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Machine learning-based automated waste sorting in the construction industry: A comparative competitiveness case study

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ABSTRACT

This article presents a comparative analysis of the circularity and cost-efficiency of two distinct construction material recycling processes: ML-based automated sorting (MLAS) and conventional sorting technologies. Empirical data was collected from two Finnish companies, providing a robust foundation for this comparison. Our study examines the operational specifics, economic implications, and environmental impacts of each method, highlighting the advantages and drawbacks. By leveraging data-driven insights, we aim to illustrate how MLAS can enhance recycling efficiency and sustainability compared to traditional methods. In our cost modeling over a seven-year period, MLAS achieved a cumulative cost of €12.76 million, significantly lower than CS, which incurred €21.47 million, underscoring the long-term cost efficiency of MLAS. The findings underscore the potential for advanced AI technologies to revolutionize waste management practices, offering significant improvements in sorting accuracy, material recovery rates, and overall cost-effectiveness. This analysis provides valuable perspectives for stakeholders in the construction and waste management industries, emphasizing the importance of integrating innovative technologies to achieve higher circularity and sustainability goals.

1. Introduction

The construction and demolition (C&D) industry faces significant challenges in waste management (Zoghi & Kim, 2020). According to Yuan and Shen (2011), the C&D industry has substantial contribution to the global waste stream, including concrete, wood, metals, and plastics, which, if not properly managed, can lead to environmental pollution and resource depletion. Mismanagement of C&D waste, results in harmful environmental effects such as soil and water contamination, air pollution, and greenhouse gas emissions (Chen et al., 2021). Inefficient handling of this waste further squanders valuable resources that could otherwise be recycled or reused. Effective waste management in the C&D industry involves collecting, sorting, and processing construction debris to repurpose it for new projects (Kabirifar et al., 2020). Recycling reduces the need for virgin materials, lowers landfill use, and minimizes environmental impacts and costs.

The growing focus on sustainability has aligned waste management practices with circular economy (CE) principles, emphasizing recycling, collaboration, and the integration of new technologies. CE aims to reduce waste, energy consumption, and environmental harm while promoting economic development (HaitherAli & Anjali, 2024). Recycling and resource recovery are central to this approach, especially in the C&D industry, where waste diversion from landfills and the extended lifecycle of materials can enhance both environmental sustainability and economic efficiency (Arora et al., 2020; Nie et al., 2024). However, technological challenges hinder the full adoption of CE principles in construction (Rodrigo et al., 2024).

Machine learning (ML) is a technology that has been extensively studied in various fields, including waste management. ML involves methods that automatically identify patterns in data to predict trends or make decisions under uncertainty (Murphy, 2012). The synergy between ML and computer vision drives innovation across many sectors, including waste management.

In the C&D industry, ML technologies optimize waste handling processes by estimating recycling rates and predicting generated waste volumes during construction (Farshadfar et al., 2024). Moreover, ML can categorize and identify waste types, automate C&D waste classification, streamlining the sorting process and improving recycling rates (Sirimewan et al., 2024; Davis et al., 2021; Hoong et al., 2020).

Despite the growing interest in ML for construction waste recycling,

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there is little empirical research comparing the performance of ML-based automated sorting (MLAS) with conventional sorting (CS). While previous studies have explored ML for predicting waste generation (Çetin et al., 2021; Talla & McIlwaine, 2022) and classifying materials (Davis et al., 2021), few have examined the economic and environmental benefits of MLAS.

This paper contributes to the empirical study of ML-driven disruptive innovation in the C&D industry. Our study fills these gaps by comparing MLAS with CS, focusing on cost and circularity. Drawing on interviews and case studies with stakeholders from waste management and technology companies, including a Recycling Facility and ZenRobotics (Terex), this research offers valuable insights into the role of ML in improving C&D waste management efficiency. The findings will help industry practitioners align their waste management strategies with sustainable practices and CE principles.

Considering the complexities of integrating ML technologies into C&D waste management, this study addresses the following research questions:

RQ1: What are the environmental advantages of ML-based automated sorting compared to conventional construction and demolition waste sorting from a circular economy perspective (e.g., throughput capacity, sorting and recycling rate, purity, waste type, and quality)?

RQ2: What are the economic advantages (cost) of ML-based automated waste sorting compared to conventional construction and demolition waste sorting?

This paper is structured as follows: Following the introduction, Section 2 presents a literature review. Section 3 describes the research methodology used in this study. Section 4 details the results. The paper concludes with Section 5, offering conclusions of the findings and suggesting potential areas for future research.

2. Literature review

2.1. Waste management in the C&D industry

There are multiple studies of waste management in the C&D industry. Dos Santos Lobatoa et al. (2024) use a bibliometric analysis to explore reverse logistics, emphasizing its ability to recycle 90 % of waste and the need for advanced technologies and partnerships to improve efficiency. Islam et al. (2024) conduct a literature review identifying barriers such as operational limitations, inadequate legislative monitoring, and poor stakeholder collaboration, proposing improved legislative frameworks, robust markets for recycled materials, and innovative management systems. Gumusburun Ayalp and Anaç (2024) employ a bibliometric approach to identify managerial, cultural, and financial challenges, while Victar and Waidyasekara (2024) examine CE strategies in Sri Lanka's construction sector, focusing on modular design and material reuse. Ma & Hao (2024) focus on stakeholder engagement and closed-loop strategies in C&D waste management of China, highlighting the government's role and the importance of secondary material quality. Colmenero Fonseca et al. (2023) discuss regulations, particularly within the European Union, play a key role in promoting sustainability in C&D waste management. For instance, Finnish regulations require recyclers to report waste handling processes, including collected amounts, processing methods, and recycling percentages (Deloitte, 2015), fostering innovation in recycling technologies. These studies collectively emphasize the importance of advanced technologies, regulatory frameworks, and stakeholder collaboration in optimizing waste management.

2.2. ML applications in waste management

In C&D waste management, ML technologies have been integrated to improve recycling and waste handling processes. Çetin et al. (2021) and Talla and McIlwaine (2022) employ neural networks to estimate recyclable material volumes and waste generation during construction, optimizing resource usage and minimizing waste output. Davis et al. (2021) demonstrate the use of deep learning for automated C&D waste classification at worksites, increasing productivity and recycling rates. Similarly, Hoong et al. (2020) apply deep learning to classify recycled aggregate images by composition, enhancing recycling processes. Akanbi et al. (2020) develop a predictive model using deep learning to estimate salvageable materials before demolition, aiding material recovery planning and aligning with CE principles. Farshadfar et al. (2024) emphasize the lack of empirical studies on ML applications in waste management and circular supply chains, identifying this as a critical research gap.

