Waste Management 226 (2026) 115830

Contents lists available at ScienceDirect

Waste Management

journal homepage: www.elsevier.com/locate/wasman

Review

Robotic sorting and artificial intelligence in material recovery facilities: a review of published research and expert perspectives

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ARTICLE INFO

Keywords:
Automation at materials recovery facilities
AI sorting in recycling
Robotic waste sorting
Robotic integration challenges

ABSTRACT

Material Recovery Facilities (MRFs) are essential to municipal recycling infrastructure, but face difficulties in sorting due to the growing complexity of recyclable material streams and contamination in their inputs. The limitations of traditional sorting technologies and reliance on manual sorters at MRFs have driven interest in integrating robotic systems that combine artificial intelligence (AI) detection with robotic actuation. This paper presents a review of AI and robotic sorting at MRFs, based on insights from recent literature and expert consultations. The literature review uncovered advances in AI algorithms and datasets, application of new sensors and multi-modal sensing systems, and novel robotic gripping and grasping strategies. Expert consultations identified a shift toward deploying AI systems as standalone detection tools, particularly for quality control and facility monitoring, and a movement away from robotic integration due to limitations in speed, reliability, and gripper effectiveness. The analysis reveals three key challenge areas: (1) practical deployment and economic viability of robotic sorting systems, (2) limitations in AI performance and data availability, and (3) robot-specific challenges related to gripping and grasping. The paper outlines future research directions to address these challenges and advance the field.

1. Introduction

The U.S. municipal recycling system consists of three primary stages: collection, processing, and remanufacturing (U.S. Environmental Protection Agency, 2025). Materials recovery facilities (MRFs) serve as processing facilities that sort and separate collected recyclables into compacted bales to be sold to secondary markets. Unlike 'dirty' MRFs, which aim to separate recyclables from the municipal solid waste (MSW, i.e., black bag garbage) stream, 'clean' MRFs handle source-separated recyclables from residential areas, i.e., materials consumers have already sorted from the MSW stream, typically in blue or green bins. There are over 400 MRFs operating in the United States, collectively processing more than 37 million tons of packaging material annually, collected primarily from identified sources, and often require technological upgrades to improve operational efficiency and material recovery rate (U.S. Environmental Protection Agency, 2024). This paper focuses on clean MRFs, which are the predominant type in the US and, for simplicity, will be referenced henceforth as "MRFs".

Source-separated collection and clean MRF-style processing are also practiced in other regions, like the European Union, where Extended Producer Responsibility (EPR) regulations and deposit-return schemes shape accepted material streams and bale quality standards are different from the U.S. context, as well as Australia and parts of Asia. Regional differences in accepted materials, bale market specifications, and policy drivers mean that findings from one system are not always directly transferable between regions.

A major challenge for MRFs is contamination in the incoming material stream. This includes both non-recyclable items as well as impurities on otherwise recyclable items, such as labels, food residue, or liquids. A common contributor to the former is "wish cycling," where consumers place non-accepted items in recycling bins in the hope that they will be recycled. Products that are generally not accepted at MRFs, such as packaging made from certain plastics (e.g., PVC, PS), plastic film and bags, or products requiring disassembly, complicate the sorting process. For example, flexible plastics like grocery bags and film can entangle sorting equipment, leading to mechanical failures and downtime (Lubongo and Alexandridis, 2022). Hazardous materials, including batteries and medical waste, further increase operational risk. Lithium-ion batteries are particularly dangerous, as they can ignite when damaged (Plasticsrecycling.org, 2025). Contamination not only disrupts

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https://doi.org/10.1016/j.wasman.2026.115830
Received 1 April 2026; Received in revised form 15 June 2026; Accepted 21 August 2026
Available online 1 September 2026
0956-053X/Published by Elsevier Ltd.

MRF operations but also reduces the quality of their output, and MRF bales may be rejected by downstream processors due to high contamination levels (Lubongo and Alexandridis, 2022).

MRFs use a combination of automated and manual sorting systems to separate incoming recyclables. Facilities equipped with older sorting technology often rely on manual labor to sort complex material streams, such as mixed plastics. Manual sorting is also essential across MRFs to address contamination and prevent operational disruptions. This reliance on human labor can slow processing and increase operating costs. High employee turnover is common at MRFs due to difficult working conditions that include elevated temperatures, strong odors, and physically demanding tasks. Worker safety is a persistent concern due to exposure to hazardous materials, such as sharp objects and medical waste, as well as the risk of equipment-related injuries (Rosengren, 2019).

The need to enhance sorting efficiency and reduce dependence on manual labor has made material sorting at MRFs a popular application for robotic system development. In this context, robotic sorters refer to integrated systems that combine artificial intelligence (AI)-driven detection with robotic manipulation. These advanced systems integrate perception technologies, such as cameras and AI algorithms, to identify recyclables on conveyor belts and use robots to physically separate the detected materials. Robotic sorters can identify and locate materials based on visual features such as shape and color, flexibly pick items from conveyor belts, and integrate into the spatially constrained environments of existing MRFs. Through continuous, real-time training, they can adapt to changing material streams and exhibit sorting capabilities that resemble those of human workers. These systems also offer additional functionality, such as operational monitoring, data collection, and the ability to sort items by product brand.

Several reviews have previously examined AI and robotic sorting in the broader waste management context. Fang et al. (2023) provide a comprehensive overview of AI applications for waste management in smart cities, covering collection, transportation, and sorting across diverse waste streams, establishing the wider landscape within which MRF sorting sits. Lu and Chen (2022) systematically assess computer vision methods for solid waste sorting, and Kroell et al. (2022) survey optical sensors and machine learning for material flow characterization. Maier et al. (2024) offer a broad survey of sensor-based sorting technology across industrial applications, while Kiyokawa et al. (2024) survey robotic sorting challenges specifically for mixed industrial waste. Our paper complements these works by focusing specifically on clean MRFs, with the operational context grounded primarily in the United States. The AI and robotics literature reviewed is intentionally broad and spans literature about kitchen waste facilities in China, European industrial sorting plants, and synthetic datasets because no MRF-specific literature exists for many of the technical areas covered. Where studies originate from non-U.S. or non-MRF settings, they are treated as providing transferable but indirect evidence and their testing context is noted in Table 2. The paper addresses three aspects not well covered in the existing literature: (1) the deployment and economic barriers that shape real-world adoption of AI and robotic systems at MRFs; (2) the emerging industry trend of decoupling AI detection from robotic sorting/actuation, with AI increasingly deployed alongside optical sorters rather than integrated with robots; and (3) expert perspectives on operational constraints like throughput limitations, gripper reliability, and facility economics, that are not yet well represented in the published literature.

Despite their potential, robotic sorters face significant challenges when integrated at MRFs. MRFs present highly unpredictable environments, characterized by a wide variety of items densely gathered on fast-moving conveyor belts, requiring robotic sorters to effectively separate materials at high speeds. The objective of this work is to assess the current state of robotic sorters deployed at MRFs and identify challenges they face with the intent to inform future research. The rest of the paper is structured as follows: Section 2 details the methodology used for the research; Section 3 provides background information regarding MRFs and their sorting operations; Section 4 presents descriptions of implementations of robotic and AI sorting systems discovered from the literature review and expert consultations; Section 5 outlines the challenges identified from both sources; and Section 6 offers a discussion based on the findings.

2. Methodology

The research methodology involved two phases: literature review and discussions with industry experts. The literature review included a structured search conducted in 2024 across three major academic databases, Engineering Village, Web of Science, and IEEE Xplore. These databases were selected for their broad and overlapping coverage of engineering, computer science, and applied science literature relevant to the topic. The following search string was used to gather relevant studies: (robot OR "computer vision" OR vision* OR "machine learning" OR "deep learning" OR "artificial intelligence" OR "learning" OR "grasping" OR "grasp planning" OR gripp*) AND (recycl* OR "mixed industrial waste" OR waste OR "materials recovery facilities" OR MRF OR MSW OR "municipal solid waste") AND (sort* OR separat*) AND (challenge* OR survey OR review*). It should be noted that the inclusion of 'challenge OR survey OR review*' in the final AND clause may have introduced a bias toward problem-focused literature and deployment studies that do not use these terms in titles or abstracts may have been missed. This is acknowledged as a limitation of the search strategy.

The search query resulted in 974 papers, which were initially screened for relevance based on titles and abstracts by the lead author. The gathered articles can be categorized into review articles and papers that develop robotic sorting implementations. Survey/review papers provide comprehensive overviews of prior research in the field and help summarize key challenges in the literature. The implementation papers present the latest methods for robotic sorting of MSW at recycling facilities and help clarify current research trends.

Papers that focused on automated sorting in other waste streams, like construction and demolition (C&D) waste or electronic waste, and other robotic applications, such as smart bins and mobile sorting robots, were excluded as these applications are not representative of MRF sorting environments. Another key criterion for selection was the task of object detection over simple object classification. Studies that solely performed classification of isolated objects against simple backgrounds were excluded, since they also do not reflect the real-world complexity of MRF sorting. For the purposes of this review, 'simple background' refers to images where single objects are photographed against uniform, uncluttered surfaces, such as plain white or black backgrounds, with no other objects present and no conveyor or facility context. The selection process led to 46 papers that are relevant to the sorting application at MRFs. The selected papers were published between 2016 and 2024. Intermediate screening counts including the number of duplicates removed and papers excluded at each stage were not prospectively recorded. A simplified screening flow diagram is provided in Fig. 1 to illustrate the stages of the process.

