Design and Early Deployment of a Digitally Enabled Circular EPS Value Chain Using a Low-Cost AI Vision System

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***Abstract*—Expanded Polystyrene (EPS) is a material widely used in packaging, food transport, insulation, and other industrial applications, yet it remains difficult to manage at end-of-life, especially in peripheral and insular regions. Its low density makes storage and transport inefficient, while contamination and mixed post-consumer conditions reduce reuse and recycling potential. In territories with limited local recycling or remanufacturing capacity, EPS is often directed to disposal or off-island treatment, increasing logistical and environmental burdens. This paper presents the design and early deployment of a digitally enabled circular EPS value chain in an outermost European island region. The proposed approach combines circular process redesign, a low-cost AI vision system based on RGB sensing and controlled illumination, and a FIWARE-based local data space supporting traceability, secure data exchange, and operational monitoring. The paper describes the physical and digital process flows, the system architecture, and the deployment of the vision system in a real waste-sorting environment under practical cost and infrastructure constraints. Early results indicate the feasibility of deploying the sensing and data-acquisition infrastructure required for AI-assisted EPS identification in an industrial sorting environment. Full model validation, including detection accuracy, precision, recall, and contamination-classification performance, remains part of the next validation stage. This study shows how affordable digital technologies can support circular EPS management in geographically constrained regions.**

***Keywords*—circular economy, expanded polystyrene, EPS, artificial intelligence, computer vision, FIWARE, data spaces, industrial waste sorting, island regions**

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I. Introduction

In islands and outermost regions, EPS waste management is shaped by a combination of low material density, limited local treatment capacity, and high logistics dependence. These constraints make EPS a difficult waste fraction to valorize and create a strong need for selective, locally embedded circular routes [1]–[4].

Digital technologies can support this transition by improving material identification, traceability, and coordination across waste-management and manufacturing actors. However, such technologies must remain affordable and deployable under real industrial constraints, particularly in smaller or geographically constrained regional systems.

This paper presents the design and early deployment of a digitally enabled circular EPS value chain developed within a pilot experiment on an island. The work addresses both the physical circular redesign of the EPS flow and the digital architecture required to support it. The paper makes three main contributions:

- it presents a circular value-chain design connecting EPS collection, sorting, traceability, and local industrial reuse in an island context;
- it describes a low-cost AI vision system designed to support EPS detection and characterization under real industrial conditions;
- it reports the early deployment of a FIWARE-based local data space supporting secure data exchange, operational monitoring, and traceability across the circular chain.

The emphasis of the paper is not on final large-scale validation, but on the design rationale, implementation approach, and lessons learned from early operational deployment in a real

industrial environment. The paper therefore contributes with an applied pilot study on how digital technologies can support circular-economy transitions in geographically constrained regions.

II. Problem Context and Circular Opportunity

A. EPS Management Challenges in Island Regions

EPS presents a difficult combination of characteristics from a waste-management perspective. Although physically lightweight, it is bulky and space-consuming, which makes collection, handling, and transport relatively expensive compared to its apparent material value. In addition, post-consumer EPS may exhibit significant variability in cleanliness and contamination, which affects whether it can be reused, downcycled, or must be rejected.

These difficulties become more acute in islands and outermost regions [3], [5]. Geographic isolation increases the dependence on maritime transport for both incoming products and outgoing waste. As a result, the linear model in which EPS is imported, briefly used, and then exported for treatment or disposed of generates disproportionate economic and environmental costs. At the same time, limited local industrial capacity may restrict the practical availability of recycling and re-manufacturing routes.

B. Regional Context

The pilot case presented in this paper originates in an outermost European island region. EPS is used in packaging, food logistics, and selected industrial applications throughout the region. Historically, however, the region has lacked a local circular route capable of systematically retaining suitable EPS for reuse. Within the existing model, EPS is largely handled through conventional waste-management streams and remains dependent on local disposal, namely through incineration, or on off-island treatment pathways [3], [6].

In the regional waste-management system considered here, recyclable material reaches the sorting facility mainly through blue and yellow collection streams. Although EPS should formally be collected through the yellow stream, early operational observations showed that yellow-stream EPS was generally too contaminated for the current reuse processes, while EPS found in the blue stream, often associated with cardboard packaging, was more suitable for recovery. For this reason, the current pilot benchmark focuses on this cleaner recoverable fraction, complemented by dedicated EPS collection points.