2.3. Gaps in the literature

The review of existing literature reveals significant gaps in the understanding and development of ML applications within the C&D waste management field. Firstly, there is a deficiency of empirical research on the comparative performance of MLAS and recycling systems against conventional manual methods. This gap highlights a critical need for assessing the effectiveness, efficiency, and accuracy of MLAS in handling C&D waste. Secondly, while prior studies have utilized ML for predicting waste generation (Çetin et al., 2021; Talla and McIlwaine, 2022) and classifying materials from digital images (Davis et al., 2021), there has been no exploration of the economic and environmental benefits of MLAS systems compared to conventional sorting. This lack of investigation into the potential cost efficiencies, resource effectiveness, and environmental impact reductions presents a crucial area for research. Addressing these gaps would not only advance our understanding of ML's capabilities in waste management but also underscore the transformative potential of such technologies in promoting sustainable practices within the construction industry.

3. Methodology

3.1. Research method

To investigate the role of ML technologies in enhancing CE practices within the C&D industry, we adopted a deductive case study approach based on qualitative and quantitative data. We selected our case companies through purposive sampling due to their unique characteristics and relevance to our research focus. For the quantitative and economic analysis, we used a comparative cost analysis method (Ali et al., 2013) to evaluate the costs of MLAS and CS. For the environmental analysis, we employed qualitative methods, relying on expert insights and interviews to assess the environmental benefits of each sorting method.

3.2. Case companies

One of the companies, a materials recovery facility based in Finland, is referred to as *Recycling Facility* to maintain confidentiality. Recycling Facility specializes in ML-based automated waste management services within the C&D industry, making it an ideal subject for our study. The focused nature of Recycling Facility's operations allowed for a comprehensive exploration of waste management practices.

Recycling Facility operates two lines of waste management: one for C&D waste and another for commercial and industrial (C&I) waste. Given our focus on C&D waste management, we exclusively investigated their C&D line. This line is fully automated, with ZenRobotics ML-based robots performing the final sorting of C&D waste. Our second case company, ZenRobotics (commercially known as Terex), is a Finnish manufacturer of ML-based waste sorting robots. For simplicity, we will refer to this company as *Zen* in this research. Each Zen recycler unit integrates a variety of sensors, a control unit, and industrial robots. The sensors and control unit work together to guide the robots in selecting specific materials from a waste stream conveyed on a belt and sorting them into multiple containers. The Zen recycler unit employs ML for identifying and manipulating objects and materials, making it a suitable replacement for manual labor in the final sorting stages. Additionally, it can process waste streams without the initial energy-intensive resizing step, due to its capability to handle objects of various sizes and shapes (Lukka et al., 2014).

Fig. 1 illustrates the recycler units including robotic arms that sort different fractions from the belt into containers (ZenRobotics, 2024b).

In Fig. 1, the general concept of robot sorting includes (Lukka et al., 2014; ZenRobotics, 2024b):

Control system- Brain: This central processing unit utilizes data from the sensors to make real-time sorting decisions. It employs ML algorithms to identify objects depending on the users' needs and controls the robots.
Industrial robot: Equipped with grippers, these robots pick up identified materials and place them into appropriate containers.
Recovered fractions: These are the sorted materials separated into different categories for recycling.

Moreover, there is a reject item which is for materials that typically are not recoverable and may serve incinerators.

A recycler unit handles complex waste streams. Its ability to process a variety of objects without initial resizing may reduce energy consumption and increase operational efficiency. In this paper, a Zen system is included to study the impact of MLAS technologies on recycling rates, purity levels, and overall waste management efficiency.

3.3. Data collection

Data collection involved eight semi-structured interviews and two site visits to Recycling Facility. Three researchers, two senior researchers and one junior researcher, interviewed waste management professionals, company management, and operational staff to understand the impact of ML technology on waste management practices in the C&D industry. Each interview was conducted individually, with only one participant interviewed per session, ensuring focused and in-depth discussions. The interviews, lasting from 60 to 90 min, were meticulously transcribed using both automated speech-to-text software and manual transcription techniques.

Additionally, we gathered secondary data using industry-related documents, including company publications, industry reports, relevant news articles, and YouTube videos. Specifically, we analyzed four YouTube videos about C&D waste management, Zen, and Recycling Facility, with a total duration of 77 min. We also reviewed 25 articles about C&D waste management, Zen, and Recycling Facility available online as blogs, and publicly accessible materials. A summary of collected primary data is given in Table 1; please refer to Appendix B for more details.

3.4. Research process

Fig. 2 outlines the systematic steps undertaken in the research study. The process begins with defining the preliminary research questions (RQs) which is followed by the first round of data collection through interviews, Recycling Facility site visit, and secondary sources, providing initial insights and relevant information.

After gathering the initial data, a preliminary analysis is performed, and the authors discuss findings to identify emerging trends and patterns. Based on these discussions, the RQs are refined to align with new insights. Process maps of both ML-based automated and conventional C&D waste sorting are created to visually represent workflows, aiding in data organization and structuring. A second round of interviews, site visits to Recycling Facilities, and data collection is conducted to gather detailed information, building on insights from the first round. The earlier process maps are validated to ensure accuracy, maintaining research reliability.

Next, costs associated with different sorting methods are modeled to analyze financial implications. The implications of using MLAS robots versus CS methods are discussed, focusing on competitiveness and efficiency. After cost modeling, an essential validation step involves cross-checking results with industry benchmarks and consulting interviewees, confirming model accuracy, and reinforcing the study's credibility.

Finally, the research findings, insights, conclusions, and recommendations are reported, presenting a coherent and structured approach to addressing research questions and achieving study objectives.

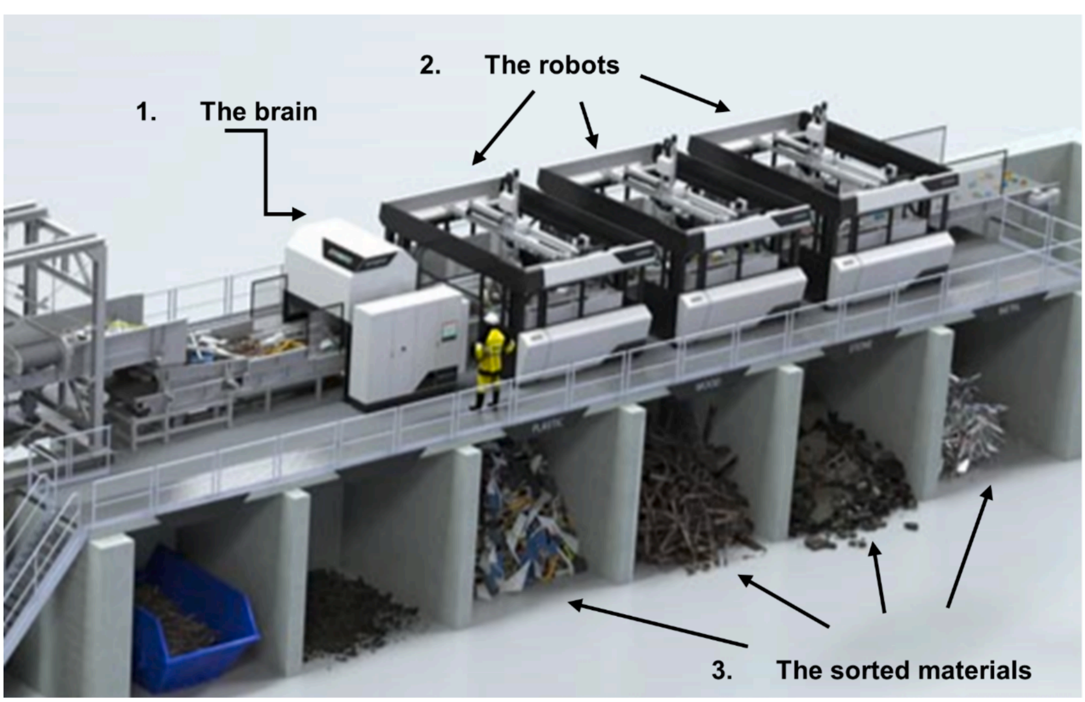

Fig. 1. Zen's ML-based automated recycler unit (courtesy of Terex Company; ZenRobotics, 2024b).

