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Artificial Intelligence applications in Reverse Logistics

How technology could improve return and waste management creating value

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Abstract

The research and the analysis will focus on applications of artificial intelligence in the field of "Reverse Logistics".

The activities included in reverse logistics processes cover the product journey from the end user back to the manufacturer with the purpose of reselling, repairing, refurbishing or recycling the item in a circular economy perspective.

The purpose of this document is to provide possible answers to the question of how to improve current processes with the help of artificial intelligence to become faster, reduce the number of unrecognized items, improve accuracy, and help generate value for the environment and businesses.

An analysis of key technologies and trends will be developed and, considering the different stages of the process, suggestions on possible improvements will be highlighted.

Businesses that stand to benefit from these opportunities include those involved in managing returns from e-commerce transactions, as well as those engaged in waste collection and broader recycling operations.

An analysis on the industrial interest based on experts' interviews will be conducted to explore the contribution that AI could bring to current operations in different industries, investigating level of knowledge and applicability of the technology.

Subsequently, a convolutional neural network model will be created to test the benefits that technology could enable in a context of waste management in terms of time reduction and accuracy.

Finally, a comparison between manual and automated processes in the assessment of waste categories will be developed, highlighting the value that a machine learning algorithm could generate in cooperation with human operators.

Keywords: Artificial Intelligence, Reverse Logistics, Computer Vision, Waste Management, Returns Management, Circular Supply Chain, Convolutional Neural Network, Waste image recognition

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1. Introduction

Nowadays, understanding the role of each activity in the supply chain is fundamental to maximize the retention of value and to avoid waste.

The linear economic model of production, characterized by the short lifespan of products, has been considered outdated and no longer sustainable. Shortage of every kind of resource and the implications on the environment are non-negligible anymore.

In response, many companies are transitioning to circular business models. In these models, once consumers no longer need an item, it re-enters the value chain, where it may be resold, reused, remanufactured, refurbished, or recycled. This approach not only extends the life of products but also allows them to continuously generate value in various forms until the resources they contain are fully utilized.

One of the critical aspects to ensure a circular model is the collection, inspection and sorting of products from the final customers back again to the retailer or manufacturer, this set of activities goes under the name of "Reverse Logistics". This concept contrasts with Forward Logistics, which encompasses the processes that deliver products to customers, while Reverse Logistics is the backward flow.

Effective reverse logistics is vital across almost every industry, not only to reclaim value from recycled materials but also to manage return processes effectively. Industries ranging from fashion to consumer goods, and from pharmaceuticals to automotive and construction, must establish robust policies that allow customers to return purchases within a specified period. Failure to offer such return policies can result in loss of market share and damage to a company's reputation, particularly in sensitive markets.

This research aims at discovering the current development and state of research regarding Reverse Logistics processes around different industries and propose some new solutions leveraging technology.

One of the most promising technologies in this context is Artificial Intelligence (AI), which holds the potential to enhance the majority of activities within the value chain and provide a competitive edge in the near future, particularly within the dynamic realm of Supply Chain & Operations.

The document will be structured in a first part of deep dive into Reverse Logistics to better understand its trends, challenges, drivers, and the open points in which an intervention of AI could be beneficial. Subsequent sections will review the literature on the applications of AI in reverse logistics, analyze current market needs, and identify priorities for companies considering technology implementation. Moreover, a series of interviews have been conducted to glean deeper insights into companies' strategies on reverse logistics and to gauge their perspectives on the role AI will play, particularly focusing on learning techniques applied to computer vision tools. Finally, the consequences of applying such technology will be further analyzed in the replication of the machine learning algorithm for waste recognition in comparison with a process manually held, underlying how a cooperation between humans and AI is capable of revolutionizing this industry.

2. Reverse Logistics at a glance

A first definition of Reverse Logistics described it as “the process of moving goods from their typical final destination for the purpose of recapturing value, or proper disposal” (Rogers, 2001) and it is one of the most critical activities for a correct implementation of a circular economy.

Following the European Parliament definition, circular economy is “a model of production and consumption, which involves sharing, leasing, reusing, repairing, refurbishing and recycling existing materials and products as long as possible. In this way, the life cycle of products is extended.” (Eurpean parliament, 2023).
The main objectives are to reduce waste and create further value and improve resource efficiency to decrease virgin material dependance and establish a more environmentally friendly economical model.

To help National Economies to follow the right direction, many regulations were published all over the world. Here are some examples:

- In Europe, the **Circular Economy Action Plan**, which is part of the Green Deal published in 2019, aims at promoting the circularity throughout the lifecycle of products, including measures to encourage recycling, reduce landfill use, and cut down on single-use plastics. (European Commission, 2019).
- In the US, the **Resource Conservation and Recovery Act**, first enacted in 1976, incentivizes waste minimization and safe disposal of waste, with particular attention to solid and hazardous waste. (EPA, 2024).
- In China, **the Circular Economy Promotion Law**, promoted in 2009, aims at increasing resource utilization rate, covering reduction, reuse, and recycling in various sector. (Shanghai Cooperation Organization Environmental Information Sharing Platform, 2008).
- Various international framework, indirectly support circular economy such as the Sustainable Development Goals (SDGs) developed by the United Nations.

In this chapter, an analysis of the main trends regarding the implementation of Reverse Logistics in the context of circular economy will be developed, then every phase regarding the process will be described and the related challenges will be outlined.
Lastly, the great problems of nowadays' returns will be delineated, uncovering the amount of wasted material and money behind easy return policies.

2.1 Trends and Drivers

Emerging trends in Reverse Logistics (RL) are profoundly influenced by a confluence of economic reasons, regulatory pressures, technological advancements, market expectations, and sustainability drivers.

The main focus of companies remains the economical one, including improvements in cost and operational efficiency and profit maximization. The possibility to access secondary market, indeed, and the exploitation of still valuable spare parts at the product's end of life represent important benefits in many industries.

Legislation, particularly in the European Union, has been a pivotal force, with directives such as the End-of-life Vehicles Directive (ELV), Waste Electrical and Electronic Equipment Directive (WEEE), and Restriction of Use of Certain Hazardous Substances Directive (RoHS) pushing firms towards environmentally responsible waste management and recycling practices (M.Şükrü Akdoğan, 2012). Another practical example of government intervention could be seen in the article (Simone Machado Santos, 2022) which describes how Brazil with the Decree 10,140 of 2020 stated that each stakeholder is responsible for implementing and operating their reverse logistics system, whose activities will be reported to the national Ministry of the Environment. These regulations underscore the imperative for companies to adopt RL as part of their operational and environmental strategy.

The role of emerging technologies in facilitating RL processes cannot be overstated. Innovations such as Barcode, E-commerce, IoT, Big Data and AI are recognized for their potential to revolutionize RL by enhancing traceability, minimization of human errors and integration within supply chains (Saman Amir, 2023), (Mohammad Amin Khoei, 2023). These technologies enable more sophisticated management of customer returns and end of life returns helping operator to optimize collection processes and correctly assess the recovery path of the item.

Specific solutions have been identified, alongside technology to correctly implement Reverse Logistics. For example, (Ramazan Kaynak, 2014) suggests that Logistics Centers would enhance centralization and consolidation of processes, improve 3PL strategic collaboration with better decision making regarding what to outsource, and it argues that the integration of transport and logistics activities tend to be more efficient and more cost effective if centrally managed.

Finally, market expectations and consumer demand for sustainable products have significantly influenced RL practices. As consumers become more environmentally conscious, firms are motivated to integrate RL into their operations to meet these expectations and maintain competitive advantage. This consumer-driven shift is further accentuated by the already cited economic and strategic benefits derived from managing EoL products effectively and improved corporate image (Pravin Kumar Mallick, Closing the loop: Establishing reverse logistics for a circular economy, a systematic review, 2023)

In the face of these trends, companies are increasingly recognizing the importance of RL as a key component of sustainable supply chain management. The shift towards sustainability is not merely a response to regulatory and market pressures but also a strategic move to capitalize on the economic opportunities presented by efficient RL practices.

2.2 Steps of Reverse Logistics

The domain of reverse logistics (RL) encompasses a diverse range of activities, essential for the efficient management of returns, waste, and end-of-life (EoL) products. Literature reviews and surveys have significantly contributed to delineating these core activities within RL practices.

According to (Pravin Kumar Mallick, Closing the loop: Establishing reverse logistics for a circular economy, a systematic review, 2023), and corroborated by the research of (Nikunja Mohan Modak, 2023) and (Kannan Govindan H. S., 2014), RL encompasses:

- Network Design and Planning
- Collection of goods, often with the help of a 3PL provider

- Integration in production planning and inventory management, through Identification and Inspection
- Decision-making processes for resource recovery, also denominated as Sorting

This comprehensive view underlines the multifaceted nature of RL, extending beyond mere collection and recycling to include strategic planning and integration within the supply chain. Moreover, the remanufacturing process, as detailed by (XIA Wen-hui, 2011), includes further steps such as evaluation, classification, disassembly, cleaning, and remanufacturing before entering the redistribution cycle. This process highlights the intricacies involved in ensuring products or materials re-enter the supply chain, emphasizing the need for meticulous assessment and processing to maintain quality and value.

In the context of the construction industry, (Lu Ding, 2023), delineates phases specific to construction-related RL, including deconstruction with on-site waste collection, product reuse, waste distribution, segregation, and material reprocessing. These stages underscore the sector-specific nuances of RL, demonstrating the adaptability and broad applicability of RL principles across different industries.

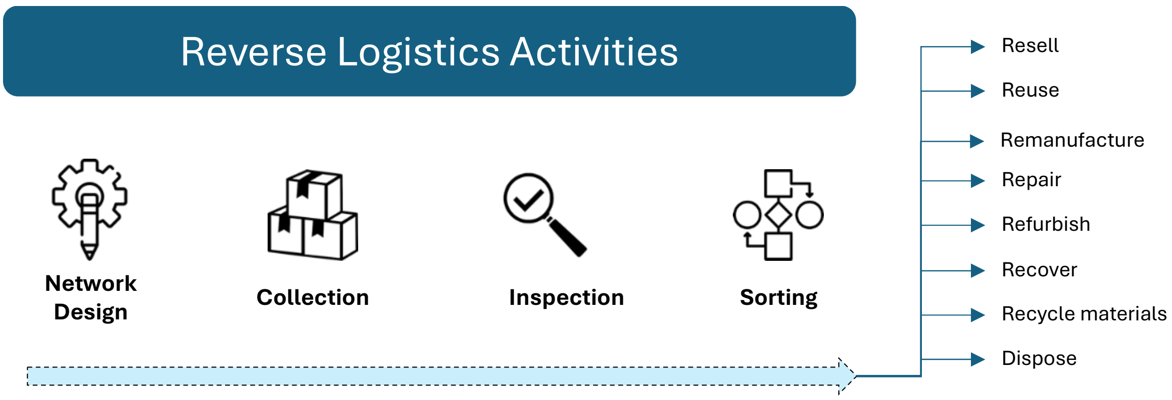

Figure 1 - Reverse Logistics Activities[1]

Figure 1 illustrates the various activities involved in Reverse Logistics, which focus on

[1] Credits from (Circular Economy Asia, 2020)

optimizing the value recovery for returned items, whether they are customer returns or at their end-of-life. Depending on the product's condition, several options are available:

1. **Resale**: The product may be sold again in the same market for its original purpose or in a secondary market.
2. **Remanufacturing**: The entire product can be rebuilt to meet original specifications.
3. **Refurbishment**: Only defective parts of the product are repaired or replaced.
4. **Recycling**: The materials from the product can be reclaimed and reintroduced into primary production, reducing the reliance on virgin materials.
5. **Disposal**: If no further value can be extracted, the product is responsibly disposed of.

These strategies ensure that each returned item is evaluated and processed in a way that maximizes its residual value and minimizes environmental impact.

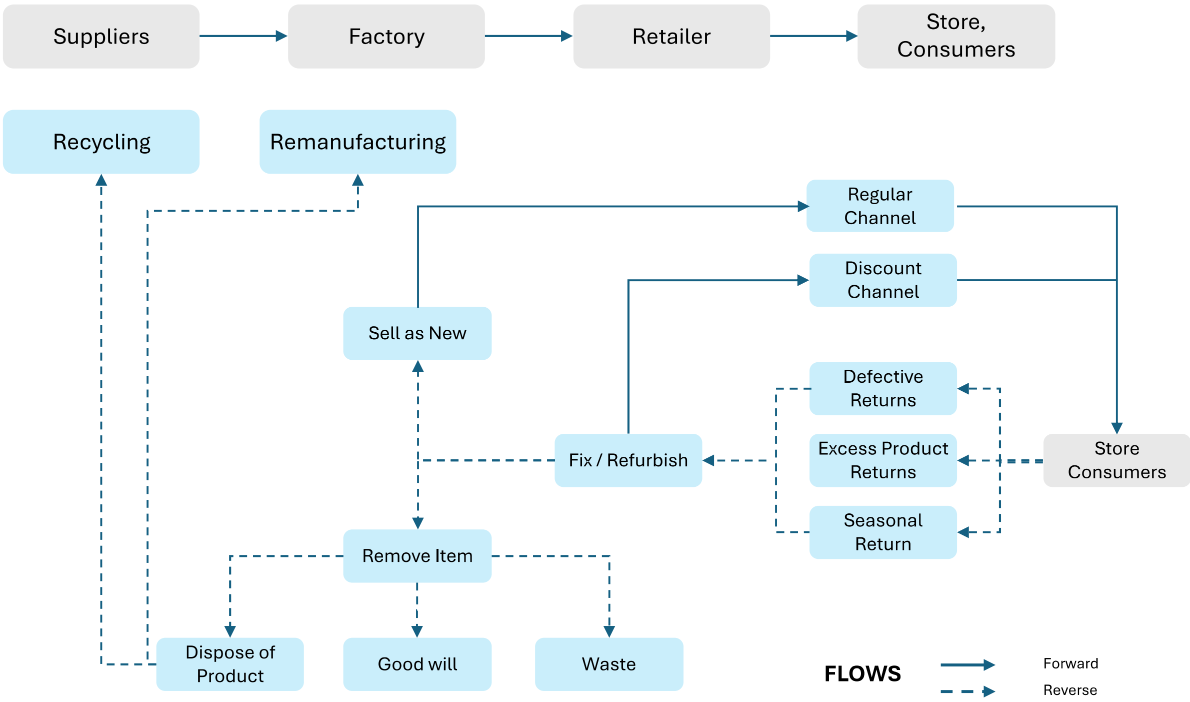

Figure 2 - Forward and Reverse Logistics Flows[2]

Figure 2 depicts the relationship between reverse logistics and forward logistics, illustrating how they form a continuous loop. The stages shown in grey represent the forward logistics

[2] Credits from Nexocode ((Nexocode, 2022)

flow, which includes the standard production and distribution processes. In contrast, the light blue stages are unique to reverse logistics, encompassing activities like returns management and recycling. Additionally, the dotted lines indicate processes that necessitate the complete implementation of reverse logistics, while the solid lines represent the existing production logistics already integrated within companies. This visual underscores the interconnected nature of forward and reverse logistics in sustaining a circular economy.

2.2.1 Stakeholders involved

The literature identifies several key stakeholders whose involvement is integral to the functioning of RL networks. (Pravin Kumar Mallick, Closing the loop: Establishing reverse logistics for a circular economy, a systematic review, 2023), emphasizes the significance of customers, retailers, suppliers, governments, waste collectors, and recyclers in the RL process. These actors contribute to various stages of RL, from the collection of returns to the processing and recycling of materials, highlighting the collaborative nature of RL operations.

Additionally, the research underscores the importance of large companies in demonstrating good RL practices (Genett Jimenez, 2019). Large firms often have the resources and infrastructure to implement sophisticated RL systems, setting benchmarks for smaller entities. Conversely, small and medium enterprises (SMEs) are encouraged to seek improvements for medium and long-term sustainability benefits, indicating the need for scalability and adaptability in RL practices across different sizes of organizations (Bak Aun Teoh, 2023).

Moreover, the involvement of third-party logistics (3PL) providers is highlighted as a critical factor in the selection and execution of RL activities (Pravin Kumar Mallick, Closing the loop: Establishing reverse logistics for a circular economy, a systematic review, 2023), (Genett Jimenez, 2019). The choice of 3PL partners, influenced by factors such as compatibility, financial performance, reputation, and the potential for long-term relationships, underscores the strategic considerations businesses must navigate to optimize their RL operations.

2.3 Challenges

The reverse logistics (RL) landscape is fraught with challenges and barriers that impede the seamless execution and optimization of RL processes. Literature identifies the following dimensions.

From the **strategical and operational** point of view the overall network management and coordination and collaboration with third-party logistics (3PL) providers are identified as significant hurdles, with mismatches between internal policies and processes often leading to inefficiencies in the return process (Saman Amir, 2023). Lack of cross-functional coordination can damage the performance and reputation of companies (Stefan Karlsson, 2023). Additionally, the lack of strategic planning and integration with supply chain processes poses barriers to effective RL implementation, highlighting the need for a more cohesive approach to managing returns and EoL products (Chandra Pakash, 2015).

The **economic** challenges such as high initial costs and lack of investment further constrain the adoption of RL practices. These financial barriers make it difficult for organizations, particularly small and medium enterprises (SMEs), to invest in the necessary infrastructure and technologies required for efficient RL operations (Chandra Pakash, 2015).

Literature identified some uncertainties regarding **regulations**. Policy issues, including the lack of clear directives and government support, especially outside specific segments such hazardous or construction waste, create an environment that complicates compliance and implementation of RL practices. The study by (Genett Jimenez, 2019), emphasizes the importance of leadership and planning in navigating these regulatory challenges, suggesting that a clear vision and a multiple steps implementation are key factors in this sense.

From the **technology** point of view, infrastructural deficits, in terms of facilities and technology for RL, along with **market-related** challenges like customer perception and demand uncertainties, further exacerbate the difficulties faced by organizations in establishing efficient RL systems. The lack of efficient information technology systems (Ramazan Kaynak, 2014) to collect and manage data and recognize problems in RL practices is highlighted as a crucial area for improvement (Starostka-Patyk, 2021).

Some specific industries, such as the construction industry, faces unique challenges in implementing RL, including compliance with new laws and regulations, openness to the use of recycled materials, and management experience in RL implementation. (Chinda, 2017).

2.4 The problem of Returns

Under the framework of a circular economy, the issue of product returns is critical and often results in a substantial amount of value being lost to landfills each year, largely because there isn't a sufficient effort to determine whether returned products can still be sold. The prevalence of e-commerce has led to higher return rates, typically ranging from 15 to 40 percent, compared to up to 10 percent for in-store purchases, (CNBC, 2019). This discrepancy largely arises because consumers cannot physically examine products before buying online and often purchase multiple variations to try at home.

Tobin Moore, CEO of Optoro, which is an American software-as-a-service (SaaS) company that specializes in providing a comprehensive returns management system (RMS) for brands, retailers, and third-party logistics providers (3PLs), predicts that the value of returned goods could exceed a trillion dollars annually in the coming years. Supporting this concern, Gartner Research has found that less than half of these returned items are resold at full price, indicating a significant loss of potential revenue. (CNBC, 2022)

Despite the high financial and environmental stakes, involving over 5 billion pounds of goods discarded annually, contributing to substantial carbon emissions, few companies have implemented structured processes that utilize technology to manage returns. As of 2024, a report by BlueYonder reveals that less than 25% of US companies have adopted an in-house digital solution to initiate returns, though 80% acknowledge the importance of enhancing the returns process. (BlueYonder, 2024)

The necessity for e-commerce platforms to offer smooth and straightforward return policies cannot be overstated, as this is a basic customer expectation. Shoppers are likely to take their business elsewhere if the return process is cumbersome. Yet, many companies have not allocated sufficient resources to this area, often lacking a dedicated team and relying heavily on manual processes handled by customer service. This situation underscores a significant gap between the need for efficient return handling and the current practices that prevail in the industry.

To better manage and mitigate the environmental impact of returns, several companies are innovatively adapting their business models to enhance revenue while promoting sustainability. For instance, B-Stock has developed a marketplace that allows retailers and brands to sell returned, liquidated, or excess merchandise in bulk to certified resellers. This approach not only recycles products that might otherwise end up in landfills but also opens new revenue channels for businesses.
Similarly, the aforementioned Optoro offers a suite of software solutions designed to help retailers and brands efficiently manage their returns by identifying the most profitable and environmentally friendly options for each returned item. Their software facilitates decisions on whether to restock, refurbish, liquidate, donate, or recycle products. Additionally, Optoro operates its own liquidation platforms, one for direct consumer sales and another for bulk reseller transactions, further enhancing the lifecycle of returned goods.
Happy Returns is another notable example, providing a logistical solution that allows customers to return online purchases in person at nearly 300 U.S. locations, even if the retailer lacks a physical storefront. This service reduces the logistical burden on retailers and provides a more customer-friendly returns process.

To further understand how companies are adapting their strategy to integrate RL, the example of Amazon, the second largest retailer in the world and a great example of tech-innovative company, has been explored.

2.4.1 The second largest retailer in the world: Amazon case study

Companies that engage in e-commerce must prioritize the effective management of reverse logistics to minimize waste and maintain high levels of customer satisfaction. This aspect of logistics is crucial because an efficient return process can significantly influence consumer loyalty and overall business success. In the realm of technology companies, a standout example of logistical excellence is seen in a major player that operates as a retailer offering a wide array of products, including electronics, books, consumer packaged goods, and fashion items.

Amazon, renowned for its expansive reach and customer-centric business model, exemplifies best practices in reverse logistics with its return policy designed to prioritize customer convenience. The policy is notable for its leniency, featuring non-strict time limits and providing customers with multiple return options. Such flexibility is crucial as it accommodates the diverse needs and preferences of consumers, making the process as straightforward as possible.

Moreover, the scale of this operation is vast, Amazon boasts over 200 million Prime members globally, to which it must ensure the same level of service to foster long-term loyalty and trust. In an interview to CNBC (CNBC, 2022), Cherris Armour, Amazon's head of North American returns, declared that Amazon's sellers throw away around one third of returns into a dumpster or landfill. This is the cheapest and easiest pathway because no inspections or repackaging should be done and the customer most of the time doesn't know about it. All of this at the expense of the planet who sees perfectly functioning products being disposed without even checking their remaining value.

