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Review

Robotised disassembly of electric vehicle batteries: A systematic literature review

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ABSTRACT

This review examines the robotic disassembly of electric vehicle batteries, a critical concern as the adoption of electric vehicles increases worldwide. This work provides a comprehensive overview of the current state of the art in robotic disassembly and outlines future directions for research and policy in this essential area. The study highlights the urgent need for sustainable management practices to mitigate the environmental impact of end-of-life batteries. It evaluates current robotic technologies, strategies for human–robot collaboration, and the role of artificial intelligence in enhancing the efficiency and safety of these processes. The investigation identifies significant challenges, including the absence of standardised designs and the inherent risks of handling batteries. The feasibility of adopting design-for-disassembly principles is explored as a way to improve recycling and repurposing efforts. The review suggests avenues for future research, focusing on developing advanced robotics solutions and establishing supportive regulatory frameworks. These efforts aim to foster sustainable practices in the lifecycle management of electric vehicle batteries, contributing to the broader goal of environmental sustainability in the electric vehicle and battery industries. Previous reviews generally focus on recycling electric vehicle battery chemistry and materials; this review complements previous research by focusing on robotised disassembly.

1. Introduction

Road transportation is an essential contributor to the buildup of carbon dioxide (CO_2) and other greenhouse gases worldwide [1–3]. To overcome the challenges of climate change, such as global warming, the reduction of emissions and energy consumption of road transportation is required. Electrifying the drivetrains of road vehicles is essential in decarbonisation and cutting local emissions produced by road vehicles. Governments worldwide are promoting sales of electric vehicles (EVs) to reduce emissions generated by road transportation to slow down climate change [4–6]. EV sales have been increasing exponentially; in 2022, over ten million passenger EVs were sold, and the sales are estimated to double by 2025 [7,8].

While the electric drivetrain is more energy efficient than the internal combustion engine and does not generate tailpipe emissions, the tradeoff is emissions generated while mining the batteries' raw materials and manufacturing process [9]. In addition, residents' environmental degradation and health issues are harmful effects of mining [10–12]. Recycling the existing end-of-life batteries to raw materials and repurposing usable batteries are required to reduce the harmful side effects of electrifying road transportation. Repurposing as building energy storage systems is an energy-efficient and environmentally friendly way to second-life electric vehicle batteries (EVBs) whose capacity has degraded below usable operational range *e.g.,* for electric vehicles. The EVBs whose capacities have degraded below usable range in any applications must be recycled into raw materials for manufacturing new batteries.

Disassembly is essential in recycling and remanufacturing used products [13]. To repurpose or recycle an assembly of various materials, disassembly and sorting the components are required before assembling reusable components into second-life products or recycling components into raw materials. Due to challenges related to the autonomous disassembly of used EVBs, disassembly is typically a work of manual labour [14]. However, the disassembly phase of degraded, end-of-life (EoL), or damaged EVBs exposes human workers to potential hazards such as toxic chemicals, fire, electric arcs, and high voltages. In

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addition, manual disassembly is uneconomic in countries where manual labour costs are high [15]. Approaches to automate certain subtasks of the EVB disassembly and sorting have been proposed to isolate the human workers from the hazardous environment and to reduce the costs of recycling [16]. The solutions presented typically utilise machine vision (MV) to sense the environment, an arm robot as the mechanism, and artificial intelligence (AI) to control disassembly.

Robotised disassembly is challenging due to variations in the product's mechanical condition, physical shape, and methods utilised during the assembly. EVBs are not standardised, and various EVB designs exist, even between EVB packs from the same manufacturer [14,17]. In industrial production, robots are typically programmed for repetitive actions on fixed objects in structured environments. However, disassembling used EVBs is less structured and requires adaptation to the battery's condition, type, and structural design. Adaptation to process, including varying parameters, requires a higher-level control and machine vision.

In addition to variations in the physical characteristics of the EVBs, the packs lack a design for disassembly (DfD). Semi-autonomous assembly tasks, welded joints, and adhesive bonding of the components used during the assembly phase of the new EVBs introduce a challenge to the robotised disassembly. Autonomous detaching of the electrical connectors, welded cell connector plates, and handling of the flexible wiring assemblies are challenging. Therefore, human–robot collaboration (HRC) is currently utilised in the most complex tasks requiring cognitive capabilities, finger dexterity, and crafting skills to bypass the challenges. While HRC enables bypassing the technical challenges, the safety challenges remain.

