), where optimized solutions were tightly coupled to local economic and material parameters. This limits the direct reuse of otherwise effective frameworks across regions.

Structural constraints within mathematical formulations further restrict model generality. Classical MILP-based approaches encounter difficulties in representing nonlinear mass balances when multiple waste streams interact across treatment processes. To preserve linearity, earlier models often rely on predefined scenarios or restricted decision pathways, resulting in scenario-based optimization that excludes potentially feasible future configurations (Sornil 2014). Although the ALOMWASTE model addresses this limitation through sub-node decomposition (Batur et al. 2020), however, it remains deterministic and single objective, excluding social impacts and uncertainty propagation.

Algorithmic limitations are also evident in metaheuristic-based decision frameworks. GA, as applied in Roberts et al. (2018), Sornil (2014), Oyebode and Abdulazeez (2023), becomes computationally demanding as problem of dimensionality increases and remains sensitive to parameter settings. These characteristics increase the risk of premature convergence toward local optima and complicate practical deployment, particularly when decision spaces expand to include additional technologies, facilities, or policy constraints.

In fuzzy-logic-based systems, subjectivity constitutes a core methodological weakness. Membership functions and linguistic variables depend heavily on expert judgment, as demonstrated in the Lagos case study (Oyebode and Abdulazeez 2023). While this enhances interpretability in data-scarce environments, it embeds normative assumptions that are difficult to validate empirically and reduces reproducibility across different urban contexts.

Model scope limitations further reduce fidelity to real operational systems. Several frameworks exclude detailed routing, spatial facility coordinates, capital goods environmental impacts, or dynamic vehicle fleet transitions, as observed in SWIMS (Roberts et al. 2018) and related optimization studies. These omissions are often driven by data scarcity rather than conceptual oversight, but they constrain the realism and policy relevance of model outputs.

Data limitations amplify these challenges across all modeling approaches. In predictive components, limited or locally constrained datasets increase the risk that models capture coincidental relationships rather than stable system dynamics, as evidenced by the performance variability reported by this study (Ali et al. 2022). In MILP-based frameworks, this risk manifests as sensitivity to long-term assumptions regarding population growth, waste generation, and technology efficiency over multi-decade horizons (Sornil 2014; Batur et al. 2020). Hybrid GA–Fuzzy systems further compound these issues through reliance on small qualitative datasets and localized calibration, necessitating separate inference systems for each administrative unit

(Oyebode and Abdulazeez 2023). Similarly, large-scale dynamic models (e.g., SWIMS) extrapolate short historical trends over extended planning horizons, introducing risks of temporal over-calibration (Roberts et al. 2018).

These limitations indicate that while AI-driven decision-support tools offer substantial strategic value, their effectiveness depends critically on contextual calibration, data quality, and transparent treatment of uncertainty. Without these safeguards, analytically optimal solutions may reduce robustness when confronted with real-world operational variability and evolving policy conditions.

From a practical perspective, the real-world value of AI-driven decision-support models in MSWM depends less on theoretical optimality and more on their capacity to structure complex planning problems under uncertainty. Models demonstrate impact when used to explore feasible alternatives, quantify trade-offs, and inform policy, rather than to prescribe fully automated solutions.

The P-graph framework (Ali et al. 2022) illustrates strategic-level applicability, generating large sets of feasible treatment pathways from minimal input data. Despite sensitivity to regional context and data quality, it supports early-stage planning and stakeholder consultation, particularly in data-constrained developing systems. MILP-based approaches (Batur et al. 2020), provide high operational realism and scalability, addressing hierarchical system structures including collection, site selection, transportation, and capacity planning, solving million-constraint problems within feasible computational times.

Hybrid GA–fuzzy logic models (Oyebode and Abdulazeez 2023) excel in socioeconomically heterogeneous urban contexts, integrating qualitative insights, informal actors, and localized operational constraints, though requiring unit-specific recalibration.

Collectively, these studies indicate that high real-world relevance arises when models function as decision-support tools rather than autonomous optimizers, account for local data and institutional capacity, facilitate scenario exploration, and deliver outputs interpretable by human decision-makers. Their primary contribution lies in enhancing transparency, reducing planning uncertainty, and enabling evidence-based decision-making, rather than producing universally optimal solutions.

Site selection

The process of selecting landfill locations is a crucial and complex aspect of MSWM, involving a multitude of spatial, environmental, and socioeconomic criteria. This study (Liu et al. 2014) addresses this challenge by integrating fuzzy logic and the extended VIKOR method, offering a robust multi-criteria decision-making (MCDM) framework that accommodates subjective human judgment using linguistic variables transformed into trapezoidal fuzzy numbers. Their model enhances decision-making by incorporating the Ordered Weighted Averaging (OWA) operator to reflect decision-makers' preferences, ultimately applied to an empirical case in Shanghai. Similarly, Paul and Ghosh (2022) proposes a Fuzzy Analytic Hierarchy Process (F-AHP) combined with Weighted Linear Combination (WLC) within a GIS environment to evaluate 17 spatial parameters across geomorphological, lithological, hydrogeological, and socioeconomic groups for landfill suitability in the Kolkata Metropolitan Area. His study concludes that only 9.64% of the area is highly suitable, underlining the urgency for strategic planning. Moreover, this study (Kamdar et al. 2019) further extends GIS–AHP methodology, emphasizing the integration of geospatial datasets to identify optimal sites in India based on criteria such as slope, land use, groundwater depth, and proximity to roads or habitations. Reinforcing these findings, Bilgilioglu et al. 2022; Malo et al. 2024 also illustrate the application of GIS-based AHP for siting landfills in Turkey and India to address the inadequacy of existing landfills and guide systematic site selection, respectively. Bilgilioglu et al. 2022 find that only 19.12% of Mersin province is suitable for landfill use, with many existing sites located in exclusion zones, while Malo et al. 2024 report that just 0.65% of the Balurghat municipality meets high suitability standards. Both studies highlight the effectiveness of combining GIS with AHP for transparent site selection, integrating critical exclusion and evaluation criteria such as groundwater vulnerability, fault proximity, slope, and land use. Each study highlights the significance of applying spatially enabled, fuzzified decision-support systems to reduce environmental risk, ensure regulatory compliance, and foster public acceptance.

