

# How Artificial Intelligence Can Empower the Robotic Recycling Industry: Toward an Adaptive, Data-Driven, and Circular Material Recovery System

Chengyao Cai\*

*Georgetown Preparatory School, Upper School, North Bethesda, MD 20814, United States*

*\*Corresponding author: Chengyao Cai*

---

## Abstract

This paper examines how artificial intelligence (AI) can strengthen the robotic recycling industry by improving material identification, adaptive sorting, process optimization, and data-driven decision-making across recycling systems. As waste streams become more heterogeneous and contaminated, conventional recycling methods—particularly manual sorting and rigid automation—face growing limitations in throughput, consistency, and economic viability. Drawing on recent institutional reports and academic research, this paper argues that AI-enabled robotics offers a socio-technical pathway for transforming recycling into a more adaptive and resilient material recovery system. Specifically, AI improves robotic recycling through enhanced perception and classification, real-time response to variable feedstocks, higher-speed sorting with quality control, and cumulative operational learning. The paper also analyzes barriers to large-scale adoption, including capital intensity, infrastructure readiness, model reliability under domain shift, workforce transition challenges, and governance requirements. It further argues that the long-term effectiveness of AI-powered robotic recycling depends on integration with policy incentives, standards, and circular economy objectives rather than technology deployment alone. Overall, the study concludes that AI can serve as a powerful enabler of robotic recycling when implemented as part of a broader socio-technical system that combines technical innovation, institutional support, and responsible governance.

## Keywords

artificial intelligence, robotic recycling, waste sorting, circular economy, material recovery

---

## 1. Introduction

The global recycling challenge is increasingly a systems-engineering problem rather than a purely environmental slogan. Waste streams are growing in volume and complexity, while many recycling systems remain constrained by contamination, labor shortages, aging infrastructure, and weak data visibility [1]. UNEP's Global Waste Management Outlook 2024 highlights that municipal solid waste generation is projected to rise substantially by mid-century, and that the economic costs of poor waste management include not only direct system costs but also pollution, health, and climate externalities [1]. In parallel, the Global E-waste Monitor 2024 reports that e-waste generation is increasing faster than documented formal collection and

recycling, underscoring a widening gap between material discard and recovery capacity [2]. These trends place pressure on recycling systems to recover more material, more precisely, and at lower operational risk.

Traditional recycling facilities—especially material recovery facilities (MRFs), mixed-waste sorting plants, and certain construction and demolition (C&D) waste operations—face a core bottleneck: they must separate heterogeneous, contaminated, and fast-moving streams into material fractions that are clean enough to be sold and reprocessed. Manual sorting is flexible but physically demanding, difficult to scale, and often inconsistent under throughput pressure [3]. Conventional automation can improve speed, but fixed-rule systems struggle when feedstocks vary or when visual cues become ambiguous (for example, crushed containers, dirt-covered plastics, and overlapping items) [4]. In other words, recycling is a high-variability industrial environment, and high variability punishes rigid systems.

This is where artificial intelligence (AI), especially when coupled with robotic handling, becomes strategically important. AI gives recycling systems enhanced perception (what is on the belt), classification (what material or object class it belongs to), adaptation (how the model improves for changing streams), and process intelligence (what the facility learns over time from sorting data) [5, 6]. AI-enabled robotics can therefore be understood not simply as “automation,” but as adaptive automation. Rather than replacing one human task with one mechanical task, AI-powered systems can transform the sorting line into a sensor-rich decision environment that supports continuous optimization of recovery, purity, labor allocation, and maintenance [3].

This essay argues that AI can materially improve the robotic recycling industry by strengthening material recognition, adaptive sorting, operational optimization, and facility-wide decision intelligence, thereby improving throughput, purity, safety, and circularity outcomes. However, the essay also argues that these gains are contingent: technological capability alone is insufficient. Long-term success depends on infrastructure readiness, robust data practices, workforce transition strategies, interoperability, governance, and policy alignment [7, 8]. A more academic assessment, therefore, must evaluate AI-powered robotic recycling not only as a technical innovation but as a socio-technical transformation embedded in broader circular economy systems.

## **2. The Structural Limits of Conventional Recycling and Why Robotic AI Matters**

Recycling has long been treated in public discourse as a straightforward chain—collection, sorting, processing, reuse—but in practice it is a fragile set of linked operations with multiple points of failure [1]. Three structural limitations make the case for AI-enabled robotics particularly compelling: (1) stream heterogeneity and contamination, (2) economic fragility under fluctuating material values and labor constraints, and (3) limited process intelligence due to insufficient data.