The disassembly methods of EVBs differ from the disassembly of other types of LiBs, e.g. consumer electronics LiBs such as laptops, smartphones, and tablets. The higher capacity of the EVB increases physical size and weight, requiring a structural frame to house the modules and control electronics. The LiBs used in modern consumer electronics are miniaturised and lightweight, featuring a thin protective casing integrated into the device frame instead of a dedicated structural frame.

The primary methods for the automated dismantling of consumer LIBs are destructive; for EVBs, non-destructive methods are preferred [18].

New EU battery regulation [19] aims to increase the sustainability of electric vehicles by obligating battery manufacturers to increase the percentage of recycled raw materials and to provide a take-back infrastructure for the used EVBs. In addition, a digital battery passport has been proposed by the European Commission (EC) to validate the authenticity and to include technical details related to recycling, repurposing and remanufacturing of the EVBs into the digital passport [20].

This publication reviews current methods to automate the EVB disassembly process to define the current level of autonomy and find the gaps and challenges in robotised disassembly, testing and sorting tasks of the EVB. Previous reviews focus primarily on EVB chemistry and material recycling; utilising automation and robotics for EVB disassembly is rarely addressed. The previous reviews addressing utilisation of robotics and automation for battery disassembly focus on robotic control, robotic autonomy and HRC applications [14,21].

The review questions for this publication were set to update and complement the knowledge provided in the previous reviews by reviewing the latest research on the topic, discussing the challenges and opportunities in automating the remaining manual tasks and introducing the benefits of EU battery regulations and battery passport proposal. In addition, approaches and methods to automate the most challenging tasks are discussed and presented to bridge the automation gaps. The following research questions were set for this publication:

1. Which disassembly and sorting tasks are automated?
2. What are the challenges and opportunities in applying robotics to automate the remaining manual tasks?
3. What are the potential benefits of battery regulations and battery passports for the EVB disassembly?

A comprehensive literature review is provided to answer the research questions. The rest of the paper is organised as follows: Section 2 presents the taxonomy and the methodology. Section 3 provides the background to justify the need for robotised disassembly and highlights the current challenges. Section 4 reviews the current EVB disassembly methods to identify the gaps in automation. Section 5 discusses the current methods and gaps in the automated EVB disassembly tasks and proposes methods to automate the remaining manual tasks. Section 6 presents future work to robotise the remaining manual tasks in the EVB disassembly. Finally, Section 7 concludes this paper.

2. Taxonomy and research methodology

This section presents the purpose of our research and the methods to collect, screen and review the literature to identify the current approaches and gaps in robotised EVB disassembly.

2.1. Taxonomy

The primary purpose of this review is to clarify the current state of robotised EVB disassembly. Therefore, the taxonomy revolves around the testing, dismantling, and sorting tasks that have been and have not been automated. The non-automated tasks are considered gaps, and recommendations for applying proven approaches from other fields to the identified gaps are presented.

2.2. Literature collection and screening methods

This publication reviews current approaches for EVB disassembly, including AI-based methods to disassemble EVBs. A three-phase strategy was used to screen the articles in the review to provide an objective view. In the first phase, articles were searched from the IEEEXplore, MDPI, Springer and Elsevier *i.e.,* Scopus and ScienceDirect databases using the following keywords: Electric vehicle AND battery AND robot AND disassembly AND recycling. The query produced 241 hits from Elsevier, 5 from IEEEXplore, 24 from MDPI, and 0 from Springer. Elsevier Scopus search includes the publication of multiple publishers, allowing access to publications of publishers not listed above. The search includes articles published before the 23rd of February 2024. In the second phase, those articles were read and manually sorted to exclude articles that did not focus (a) on the disassembly of the EVB or (b) robotised disassembly solutions; after manual sorting, 59 relevant articles were included in the bibliography. In the third phase, 58 additional articles cited in the screened articles were added to the bibliography. After including 117 articles, these 117 articles were tagged according to the content; the tags are described in Appendix. Finally, after careful final screening, 63 articles focusing on robotised EVB disassembly were included in the Review section. The search was conducted on Fig. 1 presents our methods for including, tagging and reviewing the articles.