Table 1
Primary data collection through interviews and site visits.

Item	Description	Duration	Interviewee Position	Time span
1	Semi-structured interview with Recycling Facility	1 h and 30 min	Business manager	August 2023
2	Semi-structured interview with Recycling Facility	1 h and 30 min	Production manager	May 2024
3	Semi-structured interview with robot manufacturing company (Zen)	1 h and 15 min	Head of Sales	August 2023
4	Semi-structured interview with robot manufacturing company (Zen)	1 h	General Manager and University Professor	May 2024
5	Circular economy and waste management semi-structured background interviews	1 h and 15 min	University Professor	September 2023
6	Circular economy and waste management semi-structured background interviews	1 h	Senior Scientist	September 2023
7	Circular economy and waste management semi-structured background interviews	1 h	University Professor	September 2023
8	Semi-structured interview about perspective on waste management in construction and demolition projects	1 h	Construction Project Manager	September 2023
9	Recycling Facility visit	1 h and 30 min	Production manager	September 2023
10	Recycling Facility visit	1 h and 30 min	Production manager	May 2024

4. Results and discussion

4.1. Process mapping of C&D waste sorting

Process mapping involves creating a visual representation of an organization's workflow, detailing each step, identifying inputs and outputs, and highlighting roles and responsibilities. This tool helps analyze, understand, and optimize processes to enhance efficiency, quality, and performance. (Hunt, 1996). Based on the analysis of the primary and secondary data (Yuan et al., 2013; Liu et al., 2019; Lu et al., 2021), we mapped a generic process for the C&D waste sorting, which is presented in Fig. 3, where the process starts with the collection of waste material from the sites as a result of construction, demolition, or renovation work on the buildings. Presorting is an essential step performed on the waste at the C&D site. This initial sorting helps in separating the waste into different categories, facilitating further processing. After on-site presorting, the waste undergoes either CS or automated sorting at a C&D recycling center. CS involves manual labor and mechanical machines to classify and separate the materials, whereas automated sorting uses machinery and technology (e.g., AI, computer vision, etc.,) for the same purpose. The sorted materials are then directed towards various end processes: they can be recycled, reused, or recovered to minimize environmental impact. Alternatively, some materials may be incinerated for energy recovery, and the remaining waste is sent to landfills as a last resort. This systematic approach ensures efficient handling and processing of C&D waste, promoting circularity, sustainability, and reducing the burden on landfills. In the following sections, we delve deeper into the step 3 of the Fig. 3 for further study of the C&D waste sorting.

4.2. Conventional sorting process map

Fig. 4(a) illustrates the mechanical and manual process of C&D waste sorting which in this research we refer to as conventional sorting (Ku et al., 2021; Lukka et al., 2014; Van Dyk Recycling Solutions, 2019). While there may be some variations in the stages of CS, the process

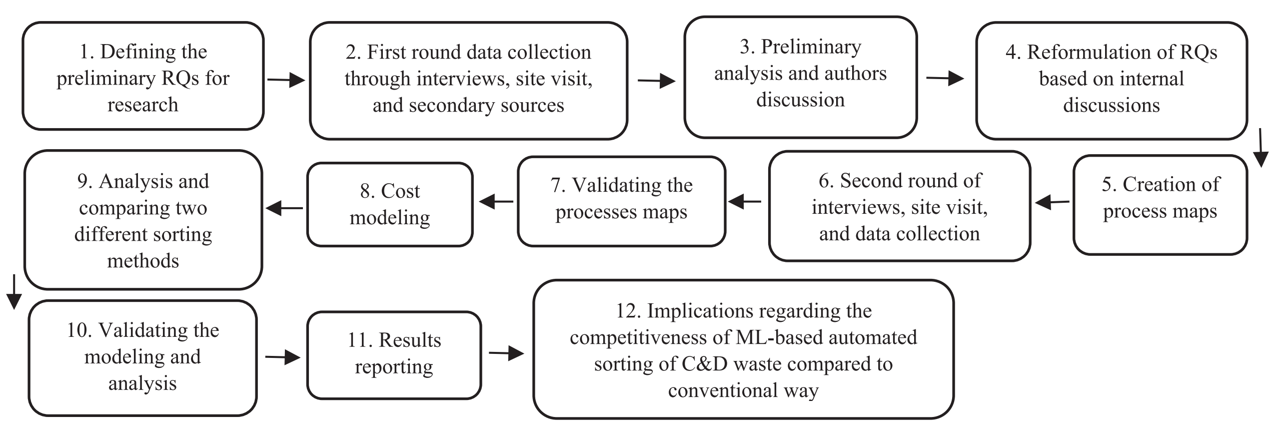

Fig. 2. Research process steps.

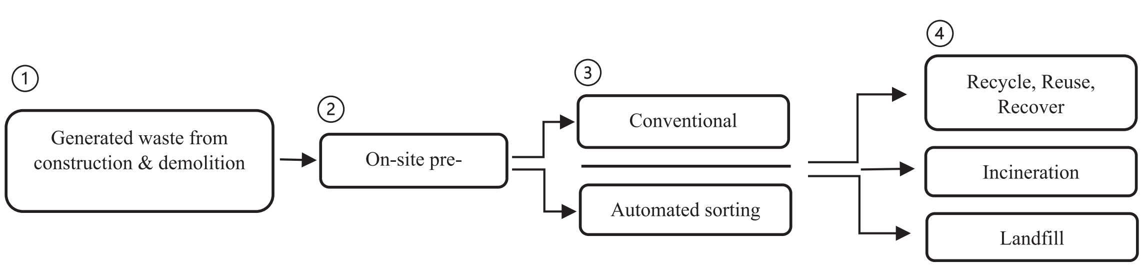

Fig. 3. C&D waste management process steps.