First, stream heterogeneity is intrinsic to recycling. Municipal streams combine packaging of different polymers, labels, food residues, deformities, multilayer materials, and non-target contaminants [4]. E-waste adds complexity through mixed assemblies, hazardous substances, and high-value but difficult-to-access components. The Global E-waste Monitor 2024 emphasizes both the scale of e-waste and the gap between generation and documented formal recycling, reinforcing the need for more capable material handling and recovery systems [2]. In such contexts, the limiting factor is often not collection volume but sorting quality and speed.

Second, recycling economics are often narrow-margin and highly sensitive to contamination and throughput disruptions. EPA’s U.S. recycling infrastructure assessment materials summarize a large national need for investment to modernize collection, sorting, processing, and end-market systems, including MRF infrastructure [8]. In this setting, AI-enabled robotics is attractive because it can potentially improve both operational efficiency and material quality, two levers that directly affect economic viability [9, 10].

Third, many facilities still lack robust process-level data. Managers may know tonnage and broad commodity outputs, but not necessarily where value loss occurs on the line, which contaminants are increasing, which shifts are underperforming, or how incoming composition changes by route, season, or customer type [5]. AI-powered vision and classification can convert the sorting process into a data-generating system, enabling measurement of composition, miss rates, contamination patterns, and recovery opportunities [3]. This shift from “mechanical sorting” to “sensor-driven sorting” is analytically significant because it changes the

managerial function of the facility: the plant becomes both a recovery operation and a real-time material characterization platform.

The broader literature on AI in waste management and sorting supports this interpretation. Recent reviews describe AI as enabling automation not only in classification but also in routing, process optimization, and integrated waste-system management, while emphasizing persistent limitations in scalability and deployment conditions [5,3]. Likewise, a systematic review of AI-based waste classification notes rapid growth in the field and identifies real-world variability, dataset imbalance, and standardization issues as major barriers to deployment—issues especially relevant to industrial sorting applications [6].

Thus, the importance of AI in robotic recycling lies not only in replacing manual picks, but in addressing a deeper mismatch: highly variable waste streams have historically been managed by either labor-intensive flexibility or rigid automation. AI-powered robotics offers a third path—programmable flexibility at industrial speed [11].

### **3. Conceptual Framework: AI in Robotic Recycling as a Socio-Technical System**

A more academic treatment of AI-enabled robotic recycling benefits from a conceptual framework that distinguishes between technical layers and organizational layers. A useful model includes five interacting layers: (1) sensing, (2) inference/classification, (3) actuation, (4) process control and optimization, and (5) governance and workforce integration.

#### **3.1 Sensing Layer: Seeing Waste as Data**

The sensing layer includes cameras, optical sensors, spectroscopic systems (e.g., NIR), depth/3D sensors, and conveyor monitoring systems. The technical objective at this layer is to convert a fast-moving, occluded, contaminated waste stream into machine-readable signals. The challenge is not merely image acquisition but signal robustness under industrial conditions: dust, variable lighting, reflective surfaces, overlapping objects, and deformation [4].

Reviews of plastic sorting technology emphasize the role of advanced sensing and the combination of optical methods with machine learning in modern sorting systems, while also noting continuing challenges with dirty or wet objects and sensor limitations [4]. This is an important point for academic analysis: sensing quality sets the upper bound on classification quality. AI does not “solve” bad sensing; it amplifies what sensing can reveal.

#### **3.2 Inference and Classification Layer: From Pixel Data to Material Decisions**

The inference layer is where machine learning and deep learning models classify objects or materials and support sorting decisions. At a minimum, this may involve object detection and category assignment (e.g., PET bottle, aluminum can, carton). More advanced systems may estimate confidence, identify brands or packaging formats, detect contamination signatures, or classify subtypes relevant to downstream value [6].

The academic literature on AI-based waste classification shows strong interest in deep learning and hybrid models and highlights both the progress and the limitations of current datasets and benchmarking practices [6]. This matters because industrial recycling performance depends on generalization, not just benchmark accuracy: models must work on real belts, not only on curated datasets. The gap between lab classification and production-grade inference is one of the central research-to-practice challenges in this field [6].