Within this current scope, the recoverable EPS baseline is approximately 8.81 t/year. Although modest in mass, this flow is logistically inefficient: separated EPS averages only 0.741 t per 40 ft maritime container. Under the original export-oriented route of over 1,200 km, this corresponds to an indicative real logistics cost of about EUR 2,100 per container, or approximately EUR 25,000/year for the recoverable fraction. This route was later abandoned in favour of local disposal, which is cheaper for the waste-management operator, at around EUR 1,065.90/year including incineration, but environmentally undesirable because incinerating 8.81 t of EPS is estimated to generate 16.15 t CO_2e.

This baseline creates three main limitations. First, EPS is not managed as a transparent and traceable secondary resource. Second, downstream industrial actors that could potentially reuse it face uncertainty regarding the quality and contamination level of the material. Third, the regional waste-management actor bears the operational burden of handling a low-density waste fraction that is costly to transport, environmentally undesirable to dispose of, and difficult to valorize. These conditions explain why the circular scenario focuses on selective local retention of suitable EPS fractions rather than on generic recovery of all EPS waste.

C. Circular Opportunity

The opportunity explored in this pilot is to redesign EPS management for the reusable fractions as a regional circular loop rather than a disposal problem. This implies not only collecting and separating suitable material, but also establishing the technical and organizational conditions required for trust and reuse. Suitable EPS must be identified under real operational conditions, properly characterized, traced across handover points, and delivered to manufacturing actors in a form compatible with industrial decision-making.

This circular opportunity depends on a combination of physical collection, sorting mechanisms, AI-assisted characterization, digital traceability, and industrial uptake by local manufacturers. Therefore, the transition from a linear to a circular model cannot be treated only as a recycling problem. It must also be understood as a coordination, information, and deployment problem.

III. Background and Motivation

A. Digital Technologies for Circular Economy Implementation

Recent literature increasingly positions digital technologies as key enablers of circular-economy implementation, particularly where coordination, traceability, and data sharing are required across multiple actors and process stages [7]–[12]. At the same time, circular implementation often remains constrained by information asymmetries and limited visibility regarding material status and reuse potential, which reinforces the importance of traceability-oriented digital infrastructures [13]. While prior work has also explored consumer-facing mobile and information-support tools for improving waste separation before collection [14], the present work focuses on downstream industrial sorting, where computer vision can support automated material recognition but remains challenged by heterogeneous waste compositions, partial occlusion, variable lighting, and limitations in available training data [15], [16].

B. AI Vision in Waste Sorting Environments

Computer vision is a promising technology for supporting waste detection and sorting. Object-detection and segmentation models can assist in identifying recyclable materials in mixed waste streams and provide input to downstream routing decisions. However, waste-sorting environments impose

significant constraints such as heterogeneous material mixes, partial occlusion, continuous movement on conveyor belts, variable lighting, and restricted deployment conditions [17], [18]. Furthermore, advanced industrial sensing systems are often costly and difficult to justify in smaller-scale or regionally constrained contexts. Still, visible-image-based sensing remains one of the most commonly used approaches in the literature, despite the growing interest in infrared and hyperspectral techniques [19].

C. Motivation for a Low-Cost and Integrated Approach

A practical circular solution for an island region must satisfy two requirements simultaneously. First, it must provide enough technical capability to support EPS identification and traceability under real conditions. Second, it must remain economically and operationally realistic for staged industrial adoption at reduced scale. This is important because island and peripheral regions often face constraints related to infrastructure, scale, and technical capacity, requiring solutions that are locally adaptable and feasible under resource-constrained conditions [4], [6]. In addition, the target deployment context is often not a highly automated sorting plant equipped with advanced industrial separation technologies, but a more manual and operationally constrained environment [17]. While advanced plastic detection and separation approaches can provide strong material-discrimination capability [1], [20], [21], they may also introduce higher equipment costs, calibration requirements, and processing complexity [20], [22]. This motivates the low-cost and integrated approach adopted in this work, where affordable sensing, modular data infrastructure, and targeted circular coordination are combined into one implementation pathway.