The most environmentally friendly solution in this case should be to limit the number of returns, targeting numbers around zero. However, Amazon cannot lose its competitive advantage on return policies because, as stated in many surveys and customers' interviews, the return policy is the key driver when choosing where to buy online. In addition, the trend unfortunately is increasing and every year more products are returned, for example between 2021 and 2022 the merchandise sold during the holiday season saw an increase in returns of 56,6%, from 10,6% to 16,6%, which is even lower than the average rate, around 21% as presented in the previous chapter. In addition, processing a return is also costly, it could be up to 66% of an item's original price and the National Retail Federation in the U.S. estimates that more than 10% of returns are fraudulent, making it even more complicated to Amazon to find the product a second life.

To limit this phenomenon Amazon launched some initiatives for reselling, liquidating and donating returns, expecting to save from landfill more than 300 million units a year. For fashion items they also started to offer a "Prime try before you buy" experience to avoid returns for size or fitting reasons.

When a product is returned to Amazon the customer must fill a form with the reasons why the object did not respect its expectations and system, in some cases, relies only on those answers without further checks to speed up the process. In this way, it does not take into consideration all the case of fraudulent return or badly filled forms. If the item is classified as disposable there is nothing the operator can do to change computer decision.

When an item is classified as not sellable as new, sellers are given four potential options for managing these returns, each carrying a different fee: Return to Seller, Disposal, Liquidation, or, selectively available through invitation, Fulfillment by Amazon (FBA) Grade and Resell.

1. **Return to Seller**: This option involves returning the item to the seller, who must then decide whether to absorb the high costs associated with recalling, repackaging, and resending the item back into Amazon's system for resale, a process deemed inefficient by many.
2. **Disposal**: Traditionally, disposal has been a common fate for returned items, not just at Amazon but across many online retailers. However, Amazon aims to eliminate landfill disposal entirely, stating that its primary goal is to resell, donate, or recycle any unsold products. When these options aren't viable, Amazon last resort is the "energy recovery," which involves burning non-recyclable materials to generate energy, a practice they are working to reduce to zero.
3. **Liquidation**: Amazon provides a liquidation option that allows sellers to recover a fraction of their sales price by auctioning off unwanted inventory through liquidation marketplaces such as Liquidity Services and B-Stock Solutions. This has become a way for resellers to obtain and redistribute items, sometimes leading to substantial followings on social medias.
4. **FBA Grade and Resell**: For certain returns, Amazon evaluates and assigns a grade (New, Very Good, Good, Acceptable) and resells them on specific sections of its website. This program, called FBA Grade and Resell, includes Amazon Warehouse Deals for used goods, Amazon Renewed for refurbished items, and Amazon Outlet for overstock items. Another novel outlet is Woot!, which offers a daily deal on a random "Bag of Crap" and serves as a playful, alternative retail space within Amazon's broader ecosystem.

Through these programs, Amazon is striving to create a more sustainable lifecycle for products returned by consumers, aligning with broader environmental goals and reducing the overall impact of returns on the planet. These efforts also tap into the growing secondary market, responding to consumer demand for sustainable shopping options and potentially transforming what would be waste into new revenue streams.

3. Literature reviews

A comprehensive literature review was conducted to ascertain the state of the art in RL processes and to understand how AI technologies could be integrated into these processes. This preliminary review helped identify existing inefficiencies and the potential for technological enhancements.

Subsequently, a more targeted literature review using specific keywords related to AI implementation in RL has been performed. This step aimed to uncover critical themes and areas of study that are pivotal in understanding how AI can address the specific challenges of reverse logistics. Through this approach, the research provides a detailed exploration of how AI can potentially transform RL, enhancing efficiency and reducing errors across various stages of the logistics chain.

3.1 Methodology

The methodology for conducting the literature reviews adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, as detailed in various sources including (Nguyen Thi Nha Trang Y. L., 2022; Ahmed Dabees, 2023; Benjamin I. Oluleye D. W., 2022) and described in details in the publication of (Matthew J Page, 2021). This method consists of four main stages, briefly described as follows:

1. *Collection of papers for review:* This initial step involves the utilization of specific research strings along with set inclusion and exclusion criteria to select pertinent articles from a vast array of available literature.
2. *Analysis and category selection:* The selected papers undergo a rigorous process of deductive and inductive categorization to organize them for detailed content analysis.
3. *Descriptive analysis of literature:* This phase focuses on analyzing demographic details such as publication year, authorship, and the geographical focus of the studies to provide a contextual background for the research.

4. *Content analysis:* The final step involves a deep, thorough analysis of the collected literature to identify core processes and explore potential opportunities for enhancing the field of study.

3.2 Literature review on reverse logistics (RL)

3.2.1 Collection of papers

The initial step of the research involved utilizing Scopus and ScienceDirect to gather documents pertinent to Reverse Logistics. This process aimed to uncover current trends, the structure of processes, potential opportunities, and identified challenges within the field. The search terms "Reverse Logistics" and the couple formed by "Reverse Supply Chain" and "Closed-Loop Supply Chain", were employed, yielding 4,310 and 3,660 articles, respectively, with a notable increase in publications in the post-COVID-19 era.

To refine the search results, the "Open Access" filter was applied, and articles specifically related to the Medical and Biological sectors were excluded as they fell outside the research scope. In an effort to ensure comprehensive coverage and avoid overlooking relevant literature, additional keywords "Green Logistics" and "Circular Supply Chain" were introduced, which added 12 pertinent articles to the dataset. However, these articles broadly addressed forward logistics, offering limited insight into reverse flows.

After a thorough review of titles, research field, and keywords, a curated set of 131 articles was selected to construct the reference database for the Reverse Logistics literature review. Articles focusing on the applications of artificial intelligence were intentionally omitted from this subset to be analyzed separately in a subsequent section of the document. This structured approach to literature review ensures a focused examination of reverse logistics while setting aside AI-related findings for detailed exploration later.

3.2.2 Analysis and category selection

Following the initial selection, each document's abstract was scrutinized to determine the relevance and specific focus of the study for inclusion in this research. Articles centered on processes prevalent before 2010 or those addressing region-specific issues with locally confined solutions were excluded to maintain the contemporary relevance and broader applicability of the research findings. This resulted in a refined dataset of 82 articles.
All the steps to build the reference database are summarized in Figure 3

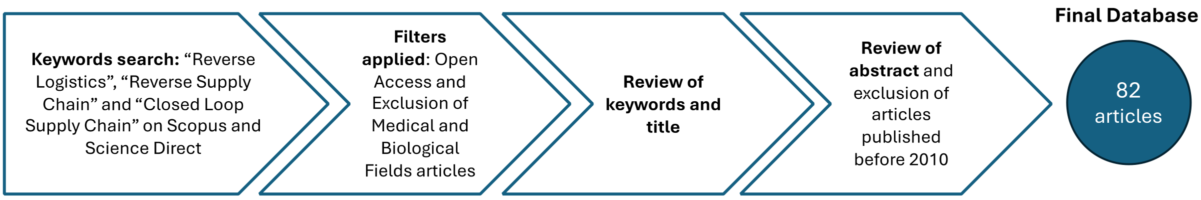

Figure 3 - Articles' database construction process

To effectively categorize and analyze the content of these articles, they were organized into clusters based on the information gleaned from their abstracts, keywords, titles, and insights from previously reviewed literature. This strategic classification has helped identify the primary themes and research dimensions within the stages of Reverse Logistics. The articles were grouped into the following clusters:

- **Collection and Network Design**: Focusing on the strategic layout and operational tactics of reverse logistics networks.
- **Decision Making and 3PL (Third-Party Logistics) Selection**: Examining the criteria and processes involved in selecting 3PL providers to enhance logistics efficiency.
- **Performance and Efficiency Evaluation**: Evaluating methods and metrics used to assess the effectiveness and efficiency of reverse logistics operations.
- **Literature Reviews and Surveys** carried out by researchers in the past.

3.2.3 Descriptive analysis of literature

In the articles founded though the identified keywords, it is possible to see a rapid increase, as shown in Figure 4, in the research after the Covid-19 era reaching a notable peak in 2023.

The research is not stopping and even if the 2024 has just started the number of selected articles has almost already reached the total number for 2021.

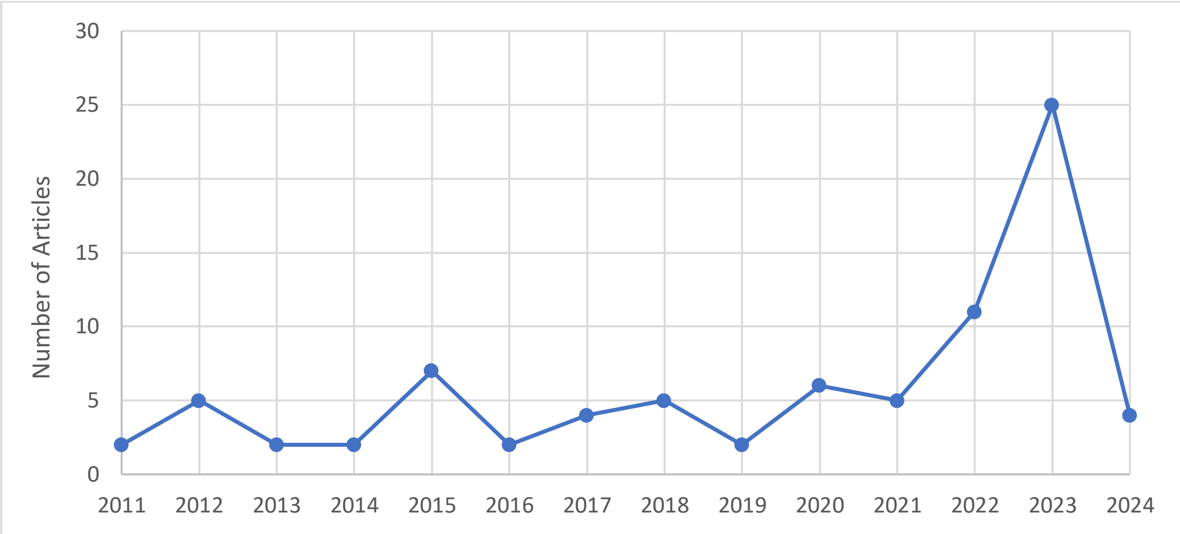

Figure 4 - Publication year of selected RL articles

In Figure 5, the frequency of articles across specific academic journals is presented. Notably, 'Procedia Engineering' emerges as the most prolific journal, accounting for six articles. This is followed closely by 'Procedia - Social and Behavioral Sciences,' and 'Procedia CIRP,' each with five articles. A number of other journals display a moderately high frequency of four publications, such as 'Journal of Environmental Management,' 'Procedia Computer Science,' and ‘Procedia Manufacturing'. In the category “Others” have been collected all the journal which accounted for one single article in the research.

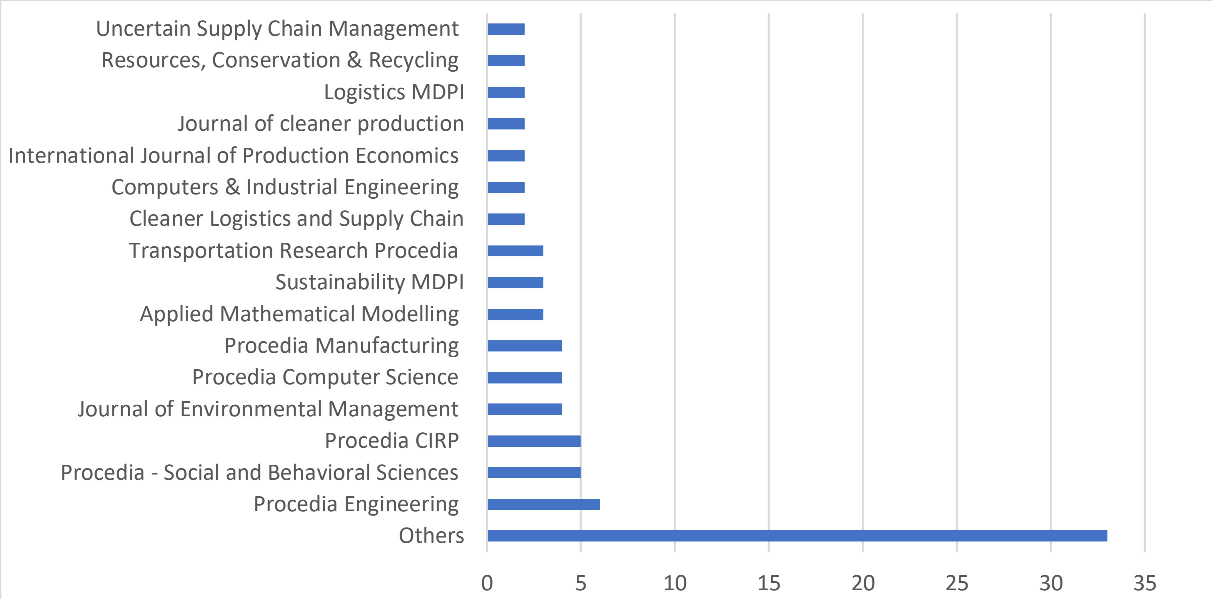

Figure 5 - Main Journals for RL articles

On the geographical spectrum, as demonstrated in Figure 6, China and India stands out as the most significant contributors with a total of 11 articles each, which suggests a robust engagement in the research community within these specific fields. Brazil is the second most prominent contributor with 6 publications, followed by Turkey, Denmark, Poland and Iran, with a moderate contribution of 4 articles. Other countries such as Colombia, and Sweden, among others, demonstrate their research presence. This outlines a strong push of emerging countries in finding solutions for Reverse Logistics issues.

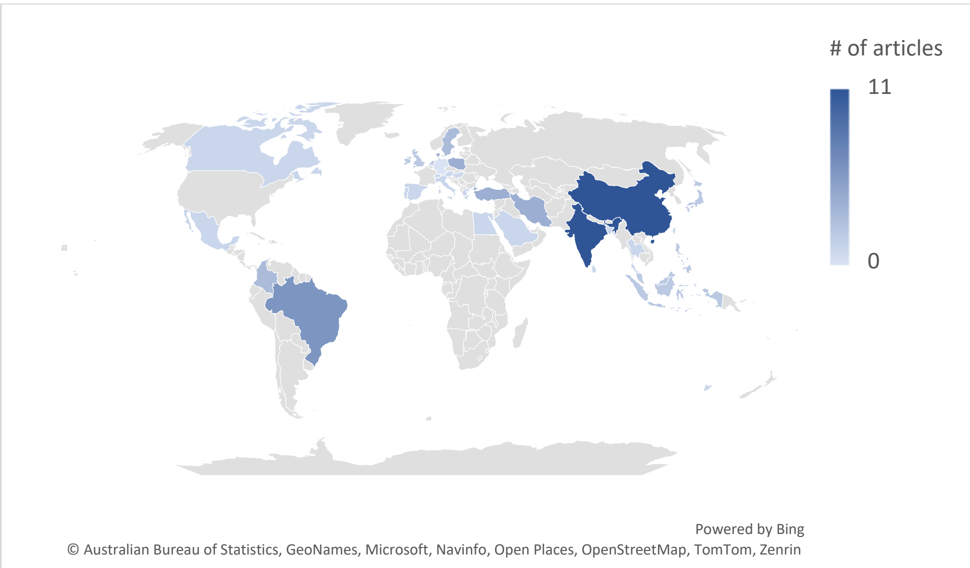

Figure 6 - Geographical distribution of RL articles

Finally, in Figure 7, the disposition of articles in the main clusters shows an almost homogeneous presence with a prevalence of research in the Decision Making and 3PL selection, followed by the concern for correctly selecting and assessing performance indicators in the efficiency evaluation system.

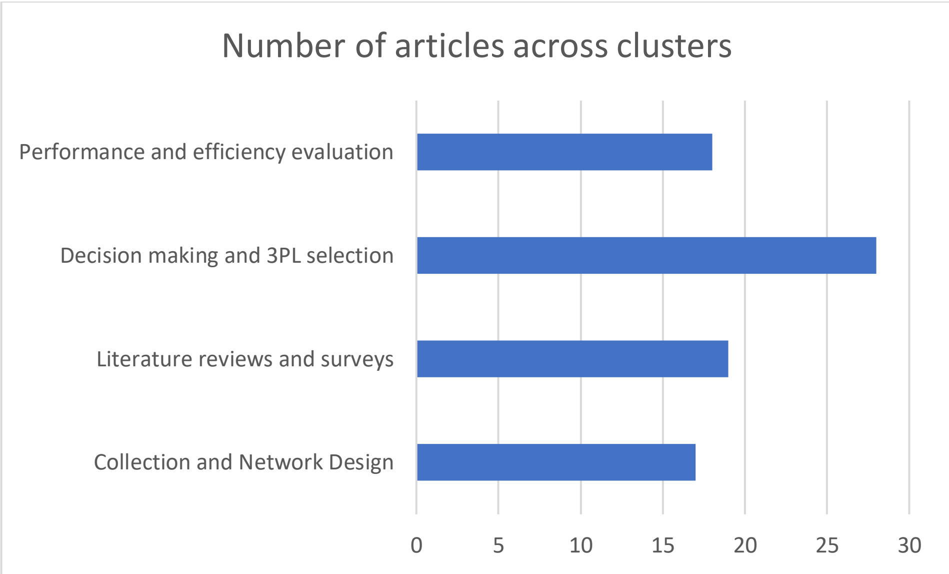

Figure 7 - Cluster distribution for RL articles

3.2.4 Content Analysis

3.2.4.1 Literature Reviews and Surveys (19 articles)

The first cluster of articles comprehends comprehensive literature reviews made through the years regarding the topics of reverse logistics, analyzing trends and drivers, pointing out which are the steps and stakeholders involved in the process, and lastly highlighting challenges in implementing an efficient reverse logistics network.

Beside these general literature reviews, more specific ones have been identified regarding the reverse logistics of items that are usually thrown away, identified as very pollutant for the environment but still rich of value at their end of life (EoL). In particular, the articles mention e-waste ((Simone Machado Santos, 2022), (Christine Cole, 2018)) and EoL electric vehicles ((Amir Hossein Azadnia, 2021), (Chong Jia Yuik, 2023), (Nguyen Thi Nha Trang Y. L., 2023)).

The content of this articles has been considered as a baseline to write the chapter denoted “Reverse Logistics at a glance”.

3.2.4.2 Collection and Delivery Network Design (17 articles)

This cluster delves into the nuances of creating robust systems for the reintegration of returned goods into the supply chain, which is a crucial aspect of reverse logistics. The intricate considerations required for system design, particularly under uncertain conditions, are exemplified in many articles which underscores the dynamic nature of reverse logistics. Moreover, specific challenges pertinent to various industries, such as the complexities associated with the disposal and recycling of electronic waste, have been analyzed.

The articles in this section have been subclustered in 3 categories: Planning, Vehicle Routing and Location-Allocation. Indeed, the general cluster has its main concerns regarding how to design an efficient network, choosing strategical position for collection points which could manage all the returned product or just a portion (Location issue). In this last case it is important to understand which portion and how this is connected to the overall network (Allocation issue). In order to build an efficient network, decision regarding costs and maximization of resources have been considered in the design phases (Planning). Finally, a network that collects products in different location in a reasonable time and without wasting fuel should follow a clear and defined route map (Routing), programmed to flexibly adapt to eventual circumstances.

Before entering in the description of each article, an overview of the main themes is proposed in Figure 8. The objectives analyzed in the "Collection and Network Design" cluster cover mostly cost reduction and efficiency improvements methods, followed by articles exploring possible answers and solutions to identified challenges. Being Reverse Logistics still partially explored by companies, it was expected that the economic spectrum could have been the main driver. Moreover, only 17% of articles mention processes with sustainability as first objective. Least mentioned scopes are in the domain of Risk minimization and Profit maximization which account both for a presence of 7%.

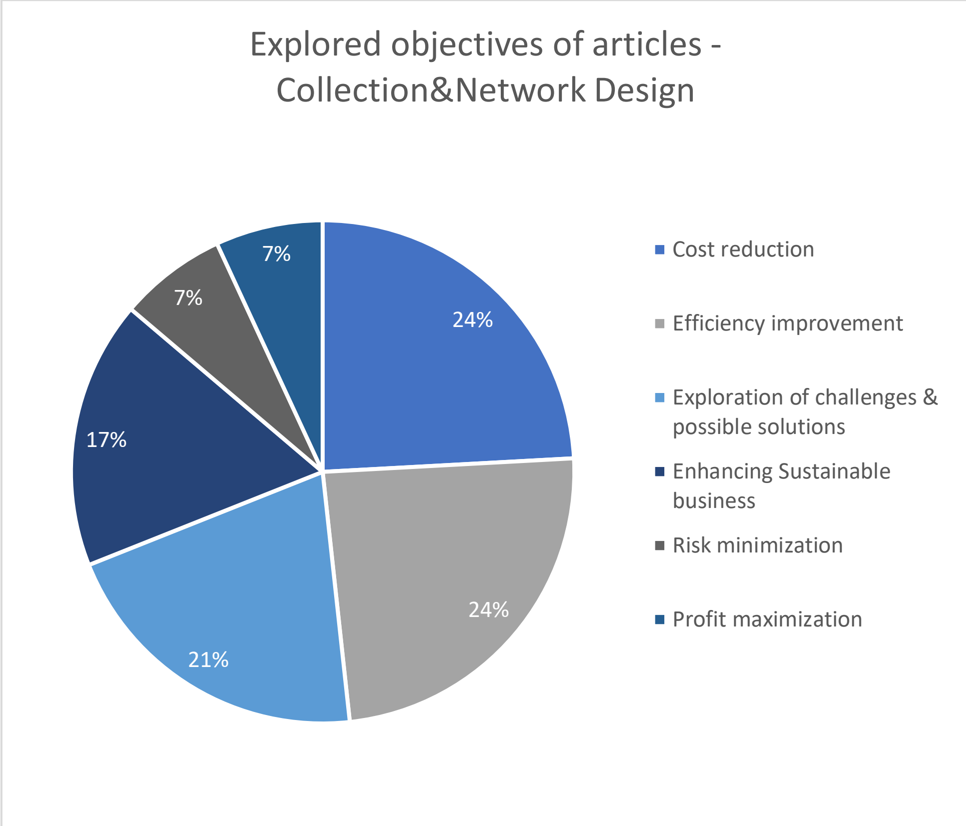

Figure 8 - Main themes explored in Collection and Network Design articles

3.2.4.2.1 Planning (8 articles)

The landscape of network design planning in various industries reveals a complex interplay of challenges and strategies, underpinned by a common goal: to enhance efficiency, sustainability, and responsiveness within reverse logistics systems.
In the following various industries will be presented and their specific challenges will be outlined.