Results synthesis

Building on these GIS–AHP applications, a broader analysis of site selection in MSWM underscores that the challenge is inherently a MCDM problem, demanding the reconciliation of environmental, technical, economic, and social considerations. Across the literature, structured frameworks such as AHP, Fuzzy-AHP, and VIKOR dominate, providing a systematic means to translate heterogeneous and often conflicting criteria into defensible spatial decisions. The integration of these methods with GIS transforms them into spatial decision-support systems (Fig. 5), converting abstract criteria (slope, proximity to infrastructure, land use, hydrology, and residential buffers) into tangible, map-based evaluations that reveal balance and guide site prioritization.

The analysis further highlights that the choice of MCDM model shapes how uncertainty, subjective judgment, and social resistance are addressed. Conventional AHP excels in structuring complex problems but assumes fully rational decision-makers, limiting its ability to capture real-world ambiguity. Fuzzy-AHP and Fuzzy-VIKOR overcome this limitation by incorporating linguistic variables and fuzzy numbers, reflecting expert perceptions more faithfully, while VIKOR's compromise-focused solutions prove particularly effective in socially sensitive contexts by mitigating opposition to technically optimal sites.

Thus, the convergence of GIS and MCDM provides a robust framework for evidence-based site selection, particularly in regions where informal or opportunistic practices dominate. When applied with high-quality data, rigorous expert input, and methodological transparency, these models advance beyond technical optimization, functioning as governance instruments that balance environmental protection, operational efficiency, and social acceptability in MSWM planning.

Methodological challenges, overfitting, and translational relevance

Despite their widespread use, GIS-integrated MCDM models for landfill site selection reveal systemic methodological constraints that undermine the robustness, transferability, and evidential strength of their outputs. A primary limitation is the strong reliance on expert-driven weighting schemes, particularly in AHP- and F-AHP-based frameworks (Paul and Ghosh 2022; Kamdar et al. 2019; Bilgilioglu et al. 2022; Malo et al. 2024). Although consistency checks reduce random error, they cannot eliminate structural subjectivity, leaving suitability maps closely tied to the expertise, disciplinary background, and assumptions of a narrow group of decision-makers. Consequently, the resulting solutions may reflect preference alignment rather than objective environmental optimality.

A further constraint arises from hierarchical and criteria sensitivity. Minor changes in criteria hierarchy, weight allocation, or exclusion buffers can substantially shift the spatial distribution of suitable zones (Kamdar et al. 2019; Bilgilioglu et al. 2022), raising concerns over reproducibility and policy defensibility. This fragility is amplified when critical datasets (subsurface hydrology, seasonal wind patterns, or contaminant transport pathways) are unavailable or omitted (Paul 2022; Malo et al. 2024).

Although these models are not classical machine learning systems, they exhibit overfitting-like behavior, excessively adapting to small expert pools and localized datasets. Studies relying on fewer than ten experts for pairwise comparisons or fuzzy membership definitions demonstrate that outputs can be disproportionately shaped by subjective input (Liu et al. 2014; Kamdar et al. 2019). For instance, this study (Liu et al. 2014) shows that adjustments in attitudinal parameters can reorder site rankings significantly, highlighting sensitivity to subjective tuning rather than stable environmental signals.

Spatial data limitations further amplify these vulnerabilities. The integration of heterogeneous datasets with generalized geological or land-use maps exceeding 1:500,000 can obscure microscale risk factors while creating an illusion of precision at the macroscale (Bilgilioglu et al. 2022; Malo et al. 2024). In addition, fuzzy-based extensions remain sensitive to parameter changes, and early defuzzification can oversimplify complex uncertainties (Liu et al. 2014).

Despite inherent methodological sensitivity and data limitations, GIS-integrated MCDM frameworks demonstrate significant real-world utility when applied as structured decision-support systems rather than deterministic siting tools. Their value lies in enabling transparent, evidence-based screening of candidate locations while systematically integrating environmental protection, regulatory compliance, and social acceptance.

This study (Bilgilioglu et al. 2022) illustrates this operational relevance by assessing existing disposal facilities, identifying compliance failures linked to proximity to settlements, fault zones, and protected forests. This retrospective validation underscores these models' capacity for regulatory auditing and risk reassessment of infrastructure, particularly in contexts with heterogeneous or incomplete datasets.

Extensions using Fuzzy MCDM and VIKOR further enhance practical applicability by targeting compromise solutions rather than purely optimal ones, accommodating uncertainty through linguistic variables and supporting decision-making in real-world governance settings (Liu et al. 2014).

Recent studies integrating GIS, AHP, and validation mechanisms demonstrate that hybrid approaches bridge theoretical suitability mapping with ground-truth conditions, ensuring sites are both technically viable and socially acceptable (Malo et al. 2024). Likewise, the F-AHP and WLC application in Kolkata confirms that regulatory alignment, empirical verification, and computational efficiency enable implementable planning outcomes, particularly in resource-constrained urban regions (Paul and Ghosh 2022).

Multidimensional decision and monitoring frameworks in waste management

The increasing complexity of MSWM has led to a growing interest in research that integrates multiple stages of the waste management life cycle within an unified analytical framework. Rather than focusing solely on isolated components such as classification, collection, or site selection, these works aim to link two or more stages, e.g., combining decision support with spatial siting analysis or merging waste characterization with collection optimization. This multistage approach allows for a more holistic understanding of system interactions, improves operational coordination, and enhances strategic decision-making. The following analysis synthesizes five representative studies that exemplify this integrated perspective, highlighting how methodological combinations contribute to more efficient, adaptive, and data-informed waste management systems across diverse regional contexts.