#### **3.3 Actuation Layer: Robotics as Decision Execution**

Once a material is identified, the system must act—through robotic arms, suction grippers, air jets, or other mechanical mechanisms. This is the point at which AI transitions from perception to physical intervention. The actuation layer introduces additional constraints: pick speed, reach, grasp reliability, item stability, belt speed synchronization, and collision avoidance [12].

A 2024 study on AI-powered robotic sorting for beverage container recycling notes that AI image recognition and high-speed suction-based grippers can sort multiple container types while also documenting practical limitations such as challenges with clear-container detection and handling deformed or liquid-

containing items [12]. This is precisely the kind of empirical nuance needed in an academic account: AI-assisted robotic sorting is promising, but performance depends on end-effector design, line stability, and object physicality—not AI alone.

### **3.4 Process Control and Optimization Layer: Facility Intelligence, Not Just Robot Intelligence**

At the process layer, AI-generated sorting data can be used to optimize line balance, identify bottlenecks, target contamination reduction, and inform maintenance and quality control [5]. This layer expands the meaning of “robotic recycling” from a single robotic station to a facility-wide control and learning system.

Recent reviews of smart waste and AI-enabled systems emphasize the importance of integrating data flows across collection, sorting, and treatment, rather than focusing on isolated devices [3]. In industrial practice, this implies that the value of AI may increase significantly when sorting data are linked to operator decisions, maintenance planning, and buyer requirements for bale quality [5].

### **3.5 Governance and Workforce Integration Layer: Trustworthy Deployment**

The final layer is governance. AI systems in industrial settings create questions about performance auditing, accountability, failure modes, and human oversight. NIST’s AI Risk Management Framework (AI RMF 1.0) emphasizes managing risk to improve trustworthiness and notes that the framework is intended to be flexible across organizations of different sizes and sectors [7]. Although NIST is not recycling-specific, its principles are highly relevant: recycling facilities adopting AI-enabled robotics need documented monitoring, maintenance of model performance, human override procedures, and role clarity [7].

A socio-technical framework is valuable because it prevents the common mistake of evaluating robotic recycling only at the “demo” level. Academic analysis should instead ask: How do sensing, inference, actuation, process control, and governance interact to produce (or fail to produce) sustained material recovery gains?

## **4. Performance Mechanisms: How AI Improves Robotic Recycling in Practice**

To assess AI’s impact rigorously, one should analyze the mechanisms by which performance improves. Four mechanisms are central: (1) enhanced recognition granularity, (2) adaptive response to variability, (3) quality-consistent high-speed sorting, and (4) cumulative learning through operational data.

### **4.1 Enhanced Recognition Granularity and Material Differentiation**

One of the strongest contributions of AI to recycling is more granular identification. Traditional systems can often separate broad classes, but AI-assisted systems can support finer distinctions (e.g., polymer type, color, object form factor, or category-specific contaminants) [4,6]. The Ellen MacArthur Foundation’s circular economy case on AMP Robotics describes AI-based visual recognition that improves categorization of mixed waste items and continuous model improvement through deep learning [13]. While such industry-linked case descriptions should be treated cautiously in scholarly writing, they are useful as evidence of how commercial systems frame the value proposition: sorting gains come from classification depth and continuous learning, not just robotic movement [13].

Granular recognition matters economically because downstream recyclers often demand cleaner and more consistent streams. In secondary materials markets, “recyclable” is not a binary condition but a quality threshold shaped by contamination tolerance, processing technology, and end-use requirements [9]. By increasing sorting resolution, AI can improve both the quantity and quality of recovered materials, which strengthens the viability of circular material flows [1].

### **4.2 Adaptive Sorting under Real-World Variability**

Recycling lines are dynamic: incoming composition changes by region, season, collection route, and consumer behavior. Packaging design changes over time. Contamination spikes can follow holidays or weather events. AI’s adaptive capacity is therefore one of its strongest theoretical advantages over rigid rule-based systems [11].

The Scientific Reports article on versatile waste sorting in flexible environments is useful here because it focuses explicitly on variability and the need for automated systems that can switch across waste types and conditions. The study frames robotic waste sorting as a problem requiring flexible segmentation and handling in changing environments, not just repetitive sorting under fixed inputs [11]. This aligns with a broader academic point: the value of AI in recycling is closely tied to distribution shift management—the ability of systems to maintain useful performance when the statistical properties of the input stream change [6].