In the **plastic recycling industry**, (Kathleen B. Aviso, 2023) presents a model that encapsulates the pressing issue of plastic waste. By applying basic and mixed integer linear programming techniques, the paper focuses on the planning of allocation of plastic waste depending on their levels of contaminants, striving to maximize recycling rates without compromising the quality of the recycled output.

(Mohammad Amin Khoei, 2023) exploration of the **network design for disposable product recycling** ventures into the realm of risk and cost management under uncertainty. Utilizing the Sample Average Approximation (SAA) method, the authors address the formidable challenge of designing a network that is both cost-effective and adaptable. The focus on big data analytics as a tool for enhancing operational efficiency introduces a forward-looking perspective, emphasizing the importance of agility and informed decision-making in contemporary supply chains.

In the **retail** field, (Matsui, 2023) developed a game-theoretic model that examines the effectiveness of dual-channel (online and offline) collection for recycling companies. It reveals two equilibrium scenarios: both companies using dual channels or each company using a distinct single channel. The analysis suggests that companies adopting asymmetric channel strategies (each focusing on a different channel) achieve higher profits compared to symmetric strategies (both using dual channels), which lead to a prisoners' dilemma situation with lower profitability. The recommendation is for competing recycling companies to opt for differentiation in their collection channels to avoid direct competition and enhance profitability.

In the **healthcare sector**, (Kannan Govindan S. N.-A., 2022) tackles the daunting task of medical waste management with a bi-objective mixed integer linear programming model that seeks to minimize risk and cost. This study, using an augmented epsilon-constraint method (AUGMECON2) to seek solutions, illuminates the critical public health considerations inherent in medical waste disposal, where the margin for error is virtually nonexistent. The scenario-based planning approach reflects a deep understanding of the uncertainties involved, pointing to the necessity of robust and flexible network designs in sensitive industries.

The work of (Mohammad Kanan, 2023) on sustainable closed-loop supply chain design brings to the fore the triple bottom line of sustainability: economic, environmental, and social. In confronting supplier selection under total quantity discount amidst demand uncertainty and refurbished and redesigned products flow uncertainty, its model uses a sequential least squares programming algorithm (SLSQP) to find optimal solutions aiming at reducing emissions and enhance worker safety without sacrificing economic viability.

(Julián David Silva-Rodríguez, 2023)'s study on the **collection of empty pesticide containers** combines mixed integer linear programming with discrete event simulation models to offer a robust framework for managing agricultural waste. The dynamic and variable nature of waste generation in this sector demands a flexible and responsive network design, where efficiency and cost-effectiveness must be balanced with environmental compliance and safety.

Similarly, (Sajan T John, 2018) introduces and validates a mixed integer linear programming model tailored for multi-stage reverse logistics network design, aimed at maximizing profits while simultaneously considering various product recovery options such as remanufacturing, repairing, and recycling, integrating product bill of materials (BOM) and validated by the design of a used refrigerator.

Lastly, embracing various business scenarios (Pravin Kumar Mallick, Towards a circular economy: Development of a support tool for designing reverse logistics systems, 2024) develop a support tool to aid business to design the Reverse Logistics network, including stakeholder management and indicators for evaluation in the decision-making process.

Across these varied landscapes, the thread that binds these studies is a collective endeavor towards smarter, adaptable, robust and more sustainable network designs.

3.2.4.2.2 Vehicle Routing (3 articles)

The challenge of routing in contemporary logistics operations encapsulates a critical tension between escalating customer expectations and the logistical complexities wrought by the surge in e-commerce.

(Kubra Sar, 2023) literature review emerges as a foundational text, offering a comprehensive analysis of the vehicle routing problem (VRP) within the context of reverse logistics. The study underscores the dual pressures of pollution from transport emissions and the associated costs, framing the VRP as a pivotal concern for sustainable logistics practices. The review delineates the VRP modeling approaches, mathematical models, and solution procedures, highlighting the predominance of single-objective frameworks aimed at cost minimization. Yet, it's the exploration of environmental and sustainability aspects that marks a significant pivot towards greener logistics. The inclusion of vehicle load, transportation mode, and multi-objective models reflects an evolving logistic landscape where efficiency intersects with ecological responsibility. Solution techniques, notably hybrid algorithms and metaheuristics, emerge as preferred tools for navigating the complexities of VRP, suggesting a trend towards more nuanced and adaptable routing strategies.

In the agribusiness distribution sector, (Gianfranco Fancello, 2017) introduces a sophisticated blend of clustering algorithms and mixed integer programming to tackle food waste collection. The essence of the authors' approach lies in its dual focus: optimizing logistical routes to reduce environmental impact and operational costs, while ensuring the effective redirection of waste towards beneficial uses. Distance traveled by collection vehicles and the volume of waste diverted are the main KPIs considered and reflect the complex balance between economic efficiency and environmental stewardship.

Complementing these studies, (Chandra Kant Upadhyay, 2020) article introduces the concept of crowd shipping as a viable solution to the chaos of urban logistics, especially in densely populated areas like India. The proposed framework advocates for improved coordination and communication among logistics stakeholders, leveraging crowd shipping to reduce vehicle movements and, by extension, transport emissions. The emphasis on collaboration to minimize empty runs and the potential of digital platforms as facilitators presents a forward-thinking approach to urban logistics, aligning with broader objectives of sustainability and efficiency.

It is clear how in each paper the need for a sustainable process to reduce emissions and empty runs is pivotal in logistics operations and a solution which considers multiple objectives is preferrable to better assess the variable related to costs, environmental impact and market demand.

3.2.4.2.3 Location – Allocation (6 articles)

The exploration of reverse logistics (RL) location – allocation problem is a multifaceted narrative that intersects various industries, each grappling with unique challenges yet converging on common goals previously cited of sustainability, efficiency, and innovation.

(Pamal R. Nanayakkara, 2022) investigates e-commerce returns through a circular RL model, determining the optimal number and locations for Integrated Collection Centers (ICC), allocating customer markets to suitable ICCs, and managing the return volumes to each fulfillment and formal recycle center efficiently. The study utilizes **ward-like hierarchical clustering and Mixed Integer Linear Programming (MILP)** for network optimization. This not only highlights the e-commerce sector's logistical complexities but also its potential for significant cost reductions through innovative network design.
In parallel, the waste electric vehicle battery (WEVB) recycling industry, as examined by (Gui Hu Wenzhu Liao, 2022), showcases a collaborative optimization model to establish the number and location of different functional facilities and determine the flow and flow route of different items, in which carbon emissions and different WEVBs are considered. The main contribution of this paper is developing a generalized **fuzzy mathematical model** to design a RL network that can accommodate variations in input parameters and multiple recovery options simultaneously, considering cost management and sustainability goals.

This dialogue between profitability and planetary well-being is echoed in (Jing Lin, 2023) exploration of end-of-life (EOL) power batteries, where to identify the location of collection centers it’s considered as input the EoL battery volume flowing to each node and the transportation volume. Through a **MILP** model, it recognized that the system is profitable, but some issues are still to be addressed such as the wide variation in scrapping volumes by district, an uneven distribution of collection sites, and few alternative sites for processing centers and waste treatment plants.

On a broader scale, (BAO Zhenqianga, 2012) constructs an RL network in uncertain environments, leveraging the **gray model** GM (1, 1) to predict the product holdings of collection points. This model is integral to carrying out cost optimization while considering the location of intermediate, manufacturing, and re-manufacturing centers, thus distributing products effectively to customers.

(Péter Egri, 2023) extends the discussion to the waste wood RL network, introducing a novel approach to facility location that considers economies of scale and robustness against breakdowns through **bilevel optimization and tabu search heuristic methods**. This highlights the evolving considerations in RL network design, from operational efficiency to resilience and scalability.

Lastly, (Anil Jindal, 2015) designs a framework for uncertain environments, which integrates multiple collection, disassembly, and refurbishing centers, addressing various costs and capacity constraints with uncertainties depicted using triangular fuzzy numbers. This comprehensive framework demonstrates the flexibility needed for adaptation across different industries and highlights the necessity for developing efficient heuristics for large-scale real-world business challenges.

Also, in this cluster resilient approaches to changing conditions are sought to address the uncertainty of RL, aiming at improving current processes in all triple bottom line perspective.

3.2.4.3 Decision Making and 3PL Selection (28 articles)

This category captures the strategic decision-making processes that underpin the reverse logistics operations, with a special focus on the selection and management of third-party logistics providers, inventory management, pricing techniques and support methods for decision making.

In each section a description of the content of the articles have been provided, while in Figure 9 a first overview of the main objectives is described.
Differently from the articles regarding the Network Design phase, in this part the concern is more focused to specific challenges and possible solutions related on uncertainty in demand, conditions of returns, recyclability of products etc. which covers a quarter of the selected documents.

These issues are explored to enhance a more sustainable business, 21% of articles, taking distances from traditional approaches and with almost equal distribution between cost reduction, profit maximization, efficiency improvement and giving support in performance assessment. This last category, absent in the previous cluster, aims at defining bottlenecks and productivity rate and it will be further explored in the next chapter.

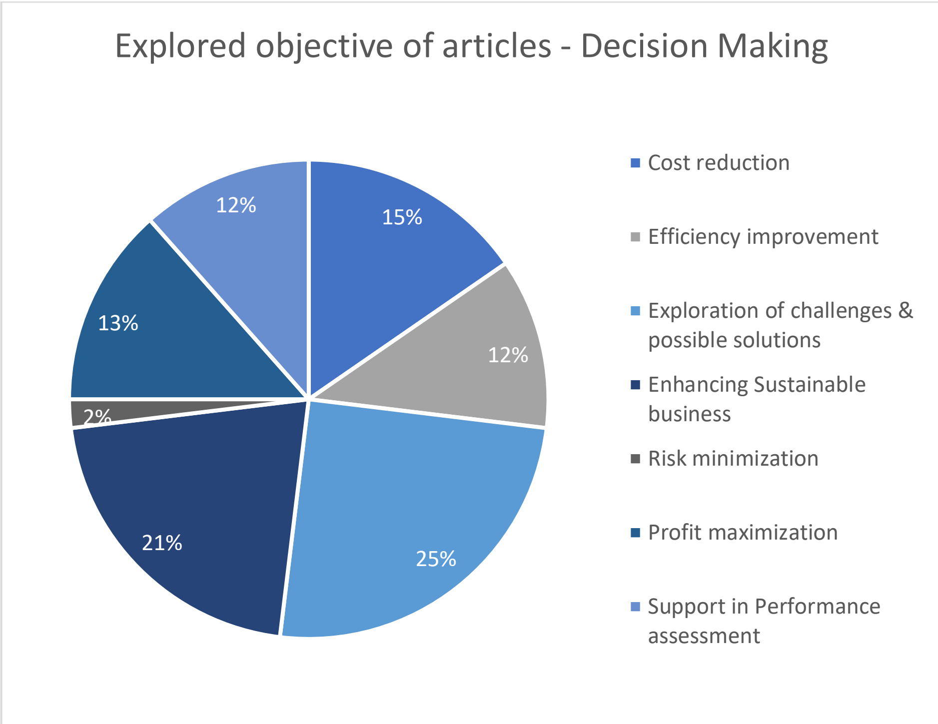

Figure 9 - Main themes explored in Decision Making and 3PL selection articles

3.2.4.3.1 3PL Selection (5 articles)

The selection of third-party logistics (3PL) providers within the realm of reverse logistics presents a fascinating exploration into decision-making processes, as various studies propose different methodologies to address this complex challenge. Since companies often do not have the capabilities to integrate an effective RL network, the choice of a 3PL is crucial to ensure a smooth path for returns and the establishment of a circular economy.

(Alireza Eydi, 2022) introduces a method that intricately combines **Data Envelopment Analysis (DEA)** models with **fuzzy** conditions, specifically tailored for the selection of 3PL providers. This approach is noteworthy for its ability to navigate dual-role data, demonstrating a sophisticated understanding of the complexities inherent in evaluating 3PL providers. By employing the **alpha-cut technique** to transition from fuzzy conditions to a deterministic framework, the study not only underscores the flexibility required in decision-making but also highlights the potential of DEA in optimizing the selection process, especially in environments laden with uncertainties.

Complementing this analytical approach, (Francisco Mendes dos Santos Junior, 2022) leverages Business Intelligence and the Simple Aggregation of Preferences Expressed by Ordinal Vectors **SAPEVO-M Multicriteria Analysis** Method to enhance decision-making in Big Bags Logistics. The creation of a dashboard through Power BI illustrates the innovative integration of technology in assessing the feasibility of reverse logistics for big bags. SAPEVO-M was applied to select the best provider of the Reverse Logistics service comparing price, lead time, and reliability.

(Robin Divahar, 2012) exploration employs **the Analytic Hierarchy Process (AHP)** to navigate the selection of a 3PL, shedding light on the multifaceted landscape criteria, where factors like cost, service quality, and environmental compliance play crucial roles. The use of AHP highlights the need for a structured, hierarchical approach to ensure a balanced and comprehensive evaluation process.

(A. Jayanta, 2014) further enriches the discussion with a detailed case study utilizing a combined **TOPSIS-AHP** approach in selecting a Reverse Logistics Service Provider (RLSP) for the mobile phone industry. This hybrid methodology uses as diverse parameters for assessing the RLSPs, such as E-Waste Storage Capacity (EWSC), Availability of Skilled Personnel (AOSP), and costs associated with inspection/sorting, disassembly, mobile phone refurbishing, and recycling.

Last in chronological order on this methodology, (Ömer Faruk Gürcan, 2016) application of the **AHP** multicriteria decision-making method to select a 3PL provider highlights the paramount importance of compatibility, followed by financial performance, reputation, and the potential for long-term relationships. This study brings to the forefront the critical factors that influence the selection of a 3PL provider, advocating for a balance between cost-efficiency and quality service provision to foster sustainable partnerships.

3.2.4.3.2 Inventory (4 articles)

The study of inventory management within the sphere of reverse logistics illuminates the complexity and strategic importance of efficiently managing returns, recycling, and remanufacturing processes. This section delves into various research contributions that shed light on inventory cooperation strategies, optimization models, and the integration of environmental considerations into inventory management practices.

(Niu Gao, 2024) investigation into inventory cooperation strategies between suppliers and recycling centers lays a foundational understanding of the intricacies involved in managing the uncertainties of reverse logistics operations. This study analyzed focus on operational strategies such as lateral transshipment, substitution and a multi strategy combing the two to obtain volume of stock and out of stock items. It proved, though the use of **Mathematica 11.3**, that lateral transshipment does not necessarily reduce recycling centers' costs, whereas substitution and multi-strategy tend to be more effective, with the multi-strategy generally outperforming substitution unless faced with low replenishment rates and high demand rates.

The paper echoes the core challenge addressed by (M. Forkan, 2022) which aims to optimize inventory management with an eye on sustainability, incorporating factors like GHG emissions and energy consumption. This model considers various factors including the collection percentage of available returns, the recovery rate, waste disposal rate, repair rate per unit time, fixed procurement cost, fixed repair batch induction cost, and holding costs at supply and repair depots.

Shifting to which mathematical models could be used for inventory management practices, including environmental factors, (Ehab Bazan, 2016) comprehensive review highlights that the primary focus of each model remains on Economic Order Quantity (EOQ) related costs and recovery process expenses for inventory management. The surveyed research often discusses decision variables such as production and remanufactured batch sizes, with some studies exploring the quality of returns, the reuse potential of repaired items, and the dynamics of return rates influenced by price and quality. The research suggests the implementation of a multi-objective model that incorporates legislative and marketing considerations in addition to a correct count of environmental and societal costs.

Continuing on the Economic Order Quantity (EOQ), (S. Sanni, 2020)'s model aims at optimizing reverse item flows for profit maximization. This approach considers price-dependent demand and the impact of return policies, and it complements Bazan's advocacy for multi-objective models by providing a practical framework for balancing economic efficiency with the dynamics of reverse logistics. The model uses **Karush-Kuhn-Tucker (KKT)** conditions to derive optimal solutions for the return policy, order quantity, cycle length, and unit selling price, presenting a structured method for tackling the nonlinear maximization problem inherent in reverse logistics scenarios.

3.2.4.3.3 Making related decisions (17 articles)

The intricate landscape of decision-making within reverse logistics (RL) presents a rich tapestry of methodologies and technologies aimed at addressing the complex and various challenges of this domain.

The foundational analysis by (Rezaei, 2015), alongside the hybrid methodologies presented by (S.Senthil, 2012) and (Han Wang, 2018) illustrates the traditional reliance on Multi Criteria Decision Making (MCDM) methods such as AHP, TOPSIS, and PROMETHEE for solving complex RL problems, including the decision of involving a 3PL, and the optimal collection mode. These approaches lay the groundwork for addressing the multifaceted nature of decision-making in RL, particularly highlighting the limitations of these algorithms and the need for versatile and comprehensive evaluation criteria that can adapt to the complexity and nuances of real-world scenarios, often found in hybrid methodologies.

Many industries have been covered and different approaches have been applied to find optimal solutions.
In **agriculture**, (Edgar H. Alfonso-Lizarazo, 2013) explores the palm oil supply chain in Colombia, offering insights into closed-loop systems and emphasizing the agricultural sector's potential benefits from integrating reverse logistics practices for cost and energy efficiency.

The **electronics and consumer goods** sector are represented by (Sadra Ahmadi, 2024) which leverages social media analytics to inform decision-making in the laptop industry, demonstrating the power of consumer feedback in shaping reverse logistics strategies.

(Devika Kannan, 2023), (Richard C. Li, 2012) and (Araujo, 2015) tackle **e-waste management**, emphasizing the urgent need for sustainable practices within the electronics industry to address the growing environmental impact and mitigate the risk of abandoned hazardous waste.

The first uses a model grounded in Multi-Objective Mixed Integer Programming (MOMIP), which integrates multiple products, recovery facilities, processing technologies, and vehicle types, aiming to maximize return yield while minimizing the overall RL network cost and environmental impacts. A novel aspect of the study is the incorporation of different green technologies for inspection, dismantling, repair/refurbishing, and recycling. (Devika Kannan, 2023)

In the second a mixed integer multi-objective linear programming model is developed to integrate formal and informal waste sectors for e-waste management, aiming to improve economic outcomes, outlining the health risk incapsulated in these substances. It underlines the benefits between the different recovery option, including producer recovery option, third party option, and group recovery option. (Richard C. Li, 2012).

The third discusses the implementation of Radio Frequency Identification RFID technology in managing Waste Electrical and Electronic Equipment (WEEE) in Brazil, emphasizing RFID's role in enhancing real-time tracking and achieving a socially optimal level of recycling, highlighting the economic value of WEEE components and the importance of technology in maximizing recycling profits and efficiency (Araujo, 2015).

The **electronics** sector finds further studies which describe the potential of RL in this field. (Yanzi Zhang, 2024) focuses on the impact of governmental subsidies and policies on LCD TVs reverse supply chain optimization under the Extended Producer Responsibility (EPR) framework. Utilizing a mixed-integer non-convex program and an outer approximation-based solution approach, the study aims to offer managerial insights on maximizing net benefits and achieving high volumes of product returns. Flexible locations for testing returned products should be implemented and they should vary with products' quality.

(Dhirendra Prajapati, 2022) model for a multi-echelon closed-loop supply chain (CLSC) focused on fresh electronics products, aiming at maximizing total revenue while considering sustainability aspects integral to the circular economy. This comprehensive approach includes managing costs associated with transportation, carbon emissions, and product handling, alongside strategies for reselling, refurbishing, or recycling returned products.

In **manufacturing** and supply chain operations, (S. R. Singh, 2013) addresses the challenges of managing deteriorating items and optimizing replenishment cycles, balancing costs, demand, quality standards, and the environmental impact of production and remanufacturing activities. (Alamri, 2023) discusses remanufacturing's nuances, offering a model that calculates the optimal number of remanufacturing cycles based on product lifecycle and quality. (Gernot Lechner, 2019) presents an integrated decision-making model focused on acquisition, grading, and disposition processes in reverse logistics, particularly relevant to companies in the reprocessing industry to maximize profit.

The **construction** industry's approach to reverse logistics is examined by Anna Sobotka J.C. in different articles, which highlight the sector's potential for minimizing waste and recycling materials. These studies advocate for the adoption of RL practices to support sustainable development within the construction sector, advocating for more sophisticated processing methods (Anna Sobotka J. C., 2015) (Anna Sobotka J. S., 2017).

Finally, in the last years researchers focused their attention to the possible applications of **innovative technologies** in RL practices in a broader sense. (Pereira, 2023) introduces the potential for leveraging Simulation and Digital Twin technologies in RL, marking a forward-looking approach to embracing Industry 4.0 solutions for complex decision-making challenges in RL, underlying the need of constant communication between the physical and virtual reality and some technical limitations of nowadays’ equipment. While the paper from (Al-Amin Abba Dabo, 2023) explores underscores the synergy between humans and intelligent systems in Industry 5.0, optimizing RL processes and enhancing sustainability, but questioning the scalability of the methodology across different industrial sectors.

3.2.4.3.4 Pricing (2 articles)

In the realm of reverse logistics and circular supply chain management, pricing strategies emerge as mechanisms to influence consumer behavior, enhance recycling efforts, and ultimately drive the economic, social, and environmental sustainability of operations.

(Ata Allah Taleizadeh, 2023) delves into the intricacies of fostering a circular supply chain through customer-centric pricing strategies. By examining Return & Loyalty Refund and Return & Loyalty Discount policies across online and offline channels, this research underscores the importance of incentivizing customer participation in the circular supply chain.

(Wang, 2023) exploration into the recycling of End-of-Life Vehicles (ELV) introduces the Stackelberg pricing strategy as a tool to navigate the complex dynamics between consumers, recyclers, and remanufacturers. The findings reveal that consumer inclination towards online recycling channels can significantly boost recycling volume and profits within the ELV reverse supply chain. The study also discusses the impact of subsidies, suggesting that allocating subsidies to remanufacturers rather than consumers can more effectively increase recycling volumes.

3.2.4.4 Performance and Efficiency Evaluation (18 articles)

Articles within this cluster are dedicated to scrutinizing the effectiveness of reverse logistics activities, assessing their impact on operational efficiency and sustainability outcomes.
The cluster has some subclusters which analyze the criteria used to evaluate a reverse logistics network, and the identified opportunities to improve efficiency.