IV. Methodology and Implementation Approach

This paper follows an applied implementation approach focused on the design, integration, and early deployment of a digitally enabled circular EPS value chain in a real regional industrial setting. The aim is not to provide final large-scale validation, but to develop and deploy an integrated pilot that connects circular process redesign, AI-assisted material characterization, interoperable data management, and operational monitoring under real geographical and infrastructural constraints. This positioning is consistent with the overall scope of the paper, which emphasises design rationale, staged deployment, and implementation lessons from early operation.

The work is structured around four complementary implementation dimensions:

- **Value-chain analysis and redesign** - current linear EPS flow was examined and a circular alternative was defined around viable recovery and reuse opportunities, including economic actors in the field;
- **Digital architecture specification** - the process flow was translated into a structured and interoperable data space design;
- **AI system specification and deployment** - a low-cost vision solution was designed for real industrial conditions and deployed in the waste-sorting environment;
- **Early operational validation** - deployed components were observed under real conditions and key implementation lessons were recorded.

V. Circular EPS Value Chain Design

A. Actors and Roles

The circular EPS value chain considered in this work connects four main functional actors with complementary roles.

The regional waste-management actor is one of the local entities responsible for the collection, sorting, and operational handling of EPS within the regional system. Its facilities provide the industrial context in which the vision system is deployed and in which material is assessed for potential recovery.

The technology provider contributes the enabling technologies associated with the circular flow. These include smart access-control solutions for dedicated EPS collection points and AI-based sensing and classification components for the industrial environment.

The manufacturing actor receives suitable EPS, performs additional visual inspection to the received material, and incorporates the accepted recycled material into product lines where such reuse is technically feasible.

The digital integration actor supports the experiment through data space architecture, interoperability design, monitoring interfaces, and alignment with wider digital ecosystem tools.

B. Physical Process Flow

The physical circular process begins with EPS generation at households, companies, and other relevant operational sites, mainly from packaging waste. To increase the intake of clean and reusable EPS, major producers were identified, such as electronics stores, and dedicated containers with controlled access were installed. Overall, material enters the system either through existing recycling channels or through these dedicated collection points for cleaner EPS fractions. At the regional waste-management facility, the incoming material is then sorted and assessed for potential circular routing.

As introduced in Section II-B, the current pilot focuses on EPS recovered from the blue waste stream and from dedicated collection containers, since early test runs showed that EPS from the yellow stream was generally too contaminated for reuse. Although EPS should formally be placed in the yellow stream, in practice a relevant share appears in the blue stream together with cardboard packaging. This operational finding shaped the selective scope of the circular process.

Within the pilot, EPS considered suitable for reuse is separated, grouped into batches, and prepared for transfer to the manufacturing actor, with the AI vision system supporting the progressive characterization of this material. Upon arrival, the material undergoes a further verification step before being accepted into reuse pathways. Material that does not meet the

relevant quality threshold is separated into a rejection flow and goes back to the waste-management facility. Accepted material is processed into recycled EPS feedstock for product lines compatible with reused content.

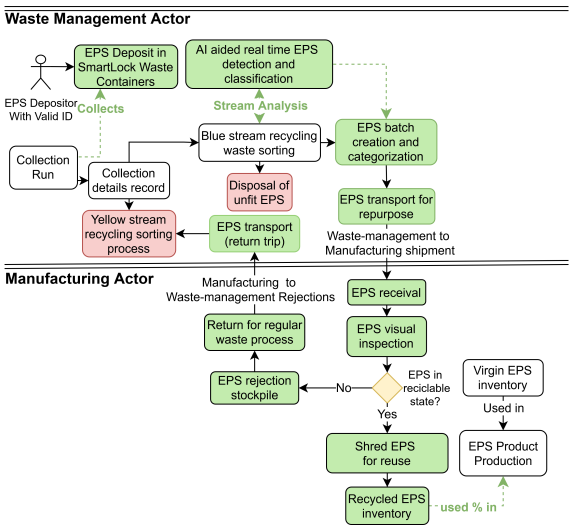


Fig. 1. Physical and operational process flow of the pilot circular EPS value chain.

Figure 1 presents a simplified physical and operational flow of the EPS within the pilot. Green elements indicate steps introduced or modified by the circular process, while red elements indicate existing routes that remain outside the current pilot scope.

At this stage, the circular model is intentionally selective. It is not assumed that all EPS can be retained in the loop or that all downstream product categories can absorb recycled content equally. Instead, the circular strategy focuses on the material fractions and reuse pathways that are technically and operationally feasible. If local applications for more contaminated EPS fractions are identified in the future, the model may be expanded accordingly.