The authors also consulted six experts from industry, including three robotics manufacturing executives, two representatives from a plastics industry association, and an executive from a large nationwide recycling firm. These engagements included informal discussions in which we aimed to learn about the expert's role in the field, their experience with and the limitations of current robotic systems deployed at MRFs, and their perspectives on the future of these systems and the need for continued research.

3. MRF operations and sorting approaches

3.1. MRF operations

In addition to classification into "clean" versus "dirty", MRFs can also

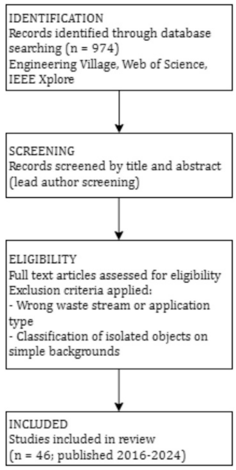

Fig. 1. Simplified screening flow for the literature review.

be categorized by how they receive recyclables, namely single- or dual-stream. Single-stream MRFs accept all recyclables as a combined input stream, while dual-stream MRFs receive fiber (paper and cardboard) products separately from other commingled materials, such as plastics, metals, and glass. The composition of accepted recyclables at MRFs is commonly described by either material type or product type. Typical product types include containers and packaging such as milk cartons, beverage cans and bottles, cups, and tubs (e.g., yogurt containers), as well as non-durable paper and fiber goods like newspaper, mixed paper, and cardboard. The containers and packaging accepted at MRFs are composed of a range of materials, which generally include ferrous and nonferrous metals, glass, polyethylene terephthalate (PET), high-density polyethylene (HDPE), and polypropylene (PP). Accepted materials vary across MRFs due to several influencing factors, like the availability of regional end markets (e.g., regional presence of processors or manufacturers that use recyclable materials), local recycling program requirements, and differences in facility infrastructure and sorting equipment. Once processed, the sorted and baled recyclables are sold to downstream facilities, such as glass beneficiation plants (e.g., secondary glass recycling facilities) and metal, paper, and plastic recycling facilities (U.S. Environmental Protection Agency, 2024).

MRF processing begins when recycling collection trucks deposit materials onto the tipping floor. From there, the material is transferred into the facility via an infeed conveyor and carried through the sorting system on a network of continuous conveyor belts. MRFs use a combination of manual sorting and automated systems, which can be categorized as direct or indirect sorters, to process incoming recyclables. Direct sorters leverage the physical properties of materials such as magnetic susceptibility, electrical conductivity, and weight to separate materials at high throughput rates. Common examples include magnetic separators for ferrous metals, eddy current separators for nonferrous metals, screens and ballistic separators to distinguish items based on shape and size (like a flattened cardboard box (2D) vs milk jug (3D)), and air classifiers to separate lighter plastic and metal containers from heavier glass containers (Gundupalli et al., 2017).

Indirect sorters use sensors to identify recyclables and machines with actuators to physically separate them. These systems are particularly effective for processing complex material streams like mixed plastics, where physical properties alone are insufficient for reliable sorting (Lubongo and Alexandridis, 2022). While a variety of sensor systems capable of identifying different types of packaging waste are detailed in the literature, optical sensors are most commonly used at MRFs, primarily for sorting plastics (Lubongo and Alexandridis, 2022). The two most prevalent types of optical sensors are vision (VIS) sensors, which detect light in the visible spectrum using three channels, and near-infrared (NIR) sensors, which operate in the near-infrared range. Their non-destructive operation, high-speed measurement capabilities, and minimal health risks make them well-suited for MRF applications (Gundupalli et al., 2017; Kroell et al., 2022; Lubongo and Alexandridis, 2022). Optical sensors are typically paired with air-jet sorters, which use an array of fast-switching pneumatic valves mounted perpendicular to the conveyor belt. These valves produce short bursts of air to rapidly eject the identified materials from the stream (Maier et al., 2024). Lubongo et al. identified 46 commercial optical sorters from 17 companies that are currently used to sort plastics in MRFs. Most of these systems utilize NIR, VIS, or a combination of both technologies (Lubongo and Alexandridis, 2022). The combined VIS + NIR configuration addresses the limitation of NIR-only systems, which have difficulty detecting black plastics (Gundupalli et al., 2017; Lubongo and Alexandridis, 2022; Maier et al., 2024). Table 1 compares some aspects of three distinct types of automated sorters used in MRFs, direct, indirect, and robotic sorters.

The selection of equipment and sorting technologies at MRFs varies based on several factors, including facility type, available space, cost, location, environmental impact, and local economic conditions (U.S. Environmental Protection Agency, 1993). Typical processing lines incorporate a combination of direct, indirect, and manual sorting methods (Maier et al., 2024). Manual sorters are stationed at pre-sort stations at the beginning of the sorting line to remove non-recyclable items and recover recyclable materials early in the process. Additional manual sorting stations are strategically placed along specific material lines to enhance sort purity in line with market requirements and to remove contaminants or misclassified items.

3.2. Development of robotic sorting for MRFs

Early implementations of robotic sorting systems in recycling streams were introduced to replace air jets, which had limited precision, flexibility, and difficulty handling heavier materials. Industrial robots are particularly well-suited for sorting streams such as construction and demolition (C&D) waste due to their ability to manage high payloads and operate with multiple degrees of freedom. An early example is the ZenRobotics Heavy Picker, developed in 2007 by ZenRobotics, designed specifically for C&D waste sorting. In 2013, RoBB, introduced by Bollegraaf Recycling Solutions, became one of the first robotic sorters developed for packaging material. These early systems integrated optical technologies, including VIS and NIR sensors, alongside additional detection tools such as metal detectors, 3D laser sensors, and RGB cameras, paired with articulated industrial robotic arms (Sarc et al., 2019).

A major advancement in robotic sorting has been the development of enhanced perception systems that use RGB cameras in combination with computer vision algorithms. Computer vision (CV), a subfield of artificial intelligence (AI), enables machines to interpret and make decisions based on images and video streams (OpenCV, 2024). The field progressed significantly with the emergence of deep learning (DL), a subset of machine learning that employs multilayered neural networks to simulate human-like decision-making. Deep learning architectures such as convolutional neural networks (CNNs) have overcome the limitations of traditional image processing techniques, particularly in complex visual recognition tasks. This progress was fueled by increased computational capabilities and the availability of large, open-access datasets, leading to the widespread adoption of CV techniques across multiple domains, including recycling (OpenCV, 2024).

AI-based robotic sorting systems have been deployed in MRFs since 2017, with early implementations from companies such as AMP Robotics, Bulk Handling Systems, Bollegraaf Recycling Solutions, and Machinex (Sarc et al., 2019). The perception systems in these AI sorters combine RGB cameras with deep learning (DL) algorithms to identify materials on conveyor belts. The most widely used robotic configurations include delta robots, six-axis articulated robots, and cartesian (gantry-style) robots, typically equipped with suction cup or vacuum

Table 1
Comparative overview of sorting technologies used in materials recovery facilities. Performance descriptors in this table reflect typical operating conditions; actual values vary significantly with factors like material stream composition, conveyor speed, occupancy density, and contamination level.

Feature	Direct sorters	Indirect sorters	Robotic sorters
Sorting principle	Physical properties (e.g., magnetism, weight, shape)	Optical detection + pneumatic ejection	AI perception + robotic manipulation
Sorting mechanism	Magnetic separators, eddy current separators, screens, air classifiers	Air jets	Robotic arms (delta, gantry, articulated) with suction grippers
Common sensor technology	Not sensor-based	NIR, VIS, or combined VIS + NIR	RGB cameras with deep learning (DL) algorithms
Material focus	Metals, glass, paper/fiber	Mixed plastics, paper/fiber	Mixed recyclables
Typical role	Early/mid-stream separation	Midstream sorting complex materials	Pre-sort, Quality control, Last Chance Recovery
Speed and accuracy	High throughput, accuracy depends on material type and stream purity	High throughput, accuracy depends on stream density, contamination level	Lower throughput than indirect sorters, accuracy depends on gripper performance, item density
Space requirements	Very large equipment footprint	Large footprint on conveyor	Comparatively compact on conveyor
Maintenance requirements	Prone to clogging by contamination	Generally reliable	Regular maintenance for grippers

grippers. Many robotics providers offer modular technologies that can be installed either as standalone units or integrated into existing MRF sorting lines. In addition to material handling, most companies also provide analytics platforms to monitor facility operations and material flow. Robotic sorters are deployed at various stages of the sorting process to perform tasks such as pre-sorting, quality control, and last-chance recovery.

4. Results

4.1. Areas of active research related to robotic sorting at MRFs

Our review of recent literature identified several active areas of research on robotic sorting at MRFs. These include Novel AI algorithms and datasets, multi-modal object detection and instance segmentation systems, and new sensing modalities, integrated sorting systems at MRFs, and novel gripping and grasping methods. The following subsections provide an overview of representative work in each domain.