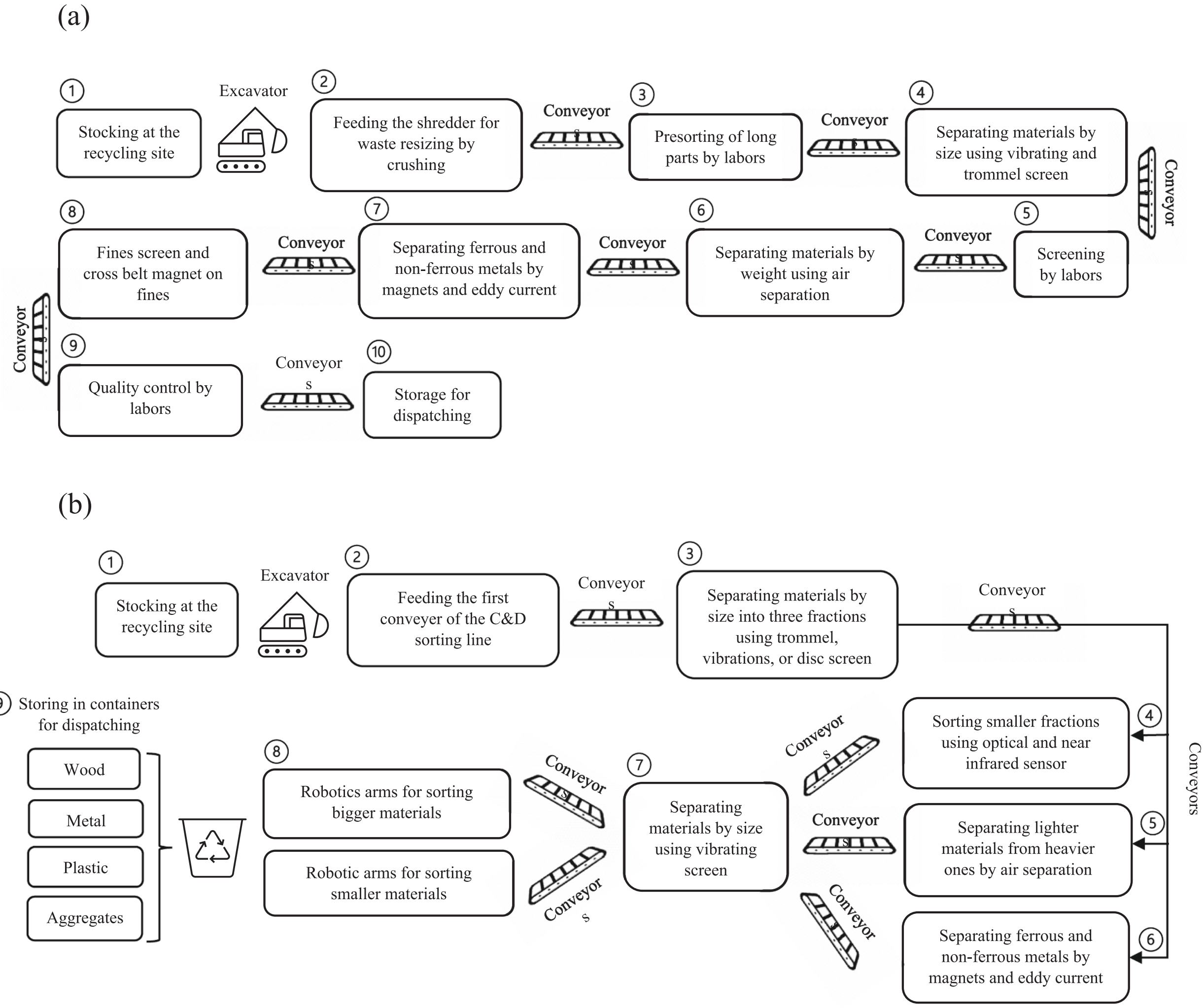

Fig. 4. (a) Mechanical and manual process of conventional sorting of construction & demolition waste (Ku et al., 2021; Lukka et al., 2014; Van Dyk Recycling Solutions, 2019). (b) ML-based automated sorting based on primary data.

described aligns with the specific approach used in our chosen case (Van Dyk Recycling Solutions, 2019). CS refers to traditional methods of separating C&D waste, relying on a combination of human labor and mechanical machinery. Workers manually sort through waste materials, often assisted by basic mechanical tools such as conveyors, shredders, and magnetic separators. This process is labor-intensive and can be inconsistent due to human error and exhaustion. The machinery involved usually lacks advanced sensors or automation capabilities, making the sorting process slower and less efficient. CS is more suited to smaller, shredded items and involves fewer separation categories, typically limited to two bins per human operator.

In Fig. 4(a), the conventional C&D waste sorting process involves several structured stages to ensure effective material separation and recycling. It begins with waste being stored at the recycling site, where collected materials are gathered. In Stage 2, an excavator feeds the waste into a shredder to crush it into smaller sizes for easier sorting. Stage 3 features manual presorting of long materials by laborers, who separate larger reusable items from general waste. This is followed by Stage 4, where vibrating and trommel screens sort materials by size, ensuring smaller particles are separated from larger ones. Stage 5 involves manual screening, where workers inspect and categorize materials for quality control. In Stage 6, air separation technology distinguishes lighter materials like plastics from heavier ones. Stage 7 uses magnets and eddy current technology to separate ferrous and non-ferrous metals. In Stage 8, fines are screened, and cross belt magnets remove metallic contaminants. Stage 9 involves manual quality control, where workers ensure sorted materials meet standards and remove any missed contaminants. Finally, sorted materials are stored for dispatch in the last stage, ready for recycling, incineration, or landfill. This systematic approach maximizes material recovery and minimizes landfill waste, highlighting the importance of each sorting step for optimal recycling outcomes.

4.3. ML-based automated sorting process map

In another type of sorting C&D waste which we call it ML-based automated sorting (MLAS) the use of sensors and automation through computer vision, robotics, and artificial intelligence (AI) is more pronounced. Based on the primary data, we mapped the process for the ML-based process in Fig. 4(b).

In Fig. 4(b), the process starts in Stage 1, where an excavator stocks collected waste at the recycling site for an organized beginning. In Stage 2, the excavator feeds the first conveyor of the C&D sorting line, ensuring a continuous material flow. Stage 3 employs a trommel screen to separate materials by size into three fractions, crucial for specialized processing. The process then splits into parallel stages. Stage 4 uses advanced optical and near-infrared (NIR) sensors to sort smaller particles, leveraging spectral analysis to identify different materials. Optical systems detect materials based on their properties, while NIR technology distinguishes them by chemical composition, enhancing sorting efficiency and reducing reliance on human labor.

Stage 5 utilizes air separation technology to distinguish lighter materials from heavier ones, while Stage 6 employs magnets and eddy current separators to extract ferrous and non-ferrous metals. Stage 7 features a vibrating screen for further size separation, improving sorting accuracy.

In Stage 8, Zen robots equipped with twelve robotic arms handle the sorted materials. These robots equipped with computer vision are capable of identifying and sorting both larger and smaller waste materials with high precision. Specifically, six of the robotic arms are dedicated to sorting smaller materials, while the other six handle larger materials. This division of labor among the robotic arms significantly reduces the reliance on manual labor and minimizes human error, ensuring an efficient and accurate sorting process. Finally, in Stage 9, sorted materials are stored in designated containers for wood, metal, plastic, and aggregates, ensuring efficient recycling and reuse. This combination of advanced machinery and automation significantly enhances the efficiency and effectiveness of C&D waste recycling.