3.2.4.4.1 Indicators and evaluation system (8 articles)

The array of studies focused on evaluating reverse logistics (RL) presents a wealth of methodologies and perspectives tailored to various industry challenges to evaluate performance depending on the needs of the specific field.

Figure 10 encapsulates the main dimensions considered in Reverse Logistics from the economic, brand image, sustainability to operational perspective and their related indicators. All identified articles take into consideration the economical and sustainable side, while depending on the objective of the document they explore the impact on brand image and operational processes.

Main considered indicators

Economic	Brand Image	Sustainability	Operation
• Collection Cost • Processing Cost • Transportation Cost • Testing cost • Landfill cost • Operating cost • Recapture Value • Value added recovery • Profit generation • Initial investment	• Green image • Enourage Recycling • Technological innovation • Green initiatives • RL awareness • Avoidance of causes of pollution	• Energy use • Carbon emissions • Use of eco-friedly materials • Environmental impact • Community welfare • Level of social acceptability • Health and safety issues • Water consuption • Customer Satisfaction • Market demad • Stakeholder’s satisfaction	• Availability of skilled labor • Technical Feasibility • Compatibility degree • Process efficiency • Recovery paths • Compliance with regulations • Innovation capability • Waste handling • Processing time • Collection time • Product quality at inspection

Figure 10 - Indicators grouped by category

Analyzing more in depth the content of the article, we could find many diverse methodologies applied to the specific challenges of the analyzed industries.

(Sangwan, 2017) considers the general process by identifying crucial Key Performance Indicators (KPIs) across the reverse logistics spectrum, from collection to product recovery. The inclusion of variables like collection cost, value-added recovery, and social acceptability illustrates the multifaceted nature of reverse logistics evaluation, where economic, environmental, and social dimensions intersect.

While (José Leonardo da Silveira Guimarães, 2015) introduces **an Analytic Network Process (ANP)** to assess reverse logistics performance within the Brazilian footwear industry, focusing on economic and social benefits. This approach underscores the critical role of Economic Programs (EP) and brand Image Programs (IP) in enhancing reverse logistics operations, highlighting operational cost, recapture value and innovation in technology as key indicators of performance.

(Zheng, 2011) and (Rana Rabnawaz Ahmed, 2021) delve into other specific sectors—city solid waste management and industrial and construction waste, respectively—highlighting the unique challenges and evaluation criteria pertinent to these areas. The first one's systematic approach to optimizing city solid waste management through a combination of subjective (**AHP**) and objective **(Entropy method)** weighting methods and the second one's **Multi-Variable Stream Analysis (MVSA)** method for managing industrial and construction waste both aim to enhance the efficiency and sustainability of reverse logistics operations. These studies underscore the importance of addressing sector-specific challenges with tailored evaluation criteria, from classified collection and transportation costs to environmental impact and process efficiency.

(Nagendra Kumar Sharma, 2021) and (Hesti Maheswari, 2020) present evaluation frameworks focused on organized retail in India and informal e-waste businesses in developing countries, respectively. The first uses **fuzzy TOPSIS** to rank retailers based on reverse logistics practices and performance integrates considerations of time, cost, environmental quality, and process efficiency, reflecting the growing importance of green initiatives and customer satisfaction in retail. The second develops a scorecard approach for evaluating informal e-waste businesses emphasizes financial, environmental, stakeholder value, internal business process, social, and innovation perspectives, highlighting the need for comprehensive evaluation systems that capture the diverse impacts of reverse logistics operations.

(Monika Kosacka - Olejnik, 2018) and (Denilson Ricardo de Lucena Nunes, 2023) further expand the evaluation framework by introducing models that assess the maturity of reverse logistics processes and the performance of reverse supply chains from multiple dimensions. Both encapsulate the operational, technological, information, innovation, and flexibility dimensions, offering structured approaches to enhance reverse logistics processes within organizations.

3.2.4.4.2 Efficiency improvement (10 articles)

As described in the previous chapters, efficiency is the most important driver when considering

Reverse Logistics processes, together with cost reduction, and here are presented some articles that describe tailored algorithms to enhance productivity addressing specific issues.

(Xueqing Zhang, 2022) introduces the Queuing System Assessment and Impact Reduction (QueSAIR) approach, integrating **queuing theory** with **simulation techniques** to manage inert construction waste within RL networks. This innovative method underscores the significance of using mathematical models and real-world data simulation to mitigate the adverse effects of queuing delays, including waste generation points, collection and recycling facilities, and landfills. The aim of the document is to reduce negative impacts, such as cost, emissions, noise pollution, and productivity losses, caused by queuing delays.
Parallelly, (Ahmed Dabees, 2023) focuses on the integration between Sustainable Service Quality and Reverse Logistics Service Quality to meet customer satisfaction regarding sustainability goals in Reverse Logistics Service Providers to elevate customer satisfaction and operational efficiency. The key dimensions included are waste reduction, energy usage, customer satisfaction, cost management, and the implementation of green practices.

(Farzad Zaare Tajabadi, 2023) employs **Data Envelopment Analysis (DEA)** models to assess the efficiency of Green Supply Chain Management (GSCM), using **Tobit regression** analysis to explore the impact of green principles on efficiency. This study highlights the crucial role of advanced analytical methods in identifying factors that positively and negatively influence the efficiency of GSCM, advocating for a data-driven approach to optimizing green supply chains.

(Janeiro, Pereira, Ferreira, Sá, & Silva, 2020) assesses RL activities for a Portuguese fashion company operated by a 3PL provider, employing Lean and Supply Chain methodologies to propose improvements. This study illustrates, through a **Value Stream Mapping**, the potential of combining lean methodologies with technology to boost productivity, reduce costs, and enhance service quality in the fashion industry, offering a comprehensive model for improving RL operations.

(Lili Dahliani, 2023) and (Liao, 2018) delve into the impact of reverse logistics and green procurement on the performance of Green Supply Chain Management in SMEs and the optimization of product recovery and remanufacturing processes, respectively. (Lili Dahliani,

2023) utilizes a structural equation model to analyze data from SMEs, highlighting the positive effects of reverse logistics and green procurement on GSCM performance. (Liao, 2018) introduces a **Mixed Integer Nonlinear Programming model**, focusing on multi-product and multi-module returnable items, demonstrating the practical applicability of advanced modeling techniques in enhancing recycling and remanufacturing efficiency.

Technology has a crucial role in the development of efficient processes and one that has caught the attention of researchers is IoT or Internet of Things, which uses connected devices and sensors to improve traceability, communication flows and identification activities. Many articles explore the use of this technologies for logistics efficiency.

(Sichao Liu, 2018) introduces **RFID**-based loading verification and real-time routing optimization for logistics vehicles, while (G. Plakas, 2020) focuses on leveraging **LoRaWAN** and **Cloud-IoT** technologies for plastic bottle lifecycle management. (Behzad Mosallanezhad, 2023) tests IoT-enabled Reverse Supply Chains for pandemic waste management in Mexico, employing various **metaheuristic algorithms** to assess efficiency. (Xu Xu, 2022), utilizing intelligent sensors, within Smart Grid and Renewable Energy Systems, enables the creation of smart trashcans for municipal hazardous which address waste disposal issues by collecting data on the volume of waste produced and gathered. Finally, (Celia Garrido-Hidalgo, 2019) discusses an IoT-based framework for managing the reverse supply chain of Waste Electrical and Electronic Equipment (WEEE), emphasizing the integration of various IoT communication for low-cost and energy-efficient operations. Cited technology are RFID for product identification, Bluetooth Low Energy (BLE) for local data transmission and inventory updates, and LoRaWAN for wide-area connectivity and environmental monitoring across industrial sites.

These studies collectively underscore the transformative potential of IoT technologies in enhancing logistics tasks, vehicle allocation, and the overall efficiency of RL operations.

3.3 Reverse Logistics literature open points

The literature review on reverse logistics highlights several open points and gaps in current practices that underline areas for potential improvement and refinement. These gaps span various aspects of the reverse logistics process, from the initial collection of returned goods to their reintroduction into the supply chain or final disposal.

Regarding **Collection and Networks Design** Planning, one of the significant challenges identified is the inefficiency in the strategic placement of collection points and the allocation of necessary resources. The current systems often struggle to manage the returned products effectively, which impedes their efficient reintegration into the supply chain. There's a need for more dynamic and responsive network design that can adapt to fluctuating volumes and types of returns, ensuring that resources are optimally utilized and that the collection points are strategically located to minimize transport costs and environmental impact.

Furthermore, the existing routing practices often overlook the potential of real-time data integration, which could dynamically adjust routes in response to traffic conditions, weather, and changes in the volume or type of returns. Such enhancements could lead to significant improvements in operational efficiency and reduce the environmental footprint of reverse logistics activities.

In the realm of **Decision Making and 3PL Selection**, current manual inspection and processing of returned goods are not only labor-intensive but also prone to errors, which can lead to misclassification and improper handling of return items. This area of reverse logistics would benefit greatly from a review and overhaul of existing practices to incorporate more automated systems that can perform these tasks more quickly and accurately. Improving quality control measures and processing efficiency could reduce costs and increase the recovery value of returned products.

A general lag in adopting technologies that could revolutionize reverse logistics practices has been found, such as advanced tracking systems, IoT, and automation technologies. These technologies have the potential to enhance transparency, improve tracking accuracy, and streamline the entire reverse logistics process, making it more efficient and less prone to human mistakes.

In summary, the literature on reverse logistics exposes several areas where improvements are necessary to enhance efficiency, reduce costs, and increase the sustainability of operations. Addressing these open points requires a concerted effort to innovate and adopt new technologies and processes that can transform the traditional approaches to reverse logistics. AI could be the answer to most of them, with its capability of taking into considerations dynamics variable, predicting returned volumes, allocating strategically resources and warehouses, and integrating real-time data collection to optimize the entire network and adapt to various scenarios. Moreover, though machine learning and computer vision could automate the inspection of returned goods, accurately sorting them based on condition and type, standardizing processes and enhancing speed and accuracy.

In the next chapter, a delve into the literature of AI applications in Reverse Logistics has been developed to analyzed which algorithms have been recognized as most useful and which phases have been explored the most.

3.4 Literature review on AI applied in Reverse Logistics

The research was conducted on the same databases as the Reverse Logistics Literature Review, Scopus and ScienceDirect and the objective was to gather information regarding the studies on AI applied to Reverse Logistics, uncovering challenges and potential benefits.

3.4.1 Collection of papers

In order to collect the papers published on the possible implementation of AI in Reverse Logistics, research has been performed with the following keywords: "AI and Reverse Logistics", "AI Reverse Network Design", "AI Reverse Supply Chain", "AI Inspection and Sorting". The filter "Open Access" has been applied to fully read the content of the found articles and publications regarding medical and biological industries have been excluded.

In total the number of articles found is 2.749 from which a selection based on titles and analysis of keywords has been performed and, after removing duplicates, a database of 77 has been built. In this number also the 10 articles found in the previous literature review have been included.

3.4.2 Analysis and category selection

Subsequently, the abstracts of all documents were reviewed to clearly understand their scope and determine their relevance to this research. Articles published before 2010, as well as those not specifically utilizing AI in the phases of Reverse Logistics, were excluded. As a result, a final database of 52 articles has been compiled.

These articles are categorized into clusters based on their scope and the specific phases of Reverse Logistics they address, as outlined below:

- General Literature Reviews
- Applicability of Technology
- Collection and Network Design
- Decision Making and Third-Party Logistics (3PL) Selection
- Performance and Efficiency Evaluation

3.4.3 Descriptive analysis of literature

As seen in the research of articles regarding Reverse Logistics in general, the application of AI in this field had an increasing interest in the last years, especially in 2022 and 2023. Indeed, the number has quadruplicated in period 2021 – 2023, as drawn in Figure 11.

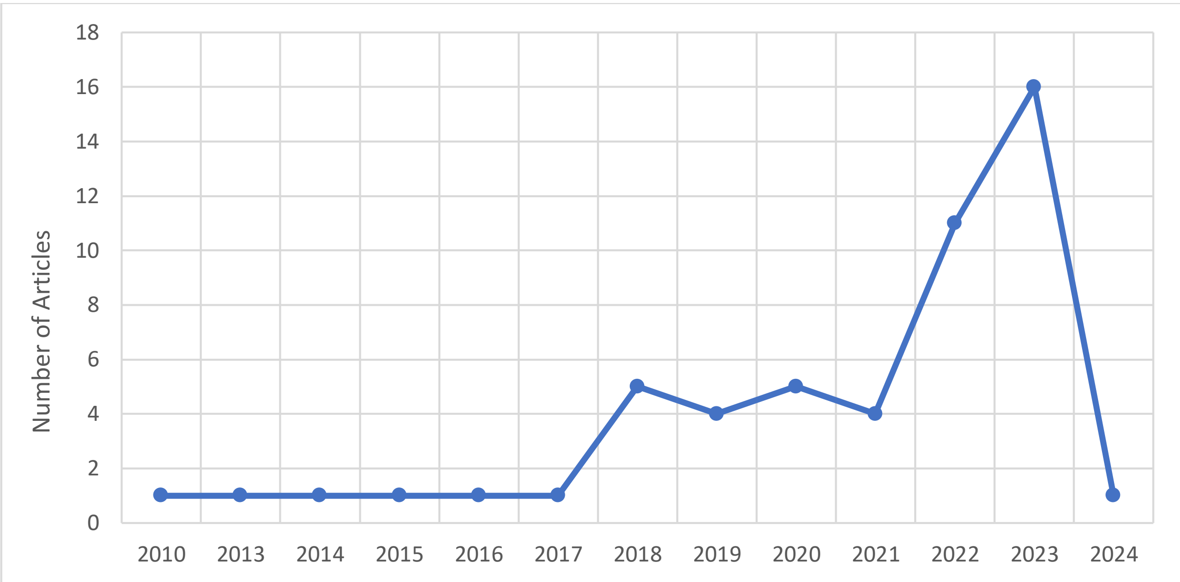

Figure 11 - Yearly distribution of AI in RL articles

The collection of articles depicts a wide distribution within various journals, Procedia CIRP and Applied Mathematical Modelling are the only ones which published more than 2 articles in the identified database, contributing with 9 and 5 document respectively. The scene is quite fragmented in many journals and in the category “Others”, presented in Figure 12, are present all the journals which account just for one publication.

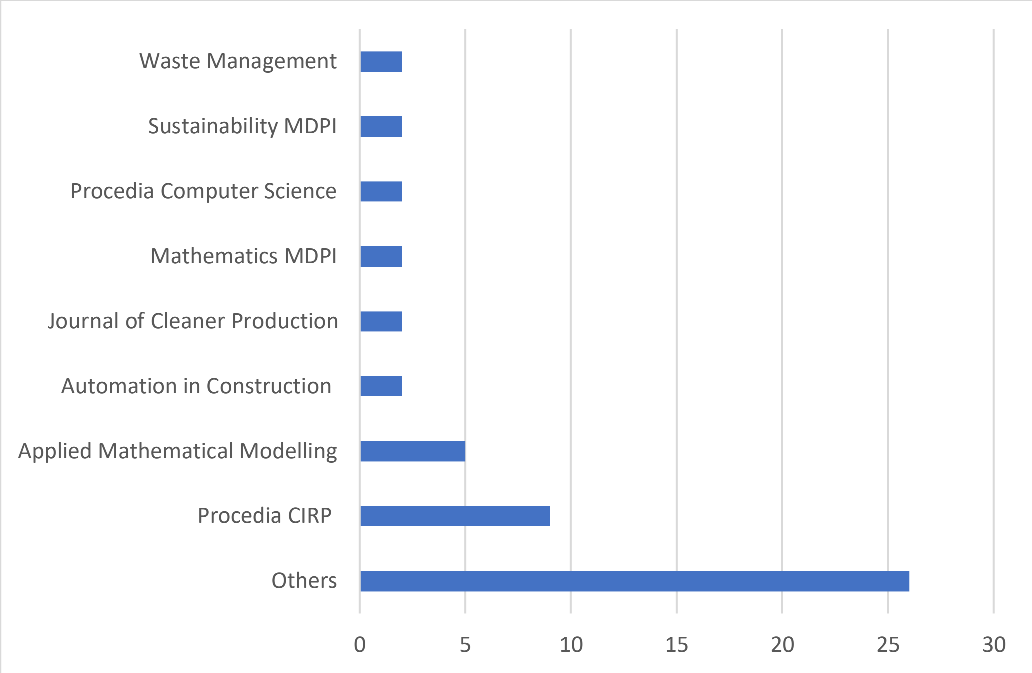

Figure 12 - RL & AI articles distribution in main journals

On the geographical spectrum, shown in Figure 13, China dominates the research field accounting for 13 articles, followed by Germany, with 6 articles, Iran with 4 articles and Italy and India with 3 publications. It is evident that, while for Reverse Logistics the deep dive into problems and solution was mostly made by emerging economies, regarding technological advancement, the western established economies have greater resources, with the only exception of China.

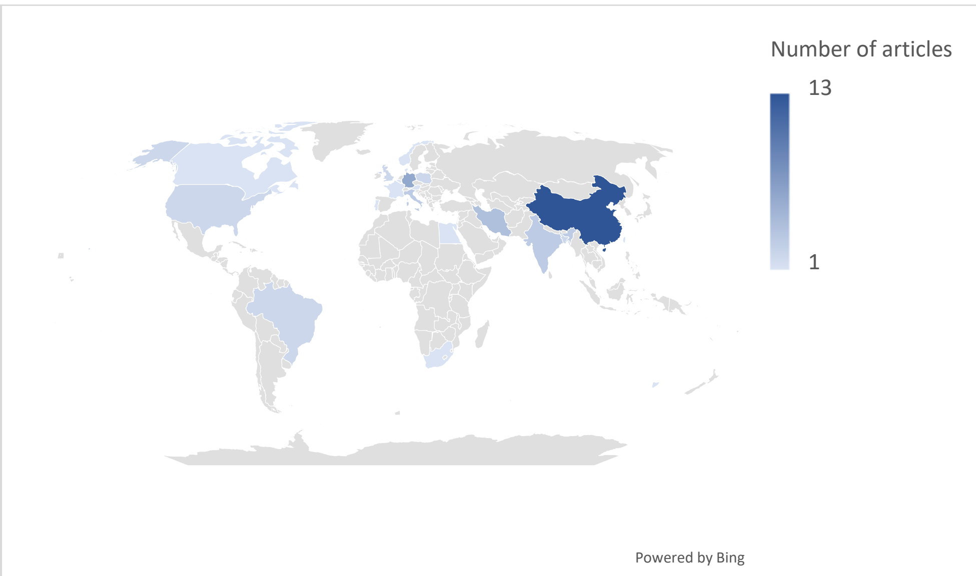

Figure 13 - AI & RL articles geographical distribution

The identified cluster show how the research regarding AI is still focusing a lot on collecting previous works and testing the applicability of the technology, the two categories account for 12 articles, Figure 14. Despite these concerns, the capabilities of AI of managing uncertainties and optimizing collection routes are at center of the studies in the academic field and are covered in half of the selected publications. Following these themes, the second point of attention regards Decision Making and 3PL selection, with specific drive on identification, inspection, and sorting techniques. The applications of Artificial Intelligence in Performance and Efficiency Evaluation seem mostly unexplored.

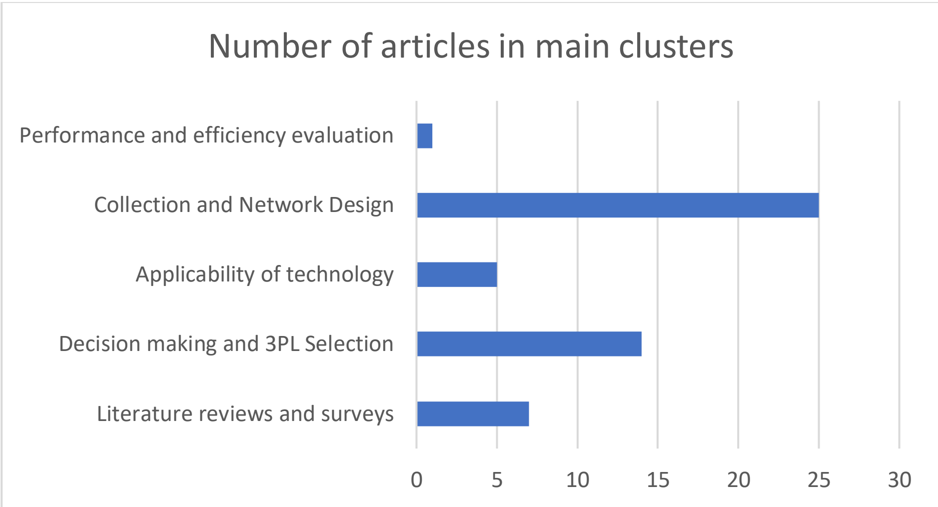

Figure 14 - AI & RL articles clusters distribution

3.4.4 Content Analysis

3.4.4.1 General Literature reviews (7 articles)

This section explores the contribution of other found literature reviews regarding the applications on AI in Reverse Logistics practices.
Different algorithms have been explored and taking as a basis their capabilities have been categorized depending on their beneficial support in various domains.

Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs), as highlighted by (Benjamin I. Oluleye D. W.-A., 2023) stand out for their prowess in image recognition and advanced pattern recognition. These AI models are instrumental in sorting and segmentation tasks, particularly within the construction sector, where they facilitate the identification and categorization of materials for recycling or remanufacturing. Their application underscores the potential to significantly improve material recovery processes, contributing to a more sustainable construction and remanufacturing industry.

Artificial Neural Networks (ANNs) and **Random Forests (RFs)** are noted for their formidable prediction capabilities, adept at modeling complex, non-linear relationships. These models find application in demand forecasting and predictive maintenance, areas crucial for optimizing reverse logistics operations. Their ability to process and learn from large volumes of data enables businesses to anticipate future trends and adapt their strategies accordingly.

Genetic Algorithms (GAs) and **Swarm Intelligence (SI)**, part of the Metaheuristics cluster discussed by (Sourabh Bhattacharya, 2024), excel in solving complex optimization problems inherent in network design and routing within reverse logistics. These algorithms optimize logistical operations by exploring vast solution spaces, offering evolutionary approaches to streamline collection routes, and efficiently design reverse logistics networks.

Decision Trees (DTs) and **Support Vector Machines (SVMs)**, though differing in approach, both contribute valuable insights into the classification and decision-making processes. DTs, with their intuitive structure, are utilized for making straightforward decisions in operational tasks, whereas SVMs, effective in high-dimensional spaces, are applied in scenarios requiring robust classification, such as quality assessment and risk management.

