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A Scoping Review of Smart Recycling Technologies: AI, IoT, and Incentive-Based PET Bottle Vending Systems

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Abstract

Innovative and cohesive applications of AI recognition, IoT-enabled monitoring, and incentive-based reverse-vending are yet to be evaluated jointly for PET bottle recycling, as most focus on separate elements. This scoping review presents the first effort to summarize peer-reviewed, English-language literature published between 2021 and 2025 on PET-rich waste streams, concentrating on the technical, operational, behavioral, environmental, and policy-related outcomes. In line with the accepted procedures for scoping reviews and PRISMA-ScR, searches were conducted in Scopus, Web of Science, ScienceDirect, Engineering Village, and Google Scholar using clusters of concepts related to PET and smart technologies and incentives. Of the 13 studies that fulfilled the criteria, most provided descriptions of elements related to AI recognition, IoT monitoring and routing, and incentive-based deposit/refund systems, as well as a limited number of integrated prototypes or system frameworks. AI recognition studies have reported remarkable achievements, including a 95% success rate in the identification of PET vs. PP, a 97.5% success rate in identifying blue PET, PET detection via polarization vision, as well as PET and PP detection and classification via CNN. Examples of incentive systems included a Portuguese pilot of 23 reverse vending machines and a campus pilot that collected over 650 kg of plastic in a duration of six months. While some improvements were made, fully integrated AI-IoT-incentive systems were largely absent from the literature, and most provided limited evidence on long-term participation and operational, economic, and environmental impacts. The review presents a consolidated smart PET recycling system and suggests future research combines the system with the Theory of Planned Behavior to consider user trust, payout reliability, and economic transparency to evaluate the system's overall impact.

Introduction

The last few decades have seen a rapid growth in the production and consumption of plastics. With such a large increase in production, waste management systems became and still are severely impacted. In that time, reports state that global production went from 1.5 million tons in 1950 to 348 million tons in 2017. This massive growth has also seen the petrochemical industry consume a significant portion of the world's oil reserves (Andreasi Bassi et al., 2022). In 2021, Europe's production alone reached 57.2 teragrams. Of the 29.5 teragrams of post-consumer plastic waste collected in Europe in 2020, most of it was simply sent to landfills or delayed at waste-to-energy facilities (Martinho et al., 2024). This was done with limited recycling efforts. The oceans see around 8 million tons of that waste each year. Other statistics note that plastic waste has caused 1 million seabird and over 100,000 marine mammal deaths (Zia et al., 2022). There are policies in place to create a circular economy with much of the focus being on improving recycling, yet the rapid growth in plastic production has outpaced worry about it (Andreasi Bassi et al., 2022; Duan et al., 2024).

The biggest concern is PET. It is a thermoplastic that is produced over 100 million tons yearly and is used in textiles, packaging, and most commonly, drink bottles (McNeeley et al 2025). Even if PET packaging and bottles can satisfy consumers' demands, they are highly dependent on fossil fuels. The world's major environmental issues are worsened by the production of about 3 million tons of PET bottles every year, which uses over 18 million tons of petrochemicals (Tan et al., 2021).

The current state of affairs strengthens reliance on virgin resin. GracidaAlvarez et al. (2023) report that almost all (about 97 in 100) of the raw materials for standard bottle production come predicated on virgin PET materials, incorporating only a trace amount of recycled content, even in the presence of other chemical recycling alternatives. Also, on the basis of their research, PET flows in 12 regions of 41 countries indicate that in 2020, those regions consumed 7297.7 kilotonnes of virgin resin and 1189.4 kilotonnes of recycled resin. A mere 23% of consumed PET was recycled (as opposed to 42% landfill and 35% incineration). That year, a study estimated that the PET supply chain emitted almost 534.6 million tonnes of CO_2 equivalent (Duan et al, 2024). It becomes a bigger concern with the very short lifespan of PET products (less than 1 year in many cases), which leads to very rapid and successive cycles of production, distribution, and disposal. In regions where good collection and recycling systems have yet to be developed, collection systems impose rapid, large volumes of waste and emissions (Duan et al, 2024).

The problems posed by single-use plastic bottles illustrate the problems posed by plastics as a whole. They are lightweight and resistant to breaking, but problems ensue when collection systems fail. Outdoor apparel companies sold about 480 billion units in 2016 (Cai et al., 2022). They are visually ugly and break to form microplastics that contaminate ecosystems (Zia et al., 2022). In Europe, some collection is done separately, but thousands of tons of mixed plastics are still landfilled or sent for energy recovery (Martinho et al., 2024). In some urban areas, PET bottles are mixed together with municipal waste, and insufficient collection and recycling systems, together with informal sorting, result in most waste remaining unrecycled, or being downcycled (Zia et al., 2022).

This picture shows that the collection of resources and infrastructure for access to quality recycling routes fails to keep pace with collection and production. Addressing this gap requires extensive modification to collection systems and behavioral adjustments to provide sufficient quality of feedstock for both mechanical and emerging chemical recycling (McNeeley et al., 2025; Duan et al., 2024).