C. Digital Process Flow

The physical process is supported by a corresponding digital process flow, where relevant events are recorded across deposit, collection, sorting, characterization, batching, transport, inspection, and production stages (Figure 2). The digital flow mirrors the physical process, capturing 18 distinct NGSI-LD entities—ranging from collection events and AI-based observations to batch traceability and final production runs—to ensure end-to-end traceability and observability across the value chain.

This data architecture captures the material's lifecycle from the moment a user interacts with access-controlled bins through to the manufacturing actor's industrial reuse. By modeling activities through standardized entities (including processes, products, batches, and observations), the system registers the operational context of waste processing and links AI-generated contamination scores to specific material batches and downstream reuse steps.

The digital process is essential for several reasons. First, it increases traceability and accountability across handover points. Second, it allows operational data to be used for dashboards and KPI tracking. Third, it provides the basis for future sustainability assessment and external platform synchronization. In this way, the digital layer does not merely document the circular process after the fact; it actively supports its coordination and observability.

VI. System Architecture

The interoperability layer is informed by the NGSI-LD information model, which provides a context-oriented representation of entities, properties, and relationships suitable for federated and semantically structured data exchange [23], [24].

A. Architecture Overview

The system architecture follows a layered design connecting edge data capture, local data management, temporal persistence, and visualization services as seen in Figure 3. The architecture was designed to support interoperability, secure access, traceability, and staged deployment.

At the centre of the implementation is a local data space environment based on open and interoperable components. This platform acts as the operational digital backbone of our pilot case, supporting the structured exchange of context information between devices, users, and services. Rather than treating data as isolated application outputs, the architecture maintains a shared contextual representation of the circular chain.

B. Platform Components, Principles and Relation to the Wider Ecosystem

The current local platform includes the main components described next. Keycloak is used for identity and access management, allowing controlled access by both human users and services. Kong provides API mediation and contributes to the secure exposure of services. Orion-LD acts as the context broker for contextual data management. Temporal persistence and retrieval services support the recording and access of time-dependent operational events. Apache Superset is used to support dashboarding, exploratory analysis, and KPI visualization.

This combination of components supports the current operational needs of the demonstrator while maintaining modularity for future evolution. It also reflects a deliberate preference for open, interoperable, and reusable building blocks, as well as secure data exchange.

The local platform is also designed to act as a bridge toward wider circular-economy digital ecosystems. In the current stage, the local stack provides the operational layer for the pilot case. Over time, selected data and services will be synchronized and aligned with external tools and platforms associated with greater value-chain coordination and sustainability assessment.

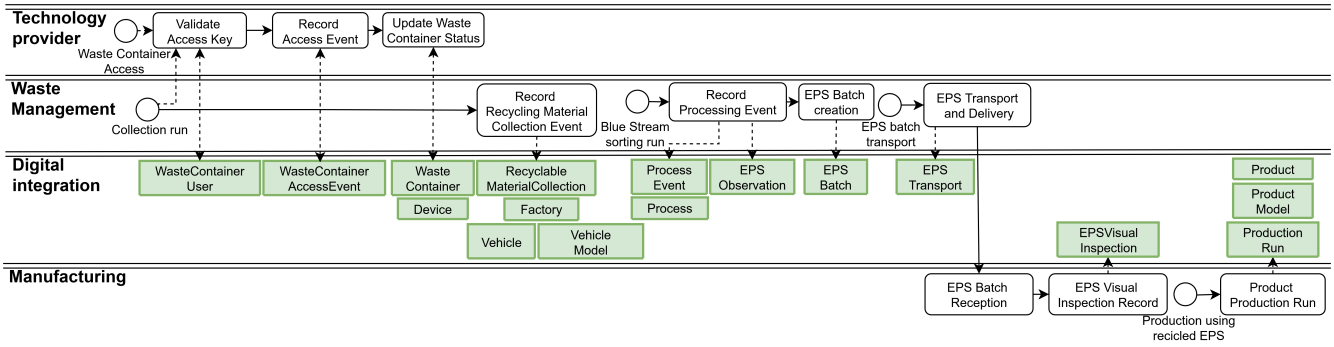


Fig. 2. Digital process flow of the pilot circular EPS value chain.