4.1.1. Novel AI algorithms and datasets

Recent research in AI-driven object detection in recycling has focused on addressing the challenges posed by the heterogeneous material streams and dynamic environments within MRFs. Many of these studies are accompanied by data collection efforts, as there remains a lack of large, high-quality datasets representative of conditions at recycling facilities. Table 2 summarizes selected studies that propose novel object detection algorithms and Table 3 presents associated datasets tailored to waste classification tasks. A brief discussion of each approach follows Table 3.

Feng et al. (2024) introduced the Statistical-Adaptive Detector (SA-Det), to address the challenges of object diversity and uneven spatial distribution of objects on MRF conveyors by leveraging statistical adaptive modeling. The authors also collected the Kitchen Waste Detection (KWD) dataset, which comprises images captured from the conveyor at a recovery facility, to support their research. An extension of KWD, called KWD-New, was also collected at a different waste sorting center and at a different time of year. Similarly, Ouyang et al. (2024) developed the Kitchen Waste Detection model (KW-Det) to overcome the challenges of object deformation and directional uncertainty in kitchen waste detection. The KWD dataset was also used to support this study. Another study by Qin et al. (2024) focused on kitchen waste detection and collection of the OD-KW dataset, which expands on previous data collection efforts by labeling additional contaminants frequently encountered in kitchen waste streams. They also introduced the AL-DETR model, which integrates active learning into the transformer-based object detector DETR, aiming to maximize detection accuracy when training data is limited. The practical effectiveness of their algorithm was tested by building a robotic sorting platform comprising a vision system, a parallel robot equipped with a combined suction cup and two-finger gripper, and a conveyor belt (Qin et al., 2024).

Ma et al. (2024) developed the MMTrash dataset and used it alongside the existing TrashNet dataset to train DSYOLO-Trash, an enhanced version of the YOLOv5 object detection network optimized for solid waste detection. Their experiments show that the modified DSYOLO-Trash network improves detection performance for small and overlapping objects in images. Zhou et al. (2023) also developed a modified version of the YOLOv5 network called TrsFu-YOLOv5, which focuses on improving C&D waste detection, particularly for small objects. A custom dataset, called the construction solid waste detection dataset, was collected to support this research (Zhou and Yang, 2023).

Another emerging trend in recent AI research is the application of state-of-the-art object detection models for recyclable material classification and detection. Ogrezeanu et al. (2024) trained various object detection models, including the YOLOv8 model, on the WaRP-C and WaRP-D datasets to classify and detect recyclables. The authors observed that model performance varies among product classes, with good detection performance for plastic bottles but poor performance for other classes, such as canisters, cardboard, and detergent. This discrepancy is likely due to class imbalance in the dataset. Shroff et al. (2023) also evaluated and compared the performance of three YOLOv8 model variations on the WaRP-D dataset. They compared the performance of the different models and illustrated the trade-off between inference time and accuracy. A similar problem of varying performance across annotated classes was observed in their results. Lv et al. (2022) trained the YOLOv5 and YOLOv3 models on the TACO (Trash Annotations in Context) dataset for recyclable detection in images. While the results from these studies show strong performance, the TACO dataset's limited size makes it difficult to verify the models' real-world performance. Researchers prefer to train single-stage detection models from the YOLO family due to their faster inference speed and real-time detection capabilities.

There are also new efforts in the literature to collect large-scale, real-world datasets for sorting recyclables. Bashkirova et al. (2022) introduced ZeroWaste, a waste dataset designed to support multiple computer vision tasks, collected from the paper stream conveyor at a single-stream recycling facility. The authors provide baseline results for various state-of-the-art fully, semi-, and weakly-supervised segmentation methods, and their results show that these models struggle with the dataset, particularly with small, rare, and deformed objects. This research was continued with the proposal of the VisDA 2022 challenge, a domain-adaptation challenge for industrial waste sorting (2023). The challenge evaluates segmentation models' ability to adapt to natural domain shifts. Participants were provided with two fully labeled datasets, ZeroWaste and a new synthetic dataset called SynthWaste, to train segmentation models. The adaptation performance of the trained models was then tested on ZeroWaste-v2, an unlabeled dataset collected following the original dataset protocol but in a different season (fall vs.

Table 2
Examples of novel AI Algorithms and Implementations proposed in literature. Reported metrics are not directly comparable across studies, as they reflect different datasets, task types (detection vs. segmentation), IoU thresholds, and evaluation protocols. Also high mAP values from laboratory datasets do not compare directly with lower AP values from real MRF conveyor datasets.

Source	Name	Modifications and improvement	MRF relevance	Reported metrics
Feng et al. (2024)	SA-Det	Present SA-Det, a plug-and-play oriented object detection framework that leverages statistical adaptive modeling to improve kitchen waste detection and can be integrated into existing state-of-the-art (SOTA) rotation detectors.	Adjacent, real kitchen waste facility conveyor, no external validation site	AP 35.1% on ZeroWaste-f (best result with YOLOv7 + SA-Det, @IoU 0.5); mAP 73.5% on KWD (@IoU 0.5)
Ouyang et al. (2024)	KW-Det	Developed KW-Det, a novel kitchen waste detector which can perform oriented object detections.	Adjacent, real kitchen waste facility conveyor, no external validation site	mAP50 71.5% on KWDD; Macro-F1 73.2% (both @IoU 0.5, score threshold 0.5)
Qin et al. (2024)	AL-DETR	Integrates Active Learning with the Detection Transformer (DETR) model.	Adjacent, real kitchen waste facility conveyor, no external validation site	mAP 59.6% on OD-KW (full annotation, IoU 0.5–0.95); AP50 73.5%
Ma et al. (2024)	DSYOLO-Trash	An enhanced version of the YOLOv5 detection algorithm, optimized for solid waste detection and tracking.	Laboratory, isolated objects, controlled conditions	mAP 97.3% on TrashNet; mAP 98.5% on MMTrash (both @IoU 0.5)
Zhou and Yang (2023)	TrsFu-YOLOv5	A modified version of the YOLOv5 model, which integrates the Vision Transformer (ViT) encoder and the Fusion-Concat module into the network.	Laboratory, static images, no conveyor	mAP 98.4% on CWD dataset (@IoU 0.5); improvement of + 1.1% over YOLOv5 baseline
Bashkirova et al. (2022)	ZeroWaste Dataset	Introduced ZeroWaste, a dataset that was collected at a US single-stream recycling facility with multiple versions to support various computer vision tasks.	Direct, real US MRF conveyor, operational conditions	Mask-RCNN baseline AP 22.8% on ZeroWaste-f (COCO-style, IoU 0.5:0.95); AP50 34.9%
Bashkirova et al. (2023)	VisDA 2022 Challenge	Proposed a Sim2Real challenge for Industrial Recycling.	Direct, real US MRF conveyor, domain adaptation across two facilities	Winning solution mIoU 59.7% on ZeroWaste-v2 test set

spring) and location (different U.S. state). From the results of the competition, the authors learned that while synthetic data increases diversity, the best results were achieved by focusing on adaptation between real domains. The competitors' results also show that segmentation quality significantly improves with models that integrate stronger backbones with more pre-training, and the winning teams used techniques such as model ensembling and data augmentation to boost model generalization. The performance metrics reported across these studies vary substantially and reflect differences in dataset complexity, task type, and evaluation protocol rather than differences in algorithm quality alone. The reported figures are summarised in Table 2 and should be interpreted in the context of each study's testing conditions as indicated in the MRF Relevance column.

4.1.2. Multi-modal detection systems and new sensing modalities

There is also a shift in recent studies towards leveraging multi-modal data, as well as new sensing modalities in waste and recyclable detection and classification. A summary of the sensor systems and implementation methods of the reviewed studies is provided in Table 4, followed by brief descriptions of the reviewed works. Table 5 links the sensor modalities identified in the reviewed literature to the material properties each detects and their known limitations in the MRF context.

The sensor modalities summarized in Table 5 address different material properties. Identifying a single sensor modality to sort the full range of recyclables encountered at a clean MRF is challenging. RGB cameras provide the shape and appearance information needed for object detection and classification but cannot identify polymer chemistry. NIR addresses polymer chemistry but fails on black plastics, and X-ray penetrates opaque materials but cannot distinguish polymers of identical density. Multimodal sensor combinations increasingly used in industry such as VIS + NIR, or RGB combined with NIR could overcome individual limitations. A fully integrated structure–property-performance framework, systematically connecting material properties to optimal sensor modalities and appropriate separation methods (air jet, vacuum tube, suction gripper, two-finger gripper), would be a valuable engineering synthesis for the field but lies beyond the scope of the current review, as the primary data required to populate such a framework, particularly the separation method linkage were not found in the reviewed literature. This is identified here as a research priority.

Konstantinidis et al. (2023) developed a multi-modal deep learning detection model that integrates RGB, VIS, and NIR data to detect waste objects using autoencoders. They also collected a multimodal waste dataset (MMWD), which captures multi-modal data from 648 unique objects, to support their research. Neo et al. (2023) developed the Multi-Modal Plastic Spectral Database (MMPSD), which includes data from 122 plastic samples covering a range of colors and sourced from post-consumer waste, processed using Fourier Transform Infrared Spectroscopy (FTIR), Raman, and Laser-Induced Breakdown Spectroscopy (LIBS). They also introduced the Spectral Conversion Autoencoder (SCAE), a generative model trained using MMPSD to convert spectral data across various modalities. The real and synthetic datasets were fused to train a multi-modal deep learning classification model.