A part of the gap can be this offered smart recycling technology which can be used to detect, sort and manage PET in a more efficient way. In the recycling system, correct identification of polymer type, colors, and level of contamination determines, in large part, the system's economic viability. Current research records AI- and automation-powered optical sorters and considerable progress (Lubongo et al., 2024). In the case of PET bottles advanced sensing and computer vision are reported to yield highly successful results (Cai et al., 2022). Charting a new course, the dramatic improvement in performance of RGB and hyper spectral imaging for sorting PET from PP and for sorting different types of blue in PET, e.g. 97.5 percent and 95 percent respectively, is especially noteworthy (Cai et al., 2022). In the case of glycol-modified PET (PETG), (Choi et al. 2023) reported, to a large extent, PET recycling stream purity, deep learning images (support vector machines) and the Polarization vision method (Tan et al., 2021) are

reported to yield over 92 percent and (Yoo et al., 2021) reported 95 percent accuracy, respectively, of real and fake Objects Detection within a Reverse Vending System.
IoT systems enable detection and collection operations tracking. Sensor networks embedded in bins in waste management identify fill levels and transmit information via LoRaWAN, Wi-Fi, and other technologies to a centralized dashboard. This information is then used by personnel to design optimal collection routes and schedules (Vishnu et al., (2021)). Processing images to identify waste and optimize collection trips to limit the number of trips is what the IoT smart city devices do (Chen, 2022). Some projects involving the use of smart bins alongside blockchain technology create secured and entry-locked data for collaborative purposes (Holanda Filho et al., 2024). Even with the advancement of smart systems and infrastructures, mixed waste which continues to dominate collection, such as PET bottles is left out of consideration of user behavior as well as engaging PET Bottle waste.
Elements related to finance and behavior influence collections. The Deposit and Refund Systems (DRS) increase the collection rates of plastic bottles and provide safe collection systems for post-consumer food grade PET. A pilot project that placed 23 Reverse Vending machines (RVMs) between 2020 and 2022 in Portugal was able to collect a large number of beverage PET bottles (Martinho et al. 2024).Compared to curb side collection, Reverse Vending machine networks and bottle deposit and refund systems rely on higher grade collection systems. This impacts policy-making related to Reverse Vending networks (Martinho et al. 2024, Andreasi Bassi et al 2022). A review of the literature from 2003 to 2023, focuses on the concern with the systems. However, the review states that research on the systems and their connection to closed-loop recovery remains scarce (Fernandes, 2025).
Newer prototypes combine incentives and smart technology. One university study found that a low-cost, deep learning-based, recognition and reward distribution reverse vending machine prototype collected over 650 kg of plastic in 6 months. The researchers highlighted that plastic production perpetually consumes about 4% of the global oil supply and plastic waste is expected to double by 2050. This suggests that such incentives-based technologies are necessary (Zia et al., 2022).
Research usually disentangles the linked areas. For example, studies focused on optical detection usually work on the accuracy of the detection elements in clean lab exercises, not in the context of the rewards and penalties of their detection in the real world (Cai et al., 2022, Choi et al., 2023, Tan et al., 2021, Yoo et al., 2021). Studies related to IoT systems work on routing and the temporary storage (bins) and do not connect to potential deposit systems and the specifications of the quality of the collected PET (Vishnu et al., 2021, Chen, 2022, Holanda Filho et al., 2024). Deposit schemes studies work on policy, uptake, and logistics and do not tackle the technical configurations of the integration of the sensing and the AI (Martinho et al., 2024, Fernandes, 2025). Most of the Integrating AI into Plastic Recycling studies work on the sorting facilities at the industrial scale, rather on the systems from which the end customers draw (Lubongo et al., 2024).
What's missing is any comprehensive picture of how AI, IoT systems, and incentive-based reverse vending converge in smart PET recycling. This scoping review attempts to close that gap by mapping and synthesizing research from 2021 to 2025 exploring smart recycling technologies that combine these thee dimensions.
The review pursues four aims. First, describe how AI contributes to PET detection and control. Second, characterize IoT architectures and data systems connecting collection sites with backend platforms. Third, examine incentive structures and the behavioural assumptions they contain. Fourth, summarize reported outcomes operational, environmental, and social alongside unresolved questions.

It addresses four linked research questions.
What types of AI and sensing tools feature in smart PET recycling, and what roles do they play?
How are IoT devices and data architecture structured to integrate collection points with backend systems?
What incentive mechanisms underpin these initiatives, and how do they link with technical components?
Where have these systems been tested, and what performance indicators or barriers emerge?

Methods

Study Design and Frameworks

A scoping review was used to identify recent studies involving smart recycling technologies for PET bottles and how Artificial Intelligence (AI), Internet of Things (IoT), and reward-based reverse vending are utilized. The scoping review involved five steps: constructing the research questions, searching for studies, applying inclusion criteria, data extraction, and overall conclusion. To the best of our understanding and according to the PRISMA-ScR criteria, the scoping review enables presentation of findings in a clear and concise format. The protocol was further developed in line with recent systematic and bibliometric studies in reverse logistics, given their reliance on structured search and review processes (Fernandes, 2025; Rodrigues et al., 2025).

Research Questions

Four interconnected questions shaped the inquiry.

- What AI and sensing tools appear in smart PET recycling, and what functions do they perform?
- How are IoT infrastructure, communication standards, and data platforms set up to connect collection systems?
- What incentive mechanisms and policy instruments feature in these projects?
- Where get these deployed, and what outcomes or barriers come through in the research?

These guided a broad scoping effort aimed at connecting design choices with actual user responses and system-wide results.

Eligibility Criteria

Selection criteria emerged from the research questions and the shape of accessible literature. Studies qualified when they satisfied every condition below.