4.4. Identifying generic key stages of C&D waste sorting

We used the process mapping presented in Figs. 3, 4(a), and 4(b) in this section for in-depth understanding of the underlying functions of the C&D waste sorting and recycling process in the CS and MLAS process types. Based on that, we classified the actions in each process to the objectives of that stage. This analysis allows us to extract a generic sorting process applicable to any C&D waste sorting method, creating a baseline for comparison. This baseline helps in systematically comparing the two different sorting processes on common grounds, ensuring an accurate evaluation of their respective efficiencies and advantages. This is presented in Table 2 and later used for operational cost and circularity comparison of the CS and MLAS processes.

Table 2 provides a clear framework that highlights the *generic key stages* of the sorting process and the specific actions and resources involved in each method. This structured approach allows for a detailed comparison of the two sorting methods, facilitating an understanding of their operational, economic, and environmental implications.

Table 2
Generic key stages of C&D waste sorting.

Generic Key Stage	Objective of the process stage	Conventional stage and machinery/ resource	ML-based automated stage and machines/ resource
GKS1	Material availability (delivery and storage)	Stage 1, Excavator	Stage 1, Excavator
GKS2	Granulation adaptation for sorting	Stage 2, Shredder	–
GKS3	Taking materials from one handling point to another one	Stage 2, Conveyors	Stage 2, Conveyors
GKS4	Material separation by size	Stages 3, 4, and 5, Human, Vibrating and trommel screen	Stages 3 and 7, 3D Trommel and vibrating screen
GKS5	Material separation based on optical properties and composition	–	Stage 4, Optical and NIR sensor
GKS6	Material separation by weight	Stage 6, Air separation	Stage 5, Air separation
GKS7	Ferrous and non-ferrous material separation	Stages 7 and 8, Magnets and eddy current	Stage 6, Magnets and eddy current
GKS8	Final manual or automated sorting of wood, metal, plastic, and inert	Stage 9, Human	Stage 8, ML-based Zen robots
GKS9	Storage for recycle, incineration, or landfill	Stage 10, Containers	Stage 9, Containers

Based on Table 2, we can identify four distinct stages where the CS differs from the MLAS method. These stages highlight the primary differences in technology and approach between the two methods.

The first key difference lies in the granulation adaptation for sorting. The CS utilizes a shredder to break down larger pieces of C&D waste into smaller, more manageable sizes before further sorting because for human separators the size and weight of the waste items are the limiting factors. This step is essential to prepare the materials for the subsequent separation processes. In contrast, the MLAS does not use a shredder. Instead, it relies on advanced robotics arms, grippers, and AI technologies to handle larger pieces directly, eliminating the need for initial shredding and streamlining the process. This is partly due to the fact that robots are capable of handling heavier (up to 40 kg) and larger (up to 1.5 m) objects than humans (ZenRobotics, 2024a).

The second significant difference is found in the material separation by size. The CS uses vibrating and trommel screens, often assisted by human labor, to separate materials based on size. On the other hand, the MLAS employs vibrating screens and trommel screens without any human intervention.

The third distinction is where the ML-based method uses advanced technologies such as optical and NIR systems for further sorting after the initial size-based separation. These systems leverage NIR and visible spectrum sensors to achieve precise and efficient separation of materials based on their optical properties and composition. Optical and NIR systems are absent in the CS.

The fourth distinct stage is the final manual or automated sorting of materials such as wood, metal, plastic, and inert materials. In the CS, this stage relies heavily on human labor, making it labor-intensive and prone to human error, which can affect the accuracy and efficiency of the sorting process. On the other hand, the MLAS uses ML-based robots, in our case Zen robots, equipped with computer vision and ML capabilities. These robots perform the final sorting with accuracy and efficiency, minimizing human intervention.

4.5. Circularity comparison

For a comprehensive comparison, we measure both qualitative and quantitative aspects, from operational specifics to broader environmental and economic impacts. This would provide a full picture of the competitiveness of MLAS against CS. For environmental and circularity advantages, we consider recycling rate as the percentage of waste that is accurately sorted and recovered for reuse and recycling. Also, we compare purity, which is the level of contamination in sorted waste streams and the cleanliness of separated materials. Waste type and quality are other criteria to be considered as types of materials that each system can handle and how the quality of input waste impacts sorting efficiency.

In comparing the circularity performance of MLAS and CS, it is evident from Zen expert insights that MLAS demonstrates superior recycling rates and material purity. While specific recycling rates for CS systems are not explicitly quantified in the interview, conventional methods are described as struggling to meet the 70 % recycling target for C&D waste set by the European Union. Factors such as reliance on energy recovery, inconsistent sorting accuracy, and contamination in output streams contribute to lower recovery rates in CS.

In contrast, MLAS overcomes many of these limitations through advanced ML algorithms and object-based recognition, enabling precise and efficient sorting of mixed and contaminated material streams. This leads to higher recovery of valuable materials and reduced contamination levels, significantly enhancing the recycling rate and material purity. These improvements underscore the environmental and operational advantages of MLAS over CS, supporting its role in advancing CE goals (Please refer to the supplementary material for the transcripts).

Based on the interviews conducted with production manager from Recycling Facility, the MLAS demonstrates impressive performance in terms of recycling rates and purity levels for various materials. The production manager provided detailed insights about recycling rates as follows:

“Metal is quite high [in terms of recycling rate] because, we have two metals robots and magnets; the magnet is quite simple [in design] working well so it can be like 95 % [recycling rate] for metals. I think metal [recycling rate including the robots] is 99 %, I can’t say 100 %. For wood, it’s also [high] if we don’t think about that what we will do with that wood in our process—it’s separated or it goes through the line to recycle. If some of our robots are not working, we do not get all, but at a practical level, we have a chance to get this [recycling rate] in wood—it can be like 90 %. And why we get [do not recover] everything is that, for example, it is so dirty that we can’t recognize it [the material].

Inert [material recycling rate] is not so big [high]; [like] 80 % because some of these [materials] are too heavy and too big and also that recognizing [is an issue]. For inert [material], NIR we have on the small fraction line is bigger than our robot line, but in total, it is like 80 %. For plastic, it is lower; we have not [reached a peak] for plastic; we have put the robots pick wood instead of plastic because that rate [plastic recycling rate] was so low before. Now we have new options [and] new testing going there, so but it can be like 60 %.”.

Further details on purity were provided: “Metals are quite sharp; when it has a sharp corner, the plastic stacks there [on the metal]… then it goes to the eddy current [separator]… and the aluminum purity is lower than ferrous… aluminum is 70 % … and for ferromagnetic [metals] 90 %… plastic it is like 90 % [purity]… for C quality wood it is like 99 % [purity]… for inert [material], put [it at] 90 % [purity].”.

This information indicates that the MLAS not only enhances the recycling rate but also ensures high purity levels, reducing contamination in the sorted waste streams. The advanced technologies used in ML-based sorting enable higher recovery rates and cleaner material streams, which contribute significantly to environmental sustainability and circularity in waste management.