Choi et al. (2023) sought to address the limitations of NIR sensors in distinguishing between PET and PET-G (PET with glycol) plastics, which

Table 3
Examples of AI datasets tailored to waste classification tasks, as proposed in the literature.

Name	Dataset size (images)	Labels	Sensor modality	Task	Collection location	MRF relevance
KWD (Feng et al., 2024; Ouyang et al., 2024)	13,873	Metal, glass, plastic bottles, tetra packs, other plastics	RGB	Oriented Detection	MRF	Adjacent, real kitchen waste facility, China
KWD-New (Feng et al., 2024)	12,458	Metal, glass, plastic bottles, tetra packs, other plastics	RGB	Oriented Detection	MRF	Adjacent, real kitchen waste facility, China
OD-KW (Qin et al., 2024)	15,994	Metal, glass, plastic bottles, tetra packs, other plastics, waste bag, shoe, carton	RGB	Detection	MRF	Adjacent, real kitchen waste facility, China
MMTrash (Ma et al., 2024)	2,332	Glass, paper, cardboard, metal plastic, general trash	RGB	Detection	Laboratory	Laboratory, controlled setting
Construction Solid Waste (Zhou and Yang, 2023)	4,873	Concrete, bricks, plastic, wood, woven bags, and painted concrete blocks	RGB	Detection	Laboratory	Laboratory, controlled setting
ZeroWaste-f (Bashkirova et al., 2022)	4,503	Cardboard, soft plastic, rigid plastic, metal	RGB	Detection and Segmentation	MRF	Direct, real US MRF stream conveyor
ZeroWasteaug (Bashkirova et al., 2022)	4,503	Cardboard, soft plastic, rigid plastic, metal	RGB	Detection and Segmentation	MRF	Direct, real US MRF stream conveyor
ZeroWaste-s (Bashkirova et al., 2022)	6,212	Cardboard, soft plastic, rigid plastic, metal	RGB	Unlabeled (Semi-supervised)	MRF	Direct, real US MRF stream conveyor
ZeroWaste-w (Bashkirova et al., 2022)	1,410	Before, after	RGB	Video-frame classification	MRF	Direct, real US MRF stream conveyor
SynthWaste (Bashkirova et al., 2023)	20,990	Cardboard, soft plastic, rigid plastic, metal	RGB	Detection and Segmentation	Synthetic dataset	Synthetic
ZeroWastev2 (Bashkirova et al., 2023)	7,720	Cardboard, soft plastic, rigid plastic, metal	RGB	Detection and Segmentation	MRF	Direct, real US MRF stream conveyor

Table 4
Examples of Novel and Multi-Modal Sensor Systems provided in the literature.

Source	Sensors	Implementation
Konstantinidis et al. (2023)	RGB-camera, VIS, NIR	Developed a multi-modal deep learning detection model for separating mixed plastic and wood waste streams.
Neo et al. (2023)	FTIR, Raman, LIBS	Introduced the Spectral Conversion Autoencoder (SCAE), a cross-modal generative model which converts spectral data between modalities.
Choi et al. (2023)	RGB	Trained a YOLOv8 detector to classify recyclables based on visual features, which was integrated with the existing NIR sorter at a recycling facility.
Gursch et al. (2024)	RGB-line, NIR, 3D	Developed an integrated multi-modal system for real-time monitoring, composition analysis, and mass estimation of shredded industrial refuse streams.
Williams et al. (2023)	MIS, RGB-camera	Combined multi-frequency magnetic induction spectroscopy and RGB image data, leveraging machine learning to classify nonferrous scrap metal.
Stiebel et al. (2018)	NIR, RGB-line	Developed a material classification system that combines NIR and RGB data, employing a convolutional neural network (CNN).
Cielecki et al. (2023)	THz-TDS	Demonstrate the use of trahertz time-domain spectroscopy (THz-TDS) combined with machine learning to accurately identify black plastic samples.
Henriksen et al. (2022)	Hyperspectral (NIR) camera	Demonstrate classification of 12 common plastic types using short-wave infrared hyperspectral imaging and unsupervised machine learning.

share similar material compositions. To overcome this challenge, they developed a YOLOv8-based object detection model that detects and identifies waste items based on visual characteristics (shape) rather than material properties. The detection model was trained on a 2,000-image dataset, collected at a recycling facility, and the trained model was integrated with the existing NIR-based optical sorting system and an air-jet classifier at the recycling facility, forming a hybrid sorting approach.

Gursch et al. (2024) explored the analysis of waste composition in an industrial shredded refuse stream by combining a multispectral camera system with deep learning-based semantic segmentation. The authors created a large synthetic training set by extracting snippets from mono-material images and superimposing them on an empty conveyor belt background to generate mixed-refuse images. They also developed a multi-modal detection model by combining a binary segmentation model, which classifies foreground versus background pixels, with a multi-label segmentation model that classifies foreground pixels into material categories. The segmentation results were further combined with 3D volumetric data to achieve mass estimation. Williams et al. (2023) demonstrated the classification of nonferrous scrap metals by combining multi-frequency Magnetic Induction Spectroscopy (MIS) and RGB images. MIS measurements are insensitive to surface contamination, unlike other optical methods such as NIR. This dual-modality approach is particularly effective for classifying metals with similar conductivities (e.g., brass vs. cast aluminum) but distinct color profiles. They built a dataset using samples collected from six different MRFs, consisting of mixed nonferrous metal and stainless steel. The authors trained various machine learning models on the collected data, and their results demonstrate the effectiveness of applying traditional models to sort metals using combined MIS and RGB data. Stiebel et al. (2018) implemented a visual inspection system that combines near-infrared (NIR) and RGB data with a modified convolutional neural network (CNN) to achieve accurate classification of both pure and layered or mixed materials placed on a conveyor belt. The proposed system can classify both single polymers and regions containing stacked or mixed materials (multi-label) in images of plastic items.

New sensing modalities and solutions to address material identification challenges in plastic sorting are also explored in recent research. Cielecki et al. (2023) addressed the inability of NIR-based optical sorting technologies to detect black plastics by utilizing Terahertz Time-Domain Spectroscopy (THz-TDS). They distinguished nine commercially available black plastic types using KNN (k nearest neighbors), Bayesian classifiers, and SVM models, demonstrating high classification accuracy unaffected by color or surface contamination. Henriksen et al. (2022) investigated detailed plastic type recognition using a hyperspectral camera operating in the near-infrared range. The study involved imaging 13 commercially available plastic types on a conveyor system using

Table 5
Sensor modalities identified from waste sorting literature, the material properties they detect, and known limitations in the MRF context.

Sensor modality	Properties detected	Known limitations	Representative citations
RGB Camera	Color, shape, size, texture, surface appearance	Cannot detect polymer chemistry, performance degrades under contamination, variable lighting, occlusion	Bashkirova et al. (2022); Ouyang et al. (2024).
Near-Infrared (NIR)	Polymer chemistry, can distinguish common plastics in recycling by resin type	Cannot detect black plastics, performance affected by surface contamination, moisture, multilayer packaging	Kroell et al. (2022); Lubongo and Alexandridis (2022)
VIS + NIR	Polymer chemistry and color and surface features	Partial improvement on black plastics, but limited for highly contaminated or dark-dyed materials	Lubongo and Alexandridis (2022); Maier et al. (2024).
Hyperspectral Imaging (HSI)	fine-grained polymer discrimination, can identify additives, degradation, and multilayer structures	High equipment and processing cost, large data volumes	Kroell et al. (2022)
X-ray / Dual-energy X-ray (DE-XRT)	Density, elemental composition, can penetrate opaque and black materials	Cannot distinguish polymers of the same density family, radiation safety requirements, high equipment cost	Maier et al. (2024)
Terahertz (THz)	Polymer identification including black plastics, penetrates packaging	Very early stage for industrial deployment, expensive, limited throughput at MRF conveyor speeds	Kroell et al. (2022)
Magnetic induction spectroscopy (MIS)	Metal alloy composition, conductivity, magnetic susceptibility	Limited to metallic fractions only	Williams et al. (2023)

an industrial hyperspectral camera and developing a plastic classification algorithm utilizing principal component analysis (PCA) and unsupervised K-means clustering. Salimian and Onwukwe (2023) developed a labeling system for food-grade plastic packaging using a thin-film metal oxide coating that is transparent to visible light but reflective in the infrared (IR) spectrum. The coating's effectiveness was evaluated using a thermal imaging camera paired with two convolutional neural networks (CNNs) for classification. The dataset consisted of 450 images captured from plastic objects with and without coated labels. They trained a custom-designed CNN and a ResNet-50 model as classifiers to demonstrate the effectiveness of their method.

4.1.3. *Integrated sorting at MRFs, and novel gripping and grasping methods*

Some studies implement integrated sorting systems for real-world deployment in MRFs. These systems, as listed in Table 6, often focus on non-intrusive monitoring or augmenting existing infrastructure to improve sorting accuracy and material characterization.