- Appeared between 1 January 2021 and 31 December 2025.
- Published as peer-reviewed journal or conference paper.
- Available as full text in English.
- Concerned PET beverage bottles or PET-rich waste streams.
- Described at minimum one of the following:
  - AI-driven models supporting classification or system control (such as deep learning, YOLO, hyperspectral imaging).
  - IoT systems monitoring collection or featuring smart bin technology.
  - Incentive systems including reverse vending or deposit schemes aimed at PET.
  - Details on technical setup plus at least one measured outcome operational, environmental, or behavioural.

If papers provided only general insights into plastics without mentioning PET, had only the mechanical steps of the process with no user engagement, provided a policy discussion with no original findings, were in grey literature, or were published prior to 2021, they were excluded. Papers that looked at multiple materials were included only if they provided a sufficient amount of PET-specific analysis.

Information Sources and Search Strategy

Source selection reflected standard practice in reverse logistics and plastic sorting literature. Scopus, Web of Science Core Collection, ScienceDirect, and Engineering Village formed the main databases. Google Scholar contributed supplementary results and supported citation chasing. Searches spanned 1 January 2021 through 31 October 2025.

The strategy brought together three concept areas: PET materials (e.g., "PET bottle*"), smart technologies (e.g., "artificial intelligence", "IoT", "smart bin"), and incentives (e.g., "reverse vending", "deposit refund"). One representative Scopus query was: ("polyethylene terephthalate" OR PET OR "PET bottle" OR "plastic bottle*") AND ("reverse vending machine" OR "reverse vending" OR "deposit refund" OR "deposit return" OR "incentive-based recycling") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "convolutional neural network" OR "YOLO" OR "Internet of Things" OR IoT OR "smart bin" OR "smart waste")*.

Citation lists from key papers were examined to locate further qualifying articles.

Study Selection and Screening

First entered all records into the reference management software. Duplicate records were removed. The selection process was done according to PRISMA. Two reviewers coded each title as ‘include’, ‘exclude’, or ‘uncertain’ in a blind fashion. For those with disagreements, discussions were held until a consensus was reached. For records coded as ‘uncertain’, full texts were obtained and reviewed against the inclusion criteria. At this step, many records were excluded as they were missing either PET, smart technology, or incentive related components.

Data Charting Process

Data charting employed an iterative method with a standardized template. Recorded variables encompassed study metadata, context, PET stream description, AI and sensing details (input types, model architecture, performance metrics), IoT characteristics (hardware, protocols, platforms), incentive approaches, and connections linking all three. Measured outcomes sorted into operational, environmental, economic, and social groups. The extraction form was tested on a diverse subset before rolling out to all included studies.

Synthesis Approach

Synthesis merged descriptive and thematic methods. First, study traits were tabulated, and frequency counts highlighted common technologies, system designs, and metrics. Second, inductive thematic work traced how AI, IoT, and incentives combined, watching particularly for what each component did and how tightly they linked. The final synthesis stressed these patterns and associated outcome trends.

Results

1. Study Selection

Figure 1 (the PRISMA-ScR flow diagram) walks through selection phases. Once duplicates vanished, the remaining records faced title and abstract review. A notable group exited here as they strayed from core interests. Full texts were obtained for remaining records; final assessment produced the included set.