In the area of infrastructure planning, this study (Asefi and Lim 2017) developed a Multi-Objective Mixed Integer Programming (MOMIP) model to simultaneously minimize facility setup costs, transport distances, and site unsuitability, using indicators derived from multi-criteria evaluations. Their approach incorporates constraints related to flow balance, technological compatibility, and expansion strategies, offering a comprehensive tool for planning the spatial layout of waste facilities. To better manage the uncertainty and subjectivity involved in expert-based decision processes, this study (Roza et al. 2020) applied a Fuzzy TOPSIS method using triangular fuzzy numbers and linguistic variables (e.g., "Low," "Medium," "High"), enabling a more nuanced evaluation of ecological, geological, and social criteria. GIS was used in both studies to generate spatial Suitability Indicators that support real-world siting decisions (Asefi and Lim 2017; Roza et al. 2020).

In parallel, technological innovations such as blockchain have been proposed to optimize transparency and economic efficiency in SWM networks. This research (Gopalakrishnan et al. 2021) presented a blockchain-based end-of-life (EOL) traceability model, connecting municipal suppliers and waste-consuming enterprises through a decentralized platform. The system tracks material flows, supports profit-sharing models, and reduces losses due to non-transparent disposal routes. Their optimization model accounts for variables such as transport frequency, the number of blockchain users, cloud storage capacity, and transaction costs, offering a quantifiable framework for cost-effective and traceable waste redistribution.

Operational monitoring is also evolving through the integration of computer vision and DL. The study (Islam et al. 2014) proposed a bin-level monitoring system using image processing and a multilayer perceptron classifier (MLP), achieving 98.5% accuracy in detecting waste levels (empty, half, full, overflowing). The system uses Gabor wavelet feature extraction and dynamic time warping (DTW) for bin localization, making it a cost-effective alternative to unreliable physical sensors. Similarly, this study (Shahab and Anjum 2022) addressed the detection of illegal waste dumping by implementing a weakly supervised multipath convolutional neural network (mp-CNN). Due to the lack of labeled datasets, they developed their own training data and achieved an F1-score of 98.34%, with strong visual alignment between predicted masks and actual waste zones.

Together, these contributions demonstrate the strategic value of integrating multistage SWM processes into integrated, technologically informed models. They illustrate how linking decision support, infrastructure planning, blockchain systems, and AI-powered monitoring can lead to efficient, transparent, and sustainable waste management practices, particularly in the context of rapid urban growth and limited institutional capacity (Gopalakrishnan et al. 2021; Shahab and Anjum 2022).

Comparative analyses: port waste management vs municipal waste management

Both municipal solid waste management (MSWM) and port solid waste management (PSWM) aim to reduce environmental harm and health risks by effectively handling waste generated from human activities. However, differences appear in terms of waste origin and type, operational challenges, and management strategies applied within each context. PSWM is further complicated by the heterogeneity of waste types such as bilge water, sludge, and oily residues, and the transient nature of sources (Port area and ships) (Pereira et al. 2014), making conventional collection and site models less applicable without adaptation (Table 5).

Transferability of AI models from municipal solid waste (MSW) to port solid waste (PSW): limits and required adaptations

Although MSW and PSW ultimately converge at final treatment or disposal facilities, the reviewed literature demonstrates that AI models developed for MSW cannot be directly transferred to port environments without substantial structural modification. This limitation arises from fundamental differences in waste origin, composition, and operational constraints.

In MSW systems, AI-based classification and routing models are trained on stationary, land-based waste streams generated by relatively stable urban populations (Bras et al. 2009; Spadaro et al. 2021). Image-based classifiers typically learn from household waste datasets dominated by organic matter, packaging plastics, paper, and glass. In contrast, PSW originates from mobile, transient sources, namely vessels, and includes operational and cargo-related waste categories regulated under MARPOL Annex V (Olatunji et al. 2022; Ülker et al. 2023). As a result, a CNN trained on household waste imagery is structurally ill-equipped to recognize oily rags, metal banding, incinerator ash, animal carcasses, or contaminated packaging, which are common in (PRFs) (Butt 2007; Olson 1994).

Similarly, AI-driven routing and collection optimization models designed for MSW assume predictable waste generation patterns, based on bin fill levels or demographic indicators