Gaussian Processes (GPs) and **Gradient Boosting (GBs)** showcase their strength in capturing uncertainties and enhancing predictive accuracy. GPs, with their probabilistic approach, offer valuable predictions in areas like environmental impact assessment, enabling more informed decisions about greener construction methods. GBs, known for their unmatched predictive accuracy, play a crucial role in optimizing various loss functions related to circular economy applications.

Some of this algorithm can be classified as Metaheuristics, which are deeply analyzed in the document (Pankaj Kumar Detwal, 2023), addressing several critical aspects including their fields of application, limitations, and research gaps.

The mentioned document highlights that **Pure Metaheuristics** such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Variable Neighborhood Search (VNS), Simulated Annealing

(SA), and Tabu Search (TS) have been more widely applied to solve complex optimization problems, including vehicle routing, production planning, supply chain design, and inventory management. While **Hybrid Metaheuristics**, which combine elements of pure metaheuristics or integrate them with other optimization techniques, have been developed to tackle specific challenges in circular supply chains. Examples include algorithms based on combinations of GA & SA (GASA), KA & SA (KASA), and KA & GA (KAGA), offering enhanced performance in terms of convergence rates and the ability to find near-optimal solutions with less likelihood of getting stuck at local optima.

Despite the promising applications, several challenges persist. The need for extensive datasets for training, as mentioned by (Benjamin I. Oluleye D. W.-A., 2023) and the complexity of AI algorithms, which often leads to a 'black box' nature as pointed out by (G.P. Agnusdei, 2022), pose significant hurdles. These challenges highlight the critical balance between leveraging AI's potential and addressing the limitations inherent in these technologies.

In the evolving landscape of reverse logistics within the circular economy, the application of Artificial Intelligence (AI) and robotics across its various phases—network design, collection, warehousing, and processing—highlights a concerted move towards enhancing operational efficiency and sustainability. The literature presents a multifaceted view of how AI technologies and robotic systems are being integrated to address the unique challenges and opportunities inherent in each phase of reverse logistics.

The different benefits that AI could bring to RL activities are summarized in Figure 15.
Between the real of **Network Design**, strategic design benefits from the analytical capabilities of AI can be exploited, as noted by (Benjamin I. Oluleye D. W.-A., 2023) and (Matthew Wilson, 2022). AI's role extends to optimizing the configuration of reverse logistics infrastructure, including the judicious selection of third-party logistics (3PL) providers. This phase underscores AI's utility in facilitating strategic decisions that enhance the efficiency and sustainability of reverse logistics networks.
The **Collection** phase leverages AI to optimize the gathering of returned goods. (Matthew Wilson, 2022) emphasizes the use of AI for solving complex location and routing challenges, thereby enhancing the efficiency of collection strategies. Additionally, robotics, equipped with

AI algorithms, begin to play a crucial role in automating the collection process, offering innovative solutions to reduce human labor and increase precision in sorting at the source.

In **Warehousing**, the adoption of robotic systems, as discussed by (Matthew Wilson, 2022) and (R. Sarc, 2019) for sorting and inspecting returned items demonstrates the tangible benefits of automation. These robots, guided by AI, not only enhance the accuracy and efficiency of sorting processes but also contribute to faster processing of returned items, showcasing the direct impact of technological advancements in automating and streamlining warehousing tasks.

The **Processing** phase benefits from both AI and robotics, with analytical and intuitive AI models supporting complex decision-making and operational optimization, as highlighted by (Matthew Wilson, 2022). Robotic systems, particularly those capable of disassembly and material separation, further augment this phase by offering precise, efficient, and safe handling of returned products for recycling or remanufacturing, as noted by (R. Sarc, 2019). This integration underscores the collaborative potential of AI and robotics in enhancing sustainable processing activities within reverse logistics.

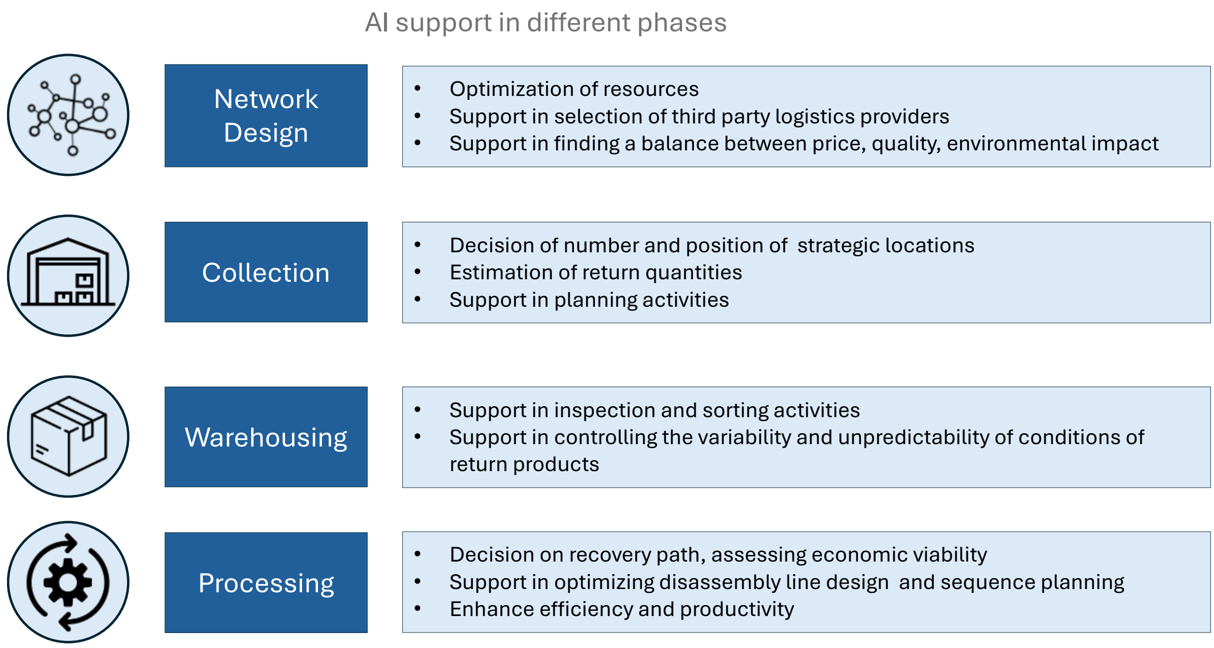

Figure 15 - AI support in RL activities

3.4.4.2 Applicability of AI in RL (5 articles)

Incorporating Artificial Intelligence (AI) into reverse logistics (RL) signifies a profound transformation within the logistics and supply chain management sectors, leveraging on the power of data. However, some industries are more suitable and more ready to implement this technology, being rewarded by immediate advantages, while others could see its true potential only in the future.

The scope of AI's application in reverse logistics is broad and impactful and many studies explored which are the key beneficial activities for its use. (Mladen Krstic G. P., 2022) highlights AI's pivotal role in fostering informed decision-making and predictive analytics, which are essential for anticipating returns and optimizing inventory and resource management. (Marian Schlü̈ter, 2023) underscores the significance of AI in enhancing the circular economy through green incremental learning, which emphasizes the accuracy and energy efficiency of AI models during the operational ramp-up phase. (Hannah Lickert, 2021) discusses the selection of suitable machine learning algorithms for reverse logistics tasks, indicating the critical need for a nuanced understanding of each algorithm's strengths and weaknesses. (Jonas L. Vilas-Boas, 2023) further elaborates on AI's application in fresh food logistics, emphasizing its utility in predictive analytics, automated sorting and processing, and decision support.

Opportunities

(Mladen Krstic G. P., 2022) articulates how AI-driven reverse logistics can lead to significant cost reductions while elevating customer service standards. (Marian Schlü̈ter, 2023) demonstrates the energy-saving potential of up to 62% without notably compromising accuracy, highlighting the benefits of employing online and incremental learning techniques with growing datasets. (Hannah Lickert, 2021) and (Jonas L. Vilas-Boas, 2023) both note AI's contribution to sustainability and waste reduction, illustrating its role in optimizing reverse logistics operations to align with circular economy principles.

(Abdulla All Noman, 2022) present in a literature review the studies regarding the possibilities in image recognition, performance evaluation, demand forecasting and general process optimization.

Limitations

However, the integration of AI within reverse logistics is not devoid of challenges. A common theme across the cited works is the dependency on high-quality, accessible data. (Mladen Krstic G. P., 2022) emphasizes the complexity of implementing AI in existing logistics systems, which requires significant technological investment and training. It also emphasizes the need for compromise and common interest among all stakeholders to select the most viable solution. (Marian Schlü̈ter, 2023) hints at the challenges in integrating and training AI in operational processes, especially where initial data is sparse. (Hannah Lickert, 2021) touches on the difficulties of selecting the most appropriate ML algorithm for specific tasks within reverse logistics, which necessitates a deep understanding of each algorithm's applicability. Finally, (Jonas L. Vilas-Boas, 2023) points out the sometimes-difficult interpretability of results given by complex algorithms, such as deep learning algorithms.

3.4.4.3 Collection and Network Design (25 articles)

The articles present in this cluster use a variety of algorithms that are part of Artificial Intelligence, to address the issues of Collection and Network Design.

The analyzed algorithms and their presence in the found papers is described in Figure 16.
The Genetic Algorithm (GA) emerges as the predominant technology, cited in almost 30% of articles. Some of them underscore its established position in solving the non-deterministic polynomial issues of the facility location allocation problems, or optimization of vehicle utilization and inventory management activities.
Stochastic programming, explored in 16% of selected papers, also gained significant interest in the literature due to its capability to simulate the uncertain environment concerning reverse logistics and make prediction regarding demand, return rates and recovery rates.
Non-Sorting Genetic Algorithms (NSGA II) with their ability to truckle multi-objective problems in hierarchical context has been considered in 10% of documents to solve vehicle routing optimization problems and find cost efficient solutions.

Particle Swarm Optimization (PSO)'s popularity, 6% coverage in the literature, may stem from its simplicity and efficacy in converging towards optimal solutions, while Artificial Bee Colony (ABC) and Ant Colony Algorithm (ACA) algorithms, both inspired by the foraging behavior of social insects, focuses on transportation and distribution models. Their inclusion in this roster of AI technologies suggests an affinity for algorithms that are adept at exploring vast and complex search spaces, making them suitable for the distributed nature of logistics networks.

Memetic Algorithms and Benders Decomposition, which account together for 9%, indicate an inclination toward approaches that either refine solutions with local search strategies or decompose large-scale logistics problems into more manageable pieces.

Gray Wolf Optimization are less frequently mentioned, but their presence signals an interest in niche algorithms that mimic natural processes or offer solutions to multi-objective optimization problems.

Lastly, the inclusion of Blockchain Technology in 6% of articles hints at the cutting-edge exploration of new methodologies capable of providing enhanced transparency and security in logistics networks.

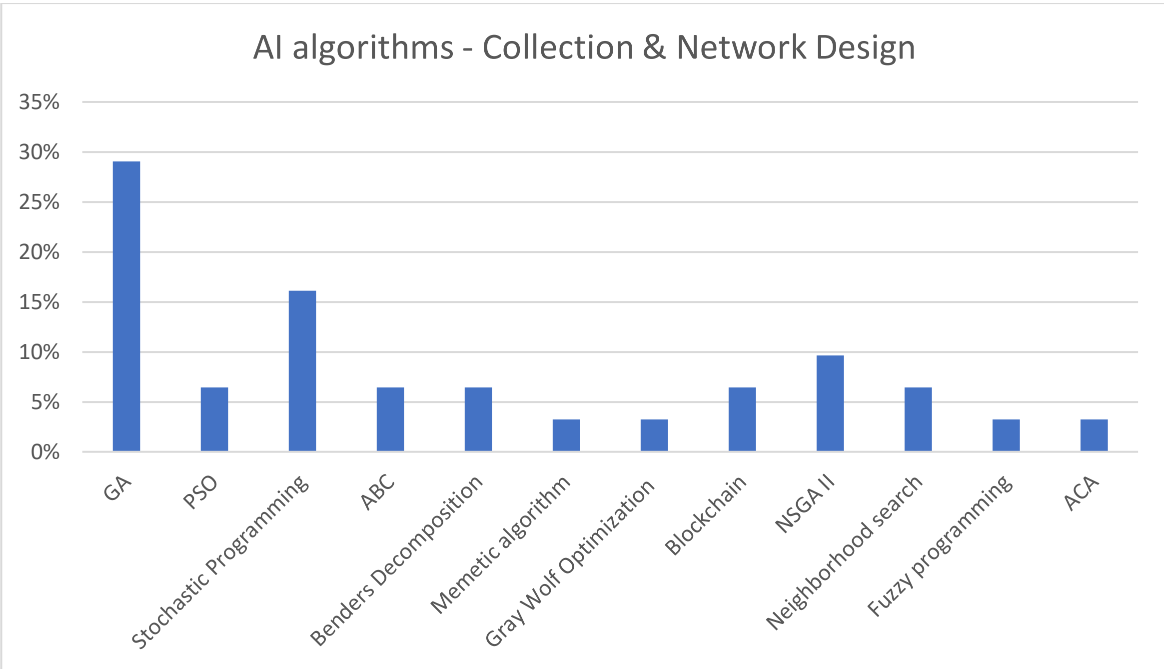

Figure 16 - Collection and Network Design AI algorithms (GA – Genetic Algorithm, PSO – Particle Swarm Optimization, ABC – Artificial Bee Colony, NSGA II – Non sorting Genetic Algorithm, ACA – Ant Colony Algorithm)

In the next sections, the article included in the cluster will be subclustered depending on their focus, following the classification of Reverse Logistics documents: Location – Allocation, Planning and Vehicle Routing.

3.4.4.3.1 Location – Allocation (11 articles)

The integration of AI in Location-Allocation problems is essential in Reverse Logistics due to the unpredictable nature of supply and demand across networks. This dynamic area leverages various optimization technologies to adapt rapidly and efficiently.

(Hamed Soleimani, 2015) introduces a hybrid optimization model that synergizes **Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)** for designing Closed-Loop Supply Chain (CLSC) networks. This model adeptly addresses the NP-hard challenges of supply chain design, enhancing the flexibility and robustness needed for multi-product, multi-echelon, and multi-period CLSC systems. A practical application of this model is demonstrated in a case study with an Iranian hospital furniture manufacturer, showcasing its effectiveness in real-world settings.

Building on the theme of integrating forward and reverse logistics, (Eslamipoor, 2023) and (Hamid Ashfari, 2014) both emphasize the necessity of managing uncertainties in customer demand and return rates. The first introduces a **two-stage stochastic planning model** focusing on product collection centers within green logistics networks, while the second employs a **stochastic mixed integer linear programming** (SMILP) model to optimize facility locations and sizes, stressing the balance between cost minimization and customer satisfaction.

The research by Yu Lin H. J. across two studies, (Yu Lin H. J., 2018), (Yu Lin H. J., 2019), further explores the optimization of recovery networks, particularly for end-of-life vehicles (ELVs) using an **Improved Artificial Bee Colony** (IABC) algorithm. These studies highlight the economic and environmental benefits of efficiently designing recovery networks, and the more recent one enhances the methodology by integrating elements of genetic algorithms, improving upon traditional approaches in handling the NP-complete problems of facility location allocation, with real-life case application examples.

Parallel to these studies, (K. Nageswara Reddy, 2022) and (Xuping Wang, 2018) address environmental sustainability through their respective models. (K. Nageswara Reddy, 2022) introduces a **mixed-integer linear programming** (MILP) model optimized for reverse logistics networks, which includes considerations for carbon emissions, showcasing that sustainable practices can be economically viable. Similarly, (Xuping Wang, 2018)'s model for managing faulty sharing bikes focuses on reducing urban congestion and environmental pollution, employing a **Modified Genetic Simulated Annealing Algorithm** (MGSA) to optimize facility locations and vehicle allocations effectively.

Furthermore, the studies by (Huailian Lin, 2023) and (Jianquan Guo, 2018) examine the strategic aspects of reverse logistics. The first one's work on recyclable packaging employs **stochastic programming** to optimize the locations of collection points and recovery centers, contrasting various decision-making methodologies. In contrast, the second study proposes a multi-objective, multi-stage model that enhances government-enterprise collaboration in product recovery, using a sophisticated two-phase heuristic algorithm that combines **Genetic Algorithm and Particle Swarm Optimization**.

Lastly, (Elham Behmanesh, 2022) and (Arthur Mahéo, 2022) explore large-scale and tactical challenges in reverse logistics. (Elham Behmanesh, 2022) introduces a flexible supply chain model that uses a **memetic algorithm** optimized with the Taguchi method, focusing on distribution-allocation challenges. Meanwhile, the other study on solid waste logistics employs a Mixed Integer Programming (MIP) formulation to optimize pre-collection network design and vehicle scheduling, demonstrating the efficacy of **Benders Decomposition** techniques in complex logistical challenges.

3.4.4.3.2 Planning (10 articles)

The landscape of reverse logistics network planning has significantly evolved with the integration of Artificial Intelligence (AI), showcasing diverse applications across various industries and the adoption of novel technologies to address environmental and operational efficiency challenges.

(Hao Yu, 2020) and (G. Kannan, 2010) both explore optimization models for CLSC planning with a strong emphasis on network flexibility. The first's **fuzzy-stochastic** multi-objective model and the second's **MILP** approach, utilizing **genetic algorithms** and incorporating procurement, production, distribution, recycling, and disposal, underscore the necessity of addressing uncertainties and enhancing environmental performance within electronic goods and battery recycling sectors, respectively.

(Abdollah babaeinesami, 2023) introduces a Stackelberg game strategy in a CLSC framework, employing **Genetic Algorithm (GA**) and **Gray Wolf Optimization (GWO)** to navigate the complexities and uncertainties of wooden products supply chain management. The game theoretic part model competitive interactions between RL participants, while the two meta-heuristic algorithms predict long-term behavior.

(A.E Matenga, 2023) further expands the application of Industry 4.0 technologies by integrating **blockchain** with cloud manufacturing (CM) to improve product lifecycle

management (PLM) in railcar manufacturing. This study showcases the versatile role of blockchain in ensuring data traceability for parts and orders and enhancing manufacturing processes.
(Wu, 2022) further explore the implications of integrating circular economy principles and **blockchain** technology in reverse logistics to enhance transparency, security, and efficiency. It also highlights the need for significant computational resources to maintain the public chain and the complexity of integrating this new technology into existing logistics systems.

The optimization of the reverse logistics network for OEMs by (Jianmai Shi, 2017) and the distribution of medical supplies by (Yuhang Han, 2023) demonstrate the adaptability of AI in addressing logistical challenges specific to urban mobility and healthcare emergencies. These studies highlight AI's role in solving logistical constraints through efficient routing and scheduling, underscoring the technology's potential in diverse contexts. The first used a **multi-objective mixed integer programming (MIP)** evaluating overall costs, carbon emissions, and the responsiveness of these networks, and then a **multi-objective genetic algorithm based on NSGA II** is developed to find optimal solutions. The second implement a multi objective scheduling model that incorporates costs associated with UAV (Unmanned Aerial Vehicle) trajectory, including distribution impact threat and other costs. It utilizes a two-stage solution algorithm combining the **multi-strategy guided adaptive differential evolution (MSGA-DE)** for UAV cooperative distribution planning in a 3D environment and an improved beluga whale optimization based on **hybrid neighborhood search (HNS-IBWO)** for vehicle-drone scheduling and distribution issues.

(D.G. Mogale, 2022) and (Behnam Vahdani, 2013) contribute to the discussion by emphasizing the integration of AI and optimization algorithms in CLSC design, addressing uncertainties, and exploring sustainable practices. Their work underlines the importance of hybrid meta-heuristic strategies and the consideration of environmental impacts and economic benefits in reverse logistics. The first adopted a hybrid meta-heuristic strategy combining **NSGA-II with Co-Kriging** for efficient trade-off analysis between costs and emissions, achieving near-optimal solutions with minimal computational expense. The second employs a combination of queuing theory, **fuzzy possibilistic programming, and fuzzy multi-objective programming** to address demand fluctuations and potential facility failures.

Finally, the study by (Kangye Tan, 2023) on the **power battery reverse supply chain** unveils another dimension of network design, where customer satisfaction intersects with logistical optimization. The intricate intersection of scheduling, collection, and recycling of power batteries demands a model that can accommodate not just the physical constraint of vehicle loads and service capacity, but also the temporal expectations of customers, highlighting the critical role of service quality in the reverse logistics of high-value products. The technique used in the study involves an integer programming model for scheduling and then it designed a **Non-dominated Sorting Genetic Algorithm-II** (NSGA-II) enough to solve the location-routing optimization problem.

3.4.4.3.3 Routing (4 articles)

The application of Artificial Intelligence (AI) in solving vehicle routing problems presents innovative solutions to enhance logistics and supply chain management and present a list of studies all developed in very recent years.

(Geraldo Cardoso de Oliveira Neto, 2023) employs **simulation and genetic algorithms** to optimize the reverse logistics network for Waste Electrical and Electronic Equipment (WEEE) in Sao Paulo, Brazil. The objective is to minimize environmental impacts and maximize economic benefits, contributing to the circular economy. The research showcases how AI can lead to efficient routing, reduce fuel consumption, insurance, depreciation, maintenance costs, and environmental impacts from abiotic, biotic, water, land, air, and greenhouse gases. The optimized structure of WEEE reverse chains results in fewer collections, maximizing cubage utilization, creating a replicable model.
Further exploring cost minimization, (Xiaoman Guan, 2023)**'**s research introduces an improved **Ant Colony Algorithm (ACA)** to optimize cold chain logistics for agricultural products. The study aims to decrease transportation costs while ensuring high customer satisfaction, addressing the delivery vehicles' crucial role in cold chain logistics. The enhanced ACA proves the effectiveness of AI in solving complex path selection problems, emphasizing the importance of algorithmic innovations in enhancing operational efficiency and customer satisfaction in cold chain logistics.

Moreover, (Mengke Li, 2023) study presents a bi-objective optimization model using **a Multi-Objective Immune Genetic Algorithm (MOIGA)** for routing optimization in reverse logistics, tailored for a hybrid fleet navigating real-time road conditions. The goal is again to reduce operational costs and improve customer satisfaction by adapting to urban environments' dynamic and unpredictable nature. The MOIGA's success in identifying optimal routing solutions underlines the value of integrating real-time data and AI in developing adaptive logistics strategies.