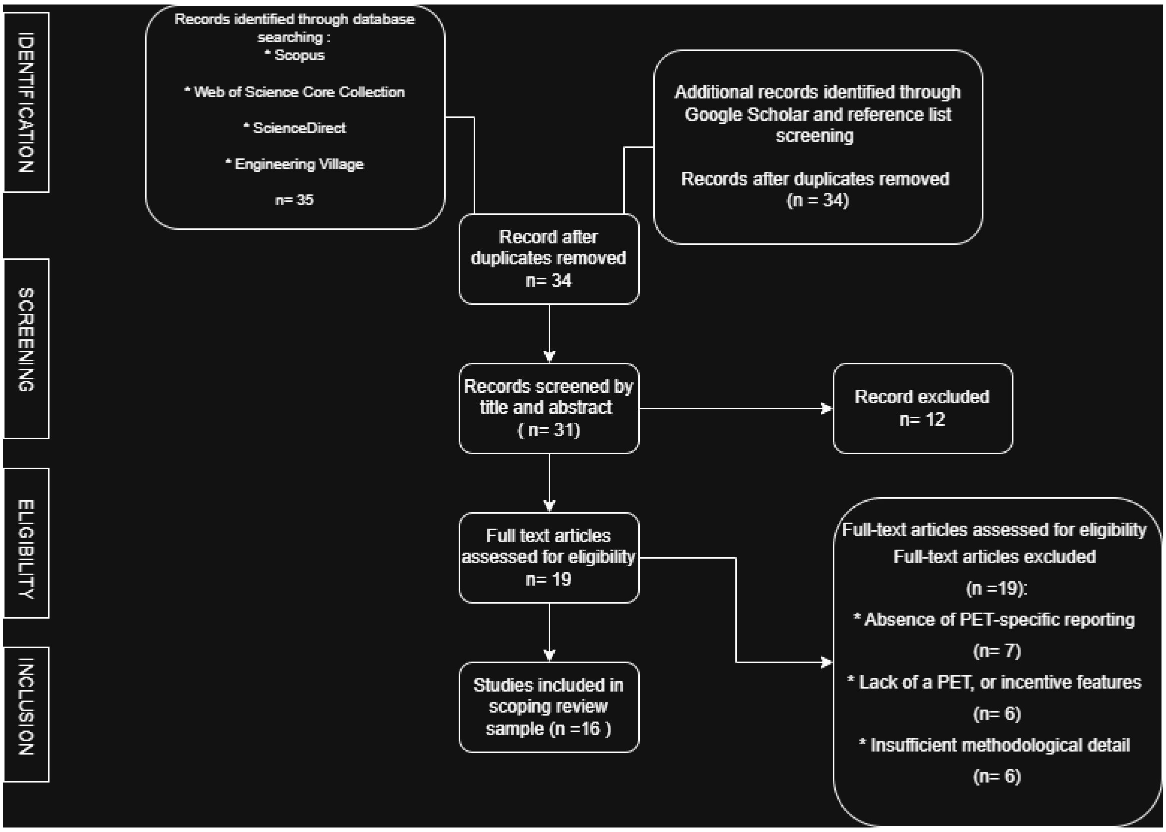

Figure 1 PRISMA-ScR flow diagram

2. Study Characteristics

Table 1 overviews the included studies. Publications date between 2021 and 2025 and span geographically Europe, Asia, Africa, and the Americas all appear. Settings vary from controlled lab benches to country-level pilots, regional modelling work, and local experiments in universities or municipalities.

Author	Year	Country or Region	Study Setting	Technology Pillar	PET Stream	Main Method
Cai	2022	Not stated	Laboratory	AI	Mixed plastic bottles with PET share	Deep learning image classification
Chen	2022	Not stated	Municipal system / smart city	IoT	Mixed recyclables including PET	IoT smart bin and ML-based routing
Choi	2023	Not stated	Laboratory	AI	PET vs PET-G bottle stream	Image sensor and deep learning experiment

Fernandes	2025	Not stated	Regional / bibliometric	Incentive	PET packaging and reverse vending	Bibliometric analysis
Holanda Filho	2024	Not stated	Municipal system	IoT	Mixed recyclables including PET	IoT blockchain-supported ecosystem
Lubongo	2024	Not stated	Laboratory / industry	AI	Mixed plastics with PET as target	Review and technical analysis
Martinho	2024	Portugal	National pilot	Incentive	PET beverage bottles	Deposit-refund pilot evaluation (23 RVMs)
McNeeley	2025	Global (41 countries)	Regional analysis	Integrated	PET packaging	PET supply chain modelling
Rodrigues	2025	Not stated	Regional / review	IoT	PET and packaging flows	Systematic review of digital tech
Tan	2021	Not stated	Laboratory	AI	Recycled PET bottles	Polarization-vision classification
Vishnu	2021	Not stated	Municipal smart city	IoT	Mixed waste including PET	IoT smart bin architecture
Yoo	2021	Not stated	Laboratory / RVM prototype	AI	Mixed bottles including PET	CNN ensemble waste-classification
Zia	2022	Not stated	University campus	Integrated	PET and plastic bottles	Deep-learning RVM with incentives

Table 1: Characteristics of Included Studies

3. System Types and Technologies

As Table 2 indicates, studies clustered into three camps: AI-focused work emphasising recognition, IoT systems centred on monitoring and logistics, and incentive-driven approaches built around returns and deposit structures.

author/year	System focus	AI or sensing approach	IoT devices and networks	Incentive type	Main task	Key performance metrics
Cai, 2022	AI-oriented	Multi-scale feature fusion with RGB + hyperspectral imaging	None reported	No explicit incentive	PET vs PP bottle classification; colour-class separation	~95% overall accuracy; ~97.5% accuracy for blue PET bottles
Chen, 2022	IoT-oriented	Image processing and ML classification (not PET-specific)	Smart bins with sensors; networked containers; IoT communication (WiFi/GSM implied)	No explicit incentive	Smart city waste classification and routing optimisation	Improved routing efficiency; reduced unnecessary vehicle movement (qualitative metrics only)
Choi, 2023	AI-oriented	Image sensors + deep learning (YOLO-type models)	None reported	No explicit incentive	PET vs PET-G discrimination; contamination detection	High discrimination accuracy (numeric values not provided)
Fernandes, 2025	Incentive-oriented	None	None	Reverse-vending related incentives (general domain)	Bibliometric analysis of reverse vending literature	Publication and keyword frequency metrics
Holanda Filho, 2024	IoT-oriented	None (focus on system architecture)	Smart bins; blockchain backend; IoT sensors; unspecified networks	No explicit incentive (system supports social	Fill-level monitoring; secure transaction recording	Descriptive system performance (no numerical metrics provided)

author/year	System focus	AI or sensing approach	IoT devices and networks	Incentive type	Main task	Key performance metrics
				benefit integration)		
Lubongo, 2024	AI-oriented	AI-based optical sorting; robotics; general plastic identification technologies	None	No explicit incentive	Overview of plastic sorting technologies	Not applicable (review article; no empirical metrics)
Martinho, 2024	Incentive-oriented	None (focus on RVM scheme, not algorithms)	Reverse vending machines (23 units)	Deposit refund	PET bottle return through RVM network	Collection indicators; characteristics of material quality (no specific numeric values in document)
McNeeley, 2025	Integrated	None explicit (system-level modelling)	None explicit (supply-chain study)	No explicit incentive	PET supply chain modelling; recycling pathway evaluation	PET flows, recycling rates, GHG emissions (e.g., 534.6 Mt CO_2eq for supply chain)
Rodrigues, 2025	IoT-oriented	None (systematic review of digital tech)	IoT technologies in reverse logistics (general)	No explicit incentive	Review of digital technologies in waste and logistics	Not applicable (review article)
Tan, 2021	AI-oriented	Polarisation imaging + SVM	None	No explicit incentive	PET bottle material identification	>92% classification accuracy
Vishnu, 2021	IoT-oriented	None (focus on sensors + routing)	Smart bins; fill-level sensors; LoRaWAN/WiFi-type networks	No explicit incentive	Fill-level monitoring; route optimisation	Improved routing efficiency (qualitative)