The reviewed publications are categorised into journal, conference and book sections in Fig. 2. Most are journal publications; book sections are rare since robotised EVB disassembly is in its infancy. The rising research activity in the last three years indicates a timely research topic.

3. Background of robotised electric vehicle battery processing

This section provides background on EVB disassembly and explains why non-destructive and automated disassembly is essential to sustainable manufacturing. Despite the variation in the designs, the EVB packs are arranged into multiple modules consisting of individual battery cells with the *so called* pack-module-cell architecture, even if the architecture pack-cell is recently emerging. EVBs can be divided into three main

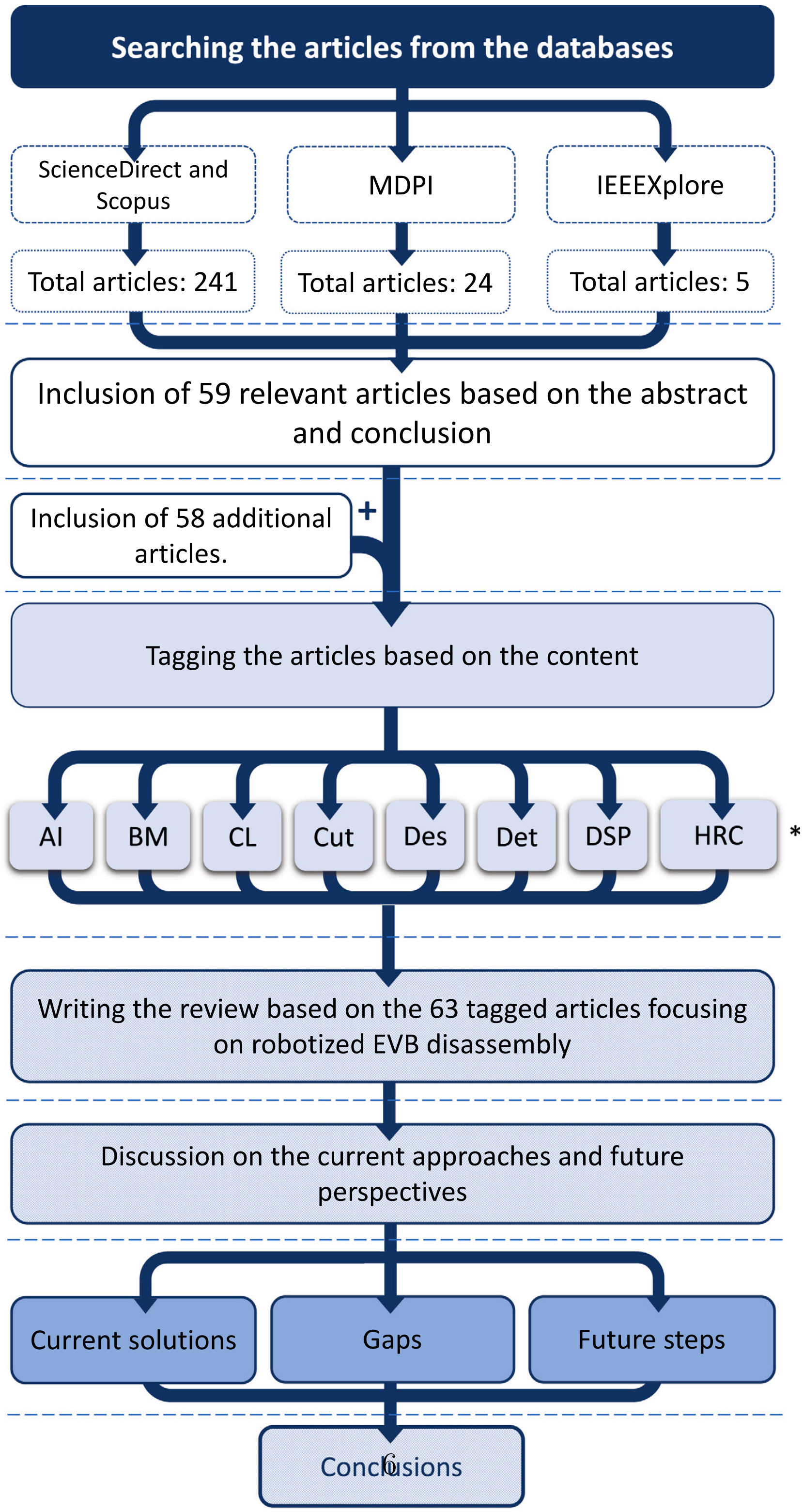

Fig. 1. Methodolygy used to search, include, organise, review and discuss the current state of robotised processing of the EVBs. * A comprehensive list of the tags is presented in Appendix.