The direct quotations from the Recycling Facility production manager reveal the following performance metrics: recycling rates for wood: up to 90 %, metal: up to 99 %, plastic: up to 60 %, and inert waste: up to 80 %. Purity levels for wood: up to 99 %, aluminum: up to 70 %, ferrous metals: up to 90 %, plastic: up to 90 %, and inert waste: up to 90 %. However, with the introduction of the new generation of Zen robots and machinery, these recycling rates and purity percentages are expected to be even higher. These figures highlight the effectiveness of the ML-based sorting method, which achieves high recycling rates and purity levels across different types of materials. By ensuring that the sorted waste streams are less contaminated, the ML-based technology facilitates higher-quality recycling processes, ultimately contributing to a more sustainable and circular economy.

The quotations from the Recycling Facility interviewees clearly demonstrate the advantages of the MLAS. The high recycling rates and purity levels indicate that this technology significantly enhances waste management efficiency, supporting environmental sustainability and circularity.

Although ML-based sorting is more capable in achieving the circularity goals, however, we determined that there are a number of factors that if improved the ML-based sorting can provide even higher circularity outcomes. Based on interviews with Recycling Facility and Zen representatives, one significant issue with ML-based robots is the performance of their grippers. These robotic grippers can occasionally fail to secure materials properly, resulting in items being dropped prematurely or incorrectly sorted, an issue less prevalent with human labor, as humans can better grip and handle materials of various shapes and sizes. Furthermore, ML-based robots struggle with detecting and sorting objects that are covered by other materials. Unlike humans, who can search, move objects, and uncover hidden items to sort them accurately, robots are limited to their sensor capabilities and cannot perform such delicate manipulations. These limitations highlight the importance of human intuition and dexterity in certain aspects of the sorting process, where manual intervention can achieve higher accuracy and reliability. In summary the human operator is more reliable in the manipulation of the environment and more secure gripping of the objects when the items are small and within the reach of a human arm however, human is vulnerable to work fatigue, loosing concentration, limited reach, and handling heavy weight. Human operators require safe working conditions as to dust, heat, etc., whereas robots can be adapted to work in non-human conditions.

4.6. Comparative cost model

Based on the analysis presented in Section 3.4, we can identify the specific objective of the stages involved in each sorting method. This understanding is crucial for developing a cost comparison model for these ML-based automated and conventional recycling processes.

Table 3, based on the interviews and secondary data, provides the basis for calculating the cost of the distinct generic key stages 2, 4, 5, and 8 in the conventional and MLAS. These stages are key points where the ML-based and CS methods diverge, allowing for a focused comparison of their respective costs.

Economic advantages of the two sorting methods can be compared by developing a cost model for the stages that differ between each sorting method. By analyzing the breakdown and cost modeling for both CS and MLAS processes, we can evaluate the cost-effectiveness of each method. This detailed comparison allows us to identify the financial benefits and potential savings associated with the adoption of advanced MLAS over CS, providing a comprehensive understanding of their economic impact.

To develop a comparative comprehensive cost model for recycling x tons of C&D waste using MLAS versus CS, the following generic formulation can be used (Coelho and de Brito, 2011). Total cost (TC):

$$TC = \left(\sum_{i \in E} C_{Pi} \times n_i\right) + \left(\sum_{i \in I} C_{m_i} \times k_i\right) + C_f \tag{1}$$

Notations and assumptions:

C_{Pi}: the salary and other costs (pension, health insurance, etc.,) associated with the i^{th} type of employee.

n_i: the number of employees of type i.

C_{m_i}: the total cost of each type of machinery i.

k_i: the number of machines of type i.

C_f: the total facility cost.

E: the set of all employee types.

I: the set of all types of machinery in the facility.

Personnel costs are calculated by identifying distinct types of employees within the plant, each represented by i. For each type, C_{Pi} specifies the salary, wage, and benefits assigned to that category of employees, and n_i indicates how many employees belong to it. The price and maintenance cost of each type of machine C_{m_i} is multiplied by the quantity of that machine type k_i, and the products are summed over all types of machinery I. This allows for different types of machinery (e.g., shredder, optical and NIR sensors, robots) to be accounted for with their specific costs and quantities. Also there is a total cost C_f that includes rent, buildings, utilities, and other facility-related expenses.

Assumptions:

Facility cost (C_f): We assume that the total facility cost (C_f) has a direct correlation with the output of the process (volume of processed material). This is because the distinct stages in the sorting methods do not affect the overall building and facility costs. The facility cost (C_f) includes expenses related to the land and building of the sorting facility, which are not influenced by the type of sorting technology employed but are correlated with throuput capacity of each sorting method.

Table 3
Distinct sorting process stages breakdown.

Generic Key Stage and machines/resource	Machinery lifespan (years)	Count	Cost per machine/Unit (Euro)	Labor requirement per shift	Annual personnel salary (Euro)
Conventional process					
GKS2: Granulation adaptation for sorting by shredder	10	1	50 k	–	–
GKS4: Material separation by size and screening by human labors	–	–	–	20	50 k
GKS8: Final quality control and manual sorting by labors	–	–	–	4	50 k
ML-based process					
GKS5: Material separation based on optical properties and composition by optical and NIR sensor	15	2	100 k	–	–
GKS8: Final automated sorting by Zen robots	10	A Zen unit including one robot and the necessary vision system	300 k*	2	60 k

* From industry sources.

Volume of material: The volume of material processed by the MLAS is assumed to be 30 tons per hour, based on insights obtained from interviews conducted with key personnel at the Recycling Facility. These interviews provided direct, firsthand information about the operational capacities of the MLAS system. For the CS, the throughput of 70 tons per hour is derived from industry references (Van Dyk Recycling Solutions, 2019). While company-issued records could have offered additional validation for these figures, such documentation was not accessible within the scope of this research. To maintain consistency, it is further assumed that the throughput capacity for both systems remains constant throughout the analysis. These assumptions are supported by discussions with industry experts and reflect realistic operational benchmarks for the considered systems. The case study interviews did not focus on quantitative process flow data due to the inherent variability in waste composition and processing rates. Instead, throughput capacity under full operational conditions was used as a stable measure for mathematical cost modeling. While real-time operational data could provide more granular insights, our approach prioritized capturing expert perspectives to complement the cost analysis.

Labor costs: The salary of personnel involved in the sorting processes is based on the standard salary rates in Finland and the salary of labours is considered to be 20 percent of supervisors Our assumption is supported by expert consultations and relevant observations in Finland's industries, where managerial roles earn approximately 2–3 times more than lower-tier roles in sectors like construction and waste management. This can provide a reasonable basis for our assumption of a 1 to 5 worker-to-supervisor salary ratio, which is plausible within this context (Finnwards 2023; Työsuojelu, 2023).It is also assumed that these salaries remain constant over time and are not adjusted for inflation.

Additional personnel benefits: Other benefits for personnel, besides the salary such as pension and health insurance, are considered to be 50 percent of the salary for each employee.