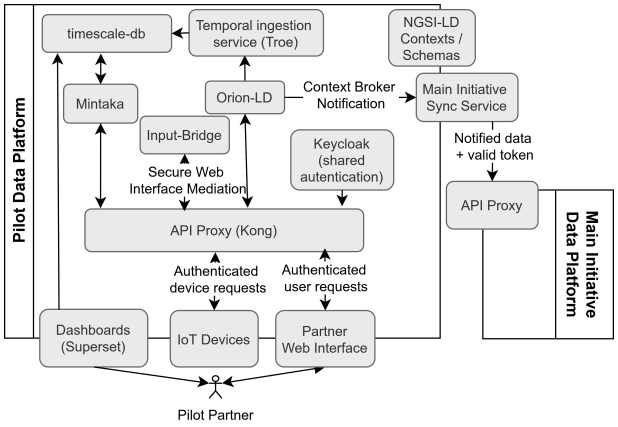


Fig. 3. System architecture supporting the circular EPS value chain.

VII. Low-Cost AI Vision System

Plastic-waste sorting research often relies on spectroscopy-based and hyperspectral techniques for material discrimination, including infrared, Raman, and multimodal sensing approaches [1], [20], [21]. Although these methods can provide strong classification capability, they may also introduce higher acquisition costs, additional calibration requirements, and greater processing and deployment complexity [20], [22]. In peripheral regional deployments constrained by cost, space, and operational simplicity, these requirements can limit practical feasibility and reinforce the relevance of the low-cost approach adopted in this pilot.

A. Design Objectives

The vision system was designed to support the detection and characterization of EPS in real industrial environments, namely in waste sorting lines and controlled collection contexts, while remaining economically feasible for staged deployment. The main objective was not to replicate high-end industrial sensing configurations, but to provide a deployable alternative based on affordable hardware, controlled acquisition conditions, and a hybrid processing architecture.

More specifically, the system was designed to satisfy four operational goals: (i) near-real-time support for EPS identification in mixed waste streams; (ii) compatibility with low-cost edge hardware; (iii) robustness to challenging industrial conditions such as motion, partial occlusion, shadows, reflections, and variable waste composition; and (iv) compatibility with the wider digital architecture of the pilot, including traceability, data exchange, and later synchronization with dataspace services. In this sense, the vision system was conceived not as an isolated AI component, but as part of a broader circular coordination infrastructure, consistent with recent work on data spaces and digital product passport concepts [11], [12].

B. Vision Hardware and Mechanical Integration

The acquisition setup is centred on high-definition RGB image capture and edge-based local processing. The core edge device is currently based on a Raspberry Pi 5 combined with a Raspberry Pi Camera Module 3, selected to balance image quality, compactness, energy efficiency, and replicability across multiple locations. The architecture also allows the future use of dedicated AI accelerators, such as Coral TPU devices.

A custom mounting structure was developed to support both the camera and the lighting system, with the explicit aim of ensuring full coverage of the conveyor belt while maintaining positional stability under operational conditions. The structure was modelled in CAD, integrated into the sorting-line CAD environment, and validated against the spatial and operational constraints of the installation site. This process also supported verification of field of view, adjustment of the mounting geometry, and confirmation that the installation could be carried out without interfering with regular operations. Prior to physical installation, the proposed setup was also reviewed for safety compliance.

Figure 4 shows the sensing device deployed in the pilot environment.

C. Camera System and Image Acquisition

The camera configuration was defined to provide image data suitable both for dataset creation and for future AI inference. The current specification targets Full HD acquisition (1920 x 1080) at approximately 30 FPS, providing a compromise between visual detail and processing feasibility. The selected

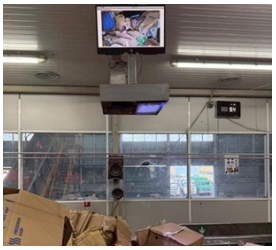


Fig. 4. Deployed vision and acquisition device in the sorting environment.

viewpoint is predominantly near top-down, with small angular adjustments where needed to improve surface visibility and reduce unwanted reflections. The system was positioned so as to cover the relevant belt width while preserving sufficient spatial resolution for small or fragmented EPS items.