Table 5 Comparative overview of MSW and PSW

	Municipal waste	Port waste	
		Shore waste	Ship generated waste
Waste type	All waste materials (household, commercial, etc.) except hazardous substances (Badran and El-Haggar 2006)	All waste materials including (hazardous, oily residues, bilge water, sludge) (Pereira et al. 2014)	
Management Challenges	Key challenges stem from rapid population growth, increased consumption, urbanization, industrialization, resource constraints, socioeconomic disparities, weak policies, and poor governance (Awino and Apitz 2024)	Inefficient solid waste management structures in ports can harm the quality of life in nearby urban and coastal communities (Pereira et al. 2014)	
Management Approaches and Processes	A MSWM system generally encompasses waste generation, source-level handling, separation, storage, and processing; followed by collection, transfer, transportation, further separation, treatment, and final disposal (Badran and El-Haggar 2006)	Port waste management includes identifying waste sources, determining the quantity and quality, defining source segregation procedures, and designing a sorting, collection, and final disposal system	
Stakeholders	National and local government, Service users, Public and private waste service providers, both formal and informal waste handlers, and non-governmental organizations (NGOs) (Awino and Apitz 2024)	Port authorities, dock companies, specialized waste management companies, and shipping companies (Pereira et al. 2014)	Port authorities, dock companies, specialized waste management companies, and shipping companies (Pereira et al. 2014)
Collection/Vehicle routing	Vehicles and containers Government authorities usually regulate collection services Either public or private operators may provide these services Operational aspects include planning collection routes and scheduling frequency (Badran and El-Haggar 2006; Awino and Apitz 2024)	Waste collection from generation locations should occur daily, with schedules, routes, equipment, and the number of collections established based on demand Different vehicle types are used based on the type of waste (Pereira et al. 2014; Badran and El-Haggar 2006)	Collection done by port reception facilities (PRFs), Ships must use a Garbage Management Plan (GMP) that includes waste collection, containment, storage, and delivery procedures according to MARPOL convention (International Maritime Organization 2022) Different vehicle types are used based on the type of waste
Classification	Generally, at households, curbside, and can be automated at treatment facilities Sorting may be formal and required by law, or it can be done informally, often by workers in the informal economy (Awino and Apitz 2024)	Segregation of waste by type and category at the time of its generation (Pereira et al. 2014)	Waste must be segregated onboard ships into specific categories (MARPOL Annex V, Regulation 4) (International Maritime Organization 2022)
Technological maturity	High in urban settings	Low to moderate	Low to moderate

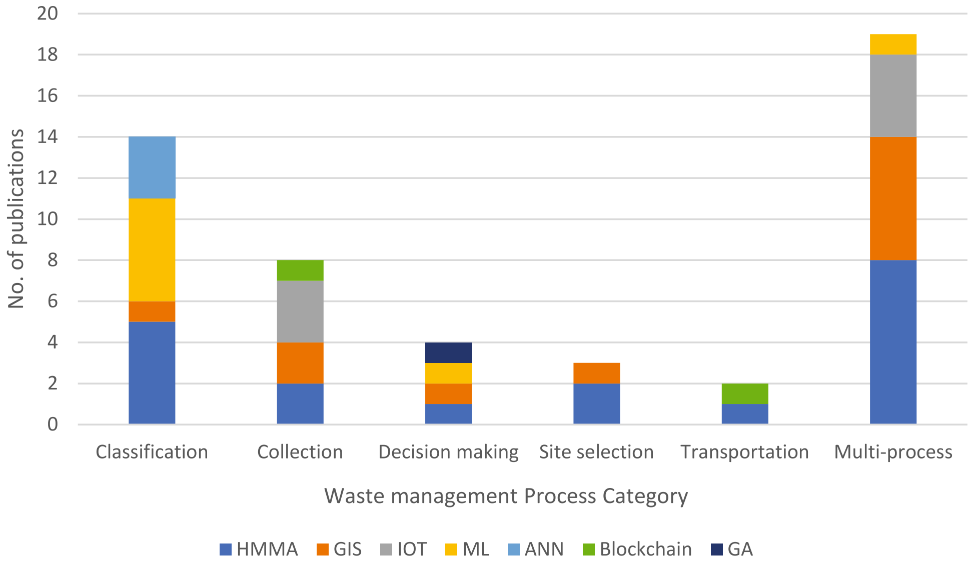

Fig. 3 Number of publications according to process category

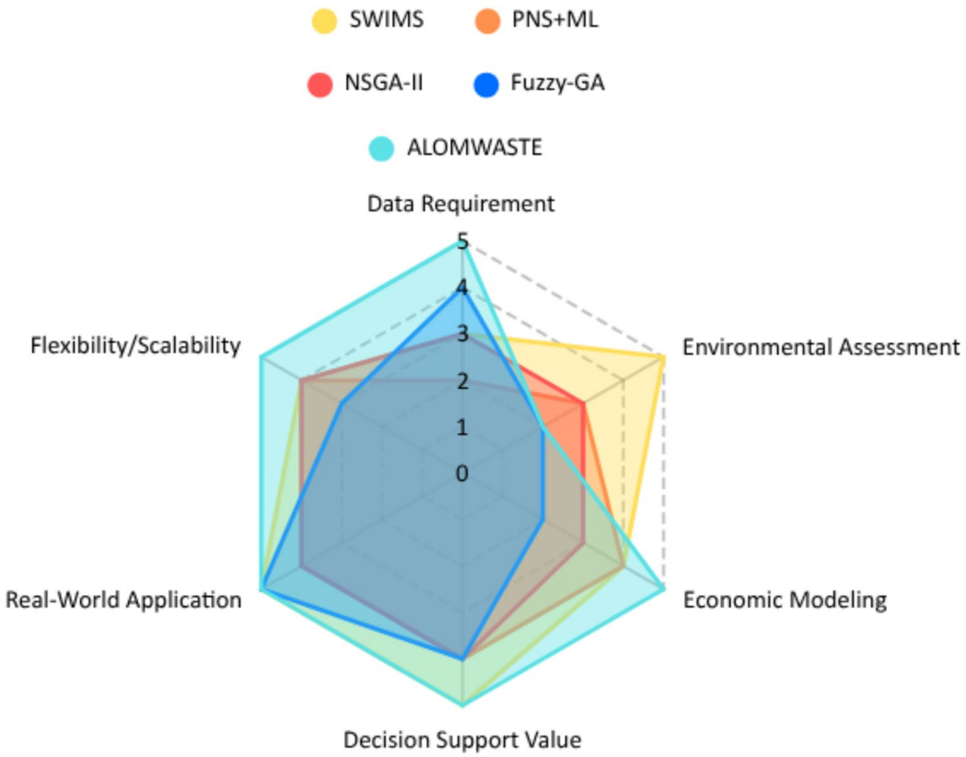

Fig. 4 Comparative impact of optimization tools in SWM decision support. Radar chart comparing five optimization models: SWIMS (Roberts et al. 2018), PNS + ML (Ali et al. 2022), NSGA-II (Sornil 2014), Fuzzy-GA (Oyebode and Abdulazeez 2023), and ALOMWASTE (Batur et al. 2020), across six decision-support criteria: data requirement, environmental assessment capacity, economic modeling, decision-support value, flexibility and scalability, and real-world application evidence. Scores are based on a qualitative assessment (1 = low, 5 = high) derived from case study performance and model characteristics