author/year	System focus	AI or sensing approach	IoT devices and networks	Incentive type	Main task	Key performance metrics
Yoo, 2021	AI-oriented	Dual-image CNN ensemble model	Reverse vending prototype (hardware unspecified)	No explicit incentive	Waste classification inside RVM	>95% accuracy; detection of fraud objects
Zia, 2022	Integrated	Deep learning image-based recognition	Reverse vending prototype; on-device control hardware	Reward-based incentives	Bottle return and automated reward issue	650 kg collected over 6 months; system throughput reported qualitatively

Table 2: System Types and Technologies

AI research favoured CNNs, YOLO variants, and other deep learning approaches, drawing on RGB, dual-image, polarization, and hyperspectral data sources. IoT studies concentrated on smart bin gear such as ultrasonic sensors, RFID components, and comms protocols like LoRaWAN and GSM. Incentive-focused work dealt with deposit and refund schemes deployed across reverse vending networks in shops, cities, or campus settings.

4. Integration Level

Table 3 maps integration depth for each paper. Single-pillar contributions dominated the sample, while a minority wove together two or three pillars into more unified systems. In fully linked systems, classification results opened or closed bottle gates, while IoT links allowed system operators to watch activity, spot problems, and settle deposits or payouts.

author / year	AI present	IoT present	Incentive present	Integration level	Data flow description
Cai, 2022	Yes	No	No	AI only	Image data were processed through feature-fusion models to classify PET and PP bottles.
Chen, 2022	Yes	Yes	No	AI + IoT	Sensor and image data from smart bins moved to a central platform for routing and classification.
Choi, 2023	Yes	No	No	AI only	Image sensor data were fed into deep learning models to identify PET and PET-G items.
Fernandes, 2025	No	No	Yes	Incentive only	No device-level data flow; study analysed publication patterns in reverse vending research.

author / year	AI present	IoT present	Incentive present	Integration level	Data flow description
Holanda Filho, 2024	No	Yes	No	IoT only	Smart bin sensors transmitted fill-level data to a blockchain-supported backend platform.
Lubongo, 2024	Yes	No	No	AI only	Review of AI-based sorting described internal data flows from sensors to recognition modules.
Martinho, 2024	No	Yes (RVM network)	Yes	IoT + Incentive	Reverse vending machines logged bottle returns and sent transaction data for deposit-refund processing.
McNeeley, 2025	No	No	No	None (system modelling)	PET flow and emissions data were aggregated within a modelling framework rather than device networks.
Rodrigues, 2025	No	Yes	No	IoT only	Reviewed systems where logistics and waste data moved through digital platforms for coordination.
Tan, 2021	Yes	No	No	AI only	Polarisation image data moved through an SVM pipeline to classify PET bottles.
Vishnu, 2021	No	Yes	No	IoT only	Fill-level sensors sent bin status data via IoT networks to a monitoring and routing dashboard.
Yoo, 2021	Yes	Partial (RVM hardware)	No	AI only	Dual-image inputs were processed by CNN ensembles for in-machine classification.
Zia, 2022	Yes	Yes	Yes	Full integration (AI + IoT + Incentive)	On-device AI classified bottles, updated machine logs, and issued rewards while sending usage data to system controllers.

Table 3: Integration Level

5. Outcomes Reported

Table 4 Reported Outcomes for each paper. Outcomes fell into four buckets: operational, behavioural, environmental or system-level, and economic. Technical metrics dominated often classification accuracy, sometimes F1 scores or inference timing and memory demands. Behavioural findings appeared chiefly in incentive or cross-pillar work, though even there reporting tended toward transaction logs or casual remarks rather than rigorous analysis. Environmental outcomes tracked waste diverted by weight and, in supply-chain work, greenhouse gas tied to different PET management paths. Economic details surfaced rarely and lacked standardised reporting.

Author / Year	Operational outcomes	Behavioural outcomes	Environmental or system outcomes	Economic outcomes
Cai, 2022	~95% overall classification accuracy; ~97.5% for blue PET bottles	Not reported	Not reported	Not reported
Chen, 2022	Improved routing efficiency; reduced unnecessary vehicle movement	Not reported	Increased collection efficiency in smart city system (qualitative)	Not reported
Choi, 2023	High PET vs PET-G discrimination accuracy (numeric values not provided)	Not reported	Not reported	Not reported
Fernandes, 2025	Publication and keyword mapping only (no operational indicators)	Not reported	Not reported	Not reported
Holanda Filho, 2024	Smart bins successfully recorded fill-level data through IoT–blockchain links	Not reported	System designed to support social benefits; no PET-specific environmental metrics	Not reported
Lubongo, 2024	Review of AI sorting technologies; no direct performance results	Not reported	Not applicable (review of technologies)	Not reported
Martinho, 2024	PET characteristics and indicators reported from 23 RVM units	User participation implied but no quantitative behaviour data given	PET collected through national deposit-refund pilot; improved material quality	Not reported
McNeeley, 2025	System modelling of PET flows (no device-level operations)	Not reported	PET supply chain emissions of 534.6 Mt CO_2eq; PET flow and recycling rate modelling	Not reported
Rodrigues, 2025	Review of digital logistics systems; no operational metrics	Not reported	Not applicable (review article)	Not reported