types according to cell type: prismatic, pouch, and cylindrical [22]. Each EVB type can be disassembled from pack to module level, and modules can be disassembled to cell level [14].

Most of the literature papers are focused on pack-to-module disassembly [23]. Disassembling the pack-to-module is a crucial step in EVB disassembly, initiating the repurposing, recycling or reusing process by separating modules from other EVB components such as the mounting frames, wirings, hoses, and printed circuit boards. Currently, there are no dedicated facilities for dismantling and sorting EVBs; EoL management of EVs typically aligns with the internal combustion engine vehicle disposal process. The network of car dismantlers collects crashed or decommissioned EVs and removes the EVBs without employ-

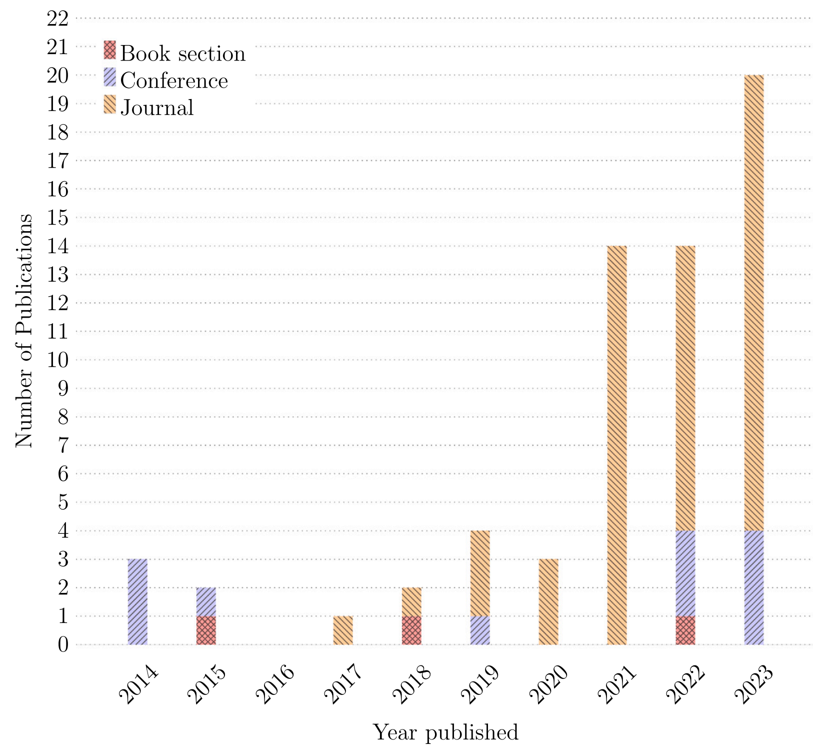

Fig. 2. Summary of the 63 publications included in the review section, categorised by publication type and year.

ing specific procedures, often resorting to manual operations without obtaining device-related information.

It is not anticipated that this practice will undergo significant changes shortly since the impact of upcoming battery regulations will take years to become evident after release. As additional obstacles to automation, companies involved in battery pack collection and dismantling are frequently small and medium-sized enterprises (SMEs) with a reduced investment capacity and low propensity to adopt automation and robotic solutions.

3.1. Current research projects

Numerous research initiatives are currently underway to support SMEs in the circular economy. Translating the latest research findings into industrial applications enables an increase in the level of automation to increase profitability and human safety in EVB processing. Noteworthy among these are several Horizon Europe projects at the European level, including Rhinoceros [24], Rebelion [25], Recirculate [26], Free4Lib [27] and BatteReverse [28], as well as national projects such ReLiB [29] in the UK, DemoBat [30] and Lithorec projects [31] in Germany, and EcoCirc [32] in Italy.