### **4.3 High-Speed Sorting with Quality Control**

Industrial adoption depends on throughput, but throughput alone is insufficient if contamination rises. AI-assisted robotics contributes by supporting high-speed identification and targeted sorting while preserving or improving quality. The relevant mechanism is not merely faster picks, but decision confidence at speed—the system’s ability to identify enough correctly, fast enough, to improve plant performance [12].

At the facility level, this can allow different deployment modes: primary positive sorting, quality control (QC) on selected streams, capture of specific under-recovered materials, or recirculation support [13, 14]. In practice, facilities may combine robotic arms and air-jet systems depending on stream type and throughput requirements [4]. Industry case descriptions, while promotional, often reveal practical drivers such as labor instability, changing material streams, and missed recovery opportunities—issues that are structurally relevant to academic analysis of adoption incentives. For example, a published AMP case page for Napa notes staffing turnover/absences and changing material streams as operational challenges in an MRF context [14].

### **4.4 Cumulative Learning, Feedback, and Facility-Level Optimization**

Perhaps the most under-discussed mechanism is cumulative learning. Every inference, pick, miss, contamination event, and line condition can be logged. Over time, this enables composition analytics, performance diagnostics, and operational optimization [5,3]. A facility can learn which materials are increasing in the stream, where contamination enters, and where line interventions have the highest return.

This data-generation role is reflected in broader reviews of AI and smart waste systems, which emphasize integration of data and process optimization as a major frontier beyond isolated sorting tasks [5,3]. Academically, this shifts the research question from “Do robots sort better than people?” to “How do AI-enabled sorting systems change plant-level learning, decision-making, and process adaptability over time?” That broader question is more consequential for long-term circularity outcomes [1].

## **5. Evidence from Research and Practice: What We Can and Cannot Conclude**

A more scholarly essay must distinguish carefully between (a) peer-reviewed evidence, (b) technical reviews, and (c) vendor case studies. The evidence base for AI-enabled robotic recycling is expanding, but it remains uneven across waste streams, geographies, and performance metrics.

### **5.1 Peer-Reviewed Evidence on Automated Sorting and Competitiveness**

Recent peer-reviewed work in construction waste sorting provides useful empirical insight. A 2025 Waste Management case study compares machine-learning-based automated sorting with conventional sorting using empirical data from Finnish companies and reports advantages in cost efficiency and circularity-related outcomes over a multi-year cost model [9]. A related 2025 Applied Sciences sensitivity analysis examines a real-world deployment of computer vision-enabled construction waste sorting and reports that cost competitiveness is highly sensitive to labor costs, machinery costs, maintenance costs, and discount rates [10].

These studies are important for two reasons. First, they move beyond conceptual optimism into comparative analysis. Second, they show that the question is not “Is AI sorting better?” in the abstract, but under what cost and operating conditions it becomes superior [9,10]. This conditionality is central to serious policy and investment decisions.

### **5.2 Evidence on Classification Research and Deployment Barriers**

The systematic review on AI-based automated waste classification provides a broader map of the research

landscape and identifies key barriers: dataset imbalance, real-world variability, domain adaptation problems, and standardization issues [6]. These findings help explain why promising classification results do not always translate into stable industrial deployment. They also suggest an agenda for future research: benchmark datasets that better represent real industrial streams, validation under production conditions, and methods for domain adaptation and continual learning [6].

In this sense, the field resembles many applied AI domains: model accuracy is necessary but not sufficient. Deployment success depends on robustness, maintainability, and system integration [7].

### **5.3 Practice-Side Evidence and Its Limits**

Industry case studies and circular economy organizations document real deployments and provide practical detail on operational motivations (labor shortages, missed capture, changing streams) and claimed benefits (capture expansion, purity, throughput consistency) [13, 14]. Such sources are valuable for identifying implementation patterns and use cases, but they also have limitations: selective reporting, non-standard metrics, and lack of counterfactual comparisons.

Therefore, academic writing should use vendor and practice-side evidence as illustrative, not definitive. The strongest conclusions should be anchored in peer-reviewed comparative studies and institutional data on system needs and constraints [1, 8, 9]. The mixed evidence base currently supports a measured conclusion: AI-enabled robotic recycling can improve performance in meaningful ways, but outcomes are highly context dependent and should be evaluated using transparent metrics [10].