Cuingnet et al. (2022) present PortiK, a real-time, computer vision-based system for automatic characterization and quality monitoring of solid waste streams in MRFs. PortiK is designed for non-intrusive measurement of the waste composition of an aluminum can stream using RGB images. Schloegl et al. (2024) evaluated the use of external sensors to enhance an existing sensor-based sorting (SBS) system at a lightweight packaging sorting facility. They introduced external NIR sensors and LiDAR sensors to monitor and predict material flow and sorting efficiency. The sensor data was combined with classic machine learning models to predict the quality of the sorted multicolored PET stream.

Table 6
Examples of on-site systems for monitoring and sorting proposed in the literature.

Source	System components	Implementation details
Cuingnet et al. (2022)	RGB camera, Industrial computer	Real-time image-based AI system to monitor the composition of an aluminum can stream, with two sub-systems (on-site and off-site).
Schloegl et al. (2024)	LiDAR and NIR	Introduced external sensors, specifically a LiDAR for volume measurement, and two NIR sensors for composition and occupation density analysis, alongside the existing sensor-based sorting (SBS) system at a recovery facility.

While there is limited research on robotic manipulation in recycling sorting as compared to AI-based detection, several studies introduce novel grippers, grasping algorithms, and motion planning techniques. These efforts are listed in Table 7 and are followed by a brief discussion.

Wang et al. (2023) developed a multi-material suction cup for robotic grippers that is self-closing, self-healing, and recyclable, addressing limitations such as wasted energy, air leaks, and damage in industrial pick-and-place operations. Through tensile testing and integration with a robot manipulator for picking various objects, the authors compared the performance of the developed suction cup with other hard and soft suction cups, verifying the construction and effectiveness of their multi-material suction cup. Engelen et al. (2023) introduced the High Airflow Vertical Conveying (HAVCO) gripper, designed for fast sorting of small, light, and irregularly shaped cast and wrought aluminum pieces. Lee et al. (2024) aimed to enhance the gripping

Table 7
Examples of novel gripper systems and grasping algorithms presented in the literature.

Source	Application	Implementation details
Wang et al. (2023)	Gripper Design	Presents a new multi-material suction cup for robotic systems, that has self-healing and self-closing ability.
Engelen et al. (2023)	Gripper Design	Introduces the High Airflow Vertical Conveying (HAVCO) gripper to sort small, light, and irregularly shaped fractions of shredded metal waste.
Lee et al. (2024)	Grasping Algorithm	Propose a jumping haptic regrasping strategy using a smart suction cup.
Lv et al. (2023)	Grasp Detection Algorithm	Proposes a real-time garbage detection and 3D localization algorithm, utilizing input from an RGB-D camera.
Guo et al. (2022)	Vision Guided Grasping	Introduce a robotic waste sorting system that integrates vision-guided grasping and tactile material recognition.
Gundupalli et al. (2020)	Genetic algorithm-based sequence planning	Presents a genetic algorithm to optimize pick and place (PAP) sequence for robotic sorting of recyclables.
Ružić et al. (2024)	Path re-planning and collision avoidance in collaborative waste sorting	Present a robotic waste sorting system that focuses on path replanning and collision avoidance, to enable safe human-robot collaboration.

capability of suction cups for reliably picking printed circuit boards (PCBs) in recycling, where conventional end-effectors struggle due to complex surfaces and surface-mounted components. The authors proposed a"jumping haptic regrasping" strategy using a smart suction cup with built-in pressure sensors. The pressure differences across four internal chambers determine the direction of the jump, and initial grasp points were determined using a Swin Transformer object detector to identify the type of PCB.

Several reviewed studies also developed methods to improve grasp generation and planning. Lv et al. (2023) developed an algorithm that combined object detection, segmentation, and point cloud processing to generate robotic grasp poses for recycled items. The integration of point cloud processing with object detection enhances robotic grasping efficiency by providing accurate spatial information for handling irregularly shaped items. The authors also collected a custom outdoor RGB-D dataset of images of recyclables to evaluate model generalization (Lv et al., 2023). Guo et al. (2022) developed a material recognition system that integrates visual detection and tactile classification for sorting materials in a single-stream recycling scenario.

Gundupalli et al. (2020) introduced a Genetic Algorithm (GA)-based approach for optimal pick-and-place sequencing in robotic sorting of source-separated recyclables using thermal cameras. The algorithm optimizes the total sorting time while accounting for robot motion and control delays. Ružić et al. (2024) presented a robotic recycling sorting system capable of real-time path re-planning and collision avoidance, facilitating safe collaboration between humans and robots. Using RGB-D camera input, the system actively detects humans in its vicinity and adjusts its speed and replans its trajectory to avoid collisions. The effectiveness of this approach was demonstrated by implementing it on a workstation with a 7-axis articulated robot and an integrated camera system.

4.2. Implementation of robotic sorting at MRFs from expert consultations

Several trends, challenges, and insights emerged from expert consultations regarding the implementation of robotic systems in MRFs. Expert consultations indicate that robotic systems at MRFs are increasingly used for quality control in later sorting stages rather than primary sorting. The consultations also revealed the main limitations of robots include ineffective suction-based gripping and lower throughput compared to air jets. We were also told AI systems are increasingly decoupled from robots and used as standalone detection tools. They are also paired with optical and X-ray sensors to enhance sorting capabilities and to support operational and material flow monitoring at MRFs.

A consistent observation from experts was the shift in robotic deployment from early-stage sorting to later-stage quality control. Experts attribute this transition to challenges associated with primary sorting, where high material density and overlapping items reduce the effectiveness of robotic systems. In contrast, downstream sorting stages involve more sparsely distributed items that have undergone preliminary separation, resulting in reduced occlusion and object motion, conditions that are more favorable for robotic picking. Experts frequently identified two major limitations of robotic systems: the limited effectiveness of suction-cup grippers and the relatively low throughput of robots compared to air-jet sorters. These constraints have contributed to the decoupling of AI-based perception systems from robotic actuators.

Expert discussions also revealed that standalone AI systems are increasingly used to monitor operational efficiency and material flow within MRFs. In addition, AI is being integrated with optical sorters to leverage the complementary strengths of each system, the AI's ability to classify items by product type, and the optical sensor's capacity to detect material composition. We were told this integration enables more refined sorting capabilities, such as distinguishing PET clamshells from PET bottles, identifying food-grade polypropylene, and separating pet food cans from beverage cans. We also learned some facilities have also combined AI systems with X-ray sensors to detect lithium-ion batteries, which can ignite when damaged by sorting equipment.

Insights from robotics solutions providers revealed a widespread shift away from robotic integration at MRFs. The providers revealed that many companies have redirected their focus toward AI-based sorting systems paired with pneumatic separation technologies, such as air jets and vacuum tubes and some providers are also integrating optical sensors to enhance material detection. Experts also identified a parallel trend of development of greenfield recycling facilities, rather than retrofitting existing MRF infrastructure. This allows solutions providers to achieve greater sorting accuracy and efficiency, using exclusively their own sorters, which are reported by experts to be capable of replacing four to five conventional direct sorters. We learned some robotics companies have also expanded their technology suite to include pneumatic sorting systems, such as air jets and vacuum tubes to expand their separation capabilities.

Despite this shift, certain robotics developers continue to pursue robot-integrated solutions. One solution provider reported during our consultation that their custom-designed robots provide greater control over low-level firmware and software, enabling improved sorting performance. Through focused R&D, they also optimized their systems to better handle plastic films and bags. While additional sensing modalities such as NIR were considered for integration, cost remains a limiting factor. Experts also revealed current research efforts at robotics companies include exploring the integration of material-specific sensors alongside RGB cameras, developing automated data annotation pipelines, and improving sorting performance for frequent contaminants at MRFs.

5. Challenges to AI and robotic sorting at MRFs

Several challenges faced by AI and robotic sorters were identified through literature review and expert consultations. We present identified challenges spanning the various research areas involved in robotic and AI systems for sorting recyclables.

5.1. Recycling complexity

The complex nature of recycling facilities poses a significant challenge to integrating sorting systems at MRFs. The stream of recyclables at these facilities is marked by inconsistent masses, irregular shapes, and random spatial distribution, making automated sorting particularly complex. Sorting systems deployed in this environment must be capable of recognizing and manipulating short-lifecycle, dirty, and damaged items in a robust and agile manner (Kiyokawa et al., 2024). The efficiency of sensor-based sorting systems is further affected by fluctuating process parameters, including object size distribution, material throughput, and material characteristics. For example, a non-static object size distribution leads to the presence of items that are small relative to the detection system's field of view on conveyors, which are more difficult to detect and sort. This is distinct from fine particles, which are typically removed upstream by screening systems before reaching the optical or robotic sorting stage, the challenge here refers to items such as small plastic lids, bottle caps, or flattened containers that pass screening but present limited visual features for detection systems and are difficult for grippers to pick reliably due to their size. Increased mass flow also negatively impacts sorting quality, as it correlates with higher occupancy density on the conveyor. This higher density often results in the formation of object clusters, which can cause occlusion, leading to identification errors when objects are obscured from the perception system's sensors, and separation errors when air jets inadvertently blow multiple objects or when robotic arms fail to pick the target object from a cluster (Maier et al., 2024).