In China, multiple research projects are funded by the Ministry of Industry and Information Technology under the 2021 High-Quality Development Project (TC210H02C) and in the US, the Department of Energy announced a funding of 192 Million USD to advance research and development of battery recycling technology [33]. The projects and fundings share a common global objective: advancing solutions rooted in automation and robotics to facilitate the non-destructive disassembly of battery packs, focusing on enabling efficient reuse and remanufacturing of EVBs.

Fig. 3 presents the geographical distribution of the current research papers on robotised EVB disassembly. The map highlights the dominance of research work from China, the UK, Germany, and the US, with a strict connection to the previously described research projects.

3.2. Hierarchy of battery disassembly

A general disassembly hierarchy can be defined despite the absent standard EVB design; Fig. 4 reports all the main tasks and subtasks of EVB dismantling. The first step before dismantling the battery pack is testing to define the state of risk (SoR) of the battery pack. Damaged and unsafe batteries fail the tests and are not dismantled for repurposing, reusing or remanufacturing; instead, the batteries in critical condition are recycled by crushing as complete units without dismantling [34].

For safe and undamaged EVBs, state of health (SoH) and remaining useful life (RUL) are the criteria for evaluating the condition and the recovery value of the used EVBs. SoH presents the battery pack's capacity compared to its ideal state and is presented as [35]

$$SoH = \frac{C_{bat}}{C_{nominal}} \times 100\%, \tag{1}$$

where C_{bat} is the present capacity, and $C_{nominal}$ is the battery's nominal capacity. RUL is the number of charge–discharge cycles left until EVB reaches 0% SoH. Various methods proposed to define the SoH and RUL are presented in Section 3.5. Battery modules with SoH higher than 80% are acceptable for vehicle applications [36].

After defining the SoH and RUL of the EVB modules, the next phase is dismantling the battery pack to the module level. Regardless of the diverse battery designs, the tasks for disassembling a battery pack from pack to cell level are uniform [37,38]. The tasks include removing the battery cover, wire assembly, battery monitoring system (BMS), bus bars, thermal management system, and battery modules. The thermal management system is optional and not present in all the EVB designs.

The internal attachment methods of the EVB typically include thread, weld, adhesive, push-in rivet, locking tab, and retaining ring. Thread joints attach the cover, BMS, modules and contactors. Adhesives seal the battery cover to the battery frame and glue the battery modules to the radiator plate to improve heat conductivity. Some designs utilise a reusable seal instead of adhesives to seal the cover to the battery

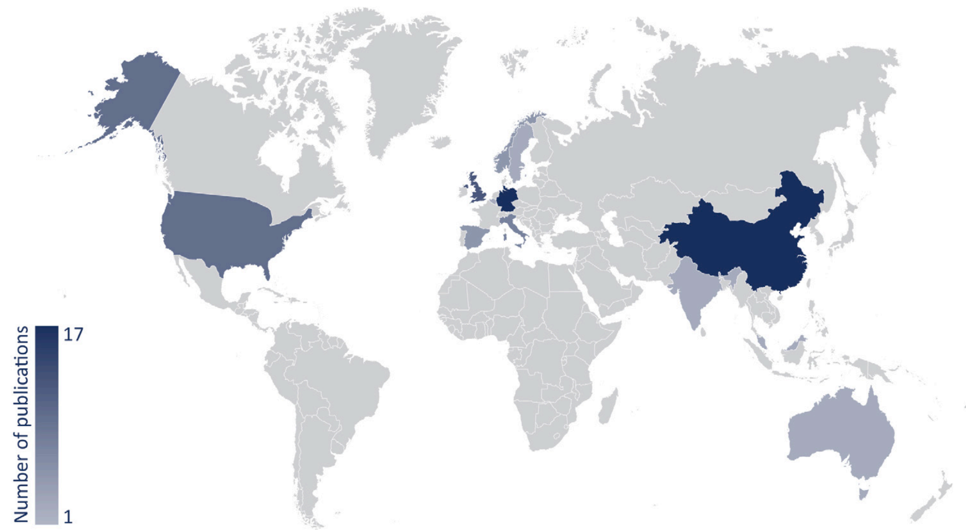

Fig. 3. Geographical heat map showing countries of the affiliation of the first authors of the publications included in this literature review.