## **6. Economic and Policy Analysis: Conditions for Scalable Adoption**

If AI-powered robotic recycling is to move from promising innovation to mainstream infrastructure, economic and policy conditions must support adoption and sustained operation. This requires attention to capital structure, infrastructure modernization, market incentives, and interoperability.

### **6.1 Capital Intensity and the Infrastructure Gap**

Many recycling facilities operate with constrained capital and aging equipment. Even when AI robotics improves long-run economics, upfront investment and integration costs can block adoption [8]. EPA's recycling infrastructure assessment materials summarize a national-scale modernization need that includes sorting and processing infrastructure, indicating that technology upgrades are embedded in larger financing and infrastructure challenges [8]. UNEP's global outlook similarly frames waste and recycling as a system requiring broad policy and investment shifts rather than isolated technical fixes [1].

This implies that AI robotics adoption may initially concentrate in higher-throughput facilities, regions with stronger policy support, or operators with access to financing. Without infrastructure and financing alignment, the risk is a two-tier system: advanced AI-enabled facilities in some regions and persistent low-performance systems elsewhere [1, 2].

### **6.2 Commodity Markets, Purity Premiums, and Risk**

Recycling revenues depend on commodity prices and buyer requirements. AI robotics can improve capture and purity, but if downstream markets are weak or purity premiums are low, the economic case may narrow. Conversely, where end markets demand cleaner feedstocks or where labor costs are high, AI-enabled sorting can become more attractive [9, 10]. The construction-waste comparative studies cited above underscore this point by showing sensitivity to labor and machinery cost structures [9, 10].

From a policy perspective, this suggests that market-shaping instruments—such as recycled-content requirements, quality standards, and procurement policies—may indirectly accelerate AI sorting adoption by increasing the value of high-purity secondary materials [1].

### **6.3 Extended Producer Responsibility and System Incentives**

The Global E-waste Monitor 2024 notes the significance of policy and regulation, including the use of Extended Producer Responsibility (EPR) in many national e-waste frameworks [2]. EPR can support AI-

enabled recycling indirectly by improving financing flows, formalization, and collection quality. More broadly, policies that reward recovery performance and penalize disposal can strengthen incentives for advanced sorting and process intelligence [1, 8].

However, policy design matters. If policies focus only on tonnage without quality metrics, facilities may optimize quantity at the expense of purity. If technology subsidies are granted without performance auditing, adoption may produce “innovation theater” rather than measurable circularity gains [7]. A systems approach should align policy metrics with material quality, worker safety, and downstream recyclability.

#### **6.4 Interoperability, Standards, and Procurement Practices**

A less visible but important issue is vendor lock-in and interoperability. AI-enabled robotic systems often combine hardware, sensors, software models, and analytics dashboards in proprietary stacks. This can create dependence on a single vendor, limit integration with other systems, and raise lifecycle costs [5].

An academic policy perspective would argue for stronger standardization efforts around data formats, interfaces, performance metrics, and reporting. Such standards would not eliminate competition; rather, they would improve comparability and reduce switching costs, making adoption safer for facilities with limited technical capacity [7].

### **7. Governance, Risk, and Responsible Deployment**

As AI becomes embedded in industrial waste systems, governance becomes a core performance issue rather than an external ethical add-on. Responsible deployment in robotic recycling includes technical reliability, safety integration, accountability, and workforce transition.

#### **7.1 Reliability, Validation, and Drift Monitoring**

Recycling environments are prone to domain shift: changes in packaging, contamination, lighting, conveyor conditions, and regional stream composition can degrade model performance over time [6, 11]. Facilities need procedures for validation, retraining, and ongoing performance monitoring. This is especially important in high-throughput environments where small degradations in accuracy can cause large contamination or value losses over time [6].

The systematic classification review’s emphasis on dataset and real-world variability problems supports the need for continuous validation and adaptation in operational settings [6]. In practice, this means that AI deployment is not a one-time installation but an ongoing operational commitment [7].

#### **7.2 Safety and Human Override**

Robotic recycling systems interact with moving conveyors, variable objects, and human workers. Safety protocols must cover not only mechanical hazards but also AI-driven misclassification or failure modes that could create downstream hazards (e.g., hazardous item misrouted, line overload due to poor sorting decisions) [12,7]. NIST’s AI RMF provides a general governance framework emphasizing risk management, trustworthiness, and organizational responsibility across the AI lifecycle [7].