(Wilk et al. 2019; Echendu 2023). These assumptions break down in ports, where waste generation is event-driven and stochastic, linked to vessel size, cargo type, voyage duration, and ship arrival schedules (Pérez et al. 2017; Abdellaoui et al. 2023). For example, a single cruise ship, representing only 1% of the global fleet, can generate waste equivalent to a small town in a single day, accounting for nearly 25% of all vessel-generated waste (Ülker et al. 2023; Verdesoto et al. 2025). Consequently, MSW routing algorithms must be fundamentally restructured to integrate vessel traffic data, port call notifications, and “no undue delay” constraints, rather than relying solely on spatial proximity or container fill rates.

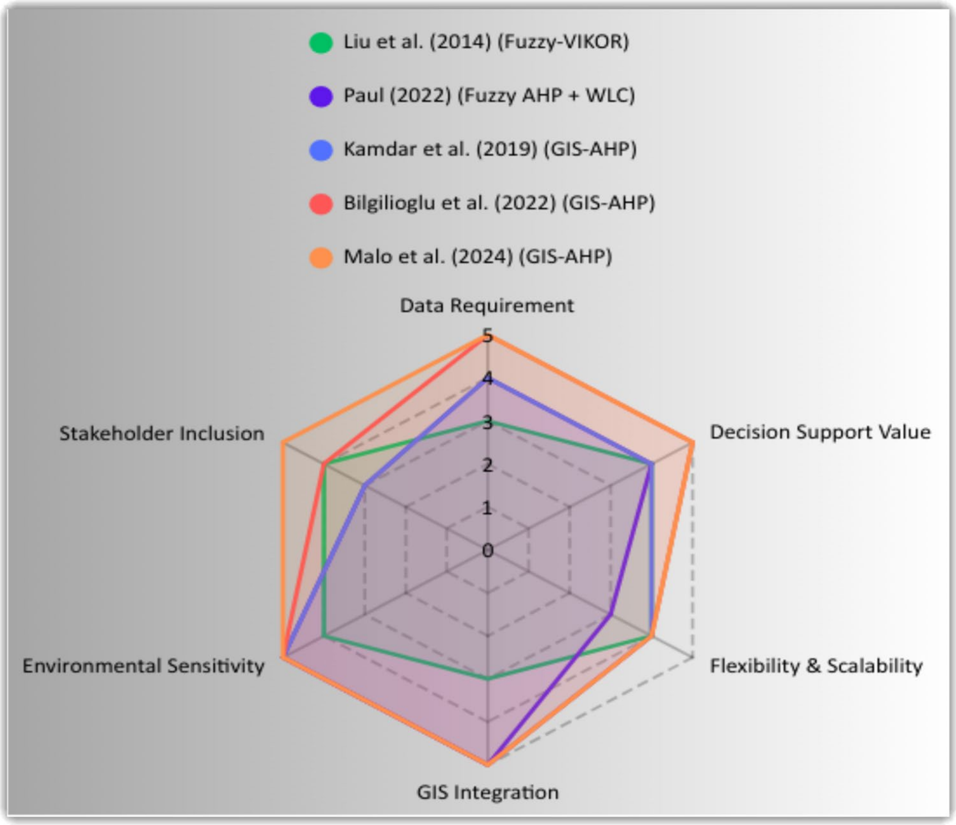

Fig. 5 Assessment of Site Selection Models Based on Technical, Environmental, and Decision-Making Criteria. Radar chart illustrating the performance of five site selection approaches: Fuzzy-VIKOR (Liu et al. 2014), Fuzzy-AHP + WLC (Paul and Ghosh 2022), GIS-AHP (Kamdar et al. 2019; Bilgilioglu et al. 2022; Malo et al. 2024), evaluated across six key criteria: data requirement, decision-support value, flexibility and scalability, GIS integration, environmental sensitivity, and stakeholder inclusion. Each method is scored on a 1–5 scale to reflect its overall decision-making utility and contextual applicability.

Structural and operational challenges in PSWM compared with municipal systems

PSW presents a higher level of technical, regulatory, and environmental complexity than MSW, making it a substantially more challenging domain for AI deployment.

On the one hand, data scarcity and heterogeneity are significantly more pronounced in ports. While MSW data are often collected through municipal censuses and routine operational monitoring, PSW data are fragmented across ship operators, port authorities, private contractors, and international reporting systems (Verdesoto et al. 2025; Rukavina 2022). This fragmentation is intensified by the international nature of maritime operations, where waste records must comply with MARPOL reporting formats and differ by vessel flag state.

On the other hand, regulatory pressure is far stricter and multilayered in PSW. Municipal waste is governed primarily by national or local legislation, such as the European Union (EU) Waste Framework Directive 2008/98/EC (Wilk et al. 2019). In contrast, PSW is regulated through an international regime dominated by MARPOL 73/78 and reinforced by regional instruments such as EU Directive 2019/883, which mandates advance notification, compulsory delivery rights, and the Indirect Fixed Fee (IFF) system (Olatunji et al. 2022; Schatz and Wanner 2025). AI systems deployed in ports must therefore adhere to legal accountability requirements that are generally absent in municipal waste management contexts, including traceability, auditability, and enforcement compatibility.

