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RESEARCH ARTICLE

Harnessing Artificial Intelligence for Integration and Advancement of Circular Economy Practices in Urban Waste Management

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Abstract

Urban waste management faces growing challenges as municipal solid waste is projected to reach 3.4 billion tons by 2050. This study examines how artificial intelligence applications contribute to circular economy transitions in urban waste management through a systematic literature review of 150 peer-reviewed studies and an analysis of commercial implementations. Using the PRISMA framework, we identified AI methods, waste management stages, and circular economy outcomes across academic research and practical deployments. Results reveal that while AI demonstrates strong technical capabilities – particularly in sorting and classification and forecasting – only 31% of studies report circular economy outcomes such as recycling rate improvements or reducing resource inputs. Both academic research and commercial implementations remain concentrated in downstream recycling activities rather than upstream prevention strategies. The findings highlight a critical gap between technical performance and systemic circular transitions, suggesting that AI adoption must be integrated with governance frameworks, standardized outcome measurement, and multi-stage coordination to effectively advance urban circular economy goals.

Keywords Artificial Intelligence · Urban Waste Management · Circularity

1. Introduction

As cities grow and household consumption increases, urban waste management has emerged as one of the most critical sustainability challenges of the past two decades. Urban waste management becomes a great challenge not only due to its increased amount but also the complexity of managing it. According to the Kaza et al. (2018) the annual municipal solid waste will grow from 2.01 billion tons in 2016 to 3.4 billion tons by 2050. The major source of this growth will come from urban areas. Moreover, waste management systems in most of the cities involve linear practices where useful materials are lost and often create environmental problems (Sarc et al., 2019; Wilts, et al., 2021). The circular economy, where the main focus is reusing, recycling, and recovering useful materials, can be the only valuable solution for urban waste management. For example, industrial wastes can be converted and reused as valuable applications (Zhang et al., 2025). However, this progress towards circular systems in urban cities has been siloed and fragmented. There is a weak synchronization between technology, governance, and urban planning (Qi et al., 2024; Li et al., 2025). It is essential to develop and include quantitative assessment tools such as the Zero-Waste Index (Cai et al., 2025) and better adapt technology for smart-city waste systems (Szpilko et al., 2023, Alves et al., 2022). Not only recycling but also contamination makes applying circular practice harder. Even where recycling policies exist, contamination in municipal streams weakens the value of secondary use of materials (Yin et al., 2024).

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Especially for plastics and food waste, inefficient collection and sorting limit the potential of closed-loop recovery (Duan et al., 2024). These limitations can be solved by using more efficient tools and techniques such as Artificial intelligence (AI) (Maiurova & Kurniawan, 2022). For example, machine learning models predict seasonal and demographic changes more effectively than traditional approaches. Therefore, the machine learning models are commonly used to improve the forecasting of waste generation (Magazzino et al., 2021b; Andeobu et al., 2022). Optimization and data-driven routing are important in smart-city waste management (Szpilko et al., 2023; Chen, 2022). Computer vision and deep learning are useful for improving the accuracy of sorting and increasing the purity of recycling streams in material recovery facilities (Wilts et al., 2021). These studies in literature usually focus on technical performance indicators such as accuracy, efficiency, or classification rates. The real impact of these innovations such as the circular outcomes like higher recycling rates, reduced landfill dependency, or CO_2 savings are under-investigated (Andeobu et al., 2022; Szpilko et al., 2023; Kurniawan & Othman, 2023).

In this study, we address that gap through a dual approach. First, we reviewed the academic literature systematically on AI applications that are used in urban waste management within a circular economy framework. By focusing on the urban context, we could highlight the benefits of AI since the waste pressures are severe and circular economy opportunities are observable. The review clarified how AI has been applied and where its contribution to circularity remains limited. Second, we revealed and supported the evidence with an analysis of real-world company cases. By looking at firms such as AMP Robotics, Winnow, Sensoneo, and Bigbelly, we evaluated how AI is actually being implemented in practice and whether the same gaps identified in literature such as limited systemic integration and weak reporting of circular outcomes are also evident on the field. This dual perspective offers a richer understanding of both the potential and the limitations of AI in progressing circular urban waste transitions. The review section generates knowledge in four ways. First, it detects the AI methods that are frequently applied and reveal whether their outcomes encompass more than technical performance to circularity (Wilts et al., 2021; Andeobu et al., 2022; Chen et al., 2024). Second, it observes how fragmented case studies can be scaled into broader systemic perspectives. This can create opportunities for integration (Qi et al., 2024; Wu et al., 2025; Li et al., 2025). Third it reveals the impact of governance and measurement in AI usage. AI's usage must be measured not only in terms of algorithms but also in relation to data governance, stakeholder participation, and inclusivity (Cai et al., 2025; Szpilko et al., 2023). Finally, by comparing academic studies with practical deployments, the paper highlights how technical innovations and real-world implementation align, diverge, or reinforce one another. This offers insight into where AI can realistically drive CE transitions and where barriers remain.

Guided by this purpose, the study addresses four research questions:

- RQ1: What types of AI methods have been applied to urban waste-management problems within a circular economy context?
- RQ2: Which stages of the waste-management chain, such as generation forecasting, collection and routing, sorting and classification, recycling and reuse, waste-to-energy, or landfill management, are most addressed by AI applications?
- RQ3: To what extent do studies report circular economy outcomes such as recycling rates, contamination reduction, CO_2 savings, or resource efficiency, rather than only technical performance indicators?
- RQ4: What research gaps remain in linking AI to systemic and city-level transitions towards circular urban waste management?

The rest of the paper is organized as follows. Section 2 explains the conceptual background that links AI applications in circular practices for urban waste management. Section 3 reveals the utilized methodology. Section 4 highlights the results of literature review. Section 5 gives real life examples. Last section concludes and gives the limitations and further suggestions.

2. Conceptual Background

The circular economy offers another way to look at production and consumption. Instead of the familiar linear pattern, take, make, dispose, it highlights the importance of keeping resources in play through reuse, repair, recycling, and recovery. This shift is crucial especially in urban areas where consumption of materials is enormous and creates most of the waste. Yet, translating circular economy principles into practice has been challenging. In many urban areas, policies exist, but waste keeps growing with population and rising demand (Magazzino et al., 2021b). Although technical efficiency can be achieved by many systems this does not deliver circularity. The systems and actors have to connect for a meaningful transformation. Sala-Garrido and Mocholí-Arce (2024) observed that the usual performance metrics do not cover qualitative aspects of waste flows, leaving a gap between goals and reality. Similar patterns show up in construction (Lu et al., 2021) and textiles (Alves et al., 2022). Household and municipal waste separation also hinges on policy design, citizen participation, and data systems developed through "zero-waste city" programs and related governance tools (Qi et al., 2024; Cai et al., 2025; Amirudin et al., 2023).