Author / Year	Operational outcomes	Behavioural outcomes	Environmental or system outcomes	Economic outcomes
Tan, 2021	>92% classification accuracy for PET bottle identification	Not reported	Not reported	Not reported
Vishnu, 2021	Fill-level monitoring improvement; more efficient route planning	Not reported	Not reported	Not reported
Yoo, 2021	>95% accuracy and detection of fraud objects in RVM classification	Not reported	Not reported	Not reported
Zia, 2022	650 kg of plastic waste collected over 6 months; RVM operated reliably	User engagement implied through machine usage (no counts provided)	Collection helped reduce mismanaged waste; contextual notes on global plastic projections	Not reported

Table 4: Reported Outcomes

Discussion

1. Overview of Main Findings

This scoping review traced recent efforts on smart PET bottle systems across AI, IoT, and incentive reverse vending. AI contributions tackled object recognition at sorting or collection stages primarily. IoT gear handled observation and orchestration for bins, routes, and sometimes money-related records. Incentive mechanisms aimed to push return volumes higher and boost material purity. Only a handful of studies stitched all three pieces into joined systems. Many papers delivered strong data on algorithm performance or machine prototypes yet offered scant evidence on how people respond, how systems hold up over time, or real environmental benefit. Prototypes and short pilots made up the bulk of the sample; truly long-term tracking fell short.

2. Comparison with Prior Work

Findings mirror earlier scholarship noting a persistent gap between PET capacity and real recycling throughput. Smart systems examined here emphasised early phases—detection, sorting with thinner connections to downstream quality, loop closure, or market readiness. As in broader plastic sorting research, AI work stressed recognition metrics under ideal circumstances but underplayed real-world grit, contamination shifts, light changes, and how models drift. Reverse logistics scholarship has also noted the splintering across technical teams and organisational units, a fracture visible in the distinct AI, IoT, and incentive camps here. Deposit schemes hold a proven track record for high pickup, and the smart systems featured here added technical depth to machines and networks without often linking results back to national goals or broader system carbon.

3. Implications for System Design and Practice

Design and practice pointers surface. For AI and sensors, accuracy with clean samples remains the focus, yet real PET streams throw labels, dirt, crumples, and bad angles at systems. Building robustness to field reality, keeping compute demands low for modest devices, needs sharper attention. Signs show feasibility of fitting large models onto cheap hardware, but evidence on lasting performance drifts with time and wear stays thin. IoT platforms often stop at bin sensing and basic routing. Tighter coupling of device data with logistics planning, payment settlement, and upkeep timing would give operators better grip on the whole picture. Linking fill alerts and sorting results with payment records, for instance, makes spotting quality lapses and fraud easier, and lets staff plan repairs better.

On incentives, user-facing experience at the machine matters enormously. Instruction clarity, recognition speed, payout reliability, and system transparency shape confidence in ways that reward magnitude alone cannot capture. A Theory of Planned Behavior (TPB) lens (Ajzen, 1991) helps explain why this matters. In AI-enabled reverse vending systems, recognition speed should influence attitudes toward the system by shaping perceived convenience and service quality; in public settings it may also affect subjective norms, because visibly smooth transactions normalise participation while repeated delays or failed scans can signal inconvenience; and it should strengthen perceived behavioural control by lowering the time and effort needed to complete a return.

Payout reliability is equally central because reverse vending depends on a credible exchange between user effort and system response. Reliable and prompt reward issuance should improve attitudes by reinforcing perceived usefulness and satisfaction, strengthen subjective norms through positive word-of-mouth and institutional credibility, and increase perceived behavioural control by reducing uncertainty about whether a completed return will generate the promised benefit. System transparency performs a complementary role. Clear acceptance criteria, intelligible rejection messages, visible payout status, and understandable explanations of AI-based sorting should improve attitudes by reducing opacity, reinforce subjective norms by making the system easier to endorse socially, and enhance perceived behavioural control by clarifying how users can complete the task successfully.

From this perspective, technical performance variables are behaviourally consequential because they shape a set of psychological mediators that current prototype studies seldom measure directly. Trust in AI recognition accuracy captures confidence that eligible PET containers are identified correctly and consistently. Trust in payout reliability captures confidence that promised rewards will be issued accurately and promptly. Perceived fairness of reward reflects whether compensation is judged proportionate to user effort and environmental contribution, while perceived effort or time cost captures the burden of queueing, retries, travel, and transaction completion time. These mediators should influence attitudes toward the system, the perceived social legitimacy of participation, and users' sense of control over the return process. The behavioural implication is clear: technically competent systems may still struggle to retain users if they are experienced as slow, opaque, effortful, or unreliable.