Lastly, (Maria João Santos, 2023) investigation into the economic and environmental impacts of VRP variants further enriches this discourse. By examining Divisible Deliveries and Pickups (VRPDDP) against traditional VRP models, Santos unveils the nuanced benefits of visit splitting in reducing costs and CO2 emissions. The study's comparative analysis across different network types reveals that flexibility in customer visit scheduling and vehicle capacity is crucial for optimizing both economic and environmental outcomes. Interestingly, the findings point towards a distinct relationship between route configurations and sustainability goals, with environmental objectives prompting more complex routing patterns. The advanced use of the **Adaptive Large Neighborhood Search** (ALNS) metaheuristic in tackling the VRPRMDDP variant highlights the ongoing evolution of solution methodologies towards greater efficiency and sustainability in routing.

A notable challenge across these studies is the complexity of integrating real-time environmental and operational data into AI-driven models, requiring advanced computational resources and algorithmic innovation. Moreover, ensuring the scalability and replicability of these AI solutions in different geographic and industrial contexts remains a critical area for future research.

3.4.4.4 Decision Making and 3PL selection (14 articles)

In the landscape of decision-making within reverse logistics, the mention of various artificial intelligence (AI) technologies and methodologies across selected articles provides insight into prevalent trends and focal areas of research.

The occurrence of the mentioned algorithms across the articles is described in Figure 17. Convolutional Neural Networks (CNNs) emerge as the most frequently discussed technology, cited in almost 30% of articles, reflecting their central role in image processing and recognition tasks crucial to sorting and classifying materials. The prominence of CNNs in the literature indicates a strong focus on enhancing the visual capabilities of robotic systems, an essential function given the diverse and often complex nature of materials handled in reverse logistics. Following closely behind, with 24% presence, is the mention of robots, underscoring the significant emphasis on physical automation within the industry. The consistent reference to robots across studies suggests a strategic drive toward operational autonomy in tasks such as disassembly, sorting, and transportation, which are integral to efficient reverse logistics systems.

Machine learning, deep learning, and R-CNN technologies are also highlighted, albeit with lesser frequency compared to CNNs and robotics. These AI technologies, especially machine learning and deep learning, are instrumental in learning from data, pattern recognition, and predictive modeling, enabling smarter decision-making within the reverse logistics framework. Notably, intuitive teaching is discussed within the context of AI, pointing to an innovative approach where human expertise collaborates with machine precision to enhance the learning process for robotic systems. This methodology reflects the evolving landscape of AI in reverse logistics, where human-robot interaction plays a vital role in adapting to various tasks and material types.

Unsupervised learning, Genetic Algorithm, and Multilayer Hybrid systems, though not as prominently featured as other technologies, still plays a role in the analysis, revealing its potential in uncovering hidden patterns and relationships in data without the need for labeled datasets.

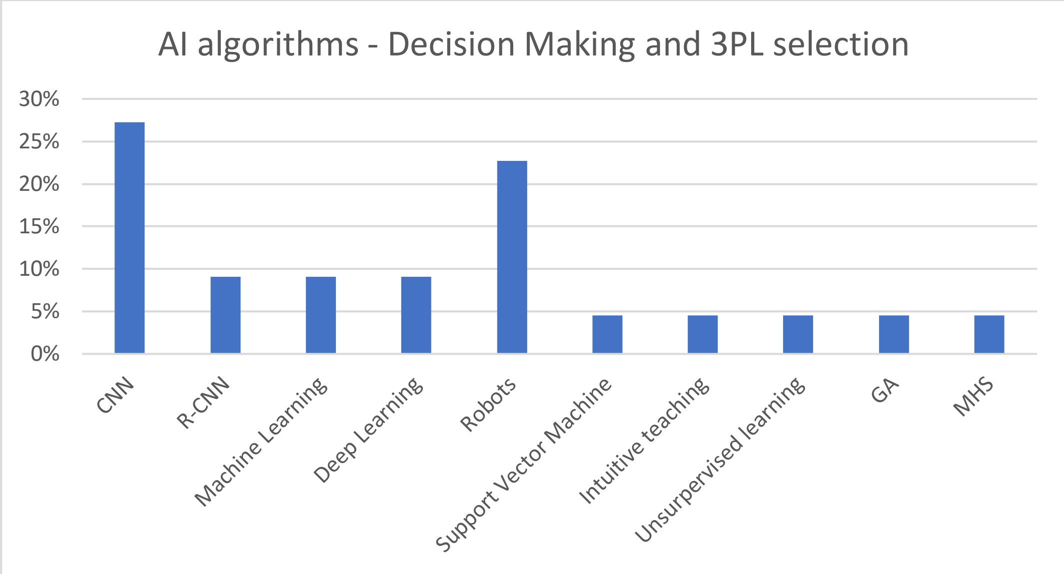

Figure 17 – Decision Making and 3PL selection AI algorithms (CNN – Convolutional Neural Network, R-CNN – Region Based Convolutional Neural Networks, GA – Genetic Algorithm, MHS – Multilayer Hybrid Deep Learning systems)

In this category documents regarding 3PL selection have not been identified, showing a preference for traditional algorithms to address these challenges.

A unique paper has been found that not specifically focus its attention on identification, inspection and sorting processing, to which the following chapter is dedicated.

Indeed, (Mostafa Setak, 2019) presents a bi-level stochastic optimization model aimed at enhancing the reliability of supply chain networks in competitive environments, employing both exact methods and a genetic algorithm. The study develops two mathematical models that account for competition and uncertainty within a three-echelon supply chain, specifically formulating the relationship as a Stackelberg game where distribution centers hold more influence over retailers. The document demonstrated that the hybrid method more effectively handles the NP-hard nature of the problem, providing robust solutions for large-scale instances, improving supply chain reliability and cost management under competitive and uncertain conditions.

3.4.4.4.1 Identification, Inspection, sorting (13 articles)

Academic research has shown a keen interest in leveraging technology, particularly Convolutional Neural Networks (CNN) and Machine Learning, to enhance identification, inspection, and sorting processes. The primary focus of these technological applications is waste recognition, aimed at improving the accuracy of recycling. This area has been more thoroughly explored compared to the specific reverse logistics activities, which are relatively new to many companies and industries. In addition, this technology can be applied to sorting robots which automatically decide the path of the returned object and to which a dedicated section in this chapter has been developed.

(Mindy Yang, 2016) opens the discussion utilizing **Support Vector Machines (SVM) and Convolutional Neural Networks (CNN)** for automating trash and recyclables classification, distinguishing the images in 6 categories (glass, paper, metal, plastic and general waste). The research highlights the potential effectiveness of SVM in waste sorting and acknowledges challenges in CNN model training.
Subsequently, (Yinghao Chu, 2018)) introduces a **multilayer hybrid deep-learning system (MHS)** for automatically sorting waste in urban public areas. Through high resolution cameras and sensors, the systems acquire images, uses a utilizing a CNN-based algorithm for image feature extraction and a multilayer perceptrons (MLP) method to classify wastes as recyclable or otherwise. This methodology demonstrates in a case study, a high level of accuracy, over 90%, exploiting innovation and mimicking human sensory and cognitive processes.

(Piotr Nowakowski, 2020) employs **Convolutional Neural Networks (CNN) and Region-based Convolutional Neural Networks (R-CNN)** for e-waste categorization and size determination, exploiting recognition of images taken directly by customers before the reverse logistics process starts. The approach demonstrates high efficiency in identification, with potential for increased accuracy through dataset expansion.
Further analysis on **CNN** can be found in (Janusz Bobulski, 2021) which develops an automated system using Convolutional Neural Networks to segregate plastic waste into 4 categories. The study highlights technology's effectiveness in classifying plastic materials, proposing a practical application in both industrial and domestic settings, using portable devices.
The last example of utilization of CNNs can be seen in (Jean David Lau Hiu Hoong, 2020), which presents a deep learning-based image analysis method for analyzing construction waste composition. The approach uses **Convolutional Neural Networks** for automated determination, for near real time determination of recycled aggregates composition,

leveraging images to estimate components' mass values. The method's accuracy reaches 97% accuracy and a comparison with manual sorting shows its potential for efficiency improvements.

Continuing searching solution for identification, inspection, and sorting in RL, (Marian Schlüter, 2021) explores how digitization and **machine learning** techniques can make the process more efficient and objective. In a practical case, the study demonstrates how reliability could be increased though AI in remanufacturing processes.

(Alim Al Ayub Ahmed, 2020) discusses leveraging **AI and ML** to enhance waste sorting, featuring robotic applications and AI-based sorting techniques. The study emphasizes the transformative potential of these technologies in reducing environmental impacts and supporting sustainable development goals. The paper discusses various AI-based sorting techniques and the use of robots in recycling, showcasing different technological approaches like the use of Radio Frequency Identification (RFID), sensor networks, and machine learning algorithms for waste segregation and management. At the end of the paper, authors acknowledge the need to explore scalability of technology across different regions and waste type, while improve accuracy of mentioned AI.

Finally, (Weisheng Lu, 2022) advances computer vision application in construction waste management. Utilizing DeepLabv3+ for semantic segmentation, the study tackles the complexity of real-life waste mixtures, highlighting **deep learning**'s potential in waste management automation.

Across these studies, the application of AI and ML technologies showcases significant potential to address the identification, inspection, and sorting challenges in waste management and recycling. While promising advancements are demonstrated, common challenges include the need for further technological refinement, dataset expansion, and integration into existing waste management systems. Future research directions emphasize enhancing model accuracy, exploring advanced algorithms, and extending applications to diverse waste types, all contributing to environmental sustainability and the advancement of the circular economy.

3.4.4.4.1.1 Robots (5 articles)

The integration of robotics in reverse logistics, particularly for tasks such as disassembly and sorting, marks a significant advancement in the pursuit of sustainable waste management and recycling processes. The use of innovative robotic systems and algorithms across different industries illustrates a concerted effort to address the challenges of end-of-life product management and the complexities of waste sorting.

In the context of **electric vehicle (EV) battery disassembly**, (B. Engelen, 2023) introduces an intuitive teaching approach utilizing a SpaceMouse sensor to guide the robot. This method significantly accelerates the programming of robotic systems for disassembly tasks, essential for handling the high product variation and unknown conditions of EV batteries. The use of custom-developed Python scripts for software integration enables efficient control over the robot, facilitating a cost-efficient and flexible demanufacturing system. This approach not only expedites the teaching process but also maintains a high degree of accuracy, demonstrating the potential for robotics to make the disassembly process more accessible and less reliant on highly skilled labor.

In the plastic recycling industry, (Doris Aschenbrenner, 2023) 's "Recyclebot" project leverages artificial intelligence and robotics to improve the sorting of plastics from municipal waste. By employing computer vision and sensor fusion, the project aims to increase the yield in automated sorting plants and develop micro-automation solutions that assist human workers. The initiative addresses the critical need for variety purity and the challenges posed by post-consumer waste's complexity. Technologies such as transformer networks and self-supervised learning are adapted to enhance process efficiency.

For construction and demolition waste (CDW) management, (Zeli Wang H. L., 2019) introduces a robot designed for sorting nails and screws, combining computer vision with a neural network. The robot, thanks to its four-degree-of-freedom arm and a complete coverage path planning (CCPP) algorithm to move autonomously, aims to enhance safety and reduce material loss, demonstrating successful identification and sorting capabilities.

The same author with (Zeli Wang H. L., 2020) presents a vision-based robotic system that utilizes Simultaneous Localization and Mapping (SLAM) technology and instance segmentation methods, specifically Mask R-CNN, for efficient navigation, identification, and sorting of CDW. This system demonstrates the potential to significantly improve CDW management by facilitating the precise identification of waste materials and enhancing the efficiency of sorting and recycling processes.

Lastly, (Henning Wilts, 2021) assesses robotic sorting systems enhanced with deep learning in **municipal waste facilities**. The study focused on the robot's performance in sorting bulky municipal waste, marking the first attempt to apply such technology in this context on a full-scale waste treatment plant. The evaluation covered sorting quality, material purity, and initial socio-economic impacts. It also suggests continuous innovation and development in AI and robotics to handle heterogeneous waste streams effectively.

4. Industrial interest in AI applications in Reverse Logistics

4.1 Research Methodology

The scope of this document is not only to understand the possible benefits of AI in Reverse Logistics processes, but also to explore the level of knowledge and curiosity of different industries regarding the technology and a possible prioritization of stages in which the need of AI is more evident.

The following research questions are investigated:

1. Which are the processes that may need the support of AI in Reverse Logistics?
2. Which are the main drivers for companies when exploring such innovations?
3. How does this reasoning change from industry to industry? And which are the readiest ones to implement the AI?

The method chosen to assess the real benefits of AI in Reverse Logistics for companies is to interview manager and consultants to explore their current interest in the field of Reverse Logistics and how AI could bring some real advantages in the present or in the future.

In order to have a clear overview of the current adopted processes and the propensity of managers to implement Artificial Intelligence into their activities a list of questions has been asked to experts in the supply chain & operations field and to managing figures in different industries.

The starting point was interviewing consultants from big corporations who have worked for improving Supply Chain and Operations processes for 10 years because of their view on multiple industries and knowledge on the most required and efficient technologies.

Secondly, after collecting opinions from consultants, the industries which have been recognized as the ones that could be mostly impacted by AI have been chosen and managers from renowned companies have been contacted. The selection of companies was made taking into consideration a considerable size to sustain considerable investments, the presence of a developed Research and Development department and a predominant position in the market.

Lastly, the example of the procedures undertaken in an Italian waste disposal and recycling center has been considered. Waste management could, indeed, act as a guide in identifying needed technologies and avoid waste of valuable materials.

When choosing which sectors were more interesting, a consideration on the industries analyzed in the literature of AI applications was made, and it is described in Figure 18. Despite a quarter of the articles do not consider a specific field, it is evident that academics have focused their attention primarily on Waste management, covered in 19% of articles, and Automotive, 15% presence. Construction, Electronics and Pharma, due to the danger of wrongly managing hazardous components, are also explored for environmental and economical causes. Surprisingly, Retail has been covered by just 8% of articles even if the majority of returns not at end of life come from this sector. Some niche articles regarding Railcar and Sharing bikes have been found but will not be further analyzed in the continuum of the document. A segment that has been mentioned a lot in general Reverse Logistics papers is the fashion industry, to which a great part of pollution is due, but to which no specific studies with AI have been developed.

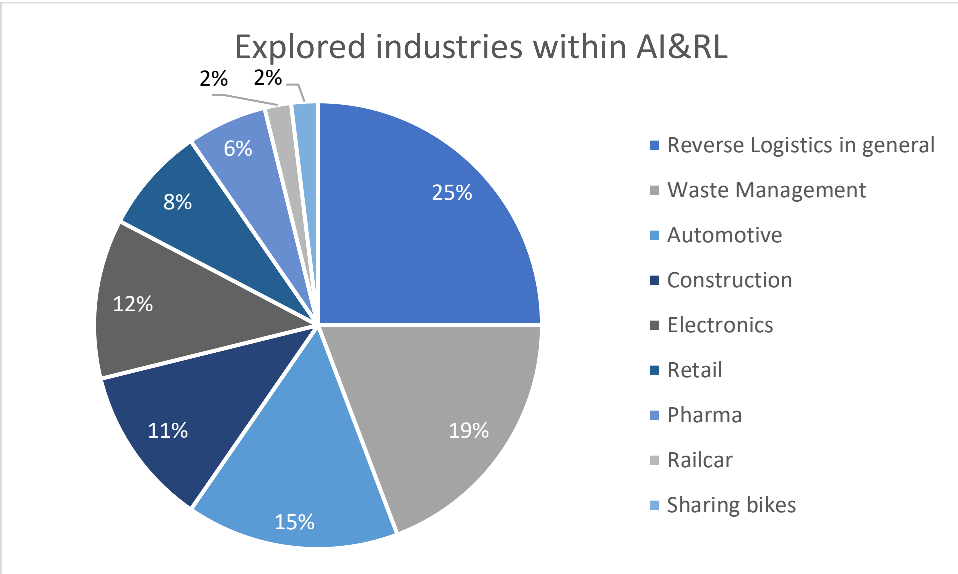

Figure 18 - Industries analyzed in AI & RL articles

The main topics covered in the interviews aimed at:

- Understanding the current Reverse Logistics process and the technology used
- Uncovering the willingness to implement AI and the evaluation criteria
- Setting the objectives of the implementation

- Analyzing the possible challenges and the relative readiness of companies
- Specifically assess the impact of Computer Vision for Identification, Inspection and Sorting activities
- Hypothesizing the role of AI in the future

A particular attention has been taken for Computer Vision, integrated in Robots and empowered with Machine Learning to recognize products and to speed up sorting operations, since in the literature was the topic more analyzed.

4.2 Analysis of Findings

During the conducted interviews many insights have been collected regarding the applications of AI in Reverse Logistics context. Specific industries have showed their interest regarding some applications, while others pointed out the limitations of the technology regarding both investment and operational viability.

Figure 19 depicts a summary of the interviewed experts and the main themes identified.

Summary of Interviews

Industry	Company	Interviewee's role	Main insights
Strategy & Management Consulting	Accenture	Manager	Overview of applications in different industries
Fashion	Miroglio	Reverse Logistics Coordinator	AI as solution to current bottlenecks
Automotive	Tire's production company	Plant Maintenance Coordinator	Possible implementation of AI in tires industry
Retail	Physical and e-commerce retailer	Reverse Logistics Operator	Limits of computer vision with wide input variety
Waste Management	Amiat (Iren)	Recycling Plant Engineer	How to use computer vision in waste recovery

Figure 19 - Interviews summary

4.2.1 Consultants’ perspective on the role of AI

During an insightful interview with a Manager at Accenture specialized in the Consumer Goods and Services practice, key observations were made about the state of reverse logistics technology in the market. During his experience with various business models of leading Italian companies, he noticed a general underutilization of reverse logistics across sectors. For instance, in the cosmetics industry, return processes are seldom integrated into the value chain, whereas in the food industry, returned products are primarily repurposed as animal feed with minimal quality controls.

He emphasized the unique requirements of different Industries in Implementing reverse logistics and he ranked the electronics sector as the most critical in terms of reverse logistics value, followed by fashion and automotive, with pharmaceuticals also receiving special attention.

In consumer goods, he identified network design and the collection phase as particularly challenging. Currently, most recovery paths are singular (e.g., animal feed), and there’s a significant risk of goods being discarded in general waste bins. Conversely, in electronics and hazardous materials, a sophisticated sorting algorithm could be essential for determining the appropriate disposal or recycling pathway due to more structured collection networks and greater public awareness.

The mentioned industry, listed in order of relevance, and the identified AI benefits are summarized in Figure 20.

Industry	Most Critical Phase	Possible Benefits
Electonics	Inspection & Sorting	• Avoid waste hazardous material • Correctly assessing the path for each components
Fashion	Collection	• Generate value from already used material
Automotive	Inspection & Sorting	• Assessing recyclability of components or materials
Pharma	Inspection & Sorting	• Avoid waste materials that do not pass quality checks from different stakeholders

Figure 20 – Possible Benefits of AI in different industries

The main KPIs considered for implementing AI in Reverse Logistics in order of importance are:

- % cost reduction, which is also the main driver
- Possibility of new revenue flow, searching for added value from waste
- % in reduction in goods destined to landfill, as part of sustainability programs

This emphasizes how, even if sustainability is one of the main drivers, companies still choose their projects on economic principles. Merely environmental initiatives are undertaken primarily if imposed by governments or international regulations.

An increasing number of companies are incorporating AI across nearly every stage of their value chain, including sales, data management, operations, sustainability, and smart manufacturing. This integration is facilitating greater data availability across various sectors. He noted that while computer vision is gaining traction in numerous sectors, its applicability in reverse logistics still needs to be determined, depending on the specific industry involved.

However, employee sentiments towards AI are predominantly negative, fueled by concerns that the technology might lead to job losses. Despite these fears, he remains confident that humans will always be essential for managing technology and addressing exceptions. He also highlighted that managing these changes is particularly challenging in Italy, where change management is considered a critical issue.

Looking ahead, he anticipates AI will become a standard feature across all parts of the supply chain, enhancing efficiency, visibility, and stakeholder satisfaction. He concluded by suggesting that now is the opportune time to explore AI's potential in reverse logistics and to prepare strategic plans for the next 5-10 years, especially in light of forthcoming regulations. Early adopters who invest in AI training and case studies are likely to achieve a competitive edge in both the short and long term.

4.2.2 The Fashion return management explained

Following the recommendation of consultants, some expert and reverse logistics operators in the Fashion industry have been contacted to better understand their current processes and capture their opinions on AI.
Initial engagements included brief interviews with managers at the flagship stores of Dior and Hermès in Paris. These luxury retailers highlighted that customer satisfaction is paramount. They provide personalized service at every step of the customer journey, leading to minimal returns. Even in their largest stores, such as those in Paris, no more than two units of any item in the same size are kept, typically stored out of sight to ensure customers receive pristine products. Unsold items are subsequently returned to general warehouses and later dispatched to outlets for the following season.
Both companies are implementing RFID (Radio Frequency Identification) technology, which uses radio waves transmitted by unique tags on each item to enhance inventory management. It allows for the immediate location and traceability of products, facilitating quick identification during store returns, even when items are still packaged.

Subsequently, I had the opportunity to speak with the referent of Reverse Logistics Operations of Miroglio, an Italian fashion retailer holding controlling 9 different brands, who introduce me to their entire chain of processes. She explained that in the present logistics and warehouse management system, SAP serves as the primary enterprise resource planning (ERP) software and stated the importance for every technology to communicate with this system, as they have no intention of changing it for now. Throughout different stages of the garment lifecycle, items are managed and processed according to seasonal cycles—such as Autumn/Winter 2023 and Spring/Summer 2024—making timely and accurate tracking critical. The current RL process primarily involves manual barcode scanning of each returned item which is assigned to a specific box, identified by another barcode. When the box is full the courier is involved to ship it to suppliers' centers, where each item is scanned, newly labeled, packaged and then ship again to Miroglio's main logistics center in Pollenzo (CN). Here products are stored for a period ranging from one to five months before going to outlets. If the products are not purchased in Outlets, they are sold to stockists for entering discounted or secondary markets.

Items returned from stores, which account for around 6% of production, which means roughly 650k products, are given a "return kit" and managed by specific ironing vendors, while customer returns, which are easier to manage, are directly delivered in Pollenzo.