Circular economy serves as the essential evaluative framework for this study. While AI is a technical tool that can be assessed on its own performance merits, the central question of this paper is not whether AI works, but whether it contributes to circular economy transitions. This requires a normative framework that specifies what progress towards circularity actually looks like. The circular economy provides exactly this: through the R-strategy hierarchy, ranging from Refuse and Reduce at the top, through Reuse, Repair, and Remanufacture, down to Recycle and Recover, it establishes a gradient of circular value against which AI applications can be systematically evaluated (Andeobu et al., 2022; Alivojvodic & Kokalj, 2024). Without this framework, the observation that AI improves sorting accuracy or reduces collection costs remains technically meaningful but circular-economy-neutral. With it, such improvements can be precisely located within the R-strategy hierarchy and assessed for their contribution to genuine circularity. The R-strategy hierarchy is also the source of this study's most important diagnostic insight: that AI applications cluster overwhelmingly at the lower-order Recycle and Recover stages, leaving the higher-order strategies, which would prevent waste generation rather than merely processing it more efficiently, largely unaddressed.

Therefore and from a more practical perspective, AI creates potential solutions for solving the complexity of urban waste systems. AI applications are used across almost all stages of waste management. In forecasting, hybrid machine learning models can predict municipal solid waste generation more accurately than traditional statistical techniques (Hoy et al., 2022). IoT-enabled systems and data-driven optimization are used to plan collection and routing in smart-city settings (Vishnu et al., 2021; Szpilko et al., 2023). Image recognition and neural networks are used in sorting plants to pick materials and improve recycling quality (Wilts et al., 2021). Recent residual-network variants also target multi-material classification in recycling streams (Castro-Bello et al., 2025). The value chains in treatment and recycling are reshaped by digitalization and robotics (Sarc et al., 2019). The optimization algorithms are used to decarbonize recycling operations (Kurniawan & Othman, 2023). Although these advances show strong technical potential, several limitations remain. Many systems rely on narrow local datasets, hard to reuse elsewhere. And most studies evaluate success by speed or accuracy, not by outcomes that matter for circular economy (CE) such as less landfill, more recovery, fewer emissions (Andeobu et al., 2022). Where outcomes are reported, source-separation and improved sorting can double carbon benefits relative to mixed incineration systems (Yin et al., 2024), but such reporting is still the exception rather than the rule.

AI and enabling technologies such as IoT and blockchain contribute to waste reduction, recycling efficiency, resource optimization, and circular economy practices across various production systems (Kumar & Shanin, 2025). Recent literature positions AI within the broader digital transformation of waste management. Sarc et al. (2019) and Wilts et al. (2021) claimed that AI, robotics, and data platforms are the enablers of smarter waste systems. City-scale initiatives likewise emphasize open data and integrated sensing—for example, OpenWasteAI links AI with IoT and open data to trace material flows and support governance (Shennib et al., 2024). Yet, digital technologies alone cannot ensure circularity. Without governance frameworks, policy design, and urban planning, efficiency gains through technological advancements remain isolated (Andeobu et al., 2022; Szpilko et al., 2023). Digital tools must be embedded within broader systemic frameworks to deliver tangible circular outcomes. Although in literature AI is considered to reshape waste management practices, its systemic contribution to CE remains insufficiently understood.

The purpose of this study is to address this gap. We focus on how AI applications in urban waste management that support circular economic goals. Figure 1 outlines the conceptual framework guiding this study. It illustrates how different AI techniques such as machine learning, computer vision, reinforcement learning, and large language models are applied to various waste management stages. They potentially lead to outcomes such as higher recycling rates, reduced contamination, lower emissions, and improved resource efficiency. This framework provides the analytical basis for the following literature review.

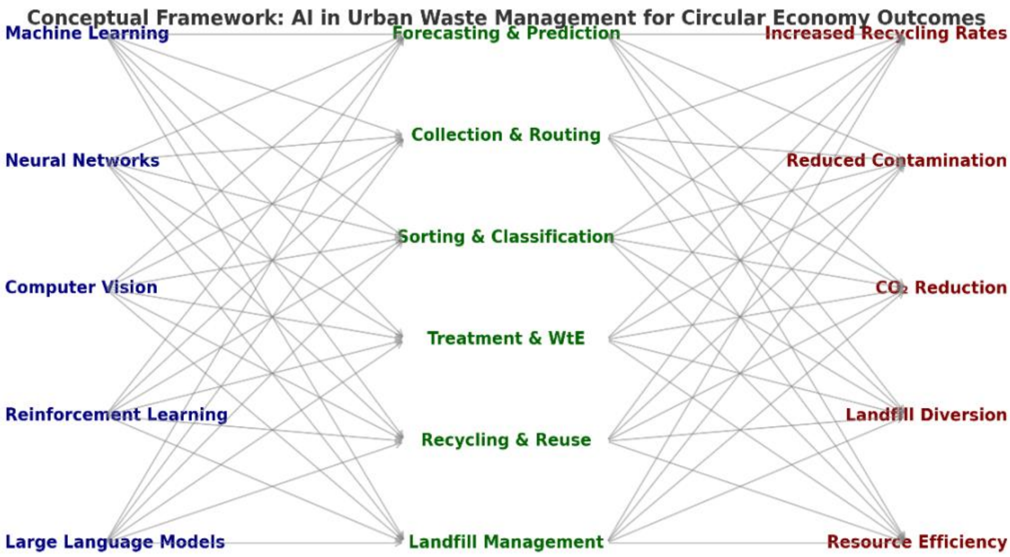

Figure 1. Conceptual framework: Artificial intelligence in urban waste management contributing to circular economy outcomes.

3. Methodology

This study provides a systematic literature review to synthesize current knowledge on the application of AI in urban waste management with a circular economy perspective. The review was conducted using the PRISMA 2020 framework. PRISMA 2020 enables clear and reproducible steps for identifying, screening, and selecting relevant studies (Page et al., 2021). Systematic reviews are particularly useful for interdisciplinary topics where research is often distributed across different disciplines such as computer science, engineering, and environmental management (Snyder, 2019). In this study, we have analyzed the usage of artificial intelligence for integration and advancement of circular economy practices in urban waste management which covers various disciplines including environmental engineering, computer science, and economy. In such a multidisciplinary study, a systematic framework is necessary to cover all the related topics. PRISMA 2020 framework enables us to identify, screen and select the relevant studies with a clear, traceable and reportable process. Scopus was selected as the only database due to its wide coverage of peer reviewed journals and widely used in sustainability and circular-economy research (Falagas et al., 2008; Donthu et al., 2021).

The search strategy combined four thematic areas: artificial intelligence, circular economy, waste management, and urban contexts. Keywords such as “artificial intelligence,” “machine learning,” “deep learning,” “neural networks,” “computer vision,” and “reinforcement learning” were paired with circular economy terms like “circular economy,” “closed-loop,” “material recovery,” and “resource efficiency.” Waste-related terms included “municipal solid waste,” “recycling,” “waste-to-energy,” and “landfill,” while the urban context was captured through “city,” “municipal,” and “smart city.” The query was limited to English language publications between 2014 and 2025, consistent with modern AI techniques such as deep learning (LeCun et al., 2015). The search was conducted on 30 August 2025, and all results available up to this date were included in the review.