Training cost: There is a one-time training cost for labour and supervisor personnel, which is considered an initiating cost and is 25,000 euros for labours and 50,000 euros for supervisiors. The work period for personnel is considered to be seven years.

Maintenance cost: The maintenance cost is considered as 5 percent of the price of the machines.

Each unit of the MLAS, including one robot and the necessary vision system, costs 300,000 euros. Therefore, in our case study of the Recovery Facility, which utilizes 12 robots across two stations (with 6 heavy picker robots at one station for heavier materials and 6 heavy picker robots at another station for lighter materials), the total cost amounts to 3,600,000 euros.

For simplicity, we have excluded any interest costs associated with financing the purchase of robots or other machinery.

Cost period: All these costs are considered within one year.

Table 4 is a summary of considered assumptions for cost modeling.

As discussed earlier in relation to Table 2, the two C&D waste sorting methods, MLAS and CS, differ significantly only in generic key stages 2, 4, 5, and 8. Consequently, we can apply the cost formula specifically to these four stages to determine the total cost under each recycling method. This targeted approach allows for a precise comparison of the economic efficiency of both methods. By focusing on these distinct stages, we can accurately assess the financial implications and benefits of adopting MLAS over CS, providing a clear basis for evaluating their respective cost-effectiveness.

$$TC_{ML} = \left(\sum_{i \in E_{ML}} C_{P_{i_{ML}}} \times n_{i_{ML}}\right) + \left(\sum_{i \in I_{ML}} C_{m_{i_{ML}}} \times k_{i_{ML}}\right) + C_{f_{ML}} \tag{2}$$

$$TC_{CO} = \left(\sum_{i \in E_{CO}} C_{P_{i_{CO}}} \times n_{i_{CO}}\right) + \left(\sum_{i \in I_{CO}} C_{m_{i_{CO}}} \times k_{i_{CO}}\right) + C_{f_{CO}} \tag{3}$$

To find the difference in total cost ΔTC between the MLAS process (TC_{ML}) and the CS process (TC_{CO}), we focus on the distinct stages of the sorting processes:

$$\Delta TC = TC_{ML} - TC_{CO} \tag{4}$$

Table 4
Considered assumptions for both sorting methods.

Assumption	Conventional sorting	ML-based automated sorting
Facility cost (C_f)	5 million, direct correlation with the output of the process	11.5 million (=5 million * 2.3), direct correlation with the output of the process
Volume of material processed	70 tons per hour	30 tons per hour
Labor costs	Finland standard rates	Finland standard rates
Labor salary	20 % of supervisor salary	20 % of supervisor salary
Additional personnel benefits	50 % of salary	50 % of salary
Training cost (One-time, 7 years period)	25,000 euros (labours)	50,000 euros (supervisors)
Annual maintenance cost	5 % of machine price	5 % of machine price
Robot stations cost	NA	3,600,000 euros (12 robots in two sations)
Cost period	Considered within one year	Considered within one year

Substituting the respective costs for the distinct stages, we get:

$$\Delta TC = \left(\left(\sum_{i \in E_{ML}} C_{P_{i_{ML}}} \times n_{i_{ML}} \right) + \left(\sum_{i \in I_{ML}} C_{m_{i_{ML}}} \times k_{i_{ML}} \right) + C_{f_{ML}} \right) - \left(\left(\sum_{i \in E_{CO}} C_{P_{i_{CO}}} \times n_{i_{CO}} \right) + \left(\sum_{i \in I_{CO}} C_{m_{i_{CO}}} \times k_{i_{CO}} \right) + C_{f_{CO}} \right) \tag{5}$$

This equation captures the difference in costs between the MLAS and the CS process for the distinct stages of sorting. Then we utilize the values of parameters presented in Table 3 and apply them to Eq. (2) for MLAS and Eq. (3) for CS. Table 3 provides the necessary parameter values, including machinery lifespan, cost per machine, labor requirements, and personnel-related costs.

We have derived the total annual cost (investment cost and operational cost) for MLAS to be approximately $TC_{ML} \approx 9,408,666€$ in the first year and $TC_{ML} \approx 558,666€$ in subsequent years. For CS the annual cost is approximately $TC_{CO} \approx 7,380,543€$ in the first year and $TC_{CO} \approx 2,347,934€$ in subsequent years. These costs for CS are adjusted values, considering the throughput difference and dividing the total cost by a factor of 2.3. To ensure a fair comparison between the two methods, considering the difference in their throughput capacities, an adjustment is necessary. The CS in our considered case processes 70 tons per hour, whereas the MLAS of our investigated handles 30 tons per hour. To normalize the cost comparison reflective of their throughput differences, we divide the CS's total cost by a factor of 2.3, which corresponds to the ratio of their throughput capacities. This adjustment provides a more accurate basis for comparing the economic efficiency of the two systems, making the costs comparable on a per ton basis. This adjustment makes it possible to compare more accurately the costs per ton processed between the CS and MLAS.

Initially, the first-year cost for MLAS is higher than that of CS. This is due to the substantial initial investment required for purchasing and implementing advanced machinery and technologies. However, in the second year and beyond, the annual costs for MLAS drop dramatically to $558,666€$, primarily covering maintenance and personnel salaries. In contrast, the CS method continues to incur relatively high annual costs of approximately $2,347,934€$ due to ongoing operational and personnel expenses.

When we examine the cumulative costs over a seven-year period, the financial benefits of MLAS become clear. The cumulative cost for MLAS is 12,760,666€, whereas for CS, it is significantly higher at 21,468,152€. This substantial difference highlights the long-term cost efficiency of ML-based systems.

The cost trajectory emphasizes the high initial cost of MLAS followed by significantly lower costs in subsequent years, while CS shows consistently high costs throughout. This reinforces the long-term economic benefits of MLAS, supporting the strategic decision to invest in advanced sorting technologies for sustainable waste management.

Up until the second year, the cumulative cost of MLAS is higher or roughly equal to CS due to the substantial initial investment in advanced machinery and AI systems. However, starting from the second year, MLAS operational costs drop significantly compared to CS, which continues to incur high yearly expenses.

In the second year, the cumulative costs of both methods converge, marking the point where MLAS starts to provide financial benefits over CS. After this, CS costs rise sharply, while MLAS costs increase at a much slower pace, highlighting the long-term economic advantage of MLAS.

The second-year intersection emphasizes the importance of a long-term view when evaluating the financial viability of MLAS. While initial costs are high, the substantial reduction in ongoing expenses justifies the investment, offering sustained economic and environmental benefits.

To assess the financial viability of the MLAS, it is essential to consider its expected revenue and calculate the return on investment (ROI). The ROI can be calculated using the following formula:

$$ROI = \frac{Revenue - TotalCost}{TotalCost} \tag{6}$$

For the MLAS, the expected revenue (R_{ML}) should be sufficiently high to compensate for its higher cost. The revenue must cover the total cost and provide a reasonable profit margin which is the percentage of revenue that exceeds the costs.