In a recycling context, this implies concrete design choices: audit logs, performance dashboards, maintenance records, incident reporting, and clearly defined human override authority [7]. “Responsible AI” in this sector should be operationalized in plant procedures, not only in policy statements.

#### **7.3 Workforce Transition, Skills, and Labor Justice**

Automation in recycling raises legitimate labor concerns. Manual sorting roles are often physically demanding and hazardous, and reducing those exposures can be a major benefit [1]. At the same time, technology adoption can displace workers if transitions are not managed. A responsible pathway is task redesign: shifting labor from repetitive manual sorting toward inspection, exception handling, quality assurance, maintenance, and digital operations [3].

This transition requires training and institutional support. The point is not simply to claim that “new jobs

will appear,” but to build pathways by which existing workers can move into safer, higher-skill roles. In this sense, workforce transition is part of system resilience. A facility that adopts AI but loses operational knowledge or worker trust may underperform despite better machinery [5].

#### 7.4 Equity and Global Deployment

A final governance issue is uneven access. Advanced AI-powered robotic recycling may scale fastest in high-income settings, while many low- and middle-income regions face acute infrastructure and financing constraints [1,2]. If AI robotics becomes a key enabler of higher-value circularity, unequal access to such technologies could widen existing environmental and economic disparities [1].

For this reason, discussions of AI in recycling should not be limited to technical efficiency. They should also consider transferability, financing mechanisms, and context-appropriate deployment strategies [1, 8].

### 8. Research Agenda and Future Directions

From an academic perspective, AI-enabled robotic recycling is a fertile area for interdisciplinary research spanning robotics, machine learning, industrial engineering, environmental economics, public policy, and labor studies. Several research directions appear particularly important.

First, the field needs more standardized, real-world performance metrics. Many claims still rely on proprietary case data or non-comparable benchmarks. Metrics should include not only pick rate and classification accuracy but also purity, recovery yield, downtime, maintenance burden, energy intensity, and lifecycle cost [9,10].

Second, more work is needed on domain adaptation and continual learning in industrial waste streams. The review literature already identifies real-world variability and dataset limitations as central barriers [6]. Research that closes the gap between benchmark datasets and production environments will have outsized practical value [6, 11].

Third, there is a need for comparative techno-economic and policy analyses across facility types and regions. The Finnish construction sorting studies offer a useful model by explicitly examining cost competitiveness under different assumptions [9,10]. Similar analyses for MRFs, mixed-waste systems, and e-waste facilities would help policymakers and operators make better investment decisions [8,2].

Fourth, future work should integrate worker-centered design and governance-by-design into technical development. AI systems that are easier to audit, retrain, and supervise are more likely to be adopted and trusted in industrial settings [7]. NIST’s risk management framing can inform this line of work, even if sector-specific adaptation is needed [7].

Finally, researchers should connect robotic recycling performance to circular economy outcomes, not just plant-level efficiency. The core question is whether AI-powered sorting materially improves the quantity and quality of secondary materials entering productive reuse, and under what policy and market conditions that improvement persists [1, 13].

### 9. Conclusion

AI-powered robotics offers one of the most promising pathways for upgrading recycling from a labor-intensive, variable, and often economically fragile process into an adaptive, data-driven recovery system. The strongest case for AI in robotic recycling is not simply that robots can sort faster; it is that AI enables better perception, finer classification, adaptation to variability, and continuous process learning—capabilities that directly address the structural weaknesses of conventional sorting systems [6, 11] In sectors such as MRFs, mixed-waste recovery, C&D waste sorting, and e-waste processing, these capabilities can improve throughput, material purity, safety, and operational resilience [2, 9, 10].

At the same time, the evidence supports a measured rather than deterministic conclusion. AI-enabled robotic recycling is not universally cost-effective under all conditions, and its performance depends on facility design, data quality, maintenance capacity, labor cost structures, and downstream market incentives [9, 10]. Peer-reviewed studies and reviews show strong potential but also highlight deployment barriers such as dataset

limitations, domain shift, and system integration challenges [6,5]. Institutional assessments from UNEP, EPA, and UNITAR/ITU further indicate that sorting technology innovation must be embedded in broader infrastructure and policy modernization [1, 2, 8].