The Boolean query used in Scopus was: TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "convolutional neural network*" OR "recurrent neural network*" OR "large language model*" OR LLM OR "computer vision" OR "reinforcement learning") AND ("circular economy" OR "closed-loop" OR "material recovery" OR "resource efficiency" OR "zero waste" OR "sustainable waste") AND ("waste management" OR "municipal solid waste" OR MSW OR "waste sorting" OR "collection routing" OR "waste-to-energy" OR WtE OR landfill) AND (urban OR city OR municipal OR municipality OR "smart city")) AND (LIMIT-TO(LANGUAGE, "English")) AND (PUBYEAR > 2013)

The initial search showed 258 records. After removing duplicates, non-English and irrelevant to urban waste or AI, 222 unique publications were obtained. To obtain an unbiased overview of the field, thematic analysis was obtained with VOSViewer tool using this full set of 222 papers (before elimination). This enabled us to see the full picture of themes, linkages, and emerging topics in the literature before moving to the more detailed analyses. In order to minimize the reliance on subjective criteria, we used quality appraisal and relevance screening matrix with standardized criteria for further analyzing the full-text articles. We evaluated each article with one ordinal criterion that shows content richness (content richness, scored 1-3) and three relevance criteria (AI, urban/municipal and CE relevance, they were scored as Yes/No). An article is selected only with high content richness and related with all the thematic areas. This was in line with PRISMA framework and overall focus of the study to have open, traceable evaluation criteria. The final set resulted with 150 articles for systematic analysis. To ensure scientific consistency, only peer-reviewed journal articles and review papers were retained for full-text reading, while conference papers, book chapters, and editorials were excluded. This filtering resulted in a set of 164 studies. Screening was conducted in two stages: first, titles and abstracts were reviewed to exclude studies that did not explicitly involve AI or lacked a clear connection to circular economy principles; second, full-text reading was used to confirm eligibility. At this stage, papers were assessed to ensure that AI was the central methodological component, that the context was clearly urban or municipal, and that the reported outcomes were relevant to circular economy objectives. The final set of 150 studies have been analyzed. Following PRISMA framework, the process of identification, screening, eligibility, and inclusion is summarized in Figure 2.

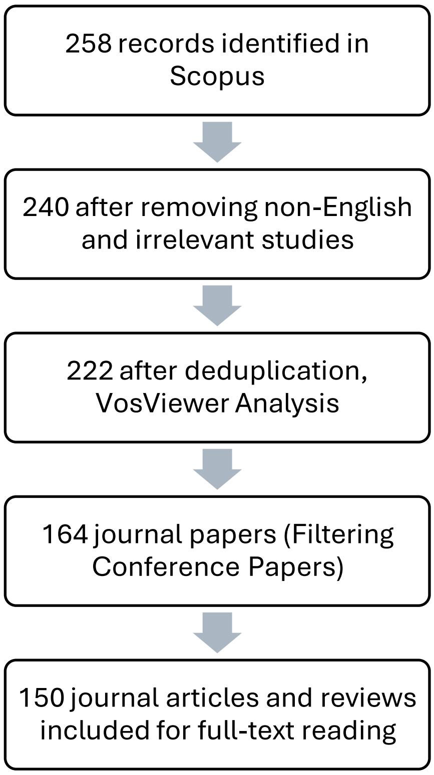

Figure 2. PRISMA flow diagram

Data from the included papers were extracted into a structured Excel template. Each entry recorded bibliographic details, geographic scope, type of waste stream, AI method applied, stage of the waste-management chain, dataset used, and outcomes. Outcomes were coded both for technical performance, such as prediction accuracy or cost reduction, and for CE objectives, such as recycling rate improvement, contamination reduction, landfill diversion, and CO_2 savings. This dual coding helped distinguish between studies that focused on algorithmic efficiency and those that explicitly measured circular outcomes (Tranfield et al., 2003). The evaluation of the studies was carried out in a straightforward way. We checked how clearly each paper explained its methods, how well the datasets were described, and whether the AI applications appeared robust. Particular attention was given to whether studies went beyond algorithmic accuracy and connected their results to CE goals. Stronger studies tended to provide transparent methods, include comparisons with baseline models, and report measurable outcomes such as CO_2 reduction, recycling rates, or contamination levels. To ensure consistency, the evaluation criteria were grouped into five categories, summarized in Table 1.

Table 1. Evaluation criteria used to assess the quality and relevance of included studies.

Criterion	Description
Study type	Case study, empirical study, review, or conceptual framework.
AI method	AI techniques applied (e.g., machine learning, neural networks, computer vision, reinforcement learning, LLMs).
CE outcome reported	Whether results focused only on technical metrics (e.g., accuracy, cost savings) or also on CE goals (recycling rates, CO_2 reduction, landfill diversion).
Dataset quality	Dataset characteristics, including size, type (sensor, image, time-series), availability, and robustness.
Reproducibility & transparency	Whether methods, code, or data were reproducible, and whether results were compared against baseline models.

In addition to qualitative synthesis, bibliometric analysis was used to better understand the research landscape. The Scopus export was analyzed with VOSviewer, a tool widely used for mapping scientific domains (van Eck & Waltman, 2010). Keyword co-occurrence revealed thematic clusters such as "machine learning and forecasting" or "computer vision and waste sorting." Temporal overlay of the keyword co-occurrence network is used to highlight the change of concepts over the years. These bibliometric insights complemented the systematic review by showing how research has evolved and where gaps and integration opportunities remain.

4. Results

4.1. Keyword co-occurrence analysis

A keyword co-occurrence analysis was conducted in VOSviewer to reveal the thematic structure of the field. Both author and index keywords from the 222 papers were included, and a thesaurus file was applied to unify variants (e.g., MSW → municipal solid waste; CNN → convolutional neural network; WTE → waste-to-energy) and remove generic descriptors (article, study, model, method). This cleaning step reduced noise and provided a clearer conceptual structure. Using association strength normalization and full counting, and applying a threshold of six occurrences, the network contained 106 keywords. The standard co-occurrence network (Figure 3a) highlights five clusters that represent major research streams.