A further implication for system design and practice concerns the economic transparency of smart PET recycling systems. As Table 4 showed, economic outcomes were rarely reported across the included studies, even when classification accuracy, routing efficiency, or collection performance were described in detail. This gap is not only a reporting limitation; it is a practical barrier to implementation. Without transparent cost-benefit analysis (CBA), municipal adoption of AI-, IoT-, and incentive-based PET recycling systems is likely to remain stalled at the pilot stage. For local governments, technical feasibility alone is not enough to justify procurement or long-term investment. Decision-makers need clear evidence that these systems can deliver net public value when compared with conventional collection and sorting arrangements. That assessment must extend beyond purchase price alone. Capital expenditure includes AI hardware, smart bins, sensors, embedded processors, communication modules, and reverse vending machines. Operational expenditure includes the energy consumption of edge AI models during classification, IoT maintenance, connectivity fees, routine calibration, software support, and fraud monitoring. Lifecycle replacement costs must also be considered, since cameras, sensors, user interfaces, communication components, and dispensing mechanisms are all subject to wear, malfunction, and obsolescence over time. Without visibility across these cost layers, it remains difficult for municipalities to judge whether reported technical gains can be sustained under real operating conditions and within constrained public budgets.

Future deployments should therefore report a structured CBA alongside technical and behavioural outcomes. At minimum, this framework should include upfront infrastructure cost, energy consumption per classification event, maintenance frequency, cost per kilogram of PET collected, avoided landfill or incineration costs, and potential carbon credit valuation where relevant policy mechanisms exist. These indicators should be tracked over a defined operating period and interpreted together with system uptime, contamination rates, participation levels, and material quality. Reporting in this way would allow municipalities to compare smart PET recycling systems with existing waste-management options on a common economic basis rather than treating them only as technically promising prototypes. In turn, greater economic transparency would strengthen procurement decisions, support long-term municipal scalability, and improve the prospects for broader policy adoption.

4. Research Gaps and Future Work

Clear gaps remain. Integrated systems linking recognition, observation, and rewards from chip to network stay few and far between, and the behavioural foundations of participation remain under-specified. Future work should therefore move beyond descriptive reporting of accuracy and throughput and test a structured TPB-based research framework in which recognition speed, payout reliability, and system transparency are modelled as exogenous technical performance variables; trust in AI recognition accuracy, trust in payout reliability, perceived fairness of reward, and perceived effort or time cost are treated as psychological mediators; and attitude, subjective norms, and perceived behavioural control are specified as proximal predictors of intention to reuse the machine and long-term participation behaviour.

Conceptually, the pathway runs as follows: recognition speed, payout reliability, and system transparency shape trust in AI recognition accuracy, trust in payout reliability, perceived fairness of reward, and perceived effort or time cost; these mediators then influence attitudes toward the system, subjective norms, and perceived behavioural control; and these TPB components in turn shape intention to reuse the machine and observed long-term participation behaviour. Framed in this way, sustained circular economy participation depends not only on whether a machine functions, but on whether its technical performance is interpreted by users as trustworthy, fair, and manageable.

This framework can be operationalised through mixed-method empirical designs that combine user surveys with system log data. Survey instruments can measure trust in AI recognition accuracy, trust in payout reliability, perceived fairness of reward, perceived effort or time cost, attitude toward the machine, perceived social approval, perceived ease of use and control, and intention to reuse. System logs can provide objective indicators such as recognition latency, retry counts, rejection events, payout delays, payout failures, uptime, transaction frequency, inter-return intervals, and active months of participation. Linking these sources through anonymised identifiers would make it possible to distinguish between what the system does technically and how users interpret that performance behaviourally.

Methodologically, this agenda lends itself to structural equation modelling. Future studies could first validate the latent constructs through confirmatory factor analysis and then estimate direct and indirect paths from technical performance variables to sustained participation outcomes. Such models would allow researchers to test, for example, whether faster recognition reduces perceived effort, whether payout reliability strengthens perceived fairness and trust, and whether transparency increases perceived behavioural control, with these pathways ultimately shaping reuse intention and observed repeat participation. Longitudinal and multi-site designs would be especially valuable, since a prototype that attracts initial curiosity may not produce durable recycling routines once novelty fades or operational problems emerge.

In this sense, behavioural rigour is not an optional add-on to smart PET recycling research but a condition for translational relevance. The field will not move convincingly from pilot prototypes to sustained circular economy participation unless technically promising systems are evaluated alongside the trust, fairness, effort, and control beliefs that determine whether people return to them repeatedly over time.

To address the integration gaps identified in the Results section, Figure 2 proposes a conceptual architecture of a fully integrated Smart PET recycling system that links edge AI, IoT-enabled backend coordination, and incentive-based user interfaces within a single end-to-end recovery pathway.