Barcode scanners are equipped with digital screens and are used to scan items, print and apply new barcode labels, and facilitate the tracking and organization of goods into batches for shipment. The use of these devices helps ensure that the correct items are processed and shipped to their respective destinations. However, this process is heavily reliant on manual input and susceptible to human error, leading to mismatches between items shipped and items received, as well as issues in inventory accuracy. In addition, it is very time-consuming activities, taking up to a day for the entire process, being considered a real bottleneck.

To resolve this issue, for their luxury brand "Fiorella Rubino" they are implementing RFIDs, as the other luxury brands previously cited, which considerably sped up the process and ensure a more accurate recognition. To identify items with this technology a Faraday's cage has been built and inside the presence of item is collected and reported in the system, substituting the manual process. They consider the investment in RFIDs perfectly affordable so once they will have finished testing them on Fiorella Rubino's products, if the results are as expected, they will implement them to every brand. At the same time, she showed some interest in both computer vision and robots. Indeed, an automated process that reads barcode of boxes at the entrance could signify huge time savings, leading to as many cost reductions. A robot equipped with computer vision could autonomously sort returns and strategically stock them according to demand and destination.

Taking the example of the last robot they introduced in the warehouse, which serves as a sorter for outbound logistics operations and manages 400 orders at a time, she extremely values an automation process for efficiency improvement.

In conclusion, she can imagine a future warehouse where Robots and human operators cooperate, robots with computer vision could be used to read the barcode in a first moment, and, following the full implementation of RFIDs, to assist in extracting items from boxes and managing stock locations and transport.

4.2.3 The challenges of big retailers

Shifting focus to the retail sector, discussions with major companies reveal varied perspectives on the integration of AI in reverse logistics. While these companies possess the resources necessary for such technological implementations, many have not explicitly committed to adopting them.
A Reverse Logistics Operator from a corporation active in diverse retail sectors, ranging from books and electronics to food and fashion, shared insights on the potential integration of AI within their processes. This corporation, with a significant presence across Europe, dedicates only 5% of its warehouses specifically to reverse logistics, indicating that the process is still in its nascent stages. Nevertheless, the designated facilities that manage returns employ a structured approach to analyze and maximize the value of returned items.
Upon arrival at the warehouse, following collection by outsourced courier services from either the client's home or collection centers, each item undergoes an inspection phase. This phase involves operators verifying that the returned item matches the product description in the system and completing a detailed form that begins with the client's reasons for return. Operators are tasked with testing the primary functions of the product to determine whether it can be resold as new, sold in secondary markets, or if it is unsellable. Recognizable issues like stained clothing or electronics with chipped screens are identified quickly, while other items may require more thorough testing procedures, such as powering on and operational checks.
Given the vast array of items the retailer handles, the time required for inspection varies significantly based on each item's characteristics. If a product is deemed unsellable, the software dictates whether it should be refurbished, remanufactured, recycled, or disposed of, with all these processes handled externally.

The evaluation phase, aiming at determining the resale potential of each item, is critical and highlighted as the most challenging due to the need for objectivity and precision, minimizing the influence of operators' subjective judgments and reducing error margins, and taking into account the variability in the non-specialized workforce's evaluations.

In this context, he greatly appreciated the potential of AI for its ability to increasingly refine object classification, continuously adapting to new products' characteristics and features entering the market. However, he highlighted that the substantial variability in inputs currently prevents AI from fully replacing human oversight. The significant costs associated with accurately training AI to recognize every distinct item render it prohibitive given the present technological capabilities, while human operators do not represent heavy expenditures. Nonetheless, he believed that computer vision and AI are practical for companies with a limited range of products to identify. This technology is particularly advantageous for manufacturing companies that control all aspects of their product features directly.

The primary advantages of integrating AI in reverse logistics include increased accuracy and cost reduction, as a more efficient evaluation process preserves more value, offsetting the high costs associated with returns. While time is not deemed a critical factor in either the collection or evaluation phases, the potential of AI to improve resource allocation across reverse logistics and broader warehouse operations was acknowledged as another significant benefit.

4.2.4 The automotive sector: insights from the tire industry

Within the industrial processes, an analysis of tire recycling and maintenance operations at one of the main pneumatics players in Europe has been conducted. Insights drawn from an interview with the Maintenance Coordinator in one of the Italian Facilities are used to delve into current practices, challenges, and technological innovations shaping the future of tire recycling and industrial maintenance.

The approach to tire recycling involves a shift towards using less chemical-intensive and more organic materials to facilitate easier recycling and avoid landfill taxes on disposed items. Currently, the only paths available for used tires are in blast furnaces for energy recovery or contributing to cement manufacturing, especially for kids' playgrounds, or repurposing them into mats for vehicle interiors. In Europe, tire recycling focuses on retreading for trucks rather than cars, due to safety concerns related to high-speed tire bursts.

Despite advancements, there are significant gaps in the technology used for tire recycling. Currently, no machines can accurately assess the status of tires, which is a crucial step for effective material recovery. However, AI presents a promising solution by potentially serving a critical role in evaluating tire condition, monitoring internal temperatures, and analyzing wear patterns based on different road types.

The company is currently applying AI and machine learning techniques, also through the aid of computer vision, in many of its production processes. In 2020 it launched an initiative to collect extensive process data to refine AI applications in machinery and material vision within tires. Development is underway to enhance the accuracy of material presence and placement detection, improving operational efficiency across facilities. Innovations such as Amazon's conveyor belt monitoring system illustrate the potential of AI to predict and prevent equipment failures. Additionally, the use of cameras and AI in quality control is growing, focusing on meticulous monitoring to ensure product integrity and reduce waste. However, since the reverse logistics pathways are still few and almost not developed, he does not see an immediate value in implementing AI for those purposes.

He sure sees a future in which AI will have a predominant role, especially in production phases, but also in recycling activities, but this could be distant in time and not without challenges. Having efficiency as the main driver, the company will have to deal with a demand for more specialized personnel always increasing, while un-qualified workforce will be replaced by machines.

4.2.5 AI and waste management how does it work in Turin, Italy

Companies can take inspiration from waste management organizations that are at the forefront of implementing reverse logistics activities and have been focused on enhancing efficiency for some time. As illustrated by the following example of a recycling plant in Italy, integrating innovative practices can significantly improve the recovery of various materials, showcasing how technology and efficient processes are critical in advancing waste management.

In Turin, the responsibility for waste management falls to AMIAT ("Azienda Multiservizi Igiene Ambientale Torino"), a subsidiary of the energy company Iren, which is primarily owned by the municipalities of Turin, Genoa, and several smaller cities. AMIAT handles the management of specific types of waste including plastics, bulky items, and electronic waste, while it oversees only the collection of paper, organic, and other waste types, which are then processed by other entities within the Iren Group.

AMIAT operates three main recycling plants located in the greater metropolitan area of Turin, beyond the city limits. These plants are pivotal in the region's waste management strategy:

- Circular Plastic plant in Borgaro Torinese, one of the biggest plants for selection and storage of plastic in Italy
- Plant for Recovery of Materials in Collegno, with the specific focus on plastic packages, but also iron and wood
- Plant for e - waste in Volpiano, dedicated to different categories of electronics (washing machines/dishwashers, TVs/Monitors, Computers/Smartphones and other small appliance)

At the first plant, plastic waste is sorted into three size-based categories. The smallest items are first sieved to remove particles that are too tiny and then processed through optical readers that identify and select packages suitable for valorization. Intermediate-sized items are weighed to classify them into rigid or flexible types and further sorted, using 22 computer vision systems, into 17 distinct categories based on the type of polymer and color. A manual inspection is conducted as the final step to ensure quality control. The largest items are handled directly by operators.

Once the sorting process is complete, the separated items are compressed into uniform bales of single materials. These bales are then stored and subsequently transported to specialized consortia that recycle the materials into new products.

While the second plant continues to depend on manual activities, an engineer from the third facility located in Volpiano has shared insights into their use of collaborative robots for managing e-waste. This plant, with an operational capacity of 22 tons per year, aims to treat waste by removing hazardous materials and extracting valuable fractions such as copper, iron, aluminum, plastics, glass, wood, boards, and electronic components to maximize material recovery.

The process for handling dishwashers and washing machines involves removing dangerous materials and then disassembling them into components. Computers, smartphones, printers, and other small appliances are crushed to recover materials. Meanwhile, TVs and monitors are dismantled by cooperative robots. In 2020, the facility launched an innovative experiment in collaboration with HIRO Robotics, focusing specifically on the treatment of Flat Panel Display (FPD) TVs and monitors. HIRO Robotics is an Italian startup that has developed a new patented system for guiding robots through computer vision, designed to enhance accuracy, increase productivity, and improve the quality of operations.

The engineer explained that manual processing involves significant labor costs due to the poor ergonomics of the tasks and the lengthy times required for recycling, which lead to high material recovery costs. With the introduction of this robotic solution, system performance is expected to improve several lines, yielding economic and environmental benefits.

The project entails revamping the line dedicated to disassembling Flat Panel Displays by introducing a semi-automated robotic line that employs intelligent vision systems to unscrew specific parts/components of the device, such as plastic frames and internal electronic components. Utilizing artificial intelligence, the robot is capable of progressively improving its performance as it acquires new data with each product inspection. It could also be trained to recognize the characteristics of newer TV or monitor models in advance.

The engineer highlighted that AI is increasingly used in the sector, with operators primarily needed to manage exceptions and ensure quality control across all lines. While specific tasks related to a minority of objects will still require human intervention, for standardized operations, AI, especially implemented in robots equipped with computer vision, will be essential. This integration not only streamlines processes but also enhances efficiency and precision in material recovery.

5. A convolutional neural network for Identification, Inspection & Sorting

5.1 Proposed approach

In literature reviews on Reverse Logistics and the application of AI in its various phases, as well as in interviews with industry experts, Identification, Inspection, and Sorting have been identified as the most critical phases across numerous sectors, particularly in electronics, automotive, and fashion industries.

To understand the real impact of AI technology in making accurate and efficient decisions in the least possible amount of time in these steps, the example of waste management has been replicated to derive considerations applicable to industries seeking to improve their reverse logistics processes.

A Convolutional Neural Network (CNN) has been developed to recognize images of inputs and categorize them into predefined clusters. In this way, the operating time to assess the typology of the object could be considerably reduced, and human intervention could be required only to handle exceptions.

The differences between an automated process and a completely manual one have been compared conducting the same analysis over a sample of people.

The objective for both the algorithm and participants was to identify the typology of waste depending on the material, as if recycling bins did not exist, and divide them into glass, plastic, paper, metal and trash.

Finally, considerations on further applications of this technology have been analyzed and discussed for different sectors.

5.2 Algorithm’s description and results

In this chapter, the comprehensive steps taken to develop and evaluate an AI-based waste recognition system are presented.

An appropriate dataset has been identified on which a model based on Convolutional Neural Network has been tested multiple times to find the optimal parameters. Subsequently, some experimental trials with human participants have been conducted to finally compare the performances of AI against manual sorting.

5.2.1 Dataset acquisition

The first step included the research for publicly available datasets of waste images that comprehend all categories (paper, plastic, glass, metal, trash) with an exhaustive representation.

The selected one was found on the platform Kaggle and it was used by a programmer to develop a similar algorithm for waste classification. (Kaggle, 2023)

The database consists of 2,527 images in JPEG format with the following distribution per category:

- Cardboard: 403 images
- Glass: 501 images
- Metal: 410 images
- Paper: 594 images
- Plastic: 482 images
- Trash: 137 images

Even though trash is less represented in this dataset, between the other alternative overall it has been considered enough complete.

However, during the training part of the model, image data augmentation was necessary to enlarge the database and ensure an adequate volume of data.

Lastly, before running the training development phase some images have been taken out the original set to construct the testing database. It is crucial that after the learning phase, the model is tested on images never encountered before. So, a new folder containing 220 images (40 for the first five groups and 20 representing trash) has been created.

In the following some sample images from the database have been reported.

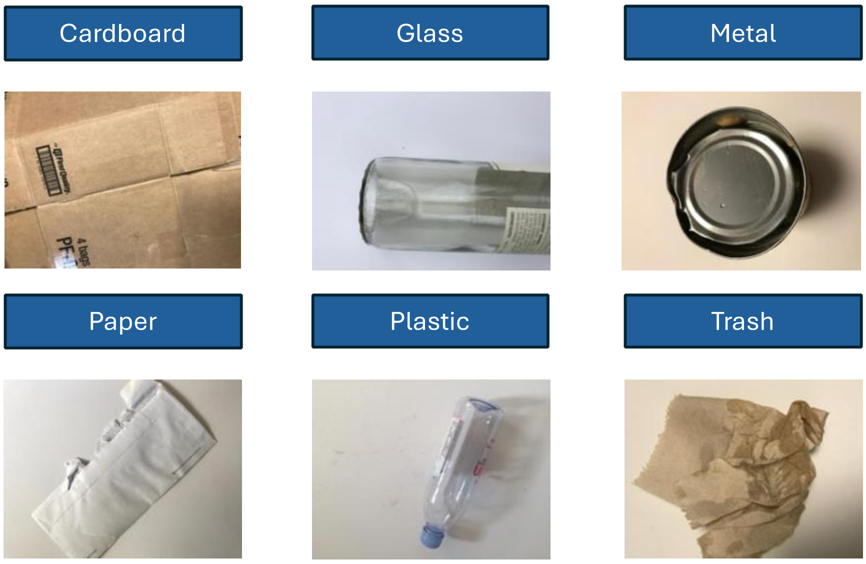

Figure 21 - Examples of images per category

5.2.2 The convolutional neural network code

In the following a description of the developed code is provided.

The algorithm was developed in Python coding language on Google Colab environment. This choice has been made in order to exploit the potentialities of a GPU processor, which ensures faster performances than a normal CPU and avoid overloading the computer.

```
import os
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
from PIL import Image
from sklearn.model_selection import train_test_split
import numpy as np
from tensorflow.keras.models import Model
from sklearn.model_selection import StratifiedKFold
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout, Input
from tensorflow.keras.optimizers.schedules import ExponentialDecay
from tensorflow.keras.callbacks import LearningRateScheduler, EarlyStopping, ModelCheckpoint, ReduceLROnPlateau
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from google.colab import drive
drive.mount("/content/drive")
```

Figure 22 - Importing libraries

In Figure 22, the needed libraries to run the code have been imported. Tensorflow has been used to build the machine learning model as it offers a comprehensive suite of tools and libraries for developing neural networks and other machine learning algorithms. Keras, a high -level API for TensorFlow has been chosen for its simplicity in the process of building and training neural networks. From Keras various layers that construct the model itself can be selected depending on the function of each layer.

- **Conv2D** is used for convolutional layers to extract features and detect patterns such as edges, textures and shape;
- **MaxPooling2D** for pooling layers to reduce the spatial dimensions and retain the essential features, reducing computational complexity,
- **Flatten** for flattening inputs to convert the output of previous layers into a 1D vector;
- **Dense** for combining the features extracted, connecting neurons and produce the final output with the predicted category;
- **Dropout** for regularization and prevention from overfitting, selecting a random fraction of inputs;
- **Input** for model input specification.

In Keras different method could be used to improve the training process, such as varying the learning rate or scheduling, stopping the process if the performances do not improve and saving the best version of the model. These functions are imported from the library "callbacks" of Keras.

Finally, the function from sklearn.model_selection are added to perform a k-fold cross validation, ensuring each fold has an equal distribution of classes in the dataset of both training and validation. This is crucial in imbalanced databases as the categories could not be represented enough if a random distribution is utilized.

The cross – validation technique has been used to train the model multiple times using different subsets or folds and provide better estimation regarding the performance and generalizability of the model.

```
!ls /content/drive/MyDrive/dataset-resized/

dataset_path = '/content/drive/MyDrive/dataset-resized/train/'
dataset_val='/content/drive/MyDrive/dataset-resized/test/'

if not os.path.exists(dataset_path):
    print(f"Training data path does not exist: {dataset_path}")
else:
    print(f"Training data path exists: {dataset_path}")

IMAGE_WIDTH = 150
IMAGE_HEIGHT = 150
IMAGE_CHANNELS = 3
BATCH_SIZE = 64
EPOCHS = 50
TRAIN_DATA_PATH = dataset_path
```

Figure 23 - Parameters definition

Next, to smooth the process the database was uploaded on Google Drive and access has been granted to both sets, training and testing. Some parameters have been defined for images size, as well as batch sizes for training and the number of epochs the algorithm should run to learn, Figure 23.

```
def load_and_preprocess_image(path):
    try:
        image = tf.io.read_file(path)
        image = tf.image.decode_jpeg(image, channels=3)
        image = tf.image.resize(image, [IMAGE_HEIGHT, IMAGE_WIDTH])
        image = tf.cast(image, tf.float32) / 255.0
        return image
    except tf.errors.NotFoundError:
        print("File not found:", path)
        return None


def get_filenames_and_labels(directory):
    filenames = []
    labels = []
    class_names = sorted(os.listdir(directory)) [1:] # Make sure directory only contains valid class folders
    label_dict = {name: index for index, name in enumerate(class_names)}

    for label_name in class_names:
        class_dir = os.path.join(directory, label_name)
        class_files = [os.path.join(class_dir, name) for name in os.listdir(class_dir) if
                       name.endswith(('.png', '.jpg', '.jpeg'))]  # Make sure to filter only image files
        filenames.extend(class_files)
        labels.extend([label_dict[label_name]] * len(class_files))

    return filenames, labels, class_names
```

Figure 24 - Images loading functions

Two functions are then defined to elaborate images from the dataset in preparation to be put as input in the machine learning model, Figure 24.

The first, “load_and_prepocess_image” reads the image, then it converts it from jpeg to a format processable by TensorFlow, resized the image and normalize it to ensure stability. In the end the management of exception is guaranteed, and the process is stopped if the file cannot be found.

The second function, “get_filenames_and_labels” extracts the file path and corresponding label stored in the dataset. It retrieves the names specified in the subdirectory and sort them to derive the list of present classes, then each class is mapped and file paths, their associate labels and class names are retuned.

```
# Function for data augmentation
def augment_image(image, label):
    image = tf.image.random_flip_left_right(image)
    image = tf.image.random_flip_up_down(image)
    image = tf.image.random_brightness(image, max_delta=0.2)
    image = tf.image.random_contrast(image, lower=0.95, upper=1.05)
    image = tf.image.random_saturation(image, lower=0.95, upper=1.05)
    image = tf.clip_by_value(image, 0.0, 1.0)
    return image, label

def create_datasets_for_fold(train_files, train_labels, val_files, val_labels, class_names):
    # Creating file datasets for both training and validation
    train_data = tf.data.Dataset.from_tensor_slices((train_files, train_labels))
    val_data = tf.data.Dataset.from_tensor_slices((val_files, val_labels))

    # Apply the original function to prepare datasets
    train_dataset = train_data.map(lambda x, y: (load_and_preprocess_image(x), tf.one_hot(y, depth=len(class_names))))
    validation_dataset = val_data.map(lambda x, y: (load_and_preprocess_image(x), tf.one_hot(y, depth=len(class_names))))

    #Create augmented datasets
    augmented_datasets = [train_dataset.map(augment_image) for _ in range(18)]  # Create 18 augmented datasets for train
    augmented_datasets_val = [validation_dataset.map(augment_image) for _ in range(18)]

    # Concatenate original and augmented datasets
    full_train_dataset = train_dataset.concatenate(augmented_datasets[0])
    for aug_dataset in augmented_datasets[1:]:
        full_train_dataset = full_train_dataset.concatenate(aug_dataset)
    full_val_dataset = validation_dataset.concatenate(augmented_datasets_val[0])
    for aug_dataset in augmented_datasets_val[1:]:
        full_val_dataset = full_val_dataset.concatenate(aug_dataset)

    # Batch the datasets
    train_dataset = full_train_dataset.shuffle(buffer_size=1024).batch(BATCH_SIZE).prefetch(tf.data.AUTOTUNE)
    validation_dataset = full_val_dataset.shuffle(buffer_size=1024).batch(BATCH_SIZE).prefetch(tf.data.AUTOTUNE)

    return train_dataset, validation_dataset
```

Figure 25 - Data augmentation & creation of training and validation datasets

Since the dataset was not large enough to train a machine learning model a process of data augmentation has been implemented though the functions shown in Figure 25.

With the first function “augment_image” the image, taken from the dataset, is randomly flipped in all directions, then its brightness, contrast and saturation are changed, and its final pixel dimensions are checked after augmentation.

In “create_datasets_for_fold” function, two datasets are created one for training and the other for validation including the augmented images. 18 sets of augmented images have been added to the original database for training and validation and the final datasets is then batched, shuffled and prefetched. In this way the training and validation images summed are around 44,000 which is enough to capture the characteristics of each kind of waste.

```
def build_model(num_classes):
    model = tf.keras.Sequential([
        Input(shape=(IMAGE_HEIGHT, IMAGE_WIDTH, IMAGE_CHANNELS)),
        Conv2D(32, (3, 3), activation='relu'),
        MaxPooling2D(2, 2),
        Dropout(0.35),
        Conv2D(64, (3, 3), activation='relu'),
        MaxPooling2D(2, 2),
        Dropout(0.35),
        Conv2D(64, (3, 3), activation='relu'),
        MaxPooling2D(2, 2),
        Dropout(0.35),
        Conv2D(128,(3,3), activation='relu'),
        MaxPooling2D(2,2),
        Dropout(0.35),
        Conv2D(128,(3,3), activation='relu'),
        MaxPooling2D(2,2),
        Dropout(0.35),
        Flatten(),
        Dense(512, activation='relu'),
        Dropout(0.8),
        Dense(num_classes, activation='softmax')
    ])

    initial_learning_rate = 0.0001
    lr_schedule = ExponentialDecay(
        initial_learning_rate,
        decay_steps=1000,
        decay_rate=0.97,
        staircase=True)

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=lr_schedule),
        loss='categorical_crossentropy',
        metrics=['accuracy']
    )

    return model
```

Figure 26 - CNN model

The model of the convolutional neural network is built and shown in Figure 26, using as input shape the characteristics of the image previously defined. Five convolutional layers with increasing number of filters (32,64,128) are followed by a max pooling layer to downsample the features maps. Dropout Layers are applied to randomly drop a percentage, firstly 35% and in the end 80% for the fully connected layer, of neuron outputs during training to prevent from overfitting. The Flatten layer converts the feature maps into a 1D vector, preparing the data for the fully connected layers, while the Dense layers are used for classification.