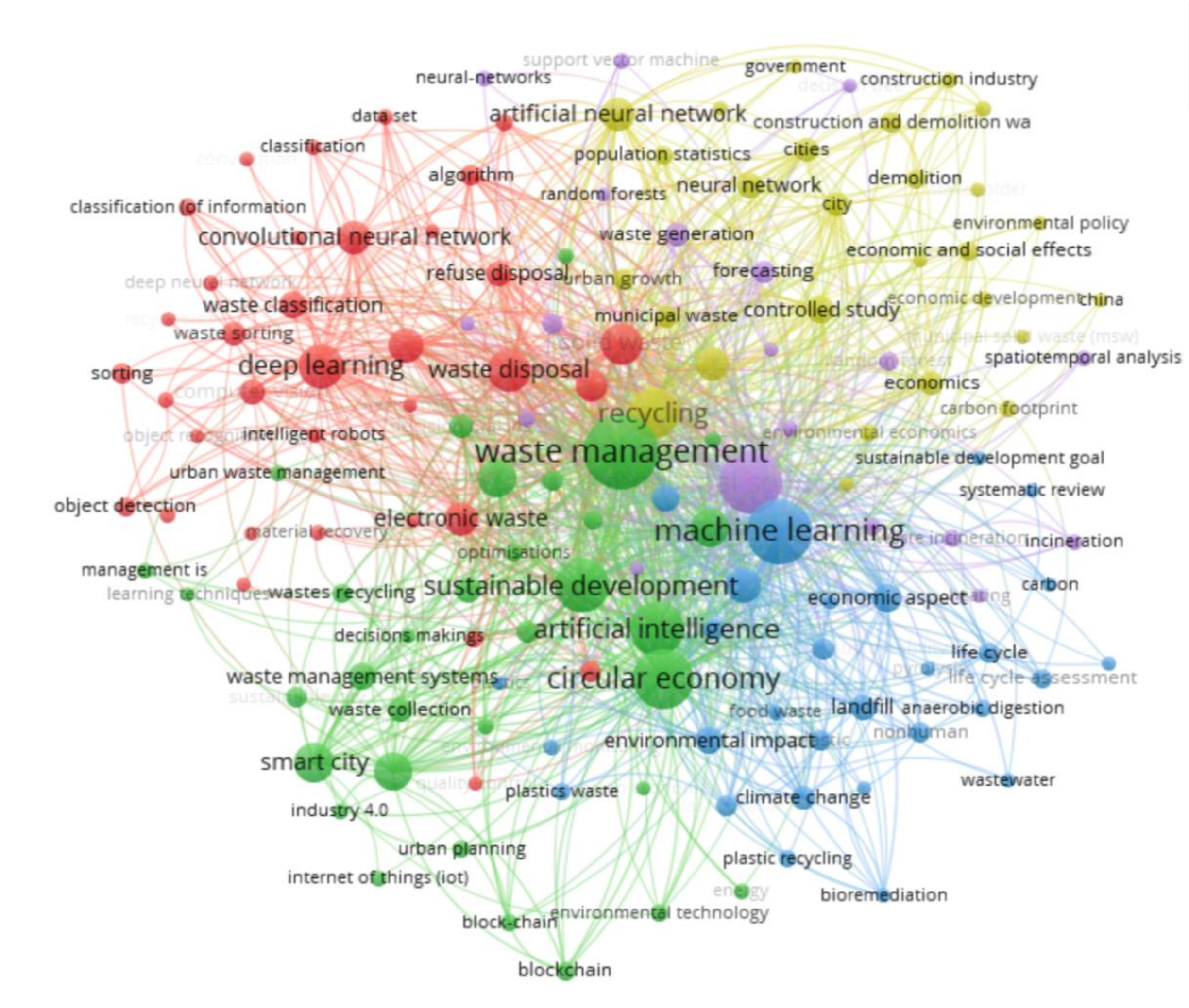

Figure 3a. Keyword co-occurrence network (threshold: six occurrences, 106 keywords). Red = deep learning and classification; Green = waste management and sustainability; Blue = Circular economic outcomes and environmental impacts; Yellow = policy and economics; Purple = municipal solid waste and forecasting

The red cluster focuses on deep learning and classification systems, where terms like deep learning, convolutional neural network, waste classification, object detection, and intelligent robots dominate. This cluster reflects the computer vision tradition in AI for waste recognition and sorting. The green cluster is organized around waste management and includes sustainable development, recycling, waste collection, waste management systems, electronic waste, and smart city. It represents the operational integration of AI into urban waste services and sustainability practices. The blue cluster emphasizes circular economy outcomes and environmental impacts, featuring circular economy, life cycle assessment, environmental impact, bioremediation, landfill, anaerobic digestion, wastewater, and climate change. It shows how AI is used to evaluate environmental performance and support CE objectives. The yellow cluster focuses on policy, economics, and construction waste, including economics, economic development, environmental policy, sustainable development goal, spatiotemporal analysis, and construction and demolition waste. This cluster highlights governance and policy-related perspectives on AI in waste management. Finally, the purple cluster is centered on municipal solid waste and forecasting, combining waste generation, population statistics, forecasting, and methods such as random forests and artificial neural networks. To trace the evolution of research, an overlay visualization was produced (Figure 3b).

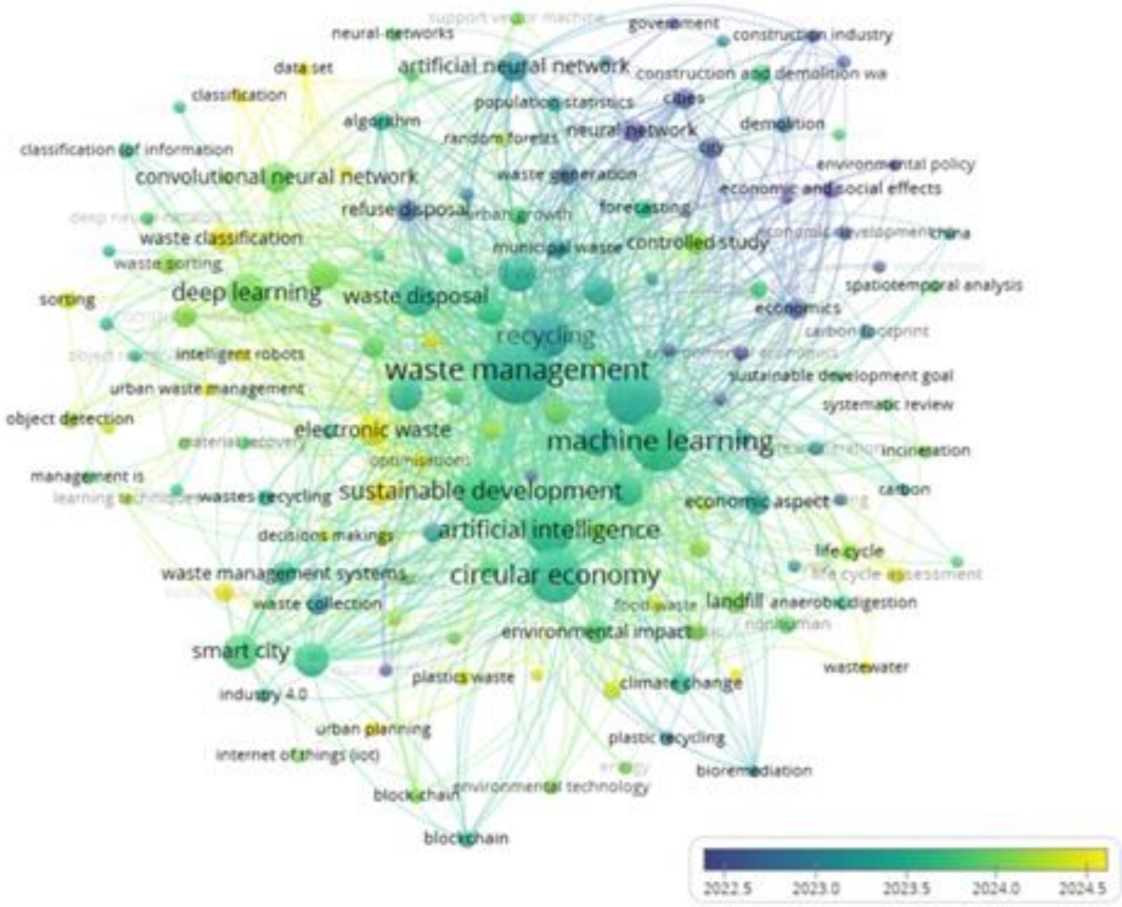

Figure 3b. Temporal overlay of the keyword co-occurrence network. Blue nodes indicate earlier themes (e.g., waste management, recycling, MSW), while yellow nodes highlight emerging hotspots (e.g., deep learning, IoT, blockchain, climate change, plastic recycling).