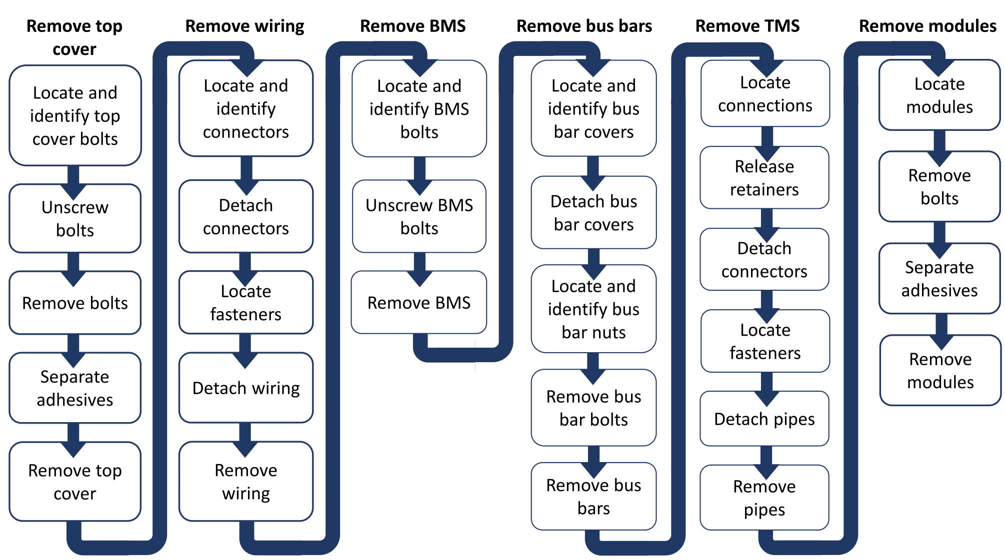

Fig. 4. The hierarchy of EVB dismantling.

frame. Push-in rivets mount flexible wiring assemblies to the pack, and locking tabs hold the electrical connector pairs together. In addition to wire assemblies, hose assemblies utilise push-in rivets for mounting, and the hose quick-fittings are locked in place with retaining rings. Fig. 5 presents a Ford Transit plug-in hybrid electric vehicle (PHEV) battery's main components and joint methods.

The attachment methods of the battery cells depend on the cell type. Pouch cells are typically stacked together using thread bars on the corners and metal end plates to create compression, and the conduction plates between the cells are spot-welded together. Modules consisting of cylindrical cells utilise spot-welded conduction plates to bind the cells together and plastic housing glued around the cell group. Prismatic cells are mounted to the battery frame using thread bars or screws, and bus bars connect the battery modules together.

The tasks required to separate the joints during EVB disassembly are unscrewing, cutting, grasping, and separation. In addition, handling is required to sort the parts for efficient recycling and testing to define the SoH and RUL. A high-level task controller is required to plan the order of the disassembly sequence. Artificial intelligence enables cognitive capabilities for the high-level controller to detect the components and plan the sequence for disassembling. The utilisation of AI in disassembly sequencing is explained in more detail in Section 4.1.2.

3.3. Safety challenges

The challenges related to the safety of the labourers manually performing the disassembly tasks justify the need for robotised dismantling and sorting solutions. The challenges related to the lack of standardisation enable variety in the EVB physical characteristics, complicating the automated processing of second-hand EVBs. The absence of the battery information limits the availability of technical details, disassembly sequences, and chemical compositions of the EVBs. Manually dismantling EVB necessitates employing highly skilled workers and implementing stringent safety protocols, escalating costs, as noted by Harper et al. [15] in their 2019 study on recycling.