However, PSW poses unique biosecurity and environmental risks absent in MSW systems. For example, International Catering Waste (ICW) must be handled separately to prevent the transmission of animal diseases, requiring leak-proof containers and controlled destruction pathways (Wilewska-Bien et al. 2019). Additionally, ports serve as vectors for invasive marine species via ballast water residues and contaminated waste streams, representing ecological risks that MSW-AI systems are not designed to detect or manage (Ryan et al. 2020; Ioraş 2025).

Finally, economic incentives differ fundamentally. In MSW systems, underfunding often leads to illegal dumping in urban waterways, particularly in developing regions (Echendu 2023). However, in PSW systems, the economic risk lies in free-rider effects under the IFF regime, where low-waste vessels may subsidize high-waste generators such as cruise ships if fee structures are not adequately differentiated by ship type and gross tonnage (Verdesoto et al. 2025; Carpenter and Macgill 2001). AI-based optimization in ports must therefore account for economic fairness and competitive neutrality, considerations that are largely absent in municipal waste routing models.

Port-specific challenges and emerging AI research directions

Despite growing advances in AI for MSW, its application in PSW management remains limited, leaving a critical gap in both operational effectiveness and transferability. This gap arises primarily from the lack of port-specific datasets, particularly for waste classification, as existing image and sensor repositories are overwhelmingly MSW-oriented, which may fail to capture the visual, chemical, and operational complexity of PSW, including contaminated materials, mixed hazardous residues, and cargo-associated waste (Ülker et al. 2023; Özbay 2024). Without such tailored datasets, AI models risk producing outputs that are speculative or poorly aligned with port realities.

Consequently, routing and logistics models for PSW must advance beyond static optimization to incorporate vessel arrival schedules, berth allocation, and port congestion dynamics. Unlike municipal waste collection, port operations operate under strict temporal constraints, where delays can directly affect competitiveness, efficiency, and maritime safety (Pérez et al. 2017; Abdellaoui et al. 2023). Moreover, AI systems must integrate regulatory intelligence, embedding MARPOL compliance, fee system optimization (IFF), and enforcement mechanisms into decision-making frameworks. This represents a design paradigm fundamentally distinct from MSW-AI systems, which rarely interface with international legal regimes (Rukavina 2022; Schatz and Wanner 2025).

Addressing this gap further requires the exploration of integrated urban–port governance models, acknowledging that ports and cities, while often managed separately, share critical infrastructure as illustrated in Fig. 6. AI offers the potential to bridge this divide, enabling coordinated waste management that mitigates environmental leakage, infrastructure overload, and social conflict in port cities (Spadaro et al. 2021; Olson 1994).

Proposed AI-based framework for integrated port waste management: insights from municipal systems

Integrating AI into PSWM presents a complex challenge that cannot rely on the direct transfer of MSW solutions. While AI applications in MSW offer valuable methodological insights, the port context introduces numerous constraints, necessitating a comprehensive, system-level study before practical implementation. The proposed framework emphasizes systematic adaptation, identifying components that are reusable, those requiring domain-specific redesign, and those unsuitable for direct deployment in ports.

Sensor networks: from urban IoT to maritime sensing

In MSW, sensor systems typically monitor bin fill levels (ultrasonic), container identity (RFID), vehicle locations (GPS), and weight-based pay-as-you-throw schemes. For PSWM, these capabilities require contextual re-engineering:

- *Vessel–Port Interface Sensors* Radio Frequency Identification (RFID) and Automatic Identification System (AIS) data track waste streams in relation to vessel identity, gross tonnage, flag state, and voyage history.
- *Hazard-Aware Containers* Load cells and sealed weight sensors monitor oily rags, sludge containers, and ICW, where manual inspection is prohibited.
- *Environmental and Safety Sensors* Gas and temperature sensors are essential in enclosed storage areas to monitor hazardous waste conditions.
- *Mobile Sensing Units* Ports rely on mobile sensors mounted on barges and trucks to track real-time waste flows, unlike MSW fixed urban bins.

Algorithmic layer: model selection for port constraints

Algorithms for PSWM are selected based on port-specific operational, regulatory, and safety requirements rather than MSW popularity.

- *Route and Resource Optimization* Improved ACO is preferred over classical shortest path or static VRP models, because it adapts to dynamic vessel arrivals and congestion, ensuring responsiveness under strict turnaround windows.
- *Waste Classification and Compliance* CNN-based image classification models require retraining on port-specific datasets and integration with rule-based layers encoding MARPOL Annex V constraints.
- *Decision Support and Policy Simulation* Multi-objective optimization models (e.g., NSGA-II) are retained but reformulated to consider compliance risk, ship delay penalties, and PRF capacity saturation. Linear planning is insufficient due to nonlinear interactions among ship type, waste composition, and regulatory obligations.

As illustrated in Fig. 7, the proposed AI-based framework for PSWM is organized into four interlinked modules: waste classification, smart collection and vehicle routing, site selection/infrastructure planning, and integrated decision-support with monitoring and feedback loops. Waste classification leverages both on-ship and port-side identification, MARPOL segregation rules, and treatment facility reclassification to accommodate the heterogeneous nature of port waste. Smart collection and vehicle routing integrate