In temporal overlay of the keyword co-occurrence network, the color of each keyword reflects its average publication year, ranging from blue (earlier) to yellow (more recent). Established themes such as waste management, recycling, and municipal solid waste appear in blue and green shades, indicating their early and enduring importance in the field. In contrast, recent hotspots appear in yellow, including deep learning, object detection, blockchain, Internet of Things (IoT), plastic recycling, and climate change. This temporal overlay shows a shift in focus, while earlier research concentrated on traditional waste management and recycling practices, newer contributions emphasize advanced AI techniques, smart technologies, and their potential to contribute to sustainability and CE transitions.

Together, the two maps suggest a clear trajectory. The standard network shows how the field is structured into complementary clusters, technical AI innovations, operational waste management, environmental and CE outcomes, and policy contexts. The temporal overlay adds another layer, showing how these clusters are dynamically evolving. The newest innovations, particularly in deep learning, IoT, and blockchain, are not isolated: they are increasingly linked to the green cluster on waste management (e.g., smart city applications, optimization of collection systems) and the blue cluster on CE outcomes (e.g., plastic recycling, climate change, life cycle assessment). This convergence indicates that technical advances in AI are progressively being integrated into sustainability-oriented frameworks, creating opportunities for more holistic and human-centered approaches to urban circular economy transitions.

4.2. Thematic synthesis of full-text studies

This section synthesizes the findings from the 150 peer-reviewed journal articles and reviews that were retained after full-text screening. The studies were classified according to AI methods, waste-management stages, waste streams, and whether circular economy (CE) outcomes were reported. For the stage-based graphics, we excluded nine papers that could not be reliably assigned to a primary waste-management stage and could not be classified. This step was taken purely to avoid forcing ambiguous cases into stage categories and to keep the visual comparisons interpretable. The results are presented in three steps: distribution of AI methods across stages, their connection to CE outcomes, and a system-level flow analysis linking methods, stages, and outcomes.

4.2.1. AI methods applied (RQ1) The classification shows that machine learning (ML) remains the most widely used category (64 studies), particularly for planning & forecasting waste generation (Magazzino et al., 2021a; Lu et al., 2021). Deep learning / computer vision (36 studies) and artificial neural networks (18 studies) are also important in sorting & classification (Sarc, 2019; Maiurova & Kurniawan 2022).

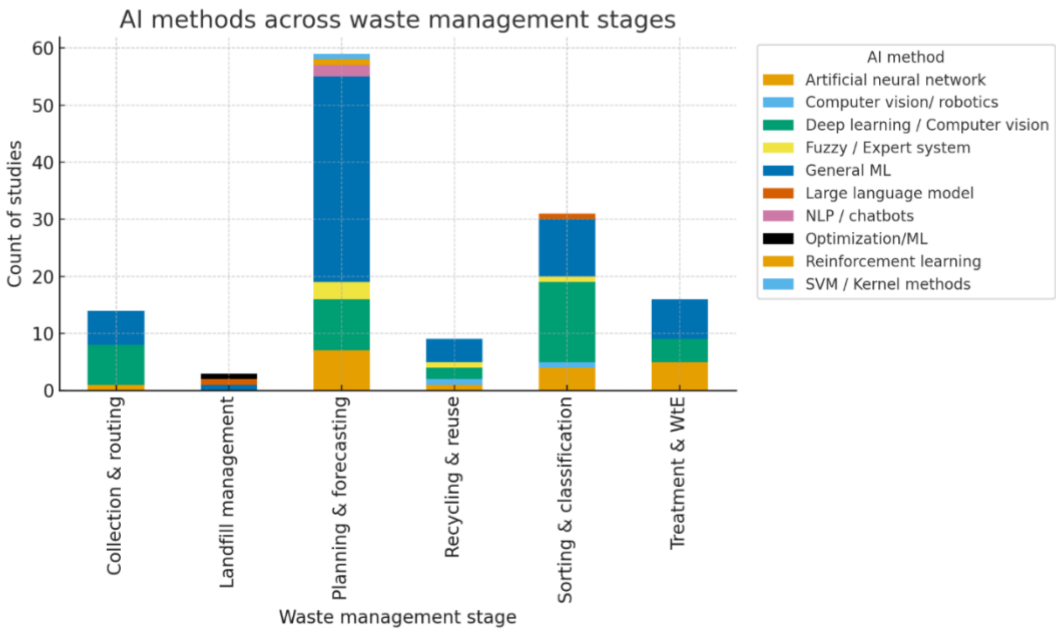

Figure 4. AI Methods Across Waste-Management Stages (150 studies)

Figure 4 highlights strong method stage pairings. Deep learning and computer vision for sorting and classification, and ML/ANNs with planning and forecasting. Other methods are spread across routing, recycling, and treatment but lack the same critical mass.

4.3. Waste-management stages (RQ2)

The most studied stages are planning and forecasting (64 papers) and sorting and classification (32 papers). Sorting studies show how AI improves purity in material recovery, reduces contamination, and supports automation in material recovery facilities (Wilts et al., 2021; Szpilko et al., 2023). Forecasting studies highlight AI's capacity to anticipate waste generation patterns more accurately than statistical models, improving planning and infrastructure investment (Magazzino et al., 2021a).

Smaller clusters include collection and routing (17 papers), which focus on smart bins and IoT-enabled fleet management (Sarc et al., 2019), and recycling and reuse (9 papers), which often report contamination reduction or purity improvements (Kurniawan et al., 2023; Sadeghi et al., 2021).

4.3.1. Circular economy outcomes (RQ3) A major finding is that only 47 of the 150 studies (31%) explicitly report CE outcomes such as recycling rate improvements, contamination reduction, CO_2/GHG reduction, or landfill diversion. The majority focus exclusively on technical performance metrics, such as model accuracy or optimization percentages. Figure 5 shows AI methods and CE outcome reporting.