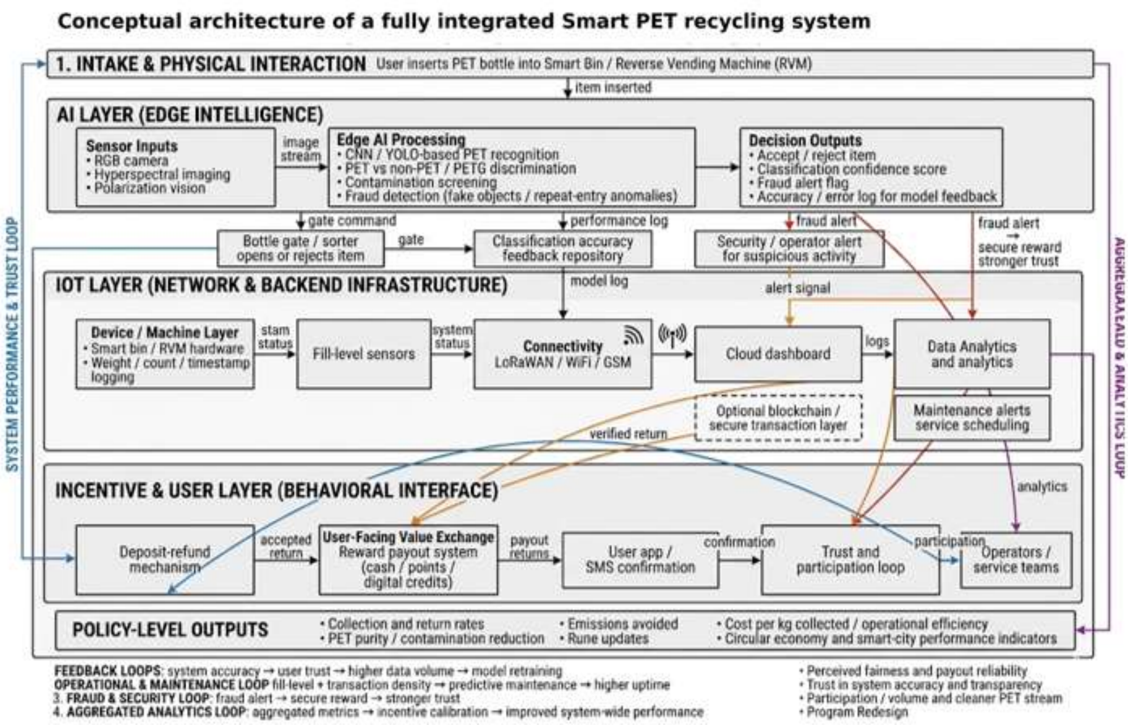

Figure 2. Conceptual architecture of a fully integrated Smart PET recycling system.

Fiugre 2 shows a conceptual design of a completely integrated Smart PET recycling system. The design demonstrates the data and value flows across three layers: edge Artificial Intelligence (AI) for PET recognition and fraud detection, Internet of Things (IoT) for monitoring, analysis, maintenance, and infrastructure, and user reflexive systems for deposit-return incentive and reward systems. The feedback loops interconnect the system's performance, level of trust, user participation, data, and model improvement, while the aggregated data support policy assessment through collection, emissions, and cost metrics.

The conceptual framework places smart PET recycling as a socio-technical system where AI, IoT, and rewards are integrated, a system where each is a critical, self-reinforcing, interconnected component. Edge intelligence, at the point of bottle return, uses RGB, hyperspectral, and polarized light to process data to recognize PET, screen for contaminants, and detect fraud, and do all three in real time. Accept/reject

decisions, as well as confidence scores, are generated by CNN- or YOLO-based models, and an internal learning loop, for model refinement, is generated by classification error logs. The integration is impressive, given that many of the studies of the related literature that were reviewed presented classification as an accurate, stand-alone, technical accomplishment, and gave little to no focus on the impact of recognition quality on operational workflows and/or transactions that relate to end-user interaction (Cai et al., 2022; Choi et al., 2023; Tan et al., 2021; Yoo et al., 2021).
The IoT layer interprets decisions made on the device level and oversees action on the backend. Smart bins and reverse vending machines rely on LoRaWAN, WiFi, or GSM technologies to transmit data to the cloud, where analytical, predictive maintenance, fraud detection, and alerting services are available, along with real-time maintenance scheduling and collection planning (Vishnu et al., 2021; Chen, 2022; Holanda Filho et al., 2024). These features enhance machine availability and reward management. The incentive and user layers of the system provide closure by converting verified returns into deposits, cash, points, or digital credit, which are then delivered via mobile apps or SMS notifications.Importantly, the framework makes explicit the recursive pathway through which system performance shapes user trust, trust influences participation, and greater participation expands the data available for model improvement and policy evaluation. In this sense, collection rates, emissions avoided, material purity, and cost performance emerge not as isolated outputs but as system-level effects of successful integration across AI, IoT, and behavioural design. The framework therefore offers a synthesis-oriented architecture for future empirical testing and for the translation of fragmented prototypes into scalable circular PET recovery systems.

5. Strengths and Limitations

The review employed a systematic, clear approach to chart work on smart PET systems, spelling out entry rules and following a protocol for data pulls. The three-pillar framing let us organise a range of tech and scenarios. Still, gaps exist. Sticking to English from 2021-2025 shut out older work and non-English papers. Zeroing in on PET misses learnings from systems handling mixed plastics where PET plays a bit part. Uneven reporting depth across the primary studies hindered deeper analysis in behaviour, cost, and durability zones.

Conclusion

This scoping review examined smart PET recycling at the juncture of AI sensing, IoT systems, and incentive reverse vending. The literature shows fast growth in AI and IoT, chiefly in lab trials and quick pilots. Systems truly binding recognition, observation, and rewards into coherent wholes stay rare, and published accounts of behaviour, costs, and environmental results often feel thin.

Paths forward point to AI tuned for real, messy conditions, IoT wiring that keeps data flowing safely across gear and backends, and reward setups matching what users expect and what policy demands. Working across engineers, behaviour experts, and public figures seems vital for systems that work reliably while fitting where they will be used. The road to real progress runs through moving past single-layer tests toward true integration and long-haul assessment. Behavioural rigour grounded in theory and linked to system data is especially important if smart PET recycling is to move from technically successful pilots to durable participation in circular systems.

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