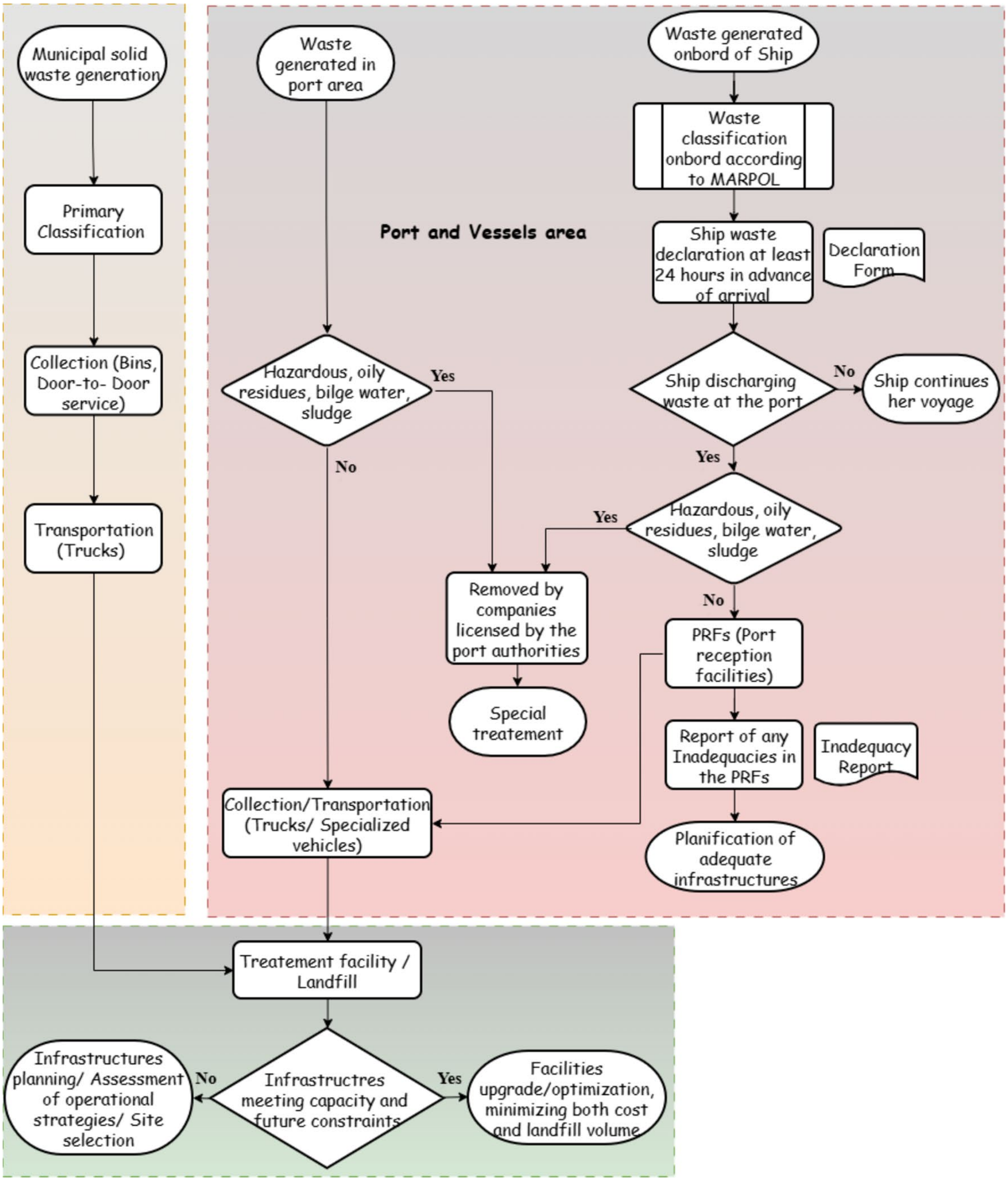

Fig. 6 Waste management process flowchart (Both Municipal and Port)

IoT sensors, real-time scheduling, and advanced optimization algorithms (e.g., ACO, SGA) to ensure timely, safe, and compliant waste flows. Site selection and infrastructure planning combine GIS and Fuzzy-AHP for placement of temporary storage, port treatment facilities, and port-related PRFs, while the integrated decision-support layer embeds system-wide planning, life-cycle optimization, and continuous monitoring using blockchain, computer vision, and GIS-enabled feedback loops.

Key success factors adapted from MSW

The adaptation of AI-based frameworks from MSW to PSWM highlights several critical success factors. Systems demonstrate robust performance when end-to-end data continuity is ensured, integrating sensor networks, operational decisions, and regulatory reporting into a unified pipeline. The use of hybrid intelligence is also critical, as it combines AI predictions with expert knowledge and regulatory