This acquisition setup was also used for the creation of the initial project-specific dataset. In the initial stage, 50 videos of approximately 30 seconds each were recorded under real sorting-line conditions, corresponding to roughly 4,500 extracted frames. From this pool, 100 images were selected for initial annotation using an embedding-based diversity criterion intended to reduce redundancy and maximize variation across the sample.

D. Controlled Illumination

Lighting control was introduced to reduce image variability and improve the visibility of relevant material characteristics. In industrial sorting environments, ambient illumination is rarely stable: shadows, reflections, non-uniform lighting, dust, and heterogeneous waste compositions can all reduce image consistency and make classification more difficult. The technical design therefore includes a controlled lighting setup associated with the camera system, with the broader specification considering white, UV/blue, and near-infrared illumination to improve visibility of contaminants and support more stable acquisition conditions.

E. Dataset Baseline and Annotation Implications

The current AI work is grounded in an initial project-specific dataset collected at the sorting facility under real industrial conditions. These conditions include conveyor-belt motion, high variability in object types, frequent object overlap, partial occlusion, and non-uniform lighting with shadows and reflections. Such characteristics are important because they are largely absent, or only partially represented, in public waste datasets.

The first annotated baseline was constructed from 100 selected images using manual bounding-box annotation. The primary class of interest was EPS, complemented by the additional classes cardboard, rigid plastic, and soft plastic in order to improve discrimination against visually similar materials. The annotation process followed defined guidelines and included quality-control steps with two annotators, including the use of adjacent video frames to resolve ambiguous cases. This baseline is not sufficient for production-ready model training, but it provides a realistic initial dataset for experimentation, workflow validation, and iterative model refinement.

F. AI Strategy

The AI strategy follows a hybrid two-stage logic that balances responsiveness, deployability, and detection accuracy. This is particularly important in the ISLOPOL context, where EPS must be detected in mixed waste streams under real industrial conditions, while operating with low-cost edge hardware and constrained connectivity.

The first stage prioritizes fast deployment-oriented models, particularly YOLO and RT-DETR, for rapid candidate detection close to image acquisition. Its role is not to make the final classification decision, but to identify candidate EPS regions and reduce the amount of visual data requiring more computationally demanding analysis.

The second stage supports higher-accuracy validation and refinement in fog infrastructure when computational resources and connectivity permit. Slower but more accurate models, such as Faster R-CNN, Mask R-CNN, PointRend, RetinaNet, and Trident Network, can then be used to reduce false positives and improve robustness in difficult cases involving occlusion, visually similar materials, small fragments, or contamination.

The baseline results obtained for the evaluated models are summarized in Table I. These values should be interpreted as an initial benchmark for guiding the staged AI strategy, rather than as final project performance. The current dataset remains limited and project-specific training is still evolving; therefore, the immediate objective is to establish a viable AI pipeline that supports iterative improvement as more annotated data becomes available.

TABLE I
BASELINE PERFORMANCE OF CANDIDATE DETECTION MODELS.

Model	mAP@50	mAP@75	Improvement (mAP@50)
Faster R-CNN	47.8%	34.2%	+3.7%
Mask R-CNN	47.8%	36.7%	+3.9%
PointRend	43.2%	26.7%	+3.1%
RetinaNet	43.5%	34.5%	+1.9%
TridentNet	42.3%	24.1%	-4.2%
RT-DETR	46.1%	38.0%	+1.6%

G. Edge and Fog Processing Logic

The edge-fog design was adopted in response to both computational and infrastructural constraints. At the edge, the system supports local image acquisition, temporary storage, and selected lightweight processing tasks. This reduces latency and lowers dependence on continuous high-bandwidth communication. At the fog level, more computationally intensive processing can be executed when needed, including higher-accuracy validation steps and future model evolution.

This architecture also proved important during deployment. Initial assumptions based on a streaming-oriented acquisition pipeline were found to be difficult to sustain under the network conditions of the industrial environment. As a result, the acquisition logic was revised toward a more robust store-and-forward model based on local storage and asynchronous

upload. This revision was not incidental, but a key deployment lesson: in constrained industrial settings, robust data capture and deferred synchronization may be more important than continuous streaming assumptions.

VIII. Early Deployment in an Industrial Environment

A. Deployment Context

A major contribution of the work lies in the transition from conceptual design to physical deployment in a real waste-sorting environment. The prototype was installed at the facilities of the regional waste-management actor, allowing the system to operate in the same context where future EPS identification and routing decisions must be supported. This enabled validation not only of the sensing setup itself, but also of its mechanical integration, field of view, stability, and compatibility with the operational environment.