To illustrate, if the MLAS is to be justified, the revenue should at least match the cost. For an ROI of 0 (break-even point), the revenue should be equal to the total cost:

$$R_{ML} = TC_{ML} = 9,408,666€ \tag{7}$$

To achieve a positive ROI, the revenue must exceed this amount. For instance, if we aim for an ROI of 10 %, the required revenue would be:

$$R_{ML} = TC_{ML}(1 + 0.10) = 9,408,666€ \times 1.10 = 10,349,533€ \tag{8}$$

Furthermore, considering the ROI over a period of, for instance, five years to compensate for the high initial costs of MLAS, we should aim to cover not just the annual costs but also the cumulative costs over five years. Therefore, if the MLAS is to be financially viable over a five-year period, the revenue needs to account for the total cost incurred during this period.

The total five-year cost for MLAS is:

$$Five - YearTC_{ML} = 9,408,666€ + 558,666€ \times 4 = 11,643,330€ \tag{9}$$

To achieve an ROI of 10 % over five years, the revenue should be:

$$R_{ML} = 11,643,330€ \times 1.10 = 12,807,663€ \tag{10}$$

This calculation highlights the importance of optimizing the MLAS process and exploring avenues for increasing revenue through improved sorting efficiency, higher recovery rates of valuable materials, and potentially tapping into premium markets for high-quality recycled products.

Overall, although the initial investment and first-year cost of MLAS are significantly higher compared to CS, the long-term savings and efficiency gains make it a financially viable option. From the second year onward, the annual cost for ML-based sorting is significantly lower than that of CS. When considering the cumulative costs over a seven-year period, ML-based sorting proves to be more cost-effective. This realization underscores the financial viability of ML-based systems, bolstered further by the potential to generate higher revenue through advanced technology and efficiency improvements. Thus, the lower operational costs combined with the advanced capabilities of ML-based technologies position them as a more economically and environmentally sustainable option compared to traditional methods.

4.7. Operational and theoretical implications of MLAS

The major benefits of MLAS over the CS of C&D waste are the followings, elimination of the need for training the new workforce and ease of expansion by adding new robots, the shortage of human labor in markets such as Finland needed for the conventional process makes the process expansion more difficult which is not the case for the MLAS. And finally, the elimination of the shredding of the waste material in the beginning of the process in the ML-based system reduces the fine particles and also significantly increases the reuse and circularity of the waste material.

This study enhances the theoretical understanding of how ML-based technologies contribute to the CE in the C&D industry. By addressing RQ1, it highlights the environmental benefits of ML-based sorting, such as increased throughput, higher recycling rates, and improved material purity. The research demonstrates how AI and ML can optimize resource recovery, promoting sustainable waste management. In answering RQ2, it reveals the economic advantages of MLAS, showing that, despite high initial costs, they offer long-term financial sustainability through reduced operational costs and higher material recovery, making them as enablers of CE goals.

5. Conclusions

This is an empirical research conducted at a cutting edge C&D waste recycling facility in Finland where the computer vision and robotics is used for the process automation. We collected data through site visits and interviews as well as literature study.

Our research pointed out that MLAS achieves higher recycling and material purity rates. Also, we found that although MLAS has higher initial costs compared to CS, it offers significant cost savings and revenue potential over time. While the first year's costs for MLAS are higher due to initial investments, the operational costs become lower than CS from the second year onwards. By the end of the second year, the cumulative cost of MLAS is lower, highlighting the long-term financial benefits of investing in advanced sorting technologies. Hence, enhancing the economic viability and reducing environmental impact justify the adoption of MLAS in the waste management industry.

The findings of this study have significant policy implications. Policymakers can support the adoption of MLAS through targeted measures that mitigate initial investment barriers and accelerate its integration into the waste management sector. Financial incentives, such as subsidies or tax reliefs for companies implementing MLAS, could facilitate technology adoption while aligning with broader environmental goals. Additionally, introducing regulatory requirements for higher material purity levels and recycling rates could encourage industry-wide adoption of advanced sorting technologies like MLAS, which are capable of meeting such standards more effectively than conventional methods. Furthermore, fostering research and development initiatives for AI and robotics in waste management could address current technological limitations, such as the detection of occluded objects and robotic gripper performance, further enhancing the efficiency and viability of MLAS systems. By aligning policies with technological advancements, governments and regulatory bodies can significantly contribute to achieving sustainability goals while promoting innovation in the waste management industry.

Our academic contributions is towards the field of C&D waste management by studying the ML technology integration into existing practices. This research contributes to the filling of the gap in the literature (Farshadfar et al., 2024; Çetin et al., 2021; Talla and McIlwaine, 2022; Davis et al., 2021) by conducting an empirical research on MLAS and its economical and environmental impact in comparison to CS. This study provides valuable insights into the efficiency and effectiveness of MLAS and its potential cost savings, resource optimization, and environmental impact mitigation.

The managerial and practical contributions are the demonstration of operational efficiency gains through the adoption of MLAS, to reduce manual labor, and decrease the time taken to sort waste materials. Also, this study highlights the economic benefits of ML technologies, helping managers make informed decisions on adoption and capital allocation by detailing ROI and profitability scenarios, aiding long-term planning and sustainability. Additionally, the analysis reveals that shredding is unnecessary in MLAS, as robots can handle large objects up to 40 kg. This not only enhances material reusability but also reduces energy consumption, dust production, and contamination, ultimately improving the reuse and circularity of materials.

The limitations of this work were related to the lack of access to direct operational data from facilities using CS and studying only one case study related to the recycling facility and one case company related to the MLAS system provision. Additionally, this study did not incorporate interest rate estimations for financing the purchase of robots and other machinery, which could provide a more comprehensive analysis of the financial burden associated with MLAS. The decision to exclude these interest costs was made to maintain simplicity and focus on the primary research objectives. However, this remains an important consideration for businesses evaluating the financial feasibility of MLAS systems.

A key area for future research is conducting a detailed survey on CS facilities to gather empirical data on operational workflows, recycling rates, and cost structures. This would provide additional validation and enrich comparisons with MLAS, helping to clarify their relative advantages. Moreover, incorporating statistical methods or factor analysis in such surveys could provide a more nuanced understanding of the key variables and their interrelationships, offering deeper insights into the operational efficiency and financial implications of different sorting systems.

Additionally, calculating the revenue from both MLAS and CS by analyzing recycled material prices, grades, and market fluctuations, researchers could gain deeper insights into the economic viability and profitability of each approach. Future studies could also include detailed financing scenarios, such as varying interest rates and repayment schedules, to enhance the understanding of financial feasibility.

Furthermore, the future research could expand this work by exploring the integration of advanced technologies like GPT-vision based systems for waste detection and humanoid robots for waste separation enhancing sorting efficiency and cost-effectiveness.

CRediT authorship contribution statement

Zeinab Farshadfar: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Siavash H. Khajavi:** Writing – review & editing, Validation, Investigation, Formal analysis, Data curation. **Tomasz Mucha:** Investigation, Formal analysis, Data curation. **Kari Tanskanen:** Supervision, Investigation, Formal analysis, Data curation.

Declaration of competing interest

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

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wasman.2025.01.008.

Data availability

Data will be made available on request.

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