An exponential decay with Adam optimizer has been defined, decreasing the rate at discrete intervals dictated by decay_steps. The same optimizer has been used to compile the model, while categorical_crossentropy was used as loss function and accuracy as evaluating metric. This constitutes a Sequential Keras model suitable for image classification.

```python
def perform_cross_validation(filenames, labels, class_names, num_folds=5):
    skf = StratifiedKFold(n_splits=num_folds, shuffle=True, random_state=42)
    fold_no = 1
    results = []

    num_classes= len(class_names)

    for train_index, val_index in skf.split(filenames, labels):
        print(f"Training on fold {fold_no}...")

        train_files, val_files = filenames[train_index], filenames[val_index]
        train_labels, val_labels = labels[train_index], labels[val_index]

        # Create datasets for this fold
        train_dataset, validation_dataset = create_datasets_for_fold(train_files, train_labels, val_files, val_labels, class_names)

        # Build a new model for this fold
        model = build_model(num_classes)

        reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=3, min_lr=1e-6)
        early_stopping = EarlyStopping(monitor='val_accuracy', patience=7, restore_best_weights=True)
        checkpoint = ModelCheckpoint('best_model.keras', monitor='val_loss', save_best_only=True)

        # Train the model
        history = model.fit(
            train_dataset,
            epochs=EPOCHS,
            validation_data=validation_dataset,
            callbacks=[reduce_lr, early_stopping, checkpoint]
        )

        # Evaluate the model on the validation dataset
        loss, accuracy = model.evaluate(validation_dataset)
        print(f"Fold {fold_no} - Loss: {loss}, Accuracy: {accuracy}")

        results.append((loss, accuracy))
        fold_no += 1

    return results
```

Figure 27 - Cross validation training

In order to create an accurate model a cross-validation function has been implemented to assess how well the model generalize to unseen data, Figure 27. It involves partitioning the dataset into multiple subsets (folds), training the model on some of these, and evaluating it on the remaining ones. This process provides more reliable estimates of model performances compared to a single train-test split. To preserve the percentages of classes in each fold a stratified fold has been implemented and callbacks are defined to monitor and improve the process. The early stopping function has been used to prevent from wasting GPU power over a model experiencing overfitting, once the accuracy is not improved after seven epochs the model continues to the next fold.

For each fold the model is evaluated on the validation set and the results are printed with the fold accuracy and loss.

```python
def main():
    # Check data paths
    if not os.path.exists(TRAIN_DATA_PATH):
        raise Exception(f"Training data path does not exist: {TRAIN_DATA_PATH}")

    filenames, labels, class_names = get_filenames_and_labels(TRAIN_DATA_PATH)
    filenames = np.array(filenames)
    labels = np.array(labels)

    # Perform cross-validation
    results = perform_cross_validation(filenames, labels, class_names, num_folds=2)

    # Print the average performance across all folds
    avg_loss = np.mean([result[0] for result in results])
    avg_accuracy = np.mean([result[1] for result in results])
    print(f"Average Loss: {avg_loss}, Average Accuracy: {avg_accuracy}")

if __name__ == "__main__":
    main()
```

Figure 28 - Main function

In the main function, Figure 28, an exception is raised if the training data path is not found, the images are elaborated, and cross validation is performed. Finally, after the last fold the average loss and accuracy is presented stating the performances of the model.

In Figure 29 an example of the first epochs has been reported.

```
Training on fold 1...
Epoch 1/40
236/236 [==============================] - 130s 510ms/step - loss: 1.6580 - accuracy: 0.2993 - val_loss: 1.6372 - val_accuracy: 0.3555 - lr: 1.0000e-04
Epoch 2/40
236/236 [==============================] - 125s 508ms/step - loss: 1.4179 - accuracy: 0.4267 - val_loss: 1.4557 - val_accuracy: 0.4230 - lr: 1.0000e-04
Epoch 3/40
236/236 [==============================] - 149s 617ms/step - loss: 1.2898 - accuracy: 0.4900 - val_loss: 1.3758 - val_accuracy: 0.4388 - lr: 1.0000e-04
Epoch 4/40
236/236 [==============================] - 146s 608ms/step - loss: 1.2236 - accuracy: 0.5329 - val_loss: 1.3305 - val_accuracy: 0.4652 - lr: 1.0000e-04
Epoch 5/40
236/236 [==============================] - 146s 611ms/step - loss: 1.1428 - accuracy: 0.5685 - val_loss: 1.2901 - val_accuracy: 0.4747 - lr: 9.7000e-05
Epoch 6/40
236/236 [==============================] - 151s 624ms/step - loss: 1.0794 - accuracy: 0.5984 - val_loss: 1.2684 - val_accuracy: 0.4907 - lr: 9.7000e-05
Epoch 7/40
236/236 [==============================] - 124s 514ms/step - loss: 1.0165 - accuracy: 0.6285 - val_loss: 1.2173 - val_accuracy: 0.5302 - lr: 9.7000e-05
```

Figure 29 - Training phase running example

The results, including training and validation loss together with training and validation accuracy and learning rate, are printed for each epoch.

Several trials have been conducted in this phase to find the optimal solution, avoid overfitting, and ensure a stable learning process. The experiments involved varying the dropout percentage, batch size, learning rate, number of epochs, size of the augmented sets, and adding or removing layers to the convolutional model.

Finally, once an acceptable level of accuracy had been reached, the prediction class has been developed to test the model on the unseen images.

```python
model = tf.keras.models.load_model('best_model.keras')
class_names = ['cardboard', 'glass', 'metal', 'paper', 'plastic', 'trash']

def predict_all_images(data_directory):

    predictions = []
    true_labels = []

    for class_index, class_name in enumerate(class_names):
        class_path = os.path.join(data_directory, class_name)
        image_files = [os.path.join(class_path, fname) for fname in os.listdir(class_path)]

        for image_file in image_files:
            img = load_and_preprocess_image(image_file)
            if img is not None:
                img_array = tf.expand_dims(img, axis=0)  # Add a batch dimension
                prediction = model.predict(img_array)[0]
                predicted_class_index = np.argmax(prediction)
                predictions.append(predicted_class_index)
                true_labels.append(class_index)

    return true_labels, predictions

def plot_confusion_matrix(true_labels, predictions, class_names):
    cm = confusion_matrix(true_labels, predictions)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=class_names)
    disp.plot(cmap=plt.cm.Blues)
    plt.title('Confusion Matrix')
    plt.show()

if __name__ == "__main__":
    data_directory = dataset_val
    true_labels, predictions = predict_all_images(data_directory)

    for true_label, predicted_label in zip(true_labels, predictions):
         print(f'True class: {class_names[true_label]}, Predicted class: {class_names[predicted_label]}')

    class_names = ['cardboard', 'glass', 'metal', 'paper', 'plastic', 'trash']
    plot_confusion_matrix(true_labels, predictions, class_names)
```

Figure 30 - Testing code

In figure 30, the code for the predictive analysis has been reported. The model is firstly loaded, the class are specified in alphabetical order to ensure consistency with the initial part of the training model and then a prediction on each image in the folder is made.

In order to understand to which category the file is from, they are divided by typology into different subfolders so that the image path contains the belonging class.

The true and the predicted class are finally printed and compared to test the accuracy of the model. In addition, a confusion matrix has been defined to capture where the algorithm makes mistakes and which classes are more often confused.

5.2.3 Algorithm Results

The final training phase, with the best version of the model, ended in around 2 hours and 15 minute per fold with a training accuracy of 85.9% and a validation accuracy of 72.1%. These results came from a cross – validation of the model consisting of 2 folds.

In the testing phase 220 new image are analyzed by the algorithm in 1 minutes and 34 seconds showing the following results for each file.

- Accuracy: 72%
- Execution time: 0,43 seconds per object

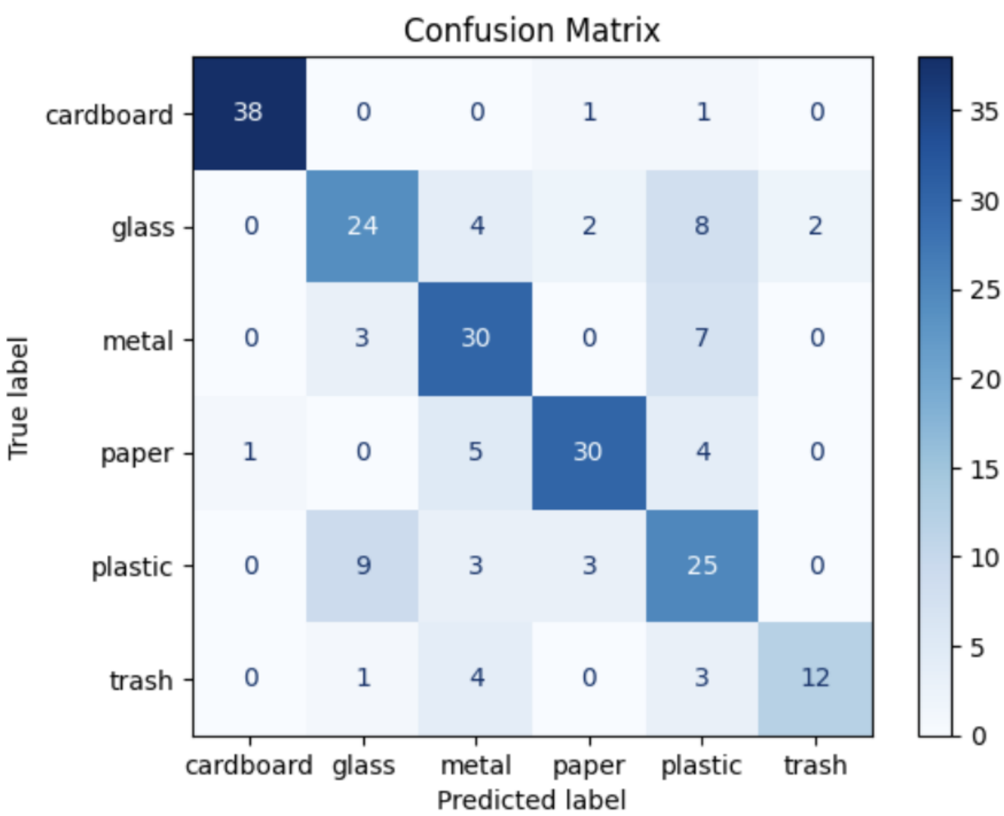

Figure 31 - Confusion Matrix

As depicted in the confusion matrix in Figure 31, different categories have been recognized by the algorithm. In particular:

- 95% of cardboard images are correctly identified
- 60% and 62.5% of accuracy has been reported for plastic and glass respectively, which seem to be often confused
- 75% of metal is precisely recognized, with some identified confusion with plastic
- 75% of paper is correctly assessed, even though some characteristics make it similar to metal and plastic.
- 60% of trash is well recognized, having a sample of just 20 images the number seems lower with respect to the others.

The confusion between glass and plastic could be further improved with a finer tuning model, taking into consideration that they have common characteristics and that human operators could easily solve this confusion.

5.3 Human participants experiment

A comparison with a process entirely manually held is conducted to understand which could be the benefits in terms of time and accuracy.

The experiment was taken on 4 people aged between 25 and 61, all particularly careful around recycling. Every participant declared to know how to recognize different type of waste as they all do this every day by at least 10 years. In this way they could be considered almost as fast as waste operators.

The categories chosen for the experiments are paper, plastic, glass, metal and trash.

Each person was timed while assessing the nature of waste in the fastest way, resembling a real operator. They were instructed not to read the instructions on recycling on packaging and to rely on their knowledge.

The first experiment was taken with 35 objects from different categories including:

- Plastic: 16 objects
- Paper: 11 objects
- Trash: 7 objects

Figure 32 - Experiment num.1 sample

Participant	Total Time needed (s)	Time per object (s)	Number of wrong objects	Accuracy
1	31,68	0,90	2	94%
2	36,59	1,04	3	91%
3	28,52	0,81	4	88%
4	30,26	0,86	2	94%
Average	**31,76**	**0,90**	**2,75**	**92%**

Table 1 - Experiment num.1 results

The participants, given the experience, recognized quickly the object's category with a precision around 90%. However, it took to each of them almost a second to assess each object and this could be biased by the peculiarity of the occasion. In an everyday scenario of a real operator it could take more time.

The major mistakes have been seen in the differences between trash and paper or plastic, which are often confused by humans and not by the algorithm.

A second experiment with the same participants was conducted to compensate the lack of metal and glass categories of the first and to resemble more the process undertaken by the algorithm. A set of 34 objects to be identified was constructed and it included:

- Plastic: 11 objects
- Paper: 9 objects
- Glass: 3 objects

- Metal: 5 objects
- Trash: 6 objects

Figure 33 – Experiment num.2 sample

Participant	***Total Time needed (s)***	***Time per object (s)***	***Number of wrong objects***	***Accuracy***
1	60,44	1,78	3	91%
2	72,73	2,14	4	88%
3	58,12	1,71	4	88%
4	65,37	1,92	2	94%
Average	**64,17**	**1,89**	**3,25**	**90%**

Table 2 - Experiment num.2 results

In this second case since the class have increased the participants recognized less easily the involved objects, more than doubling the time needed to identify them all. The accuracy remains around 90% with mistakes often made in differentiating trash and plastic or paper. Other confusions regard the identification of metal and plastic, or paper and plastic. However, these last ones seem less recurrent than the issues in recognizing trash.

The experiments prove the validity of the algorithm since the operating time is drastically reduced and a combination of the two, humans and technology, could be advantageous due to the compensation of mutual errors. In Table 3 a summary of the results obtained with the algorithm and with a manual process are compared.

	Manual Process	CNN algorithm
Number of objects	35	220
Total Time (s)	47,97	94
Time per object (s)	1,37	0,43
Accuracy	91%	72%
Mistaken Categories	glass/plastic	paper+plastic/trash

Table 3 - Comparison between results of manual and automated processes

There is a time saving of almost 70% in the implementation of the algorithm, while accuracy is reduced of 21%. This reduction in accuracy could be easily solved including human operators at the end of plastic and glass path to manage the errors of the algorithm, since the participants in the experiments never confused these categories.

A hypothetical process with mixed sorting, an initial automated sorting and a second manual check, which will solve the previously mentioned problem between glass and plastic and ensure a 90% accuracy on the other errors, will result in a process with:

- 98% accuracy
- Total added time: 83 seconds for 61 unrecognized objects
- New time per object: 0,8 seconds

In this way almost the totality of objects will be recognized reducing the needed time of 42% and allowing the process to sort a larger volume of items with an increase in accuracy of 9%.
Specific algorithms with different features depending on the need could reach higher performances than the presented algorithm, increasing the improvement in time and accuracy.

5.4 Next steps

Based on the example conducted for general waste management, it is possible to draw some general conclusions applicable to various fields.
The experiment was carried out to develop an algorithm that could recognized different typologies of objects mimicking a real situation. Exploiting the knowledge around waste management further improvements could be developed to enhance reverse logistics,

especially in sectors like electronics or industries with electronic components. Indeed, hazardous waste and small electronics components could be dangerous if incorrectly collected and disposed, and the system is quite aware of these circumstances. Robots have been developed to help assessing the viability of the returned components and the technology is ready to assist companies with image recognition, automated disassembly and categorization. Companies in these segments could leverage technology already proven by organizations and cooperatives like AMIAT to derive recycled material, components or small parts that can be included in their production chain. In this way the dependence on virgin material will be reduced, cost will drop, and a sustainability goal will be accomplished.

Considering the number of industries included in this spectrum it is possible to take into account not only mere electronics, but also automotive, aerospace, and other transportation sectors, telecommunication and industrial automation, which all have to deal with electronic components ranging from simple resistors and capacitors to complex integrated circuits and microprocessors.

Shifting the attention to the fashion industry it seems that the interest is as strong as the other segments, but the technology they may seek will be developed more for automation purposes than recycling ones. The identified need of the interviewed organization relies on recognizing which items are returned and where to store them. Since in this phase their objective is to capture value selling the product, the price tag will be probably still tied to it and a reader machine or robot with computer vision could identify the return, define a storage spot and analyze data gained by reading the returning label. In the present this represent a viable solution.

If in the future they will need to assess the quality of materials to re-enter the supply chain or exploit unsold items to create a new design, an AI algorithm with a convolutional neural network could be useful to assess the fabric purity, its shape and colors of thousands of items in few minutes.

Nevertheless, the retail industry seems to be the one with most challenges since the high variability of inputs, currently unmanageable by a reliable algorithm of image recognition. Other AI characteristics, such as objective evaluation, strategic allocation of resources and demand forecasting, are more needed in this sector.

6. Conclusions

Reverse logistics is a key component in the implementation of a circular economy model, offering significant potential for generating revenue and reducing costs through the retention of value in returned products. Historically, high operational costs and limited recognition of its benefits have discouraged from its adoption. However, a shift is occurring, driven by increasingly conscious consumers and government initiatives emphasizing sustainability. This turn has led more companies to integrate reverse logistics into their value chains, recognizing its potential to enhance both economic efficiency and environmental sustainability.

The literature provides numerous examples demonstrating how processes at various stages of reverse logistics can be optimized. Artificial Intelligence (AI) emerges as a possible solution across these stages, offering substantial improvements in efficiency and decision-making. Between the different alternatives artificial intelligence seems the one that can better respond to multiple challenges in this context and whose value can also increase in time. The application of AI varies by industry but consistently shows potential to transform the most repetitive and time-consuming tasks. The main objectives aim at optimizing collection networks and, more importantly, improving identification, inspection and sorting activities, employing computer vision and AI-driven evaluations to determine the fate of returned items. The foundation of any AI application is robust data. Fortunately, data availability is increasing, allowing more companies to leverage AI to analyze and improve their reverse logistics processes. In particular, computer vision is crucial for companies managing a limited range of returned products and multiple recovery pathways. It enhances the efficiency of sorting processes, from speeding up barcode recognition to assessing the condition and appropriate next steps for each item. AI's capability to assess the most suitable recovery path for each returned item is proving essential, ensuring that materials are reused, recycled, or disposed of in the most effective manner.

Between the different phases of RL the process undertaken after the collection phase has been seen as the most critical, as collecting time is not crucial for the majority of returned products. Objectivity in evaluation, automatization, and standardization have been considered key aspects in this stage and AI could resolve them all.

For many companies, particularly those only beginning to explore AI, integrating advanced technologies into reverse logistics is not immediately apparent. There remains a significant gap in adoption, attributed to the nascent stage of reverse logistics implementation in many sectors. In addition, employees' consideration remains skeptical and arise some concern regarding job losses and the future possible replacement of un-specialized workforce with robots or machines. However, with upcoming regulations likely impacting reverse logistics practices, now is an opportune time for companies to strategically consider how AI can not only comply with these regulations but also drive competitive advantage.

The waste management sector provides valuable examples of how AI can be effectively integrated into reverse logistics. By analyzing and adapting these models, other industries can find ways to address their unique challenges and improve sustainability practices.

It has proven that there is at least a 42% gain in operating time and the possibility to reach a 98% accuracy with the implementation of AI in cooperation with human operators, leading to significant cost reductions.

The key is to leverage this knowledge to decrease the need of virgin materials. At first, some partnership could be made with waste companies for acquiring material without high investments, and after companies could establish their own reverse logistics warehouses using robots with computer vision that accurately identify valuable components.

This strategic approach will not only prepare them for future regulatory requirements but also enable them to capitalize on the economic and environmental benefits that AI-enhanced reverse logistics has to offer.

As a continuation of this work specific challenges related to the identified industries could be further studied and addressed, testing the algorithm in a real work environment.

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Appendix

Interview guidelines

Interview guidelines for Managers and Consultants regarding the integration of AI in Reverse Logistics Processes

Scope: understand propensity of managers to integrate reverse logistics using AI, leveraging benefits and investments

1. **Reverse Logistics**

   a) For managers in companies: Do you have a structured process for reverse logistics/remanufacturing in your company? Which technology do you use?

   b) For consultants: How many companies are familiar with Reverse Logistics technologies? Did you implement some specific projects on this matter? Which technology have you recommended?

   c) Is it integrated with forward logistics or is it considered as a separate process?

   d) Which are for you the most critical phases of reverse logistics? Does the industry usually struggle in this field?

   e) For consultant: is it different for industry to industry? Assess in order of importance the **industry** that in your view would benefit the most by reverse logistics practices and implementation of AI:

   Construction, Retail, Fashion, Consumer Goods, Electronics, Automotive, Pharma

2. **Willingness to Adopt AI Technologies**

   a) For managers: What is your level of interest in integrating AI technologies into your reverse logistics processes? If you already thought about it or already implemented, which technologies you considered?

   b) What factors would increase your willingness to adopt AI in reverse logistics practices?

c) In your opinion, what are the most significant benefits that AI could bring to reverse logistics?

d) Are there any specific success stories or case studies that have influenced your perspective on AI in reverse logistics?

e) What is your perception of competitors regarding reverse logistics processes and management? Do they have a vision of integrating AI?

3. **Evaluation criteria**

a) What are the key criteria and target you would use to evaluate the potential implementation of AI technologies in reverse logistics? (ex. 10% cost savings, 5% increase in productivity)

b) How do you prioritize these criteria (e.g., cost reduction, added value from waste, efficiency improvement, environmental impact, brand image)?

4. **Perceived Challenges**

a) What do you perceive as the main challenges in integrating AI into reverse logistics operations? Readiness, Data availability, Training of staff, Initial investments, organizational changes

b) For consultants: How do these challenges vary by the scale of the operation or the specific industry sector? Do you see industries that are more facilitated or keen to implement them?

5. **Readiness for AI Integration**

a) Do you believe your organization is currently ready to integrate AI technologies into its reverse logistics processes? Why or why not?

b) What steps, if any, has your organization taken towards preparing for AI adoption in reverse logistics?

c) How much for you is the right amount of money that could destined to integrate AI in reverse logistics processes? (as % of total investments or % of revenues)

d) Assess how many of these algorithms have been mentioned in your environment: Convolution Neural Network, Genetic Algorithm, Stochastic programming, Metaheuristics, Deep learning, Robots with computer vision.

6. **Computer Vision for Identification, Inspection and Sorting**

a) Do you consider valuable a technology that recognize returns and suggest the flow to correctly implement a circular economy? Would you use it?

b) How many companies are shifting their interest into identification, inspection and sorting tools? Robots?

c) Time needed by the current process, productivity rate (boxes/hour), accuracy rate, % of employees dedicated to these tasks.

7. **Future Perspectives (Optional)**

a) How do you see the role of AI in reverse logistics evolving over the next five years?

b) What investments or innovations do you think are necessary to fully realize the potential of AI in reverse logistics?