B. Operational Data Acquisition

The deployment enabled the collection of a substantial volume of project-specific visual data under real sorting conditions. This is particularly important because one of the main limitations identified in the review of public datasets is the lack of EPS-specific labels and the insufficient representation of the industrial conditions relevant to the present use case, such as mixed waste streams, contamination, occlusion, motion, and lighting variability.

At the current stage, the deployed setup has enabled the collection of approximately 15,000 videos, corresponding to roughly 500,000 frames. Earlier curation stages based on an initial subset of 50 videos and approximately 4,500 extracted frames were used to build a first annotated baseline of 100 diverse images. Taken together, these results show that the deployed system is already serving a dual role: it supports the operational pilot while simultaneously building the data foundation required for subsequent AI development.

An example of the resulting annotated dataset is shown in Figure 5.



Fig. 5. Annotated dataset image.

C. Connectivity Constraints and Architecture Revision

One of the most important practical lessons from deployment concerned connectivity. The initial image-acquisition logic assumed a more streaming-oriented architecture, but this proved difficult to sustain in the industrial environment due to bandwidth and stability limitations. The solution therefore evolved toward a more resilient architecture based on local capture, temporary storage, and asynchronous upload.

This design revision is significant beyond the specific pilot. It shows that the feasibility of industrial AI deployment depends not only on the selected model family, but also on the realism of the supporting acquisition and communication architecture. In environments such as waste-sorting lines, robust data capture under constrained connectivity may be more valuable than more elegant but fragile streaming assumptions.

D. Current Maturity Level

The current state of the demonstrator should be understood as early deployment rather than full-scale validated operation. Core elements of the sensing setup, local acquisition logic, and supporting digital toolchain are already deployed and functional. The broader data space environment also provides an operational basis for data ingestion, storage, query, and dashboard visualization, which supports the traceability and observability of the pilot. However, full quantitative validation of AI classification accuracy, contamination-assessment performance, long-term industrial reuse outcomes, and circularity impacts remains part of the next phase of work.

IX. Dashboarding and Operational Monitoring

The digital environment deployed in the pilot also supports operational monitoring and exploratory KPI visualization. Dashboarding is important because circular-economy implementation requires visibility not only into raw events, but also into aggregated indicators that can inform actors across the value chain.

The dashboard layer provides an initial basis for monitoring selected operational, environmental, and circularity-related dimensions. These include, for example, material flow visibility, process event tracking as illustrated in Figure 6, and exploratory views of indicators relevant to the later assessment of reuse performance and environmental impact. At the current stage, these dashboards should be understood as functional monitoring tools and as evidence of end-to-end data availability, rather than as finalized business intelligence products.

The sustainability-assessment dimension of the pilot is aligned with recent literature emphasizing the need for life-cycle assessment approaches in circular systems that capture material quality, end-of-life pathways, and the environmental implications of alternative recycling and reuse configurations [2], [25], [26].

X. Discussion

A. Contribution to Digital Circular Economy Practice

The main contribution of this work does not lie in a single technical component, but in the early operationalization of an integrated circular system in which selective material recovery, AI-assisted characterization, and interoperable data exchange are combined in a real regional setting. More specifically, the case shows how a difficult low-density waste stream can be



Fig. 6. Example dashboard showing operational EPS processing events.

reorganized as a traceable circular flow by aligning physical collection and sorting practices with a digital layer capable of supporting characterization, batching, transport, inspection, and monitoring.

This contribution is relevant because the pilot does not remain at the level of conceptual architecture. The work includes the redesign of a physical EPS flow, the identification of practically recoverable fractions, the deployment of a low-cost sensing setup in the sorting environment, the creation of an initial project-specific annotated dataset, and the implementation of a local data space and dashboard layer to support traceability and observability across the chain. In this sense, the study contributes to the digital circular economy by showing how affordable AI sensing, interoperable data spaces, and traceability-oriented digital architecture can support circular coordination and industrial adoption in a real regional pilot.