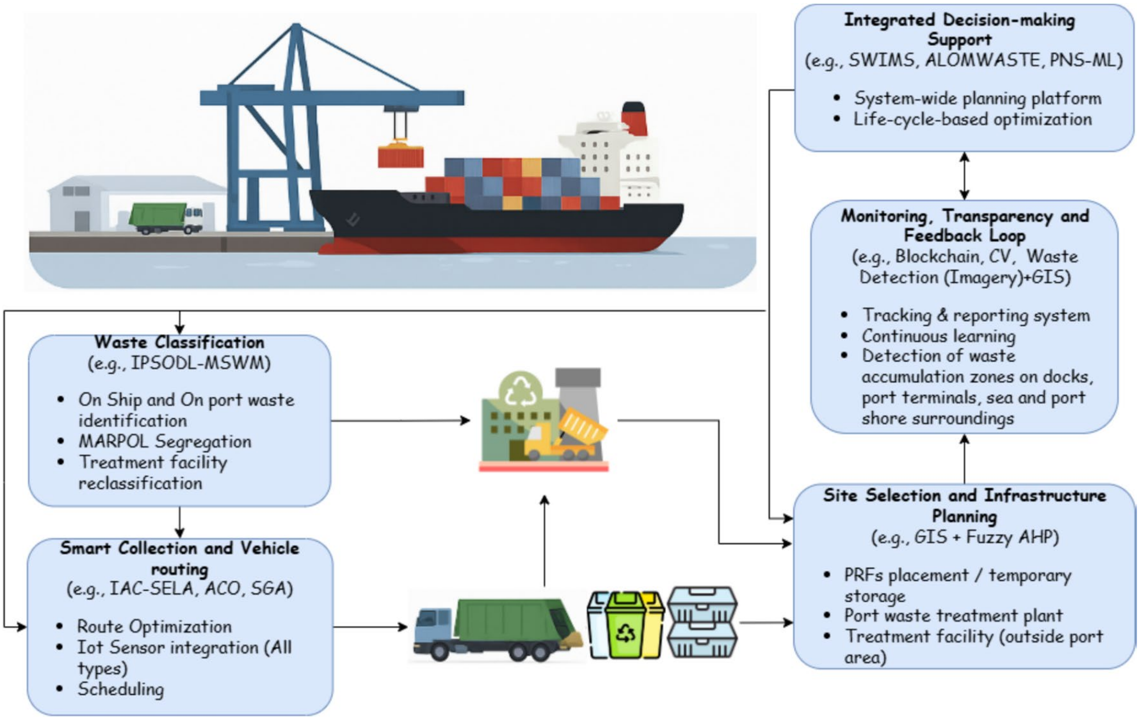

Fig. 7 AI-based architecture for integrated port waste management: a framework inspired by municipal waste practices

frameworks to support decision-making under complex, port-specific constraints. Sustained institutional support from port authorities, including enforcement capacity and long-term investment commitment, further underpins successful implementations.

Despite these enablers, recurring limitations constrain the scalability and reliability of AI in PSWM. Data scarcity, particularly the absence of labeled port-specific waste datasets, remains a fundamental challenge. Models are prone to overfitting, as validation is often limited to single ports or regions, reducing generalizability. High deployment costs, encompassing sensor networks, secure data infrastructure, and compliance verification, impose additional barriers, particularly for small and medium ports. Finally, fragmented governance across the ship–port–contractor interface complicates data sharing, accountability, and integrated decision-making. Together, these factors underscore the need for context-aware, modular frameworks and phased implementation strategies when transferring AI solutions from municipal to port environments.

Research gaps and future directions

This framework underscores that AI application in MSW is a structured methodological approach, not a fully packaged solution for ports. Addressing PSWM requires:

- Creation of open, port-specific waste datasets.
- Integration of vessel traffic, berth allocation, and waste generation models.
- AI systems explicitly designed for international regulatory compliance.
- Comprehensive technical, economic, regulatory, and environmental feasibility analysis prior to full-scale deployment.

By framing PSWM as a domain that cannot rely solely on municipal analogs, this AI-based framework highlights the need for systematic adaptation, phased implementation, and rigorous multi-dimensional evaluation to ensure operational effectiveness, compliance, and sustainability in port environments.

Conclusion

This study represents a systematic review assessing the integration of AI technologies into key components of SWM, with a focus on the waste management chain, filling a significant gap in the literature on AI-based waste management in port contexts. Based on a selected set of 50 high-quality peer-reviewed articles published between 2014 and 2024, this review highlights the emergence of intelligent systems across waste workflows, many of which demonstrate promising results in terms of operational efficiency, and system optimization. The findings suggest that both standalone and hybrid AI models have been successfully applied to various facets of MSW management, offering scalable solutions where conventional techniques fall short especially under data-scarce, complex, or dynamic operational conditions.

In particular, AI-based waste classification models using deep learning, intelligent routing algorithms for vehicle optimization, and GIS-integrated decision frameworks have enabled a shift from reactive to proactive waste system management. Moreover, the successful deployment of hybrid models illustrates that AI's strength lies in multi-criteria decision analysis and real-time adaptability. However, despite these technological advancements, several systemic and technical limitations continue to delay widespread implementation. Addressing these limitations is essential to guide future research and practical adoption in both municipal and port environments. Key challenges include:

1. *Limited and Low-Quality Data Waste* classification models effectiveness heavily counts on the existence of diverse, high-quality datasets. However, there is a persistent scarcity of sufficiently labeled and varied data, which restricts model training and reduces their ability to generalize to real-world scenarios. This issue is compounded by inconsistencies arising from environmental factors such as variable lighting, occlusion, and clutter, which blocks model accuracy.
2. *Technical Constraints of Sensor Networks and IoT Deployment* Although IoT sensors offer promising capabilities for waste monitoring, their deployment faces significant hurdles. High initial investment costs, limited battery life, environmental vulnerabilities, and cybersecurity risks pose practical challenges for widespread adoption, especially by resource-constrained municipalities. Additionally, there is a need for more cost-efficient, adaptive deployment strategies.
3. *Complexity and Specificity of Waste Types and contexts* Waste management solutions must contend with the diverse and often unpredictable nature of waste streams. As the port context, which involves heterogeneous materials like oily residues and sludge from transient sources, complicating conventional collection and processing models. Without adaptation to such unique contexts, standard waste management frameworks would struggle to deliver optimal results.
4. AI technologies offer transformative potential for future waste management systems, including port waste, where logistical complexity and regulatory heterogeneity further elevate the need for intelligent solutions. By building upon the successes and lessons of municipal AI applications, we can develop adaptive, and cost-effective tools for real-world deployment. Future efforts should prioritize interdisciplinary collaboration, model transparency, and infrastructure-readiness to ensure that AI plays a key role in making waste management sustainable and resilient.

Acknowledgements This work was supported by the Ministry of Higher Education, Scientific Research and Innovation, the Digital Development Agency (DDA) and the National Center for Scientific and Technical Research (CNRST) of Morocco, Alkhawarizmi/2020/35.

Author contributions The conception, design, data collection, analysis, and interpretation of the study were performed by Anass Hamraoui. All authors contributed significantly to drafting and revising the manuscript critically for important intellectual content. All authors have read and approved the final version of the manuscript.

Funding The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data availability All data supporting the findings of this review are included within the article and its supplementary materials. As the original datasets belong to the cited publications, direct access to raw data must be requested from the respective original sources. Any further inquiries regarding data can be directed to the corresponding author.

Declarations

Conflict of interest The authors declare no competing interests.

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