5.2. Economic challenges

In addition to technical limitations, economic factors significantly hinder the widespread adoption of robotic sorting systems at MRFs. Experts emphasized that municipal contract structures play a critical role in shaping technology adoption strategies. Unstable end markets, inconsistent demand, and supply chain volatility further discourage investment in advanced sorting technologies (Salem et al., 2023). Consequently, MRFs tend to prioritize high-throughput systems over solutions aimed at improving sorting quality, with cost considerations often driving decision-making. Although the transition from conventional to AI-driven sorting systems entails substantial upfront costs for solid waste management (SWM) organizations like MRFs, these systems can potentially offset long-term expenses by enhancing operational efficiency, worker safety, and overall productivity (Andeobu et al., 2022). In a review of AI applications for SWM in Australia, Andeobu et al. (2022) highlight the importance of bridging the gap between industry and research, fostering startups, and forming partnerships among small and medium-sized enterprises, research institutions, and SWM organizations to advance automated sorting technologies. They also observed that previous studies inadequately assessed the efficiency, effectiveness, weaknesses, and risks of AI integration in real-world MRF operations, emphasizing the need for further empirical evaluation (Andeobu et al., 2022). An important takeaway for robotic companies was the importance of ensuring minimal downtime, as unplanned downtime significantly increases operational costs at MRFs. Ensuring reliable performance and ease of maintenance remains a major focus for robotics companies developing sorting systems for MRFs.

A structured techno-economic framework for evaluating AI and robotic sorting systems at MRFs has not been identified in the reviewed literature, and such a framework would be valuable for guiding investment decisions. On the cost side, key components include capital expenditure (CAPEX) for equipment and installation, and operational expenditure (OPEX) covering costs like electricity consumption, compressed-air demand, routine maintenance, and gripper replacement costs, as well as transition costs associated with retrofitting existing facility infrastructure. These costs may be partially offset by labor displacement savings where robotic systems reduce reliance on manual sorters. On the benefits side, relevant metrics could include purity premiums from improved bale quality, revenue from increased material recovery, avoided bale rejection costs, and reductions in unplanned downtime. Unplanned downtime is a particularly critical variable, as it affects both throughput and contract compliance at MRFs. Normalizing these costs and benefits against tonnes sorted would yield a cost-per-tonne-sorted metric that enables meaningful cross-system comparison across facility types and configurations. The development of such a standardized framework is identified here as a research priority.

5.3. Challenges in AI-based detection

5.3.1. Dataset and standardization limitations

Computer vision tasks relevant to waste sorting span several distinct problem formulations that are not interchangeable. Image classification methods assign a single category label to an entire image and cannot localise individual objects, which makes them ill-suited for MRF sorting, where multiple items are present simultaneously on a conveyor. Object detection methods identify and localise multiple objects within an image using bounding boxes, and oriented detection extends this by estimating the rotation angle of each object. These methods are relevant to the MRF scenario for finding items on a cluttered conveyor belt, that can have varying orientations. Semantic segmentation assigns a class label to every pixel in an image but does not distinguish between individual instances of the same class, which limits its utility for item-level sorting decisions. Instance segmentation goes further by delineating each object instance separately, making it the most directly relevant task for robotic picking, where the system must act on individual items. Object tracking follows instances across consecutive frames, which is important for items moving on a conveyor. Finally, grasp-pose estimation determines the three-dimensional position and orientation required for a robot to physically grasp a target object, and sits at the intersection of computer vision and robot planning. In the discussion that follows, these terms are used in their precise senses, and studies are described according to the task they actually address. Against this taxonomy, research on AI recyclable sorting has concentrated disproportionately on image classification. In their review of computer vision methods for solid waste sorting, Lu and Chen (2022) report that detection-based approaches account for only one-quarter of the work focused on classification. This imbalance presents a notable challenge: most classification datasets feature isolated recyclable items against simple, uncluttered backgrounds, which are conditions that do not reflect the reality of recycling facilities, where items are often scattered, overlapping, and occluded (Arbeláez-Estrada et al., 2023; Fang et al., 2023; Lu and Chen, 2022). Similar concerns regarding oversimplified datasets have been raised in the context of construction and demolition (C&D) material sorting (Dodampegama et al., 2024).

Current image datasets are also limited to broad material categories such as plastic, glass, and metal, rather than specific polymer types or packaging distinctions (Arbeláez-Estrada et al., 2023; Basedow et al., 2024). The WaDaBa dataset is the only dataset identified to include labels for plastic subcategories: PET, HDPE, PP, PVC, and PS (Basedow et al., 2024). Available datasets also lack sufficient size, which can lead to overfitting and reduced generalization capabilities of models. Data augmentation techniques are often applied to artificially expand training datasets, but can degrade performance in some cases (Fang et al., 2023). It is worth noting that these dataset challenges are specific to academia. Robotics and AI companies invest significant resources in developing high-quality proprietary datasets for their systems. These dataset challenges could significantly impede the effectiveness of AI methods developed in research when applied on data from, or at, recycling facilities (Andeobu et al., 2022; Fang et al., 2023; Lu and Chen, 2022; Satav et al., 2023). The absence of benchmark datasets also makes it difficult to evaluate and compare AI models, reducing the reliability of research findings (Fang et al., 2023; Lu and Chen, 2022).

A further limitation of the current literature is that item-level detection accuracy is routinely reported as the primary performance metric, but this does not translate directly into the mass-flow outcomes that matter to MRF operators. A detection model may achieve high mAP on a benchmark dataset while the corresponding sorting system still loses significant material mass through false ejects, missed detections, clustering errors, air-jet carryover, and robotic gripper failures. The gap between image-level accuracy and facility-level sorting performance is therefore an important concern. To close this gap, studies evaluating AI sorting systems should report mass-flow metrics alongside detection metrics, like input mass composition, target material recovery rate, product purity, residue contamination fraction, false-eject mass, non-target carryover, and bale rejection rate. Reporting these metrics in standardized terms, normalized per tonne of input material processed, could allow meaningful comparison across systems and facilities, and prevent overclaiming of AI sorting capability on the basis of image-level accuracy alone. This is the sorting equivalent of a mass balance or selectivity check.

A critical appraisal of the reviewed literature reveals substantial variation in the quality and generalisability of reported results. The studies included in Table 2 span markedly different testing conditions, from real MRF conveyor belts with industrial lighting, moving material, occlusion, and domain shift across seasons (Bashkirova et al., 2022, 2023; Feng et al., 2024; Ouyang et al., 2024; Qin et al., 2024) to controlled laboratory settings with isolated objects under simplified conditions (Lv et al., 2022; Ma et al., 2024; Zhou and Yang, 2023). Performance figures from laboratory or isolated-object studies should not be compared directly with those from real facility deployments: the former typically report mAP values above 90%, while the latter routinely achieve 20–35% AP on the same task under operational conditions (Bashkirova et al., 2022). None of the reviewed studies reported external validation at an independent test facility, object density counts per frame, inference latency benchmarked against actual conveyor speeds, or performance under wet, dirty, or deformed object conditions. Confidence in a given study's applicability to MRF deployment should therefore be calibrated to its testing context, as indicated in Table 2: results from real facility conveyors under operational conditions carry greater evidential weight than results from laboratory benchmarks, however high the reported metric.

AI research and dataset challenges are highlighted in various review papers. For example, Rekha et al. (2024) reviewed 20 papers focused on AI-based waste sorting systems for biodegradable and non-biodegradable waste, of which one paper implemented a smart bin, while the remaining 19 focused on waste classification. These studies primarily use TrashNet or self-sourced datasets, which are simple classification datasets. Similarly, in the literature surveyed by Lahoti et al. (2024), most studies also focus on classification. Only a few papers implemented detection models from the YOLO family, and just one study modified the original YOLO algorithm. The lack of customized AI models for waste management and recycling remains a research gap (Fang et al., 2023). Collaborative research between SWM experts and computer scientists could help steer academia and AI research toward better addressing the distinctive challenges of SWM (Andeobu et al., 2022; Fang et al., 2023). Such partnerships could support the collection of more representative datasets that reflect real MRF conditions and facilitate mutual understanding of technological needs and constraints. These collaborations would help avoid previous pitfalls in literature, such as the overemphasis on classification tasks.

5.3.2. Computer vision constraints

CV algorithms face inherent limitations due to their reliance on visual features, which can be insufficient for distinguishing between materials with similar appearances but different physicochemical properties (Lu and Chen, 2022). The scarcity of publicly available multimodal datasets that combine RGB data with complementary sensing modalities, such as NIR, constrains progress in this area (Basedow et al., 2024; Lu and Chen, 2022). A similar issue is also observed in C&D waste sorting research (Dodampegama et al., 2024). Expert Consultations revealed that plastic films and bags, among the most common contaminants at MRFs, remain particularly difficult to handle. Their translucency, low structural rigidity, and tendency to entangle with other materials reduce both the detection accuracy of CV systems and picking efficiency with robots and vacuum grippers. These characteristics lead to frequent misidentification or failed picks. Additionally, labels and sleeves on plastic bottles pose challenges for color-based classification by both optical and AI systems, as they can obscure material properties or introduce misleading features. Figure 2 illustrates selected visual similarity and appearance variation challenges under simplified conditions. Real MRF conveyors introduce additional complexity including clutter, occlusion, overlapping items, deformation, food residues, translucent films, and changing conveyor densities that are not represented in the figure.