Therefore, the most academically defensible conclusion is that AI can be a powerful enabler of robotic recycling when treated as part of a socio-technical system: one that integrates sensing, inference, actuation, process optimization, governance, and workforce transition. If deployed responsibly and supported by aligned policy and market conditions, AI-powered robotics can help make circularity more operational—improving not just how waste is sorted, but how materials are recovered, valued, and returned to productive use [1, 13]

## References

- [1] UNEP. Global Waste Management Outlook 2024. Available from: <https://www.unep.org/resources/global-waste-management-outlook-2024> (accessed 28 February 2026).
- [2] UNITAR and International Telecommunication Union. The Global E-waste Monitor 2024. Available from: <https://ewastemonitor.info/the-global-e-waste-monitor-2024/> (accessed 28 February 2026).
- [3] Lakhout, A. Revolutionizing urban solid waste management with AI and IoT: A review of smart solutions for waste collection, sorting, and recycling. *Results in Engineering*. 2025, 25, p. 104018. <https://doi.org/10.1016/j.rineng.2025.104018>.
- [4] Lubongo, C., Bin Daej, M. A. A. and Alexandridis, P. Recent Developments in Technology for Sorting Plastic for Recycling: The Emergence of Artificial Intelligence and the Rise of the Robots. *Recycling*. 2024, 9(4), p. 59. <https://doi.org/10.3390/recycling9040059>.
- [5] Belyamani, I. Artificial intelligence in waste management systems: Applications, challenges, and prospects. *Waste Management Bulletin*. 2025, 3(4), p. 100269. <https://doi.org/10.1016/j.wmb.2025.100269>.
- [6] Fotovvatikhah, F., Ahmedy, I., Noor, R. M. and Munir, M. U. A Systematic Review of AI-Based Techniques for Automated Waste Classification. *Sensors*. 2025, 25(10), p. 3181. <https://doi.org/10.3390/s25103181>.
- [7] National Institute of Standards and Technology. Artificial Intelligence Risk Management Framework (AI RMF 1.0). Available from: <https://nvlpubs.nist.gov/nistpubs/ai/nist.ai.100-1.pdf> (accessed 28 February 2026).
- [8] U.S. Environmental Protection Agency. U.S. Recycling Infrastructure Assessment and State Data Collection Reports. Available from: <https://www.epa.gov/smm/us-recycling-infrastructure-assessment-and-state-data-collection-reports> (accessed 28 February 2026).
- [9] Farshadfar, Z., Khajavi, S. H., Mucha, T. and Tanskanen, K. Machine learning-based automated waste sorting in the construction industry: A comparative competitiveness case study. *Waste Management*. 2025, 194, pp. 77-87. <https://doi.org/10.1016/j.wasman.2025.01.008>.
- [10] Liu, X., Farshadfar, Z. and Khajavi, S. H. Computer Vision-Enabled Construction Waste Sorting: A Sensitivity Analysis. *Applied Sciences*. 2025, 15(19), p. 10550. <https://doi.org/10.3390/app151910550>.
- [11] Vukicevic, A. M., Petrovic, M., Jurisevic, N., Djapan, M., Knezevic, N., Novakovic, A. and Jovanovic, K. Versatile waste sorting in small batch and flexible manufacturing industries using deep learning techniques. *Scientific Reports*. 2025, 15(1), p. 3756. <https://doi.org/10.1038/s41598-025-87226-x>.
- [12] Cheng, T., Kojima, D., Hu, H., Onoda, H. and Pandyaswargo, A. H. Optimizing Waste Sorting for Sustainability: An AI-Powered Robotic Solution for Beverage Container Recycling. *Sustainability*. 2024, 16(23), p. 10155. <https://doi.org/10.3390/su162310155>.

- [13] Ellen MacArthur Foundation. Artificial Intelligence for Recycling: AMP Robotics. Available from: <https://www.ellenmacarthurfoundation.org/circular-examples/artificial-intelligence-for-recycling-amp-robotics> (accessed 28 February 2026).
- [14] AMP Robotics. Napa Recycling & Waste Services. Available from: <https://ampsortation.com/case-studies/how-napa-recycling-expanded-material-capture-and-i> (accessed 28 February 2026).

### **Funding**

This research received no external funding.

### **Conflicts of Interest**

The authors declare no conflict of interest.

### **Acknowledgment**

This paper is an output of the science project.

### **Copyrights**

Copyright for this article is retained by the author (s), with first publication rights granted to the journal. This is an open - access article distributed under the terms and conditions of the Creative Commons Attribution license (<http://creativecommons.org/licenses/by/4.0/>).