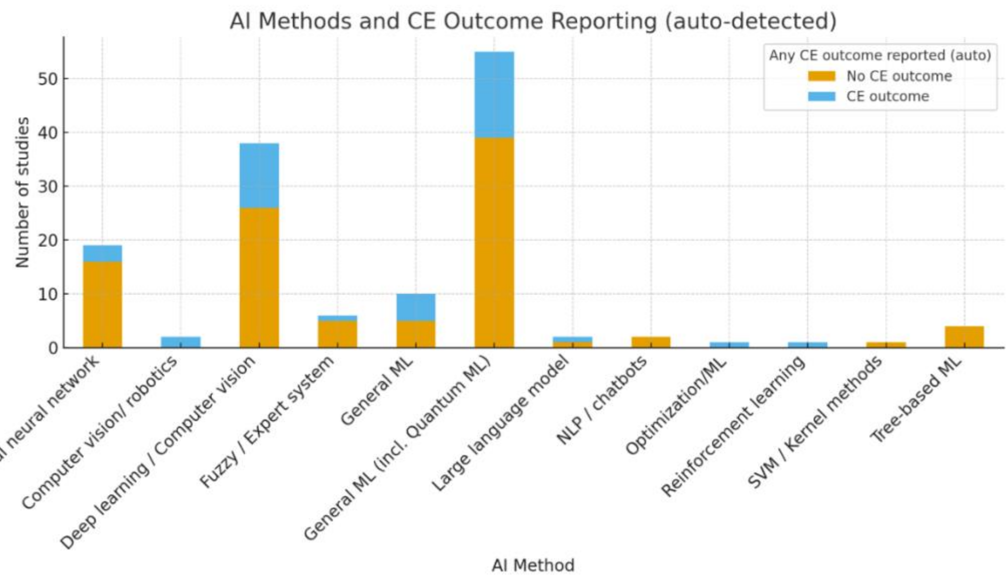

Figure 5. AI Methods and CE Outcome Reporting (150 studies)

Figure 5 shows that across nearly all AI methods, the majority of applications stop at technical results. This relationship highlights a significant evidence gap. Although AI demonstrates technical potential, its contribution to systemic CE indicators is underexplored. Without such evidence, the circular benefits of AI can be poorly explained or understood.

4.3.2. Integrated flow analysis (RQ4) To better understand how AI applications flow through the waste-management system into CE outcomes, a Sankey diagram was constructed linking AI methods → waste stages → CE reporting (Figure 6).

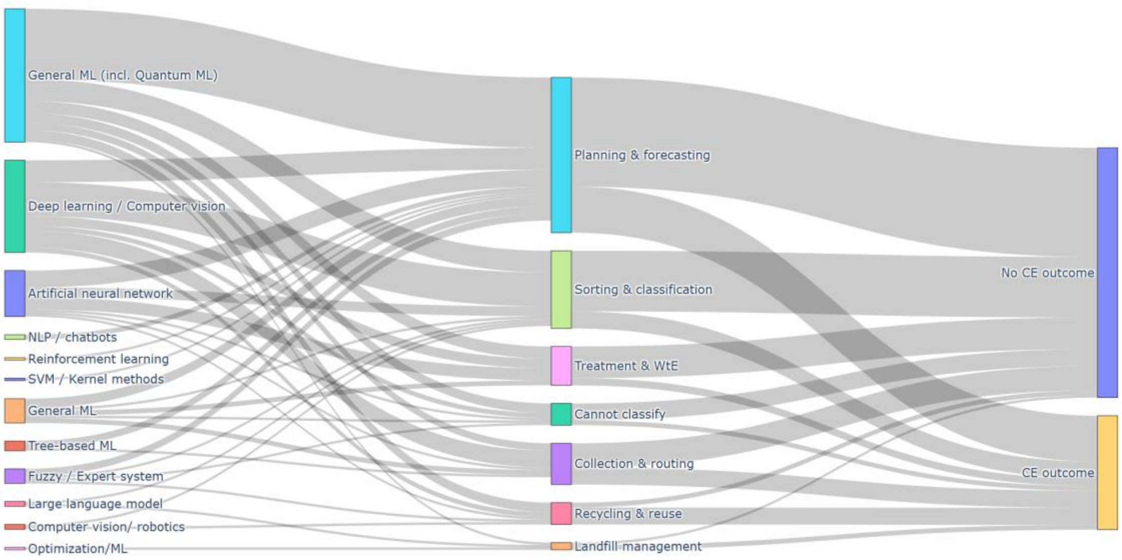

Figure 6. AI Methods → Waste Stages → CE Outcomes (150 studies)

Deep learning and computer vision show a strong association with sorting and classification and some connect to CE outcomes (purity, recycling rates) yet many outcomes remain technical. ML and ANNs dominate planning and forecasting, but most of these flows terminate in "No CE outcome". This shows that forecasting is rarely attached to diversion targets such as life cycle assessment indicators. Recycling and reuse studies, though fewer in number, show a higher proportion of connections to CE outcomes. These studies often reported recovery rates or CO_2 savings. They often showed recovery rates or CO_2 savings. The results demonstrate that AI is reshaping waste management but primarily at the technical level. Strong method and stage correlations indicate efficiency gains, but the lack of CE outcome reporting limits their relevance to circularity debates. For research, this highlights the need for multi stage AI frameworks linking forecasting, routing, and sorting into integrated systems, mandatory reporting of CE outcomes, alongside technical metrics. We need to expand beyond MSW and e-waste into underexplored streams such as plastics, organics, and wastewater. For practice and policy, the findings suggest that AI adoption should be tied to governance frameworks requiring measurable CE impacts (e.g., recycling targets, CO_2 reduction). Investments should prioritize AI driven sorting and embedding AI forecasting into municipal planning systems, but only where CE benefits are demonstrable.

These findings are broadly consistent with, yet extend, the conclusions of prior systematic reviews in adjacent domains. Andeobu et al. (2022) similarly concluded in their review of AI applications for sustainable waste management, that technical performance dominates reporting while circular economy outcomes remain peripheral. The present study refines this observation by quantifying the gap with greater precision: only 31% of reviewed studies explicitly report CE outcomes. Kurniawan and Othman (2023) argued that decarbonization in the waste-recycling industry requires AI to be embedded within broader governance and policy frameworks. A conclusion the present findings reinforce through evidence that neither academic research nor commercial implementations have yet achieved this embedding systematically. Wilts et al. (2021) identified AI, robotics and data platforms as key enablers of smarter waste systems but cautioned that technical capability alone does not translate to systemic impact. The present review validates this caution: across 150 studies and ten commercial deployments, the gap between technical performance and circular economy outcome measurement is consistent and structural rather than incidental. Where prior reviews have treated this gap as limitation to be noted, the present review treats it as a central finding requiring explanation. Locating its source in the R-strategy hierarchy, where AI applications cluster at lower-order recovery and recycling stages rather than higher-order reuse, remanufacture or waste prevention strategies. This reframing moves the conversation from documenting underperformance to diagnosing its structural causes, which is a necessary precondition for designing interventions that foster the circular economy transition.

5. Company Examples adapting AI in Waste Management

This chapter synthesizes practical implementations of artificial intelligence in urban waste management to validate and extend the findings from the systematic literature review. The analysis examines real-world deployments across multiple geographic areas and organizational scales, providing empirical examples for the theoretical frameworks identified in the literature. The practical examples demonstrate both the technical potential and – at least current – systemic limitations of AI applications in advancing circular economy transitions within urban waste management contexts.

The empirical analysis presents commercial implementations across different AI methodologies, waste management stages, and organizational contexts. Table 2 presents the mapping of selected practical examples related to the four research questions:

Table 2.

Company / System	RQ1 AI methods	RQ2 Waste-management stages	RQ3 Circular economy outcomes	RQ4 Integrated flow analysis
AMP Robotics	✓	✓	-	-
ZenRobotics	✓	✓	-	-
Winnow	✓	✓	✓	-
Leanpath	✓	✓	✓	-
KITRO	✓	✓	✓	-
Sensoneo	✓	✓	-	✓

Note: ✓ =Strong example / evidence; - = Limited example / evidence

Table 2 (cont.).