5.4. Challenges related to robotics development at MRFs

Due to their data-driven nature, AI detection systems take time to adapt to external factors, such as variations in waste composition by time of year and facility location. These systems are also very resource-intensive, and their performance relies on the amount of data used in training. Another challenge identified through our discussions with experts is the lack of a standardized assessment framework. Robotic companies often report performance metrics using proprietary benchmarks or under selective conditions, making cross-comparison difficult. The absence of standardized frameworks for assessing AI and robotic system performance impedes broader adoption and undermines confidence in their reliability at scale.

AI systems are also limited in their operating speeds as compared to optical systems. Expert consultations and industry sources indicate that, under typical single-stream MRF operating conditions, optical systems can be tuned to handle conveyor speeds of up to 1000 feet per minute as compared to 300 feet per minute for AI detectors, and can make decisions up to 10 times faster (Hottenstein, 2022). These figures reflect specific reported operating conditions and should be treated as indicative estimates rather than universal benchmarks.

5.4.1. Gripping recyclables

Reliably gripping recyclables remains a central challenge in robotic sorting at MRFs, as emphasized in both the literature and our discussions with experts. Selecting an appropriate gripper for waste or recyclable sorting requires consideration of several factors, such as object

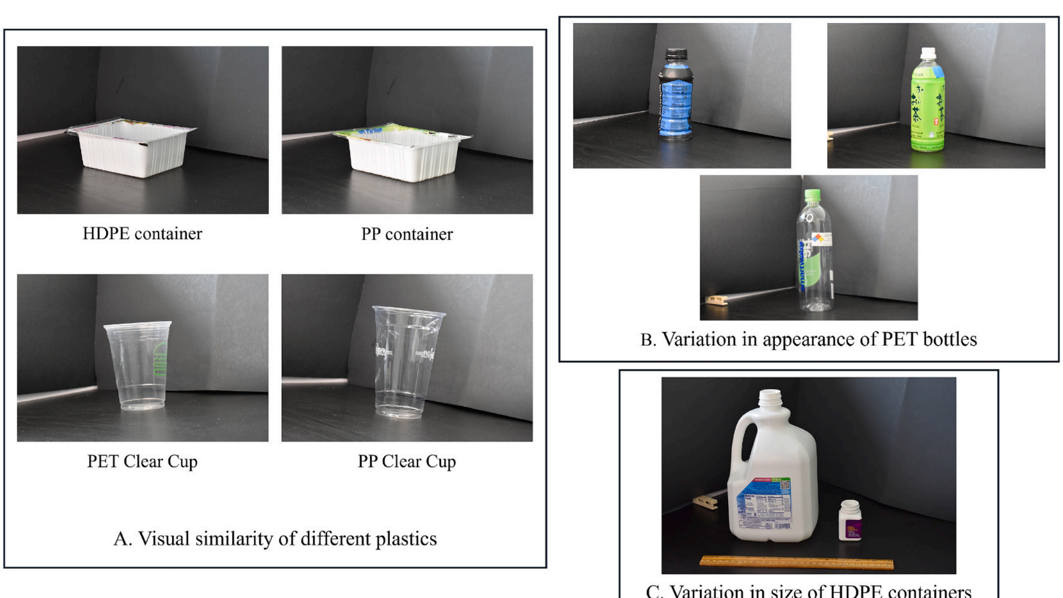

Fig. 2. Examples of visual similarity and appearance variation in plastic items, shown under simplified conditions.

dimensions, surface texture and cleanliness, placement and orientation, environmental conditions (e.g., clutter and moving items), required picking speed, and cost efficiency (Aschenbrenner et al., 2023; Engelen et al., 2024). A summary comparing common gripper mechanisms, target objects, and failure modes is presented in Table 8.

Research in recyclables gripping mainly focuses on vacuum and two-finger grippers (Aschenbrenner et al., 2023; Engelen et al., 2024). Vacuum grippers are a gripping mechanism that is fast, does not require precise alignment, is robust under ideal conditions (Engelen et al., 2024), and is the most widely used end-effector in robotic sorters at MRFs. However, their performance degrades significantly in the presence of surface irregularities, contamination, or misalignment, often resulting in grip failures due to vacuum loss (Aschenbrenner et al., 2023; Kiyokawa et al., 2024). Vacuum systems also require compressed air, which adds to operational costs. Due to frequent clogging and wear, vacuum systems at MRFs necessitate regular cleaning and, in many cases, even daily replacement of gripper components. The added operational costs and frequent maintenance requirements were repeatedly cited by experts during our engagements. To address this, robotics developers have focused on making vacuum grippers modular and easily replaceable.

Two-finger grippers, while slower and more difficult to control, offer greater flexibility and can replicate human-like grasping, making them suitable for handling irregularly shaped items. These grippers are also easier to clean due to their simpler construction (Engelen et al., 2024). Despite these advantages, they are rarely adopted at MRFs due to lower operational speeds. Through experiments, Kiyokawa et al. verify that vacuum grippers struggle with tanglers like strings, hoses, and bags, and small cylindrical items, two-finger grippers struggle to grasp plate-shaped items, and both gripper types struggle with large and/or heavy items (Kiyokawa et al., 2024).

A more structured analysis of gripper performance requires distinguishing between four distinct failure modes that have different implications for research priorities. End-effector failures occur when the gripper physically cannot achieve or maintain a secure grasp, for example, vacuum loss due to surface irregularities, contamination, or curvature preventing airtight sealing (Aschenbrenner et al., 2023; Wang et al., 2023), or two-finger grippers lacking sufficient span or force for heavy or large items (Kiyokawa et al., 2024). Perception failures occur when the detection system fails to correctly identify or localise the target item, preventing the gripper from being directed to the correct position. Grasp-planning failures occur when the system correctly detects an object but selects an inappropriate grasp point or orientation which is a common problem with deformable, occluded, or asymmetric items (Aschenbrenner et al., 2023; Engelen et al., 2024). Motion-planning failures occur when a valid grasp plan cannot be executed without collision, particularly in dense or dynamic conveyor environments (Ružić et al., 2024). These failure types require different research solutions. End-effector failures point to gripper design and material science, perception failures point to detection and segmentation research, grasp-planning failures point to grasp-pose estimation algorithms, and motion-planning failures point to path planning and collision avoidance research. Current literature would benefit from addressing these as an integrated system, rather than in isolation.

5.4.2. Robot types and pick speed limitations

The most commonly used robotic configurations for sorting at MRFs include delta robots, gantry-style robots, and six-axis articulated robots. Each type presents distinct trade-offs in terms of speed, flexibility, reach, and spatial requirements.

Delta robots are known for their relatively fast cycle times, making them the most cost-effective per pick in high-throughput settings (Aschenbrenner et al., 2023). However, their large footprint and rigid mechanical design limit their flexibility and suitability for space-constrained environments. Their gripper must remain parallel to the conveyor belt, which restricts their range of motion and adaptability.

Gantry robots, also mounted above conveyors, offer broader reach and greater flexibility than delta robots when outfitted with articulated wrists, but operate at slower speeds. Six-axis articulated robots are typically installed alongside conveyor belts and are the most space-efficient and easiest to integrate within existing MRF infrastructure. Although they offer the highest degree of picking flexibility, they are the slowest in cycle time and have the most limited conveyor coverage.

As with detectors, a critical limitation across all robotic configurations is picking speed. Based on expert consultations and industry reported data, air-jet systems can achieve over 1000 effective picks per minute (where an effective pick is defined as a correctly ejected target item) under typical MRF operating conditions, compared to an average of approximately 60 effective picks per minute for robotic arms. These figures are indicative and vary with stream composition, belt width, and system configuration. It should also be noted that these figures reflect system-level comparisons as an air-jet sorter figure of over 1,000 effective picks per minute refers to a single sorter unit with its full array of pneumatic valves, while robotic pick rates are typically quoted per arm. Multi-arm robotic systems with four to six arms achieve correspondingly higher system-level throughput, and comparisons between air-jet and robotic systems should therefore specify whether figures are reported per unit, per arm, or per installed system to be meaningful. This also makes the cost per pick of air jets much cheaper than with robots (Hottenstein, 2022). The significant disparity makes robots less favorable for high-throughput sorting operations, and consequently, air jet systems are generally preferred by facilities with adequate space and capital investment, as maximizing throughput is usually a priority.

5.4.3. Robustness and practicality in MRF environment

Expert consultations highlighted the demanding operational conditions robotic systems in MRFs face. Robots are subject to significant wear and tear due to repeated high-speed impacts with unpredictable objects on conveyor belts. These impacts often lead to mechanical failures and necessitate frequent maintenance. For example, one robotics provider reported that large items such as cat litter boxes would occasionally appear at PET sorting stations and damage their robots. In response, the company developed a detection mechanism capable of identifying oversized objects and temporarily retracting the robot to prevent collisions. This illustrates the challenge of unpredictability of material streams at MRFs, which is difficult to replicate or anticipate in laboratory testing environments. Such environmental and mechanical challenges, such as occlusion, clustering, and dynamic material flows, limit the effectiveness of AI-based detection systems and the picking performance of robots.