From a value-chain perspective, the pilot creates distinct forms of value for the participating actors. For the waste-management actor, it improves visibility and routing of a waste fraction that is operationally difficult and economically inefficient under a linear model. For the manufacturing actor, it supports the emergence of a more reliable secondary EPS feedstock by introducing additional traceability and inspection steps before reuse. For the technology actor, it provides a real industrial setting in which sensing, acquisition, and traceability mechanisms can be deployed and refined under operational constraints. For the digital integration actor, it demonstrates how interoperable data exchange can support circular coordination across heterogeneous stages, from collection and sorting to transport, inspection, and downstream production.

The low-cost orientation of the sensing architecture is a central part of the contribution. In many discussions on digital circular economy, advanced digitalization is implicitly associated with costly industrial automation and high-end sensing systems. However, the present case suggests that, for island regions and other constrained regional systems, affordability, modularity, and staged deployability may be more important than technical maximalism.

In this pilot, the choice of RGB-based acquisition, edge-oriented hardware, and incremental deployment was not simply a budgetary compromise. It was a design decision aligned with the realities of replication, maintenance, and operational adoption in a regional setting. The case therefore suggests that meaningful circular improvements can be supported by comparatively simple and affordable digital infrastructures, provided that they are well integrated into the operational context. In this sense, low-cost does not mean low relevance; rather, it may be what makes deployment feasible in the first place.

B. Value of the Island Context

The island context gives the case broader analytical value. In geographically constrained regions, the inefficiencies of linear handling models become especially visible: low-density materials such as EPS are expensive to transport, difficult to valorize, and often redirected toward environmentally undesirable disposal options. These conditions make island regions especially useful environments in which to test whether circular strategies are operationally realistic rather than only theoretically desirable.

The present case also shows that circular implementation in such contexts is necessarily selective. Not all EPS fractions are equally recoverable, and the pilot therefore concentrated on cleaner and more viable streams, particularly material recovered from the blue stream and from controlled collection points. This is an important practical lesson. In constrained regional settings, circularity may need to begin with technically and operationally feasible fractions rather than with the assumption that all waste can immediately be retained in the loop. In that sense, the island context acts not only as a background condition, but as a stress-test for the realism of the proposed circular model.

C. Limitations

This work has several limitations. First, the reported results correspond to an early deployment stage and do not yet provide a final quantitative evaluation of AI performance, long-term operational stability, or circularity outcomes. Although the pilot already includes deployed sensing, a functional data pipeline, and dashboard-based monitoring, the present paper does not claim full validation of classification accuracy or final KPI achievement.

Second, the AI development process remains dependent on continued dataset growth and iterative refinement. The initial annotated baseline is useful for experimentation and workflow validation, but it is not yet sufficient for mature large-scale model training or definitive contamination-related assessment. Third, some wider ecosystem integrations remain ongoing and therefore fall outside the scope of this paper. These include deeper synchronization with external circular-economy tools and broader sustainability-assessment services. Finally, the circular strategy itself is intentionally selective and currently

focuses on the material fractions and reuse pathways that have shown initial practical viability within the pilot setting.

XI. Conclusions and Future Work

This paper presented the design and early deployment of a digitally enabled circular EPS value chain in an outermost European island region. The proposed approach combines a selective circular redesign of the EPS flow, a low-cost AI vision system based on controlled RGB acquisition, and a local data space architecture supporting traceability, secure data exchange, and operational monitoring.

The case contributes an applied demonstration of how digital technologies can support circular-economy implementation under real geographical, infrastructural, and industrial constraints. More specifically, the work shows that it is possible to connect selective recovery of reusable EPS fractions with deployed sensing, structured contextual data, and dashboard-based observability in a way that supports coordination across waste-management and manufacturing actors.

The results obtained so far indicate the feasibility of this integrated approach, but they also highlight an important practical lesson: successful deployment depends not only on model selection, but equally on the realism of the acquisition setup, the robustness of the communication architecture, the quality of the growing dataset, and the staged alignment between physical and digital process flows. In the present case, the revision from a streaming-oriented logic toward local storage and asynchronous upload is a clear example of how operational constraints shape the final system design.

Future work will focus on continued dataset expansion, further model refinement, deeper integration with wider ecosystem tools, and the quantitative evaluation of circularity, operational, and sustainability indicators. These next steps will determine to what extent the current early demonstrator can evolve into a stable, replicable, and transferable circular infrastructure for EPS management in geographically constrained regions.

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