Company / System	RQ1 AI methods	RQ2 Waste-management stages	RQ3 Circular economy outcomes	RQ4 Integrated flow analysis
Bigbelly	✓	✓	-	-
SmartEnds Vision AI	✓	✓	-	-
NANDO (ReLearn)	✓	-	-	✓
Route Optimization Systems	✓	✓	-	✓

Note: ✓ =Strong example / evidence; - = Limited example / evidence

The empirical findings reveal significant convergence between academic research priorities and practical implementation focus, particularly in sorting and collection applications. However, the analysis also identifies critical gaps in circular economy outcome measurement and system-level integration that limit the translation of technical capabilities into comprehensive urban circular economy transitions.

5.1. AI Methods Applied in Practice (RQ1)

The analysis of AI methods applied in urban waste management reveals convergence between academic research and industrial deployment. Machine learning and neural network applications dominate both literature and practical implementations, particularly in forecasting and sorting applications.

AMP Robotics (https://ampsortation.com) exemplifies this transition through its AMP Neuron platform, which encompasses what the company claims to be the largest known real-world dataset of recyclable materials for machine learning applications. The system processes over 50 billion object recognitions annually across its installed base, demonstrating the scalability challenges highlighted in the literature review. This dataset magnitude addresses the transferability concerns identified in academic studies, where AI models developed for narrow, local datasets often exhibit reduced performance across different cities or waste streams.

Predictive analytics implementations validate the literature findings regarding improved forecasting accuracy. Systems utilizing World Bank comprehensive waste management datasets (https://data360.worldbank.org) have achieved 85% accuracy in waste generation trend prediction, primarily attributed to the integration of diverse socio-economic factors alongside traditional waste composition data. This performance level aligns with the superior accuracy reported in academic studies comparing machine learning approaches with traditional statistical methods. However, the gap between technical performance and circular economy outcome measurement persists in practical implementations, consistent with the literature analysis showing that only 31% of studies explicitly report CE outcomes.

Convolutional neural networks demonstrate the most mature commercial deployment, particularly in waste sorting applications. AMP Robotics' computer vision system achieves 99% accuracy at processing speeds of 80-120 picks per minute, substantially exceeding human sorting capabilities while addressing safety concerns inherent in manual waste processing. The system's capability to classify more than 100 different categories and characteristics of recyclables across diverse waste streams validates academic research on CNN applications for multi-material waste classification.

Food waste applications represent an emerging area where computer vision technology demonstrates significant practical impact. Winnow (https://www.winnowsolutions.com) Vision's "Throw & Go" technology exemplifies the integration of image recognition with operational workflows, eliminating the manual data entry requirements that often limit adoption in commercial settings. The system's deployment across thousands of kitchens in over 90 countries provides validation of scalability potential that remains underexplored in academic literature.

IoT-enabled sensor networks demonstrate widespread practical adoption, with Sensoneo (https://sensoneo.com) operating across 87 countries and deploying 11,100 sensors in Madrid alone, representing the largest smart waste installation globally. The technical specifications align with academic research on ultrasonic sensor applications, with capabilities spanning 3 centimeters to 12 meters measurement range and integration across multiple IoT networks including Sigfox, NB-IoT, LoRaWAN, and GPRS.

The analysis reveals several areas where practical implementations lag behind academic research potential. Advanced algorithms such as reinforcement learning for adaptive routing and large language models for knowledge integration remain largely unexplored in commercial applications. Additionally, while academic research emphasizes multi-stage AI frameworks linking forecasting, routing, and sorting into integrated systems, practical implementations remain predominantly single-stage solutions.

5.2. Waste Management Stages Implementation (RQ2)

The distribution of AI applications across waste-management stages in practical implementations closely mirrors the patterns identified in the literature review, with sorting and classification dominating deployment efforts, followed by forecasting applications.

Sorting and classification applications demonstrate the most mature transition from academic research to commercial deployment, validating the literature finding that this stage attracts the highest research attention. The above-mentioned AMP Robotics exemplifies this dominance through deployment of over 400 AI systems across North America, Asia, and Europe, with installations spanning single-stream recycling facilities, electronic waste processing centers, and construction and demolition debris sorting operations.

ZenRobotics (https://www.terex.com/zenrobotics), operating primarily in European markets, demonstrates alternative approaches to AI-driven sorting with recognition capabilities for over 350 material categories. However, the system operates at approximately half the speed of competing technologies while maintaining similar accuracy rates, illustrating the trade-offs between comprehensiveness and operational efficiency that characterize current sorting implementations.

The food waste sorting domain presents distinct characteristics, with companies like Winnow, Leanpath (https://www.leanpath.com), and KITRO (https://www.kitro.ch) focusing on identification and categorization rather than physical separation. Winnow's deployment across thousands of commercial kitchens in over 90 countries demonstrates scalability potential, while achieving documented waste reduction rates of 50% that translate directly to circular economy outcomes through reduced resource consumption and disposal requirements.

Forecasting applications show increasing practical deployment though with less mature integration compared to sorting systems. Real-world implementations validate academic findings regarding superior performance of machine learning approaches over traditional statistical methods, with documented systems achieving 85% accuracy in waste generation trend prediction through integration of socio-economic variables alongside historical waste data patterns.

Collection and routing applications demonstrate significant practical impact through IoT-enabled smart bin technologies and route optimization algorithms. Bigbelly's (https://bigbelly.com) deployment in high-traffic urban environments exemplifies this integration, achieving nearly 200% increase in total trash capacity while reducing collection frequency per bin by 50%. Route optimization implementations demonstrate quantifiable improvements, with documented reductions in transportation distance of up to 36.8% and time savings of up to 28.22%, while achieving cost savings of up to 13.35%.

Treatment and waste-to-energy applications remain significantly underrepresented in practical implementations, validating the literature finding that these stages receive minimal research attention. This implementation gap represents a critical limitation in achieving comprehensive circular economy transitions, as these stages are essential for closing material loops and minimizing environmental impact.

5.3. Circular Economy Outcomes in Practice (RQ3)

The analysis of circular economy outcome reporting in practical implementations validates the critical finding from the literature review that only 31% of studies explicitly report CE outcomes.

Food waste management systems represent the most mature domain for documented circular economy outcomes, with consistently reported material flow reductions and economic benefits. Winnow's commercial implementations demonstrate 50% food waste reduction across thousands of kitchens in over 90 countries, with purchasing cost reductions of 3-8%. Specific case documentation includes Conrad Dubai's $300,000 HKD annual savings and Hilton Dubai Jumeirah's $65,000 waste value reduction, representing direct material efficiency gains that translate to reduced resource extraction and disposal requirements.

Leanpath (https://www.leanpath.com) achieves comparable 50% waste reduction rates while delivering 2-7 times return on investment, with systems processing waste categorization and predictive recommendations that directly address contamination and collection inefficiencies. The Sheraton Grand Hotel & Spa Edinburgh documented 64% reduction in food waste value and 58% reduction in waste weight within one year of implementation, demonstrating measurable progress toward circular resource flows.