Table 8
Comparison of gripper types for MRF sorting. (Aschenbrenner et al. (2023); Engelen et al. (2023); Kiyokawa et al. (2024); Wang et al. (2023))

Gripper type	Mechanism	Suitable object class	Known limitations	Failure mode
Suction cup	Vacuum seal	Rigid, smooth, flat surfaces, bottles, cans, cardboard	Fails on curved, contaminated, deformable, or porous surfaces; air leaks under MRF conditions; daily replacement common	End-effector
High-airflow (HAVCO) gripper	Bernoulli / airflow	Small, light, irregularly shaped items; shredded material residue	Limited to lighter fractions, less effective on large or rigid items	End-effector
Two-finger gripper	Mechanical force closure	Irregularly shaped items, relatively heavier objects	Slower cycle time, struggles with flat or plate-shaped items	End-effector + motion-planning

Robotic gripping in the recycling industry also differs significantly from traditional industrial applications due to the high variability and unpredictability of the objects to be handled. Items encountered at MRFs exhibit a wide range of shapes, sizes, and material conditions, many of which may be deformed, contaminated, or partially occluded. Simultaneously using multiple gripper types could address the challenges associated with individual grippers (Aschenbrenner et al., 2023; Satav et al., 2023). However, single robot systems would require tool-changing mechanisms to switch between different gripper types, which can introduce operational delays and additional costs that negate the efficiency gains from improved gripper performance (Engelen et al., 2024; Satav et al., 2023). Research on multi-robot recyclable and waste-sorting systems is necessary to improve the overall efficiency of robotic sorting systems and potentially address these challenges (Kiyokawa et al., 2024).

Traditional grasping algorithms typically assume that objects conform to simple geometric shapes and require comprehensive descriptions of target objects, making them impractical for waste-sorting applications (Engelen et al., 2024). Aschenbrenner et al. (2023) underscore the need for further research on AI-driven grasp-generation algorithms tailored specifically for waste sorting. Energy efficiency is also a critical requirement for robotic recyclables sorting systems, as reducing energy consumption is essential for both cost-effectiveness and environmental sustainability (Aschenbrenner et al., 2023).

5.5. Environmental considerations

The environmental implications of deploying AI and robotic sorting systems at MRFs have received little attention in the reviewed literature. On the cost side, these systems introduce additional energy demands from computing infrastructure, sensors, and robotic actuators, as well as compressed-air consumption for pneumatic ejection. On the benefit side, improved sorting accuracy can deliver meaningful environmental gains like higher recycling yields, reduced bale rejection and associated reprocessing losses, and avoided landfill disposal and incineration of materials that would otherwise not be recovered. Whether the environmental costs of deploying AI and robotic systems are offset by these gains is an empirical question that has not yet been systematically addressed in the literature. Life cycle assessment (LCA) is the appropriate methodology for this comparison, yet no LCA-based evaluation of manual, optical, pneumatic, and robotic sorting configurations at MRFs was identified in the reviewed literature. Developing such a comparative LCA framework, reporting results in terms of energy intensity and carbon emissions per tonne of material processed, is identified here as a priority research need.

6. Discussion

Expert consultations indicate a shift away from deploying robots to separate recyclables from conveyors at MRFs towards optical sorters with air-jets, combined with AI detection systems. Initially, robotic systems were viewed as a cost-effective and relatively straightforward alternative to manual sorters, offering a middle ground between the flexibility of human workers and the automation of air-jet sorters. However, practical experience has revealed significant limitations. Robots struggle to match the dexterity and adaptability of human sorters, particularly when handling a wide variety of shapes, sizes, and materials, and are significantly slower than high-throughput air-jet systems.

We also learned from our consultations, that in newly designed or upgraded facilities where budget and space constraints are less restrictive, there is a trend toward integrating material processors, such as ballistic separators and screens, for preliminary direct sorting, which helps distribute items more evenly and reduces occlusion on wider conveyor belts. Subsequently, air jets paired with advanced optical sorters are employed for high-speed separation. This approach leverages the strengths of each technology, with robots increasingly reserved for specialized quality control tasks or for handling materials that conventional systems cannot process efficiently. This trend reflects the broader industry move toward automation and advanced technology to boost efficiency, while recognizing that a full replacement of human labor by robots is not yet feasible in most MRFs.

Experts also revealed that AI systems are increasingly adopted at MRFs, especially as facilities modernize and expand. These systems are often installed alongside optical sorters, enabling sorting based on shape, color, and other visual features, which complements the material-specific detection capabilities of traditional optical sorters that typically use NIR sensors. This combination enables more accurate, flexible sorting of a wide range of materials, improving both efficiency and output quality.

Beyond primary sorting, expert consultations indicate that AI systems are being considered for new applications such as quality assurance during bale audits. Traditionally, these audits required manual inspection and hand-counting, which is labor-intensive and prone to error. Companies are also offering modular AI units that can be deployed at various points within the MRF infrastructure. These modules collect data that can be used to identify operational bottlenecks, deliver data-driven insights into material flow, and even certify the quality of output bales.

Although robots are seeing reduced deployment in new and upgraded MRFs, they remain a much smaller investment compared to optical sorters and air jets. Robots and AI systems have found use as interim solutions during facility upgrades at MRFs to address immediate sorting challenges. Robotics companies also offer these systems on a lease basis, allowing MRFs to implement robotic sorting without a significant upfront capital investment. Thus, robots and AI sorters offer a viable upgrade path for lower-technology MRFs that face space and capital constraints. As the economic and operational needs of MRFs continue to evolve, robots may find their niche in supporting roles or as transitional technologies.

Having investigated the current state and challenges of robots and AI sorting systems through both the literature and expert consultations, a clear disconnect between academia and industry has become apparent. One major challenge in AI research is the lack of large-scale, real-world datasets. Many robotics companies openly share the scale of their proprietary datasets, with some reporting that their AI systems are trained on over 5 billion to even 150 billion images collected over the company's lifetime. These figures are company-reported and have not been independently verified. However, dataset scale alone is not a reliable indicator of AI capability. Label quality, class balance, domain diversity, and adaptability to new facility conditions are at least as important as image count, and these dimensions are not disclosed alongside scale figures. The true deployment accuracy of systems trained on proprietary data cannot be independently evaluated without standardized benchmarks or externally audited field metrics, neither of which currently exists for MRF sorting applications. A more defensible interpretation is that proprietary data creates a significant barrier to entry for new companies and academic researchers, and may contribute to improved performance, but this cannot be verified from scale figures alone.

The absence of comprehensive, open-access datasets significantly impedes academic research and the development of innovative AI solutions for waste sorting. This gap limits researchers' ability to understand and address the real-world challenges faced in MRFs. The high cost of generating large, fully annotated datasets is a major challenge to research and development in the field. As a result, there are active efforts to develop automated data annotation methods by leveraging multimodal sensor systems that combine infrared sensors, cameras, and AI systems.

Additionally, despite ongoing efforts by robotics companies to improve gripper and grasping capabilities, there remains a lack of academic research specifically focused on robotic gripping and grasping for waste-sorting applications. Ineffective gripping was consistently identified as a major challenge in our expert consultations. Compared with the extensive research on AI and computer vision for waste detection and classification, there is relatively little published work addressing the unique requirements and operational challenges of robotic end-effectors in the waste-sorting context.

Focused, collaborative future research could advance the reliability and efficiency of automated sorting systems in MRFs. Future research should focus on bridging the gaps between academic research and industry needs. Specifically, the development of large-scale, open-access datasets for AI research, as well as the investigation of robotic gripping and grasping for sorting applications, is necessary. Addressing these knowledge gaps can help unlock the full potential of robots and AI systems in MRFs, particularly in supporting roles or as transitional technologies that bridge the gap between manual sorting and fully automated, high-throughput systems. By doing so, researchers can help drive innovation and improve the efficiency of recycling sorting processes.

To advance MRF-applicable AI and robotics research, this review identifies the following priority areas. First, the field needs open MRF video datasets annotated with item-level labels and mass-flow metadata since existing datasets either lack mass-flow ground truth or originate from non-MRF waste streams. Second, standardised benchmark protocols that specify belt speed, conveyor occupancy density, and occlusion level are needed so that performance metrics reported across studies can be meaningfully compared. Without these, mAP figures remain facility-specific and non-transferable. Third, multimodal datasets combining RGB, NIR, and X-ray modalities would enable the sensor-fusion approaches increasingly used in industry but currently underrepresented in academic research. Fourth, field trials directly comparing AI-assisted pneumatic separation with robotic pick-and-place under matched throughput and material conditions are needed to provide the empirical basis for investment decisions. Fifth, as proposed in Section 5.2, a standardised cost-per-tonne and energy-per-tonne framework for evaluating AI sorting systems is absent from the literature. Developing and adopting such a framework would allow economic and environmental performance to be assessed alongside detection metrics. Sixth, long-duration reliability studies for gripper end-effectors under realistic MRF conditions with wet, contaminated, variable object shape and form factor, are needed to close the gap between laboratory gripper evaluations and operational deployment.

7. Disclaimers

Certain equipment, instruments, software, or materials are identified in this paper in order to specify the experimental procedure adequately. Such identification is not intended to imply recommendation or endorsement of any product or service by NIST, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

CRediT authorship contribution statement

Tanmay Haldankar: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Kelsea Schumacher:** Writing – review & editing, Supervision, Formal analysis, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Grammarly to improve readability and language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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