IoT-enabled collection systems demonstrate substantial operational improvements but inconsistent circular economy outcome measurement. Sensoneo claims 40% waste collection cost reduction and up to 60% carbon emission reduction in urban deployments. The Madrid installation with 11,100 sensors represents the largest integrated smart waste system globally, yet specific landfill diversion rates or material recovery improvements remain undocumented in publicly available reports.

The practical implementations confirm the literature finding that technical performance metrics dominate reporting while circular economy outcomes remain secondary considerations. Food waste management systems represent the notable exception, demonstrating direct material flow impacts that align with circular economy principles of waste prevention and resource efficiency.

5.4. System Integration Analysis (RQ4)

The analysis of practical implementations reveals the same fragmentation identified in the literature review, with most AI applications operating as isolated single-stage solutions rather than integrated systems spanning multiple waste management stages. However, emerging examples demonstrate both the potential and complexity of system-level integration for circular urban waste management transitions.

Practical deployments confirm the literature finding that AI applications remain concentrated in specific waste management stages without comprehensive integration. AMP Robotics' 400+ installations operate primarily as sorting-focused solutions, with limited integration into upstream forecasting or downstream recycling optimization systems. While the company's partnership with Waste Connections represents movement toward facility-scale integration, the systems remain functionally isolated from broader urban waste management ecosystems.

Sensoneo's 11,100-sensor Madrid deployment represents the largest smart waste installation globally, yet operates predominantly as a collection optimization system without documented integration with sorting facilities or recycling outcome tracking. Similarly, Bigbelly's smart bin networks optimize collection efficiency but lack systematic connection to material recovery facilities or circular economy outcome measurement systems.

NANDO (ReLearn) represents an emerging approach toward comprehensive waste intelligence, integrating monitoring, analysis, and community engagement across multiple waste management stages. The system combines waste production measurement with recycling optimization and community gamification, though specific performance metrics for cross-stage integration remain limited in available documentation.

Food waste management systems show the strongest integration potential, with Winnow, Leanpath and KITRO extending beyond waste measurement to include inventory optimization, menu planning, and supply chain integration. These systems demonstrate how AI applications can span multiple operational stages within specific waste stream domains, though broader integration with municipal waste management systems remains limited.

Practical implementations reveal significant barriers to system-level integration beyond technical capabilities. Organizational fragmentation between waste collection, processing, and recycling sectors limits data sharing and coordinated optimization across waste management stages. Proprietary data concerns prevent the comprehensive information integration necessary for system-level optimization, as evidenced by limited public documentation of cross-stage performance metrics in commercial deployments.

The analysis confirms that while individual AI applications demonstrate strong technical performance, the translation to city-wide or systemic CE transitions remains largely undocumented. Most implementations focus on operational efficiency within specific stages rather than comprehensive material flow optimization across urban waste ecosystems. The evidence suggests that achieving the systemic circular economy transitions emphasized in academic literature requires enhanced coordination frameworks, standardized data integration protocols, and governance structures that incentivize cross-stage optimization rather than isolated efficiency improvements.

6. Conclusion

This paper examined the application of AI in waste management systems, analyzing 150 peer-reviewed studies and practical implementations. The findings reveal significant technical progress in AI deployment across waste management stages, particularly in sorting and classification (32 studies) and planning & forecasting (64 studies). However, the translation of these technical capabilities into circular economy transitions remains fundamentally limited.

A critical finding is that only 31% of reviewed studies explicitly report circular economy outcomes, such as improvements in recycling rates, reduction in contamination or landfill diversion. The majority of academic papers and practical implementations emphasize the accuracy of AI applications as well as gains in operational efficiency, without making the connection to material flow indicators that could reflect actual progress in circularity. This gap between technical performance and circular progress, persisting across both academic research and commercial implementations, suggests that current AI applications optimize existing linear systems rather than fundamentally enabling a transition towards more circularity.

Practical applications validate this pattern. Companies such as AMP Robotics, Winnow and Sensoneo clearly demonstrate robust technical capabilities, however their current contributions remain on increasing efficiency within isolated waste management stages. Only food waste management systems represent a notable exception, consistently reducing input materials by 40 to 50% alongside additional economic benefits.

From a circular economy perspective, the concentration of AI applications in recycling and waste-to-energy is positioned at the lower tiers of the R-strategy hierarchy. This represents a structural limitation: while recycling and recovery are essential components of circular systems, they address end-of-life material flows rather than preventing waste generation or extending product and material lifespans through higher-order strategies. The literature review only identified minimal research attention to AI applications in e.g. waste prevention, reuse systems or repair networks. This indicates that current developments remain in downstream activities rather than upstream circular design.

The findings should be interpreted with appropriate caution, as the review represents a temporal snapshot of a rapidly evolving field. The search of literature was conducted until August 30, 2025, and was restricted to English-language and peer-review articles in Scopus. As this ensures quality of contributions, it may exclude relevant work published either in other languages or dissemination formats. Furthermore, the classification of AI methods and circular economy outcomes involves interpretive judgments that, while systematic, could lead to analytical limitations.

A further limitation concerns the scope of the contribution itself. The present study advances understanding by systematically quantifying the gap between AI's technical performance and its reported circular economy outcomes, a gap that prior reviews have acknowledged but not measured with the same precision. In this sense, the contribution is incremental rather than transformative: it consolidates and evidences a known problem rather than resolving it. This is, however, a deliberate and necessary step. Establishing a clear empirical baseline for how AI currently performs against circular economy criteria is a prerequisite for the more transformative research that must follow. Future work should move beyond firm-level and single-stage analyses towards ecosystem-level perspectives, examining how AI can coordinate actors, material flows, and information systems across entire urban waste ecosystems. A level of integration that the present findings suggest is currently absent from both academic research and commercial practice.

From our perspective, the contributions of this paper are the following: This study advances circular economy theory in three ways. At the theoretical level, circular economy scholarship has long argued that systemic integration — rather than isolated technical interventions — is the precondition for genuine material circularity (Andeobu et al., 2022; Kurniawan & Othman, 2023). The present study operationalises this argument empirically, demonstrating through systematic evidence that AI, despite its technical sophistication, has not yet bridged the gap between operational efficiency and circular economy outcomes. This finding reinforces and sharpens the theoretical claim that circularity cannot be achieved through technology alone: it requires governance structures, cross-actor coordination, and measurement frameworks aligned with circular economy criteria. Furthermore, the review demonstrates that technological development and sophistication alone do not guarantee progress in circularity, emphasizing the need for systemic integration frameworks, connecting AI capabilities with e.g. material flow. From a more methodological perspective, evaluation criteria beyond technical performance are needed to demonstrate a progress in circularity. Finally, from a practical perspective, the paper identifies specific gaps and implementation barriers that require attention.

Therefore, and as a future research outlook, it might be worth focusing on multi-stage AI frameworks that integrate forecasting, collecting, sorting and recycling into coordinated systems interfacing with e.g. supply chain management, sourcing and procurement. Reporting of circular economy outcomes alongside technical data would strengthen the evidence base for evaluating AI's contribution to circular transition. Finally, and probably most important, expanding the current focus on recycling to higher-order R-strategies, supporting not only reuse or repair networks to increase the lifespan of products and materials, but even focusing on the upper R-strategies in terms of rethinking the current use of materials.

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Declarations

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