Diekmann et al. [39] categorised the dangers associated with Lithium-ion batteries (LiBs) into the following primary groups: electrical, fire, explosion, and chemical risks. Electrical risks stem from the batteries' stored charge and high voltage. Fire and explosion risks

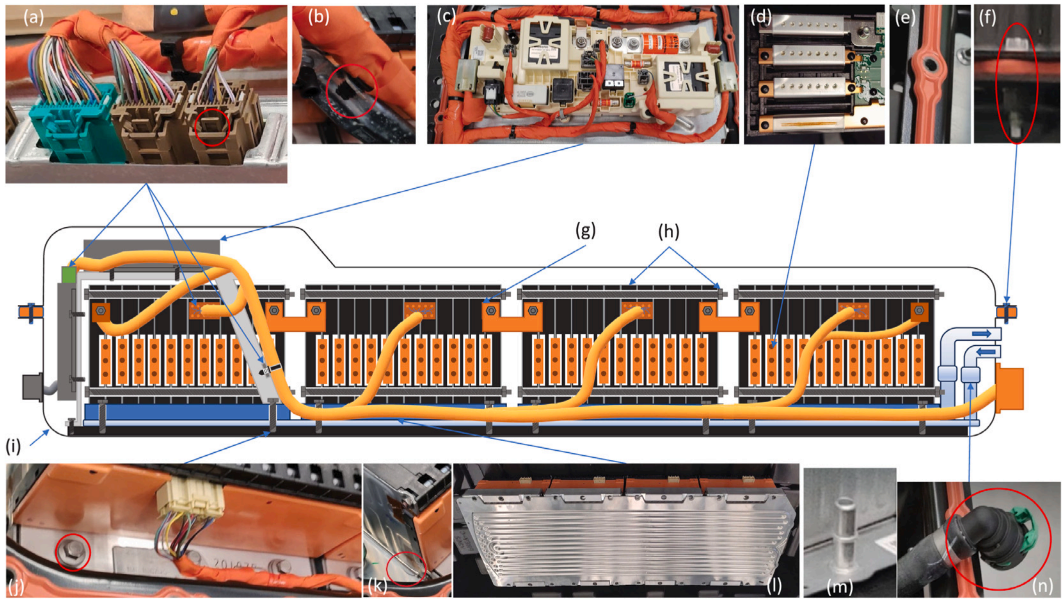

Fig. 5. Cross section view of Ford Transit PHEV battery. (a) Connector locking tab, (b) Wiring assembly push-in rivet, (c) Contactor and fuse unit, (d) Cell-to cell-connector plate spot welds, (e) Reusable cover seal joint, (f) Cover bolt and thread, (g) Bus bar to a module thread joint, (h) Cell-to-cell bar and glue joints, (i) Battery frame, (j) Module to battery frame thread joint, (k) Radiator plate to module adhesive joint, (l) Radiator plate, (m) Thermal management coolant quick fittings, (n) Retaining ring release tab.

arise from the flammable materials in electrolytes or as by-products of reactions. Chemical risks involve the production of toxic gases like carbon monoxide or hydrogen fluoride during reactions. The authors further emphasised the interconnected nature of these risks, where one type of hazard could trigger another, leading to a cascade of dangerous events [39]. Electrical risks are particularly concerning during disassembly due to the potential for electrical shocks to humans or short circuits that could cause thermal runaways, release of toxic gases, explosions, and fire. Consequently, automating the EVB disassembly process becomes essential to ensure the economic viability and safety of reusing and recycling these batteries sustainably.

The design of the disassembly system must consider the analysis of potentially explosive atmospheres (ATEX)[1] of the area around the battery pack and, if necessary, adopt tools enabled to work in the corresponding ATEX zone. In addition to risks related to the properties of the EVB, the disassembly and sorting process introduces risks to human labour. Using frozen or hot air to separate adhesive joints exposes the human worker to frost and burn injuries, or using solvents to separate the adhesive joints increases the amount of toxic fumes and the risk of fires. In addition, using rotating cutter blades to separate weld joints increases the risk of fire and eye injuries.

3.4. Lack of battery standards and regulation

As identified in various studies, a key obstacle is the significant variation in battery pack designs, which complicates the automation process [40]. Thompson et al. [41] highlighted that the diversity in battery pack designs, along with the use of various fixtures and adhesives, impedes automated disassembly. They suggested two design modifications to ease disassembly: (i) constructing battery packs without modules, using only larger cells, and (ii) employing reversible adhesives to bind the cells. Gerlitz et al. [42] also noted the difficulty posed by non-detachable joints, such as welding or adhesives, in battery disassembly. This is especially problematic given the inherent risks of the process, as non-detachable joints often require some form of destructive separation, increasing the risk of explosions or other accidents.

Furthermore, Thompson et al. emphasised the need for standardising battery pack designs and labelling. The proposed EU Battery Regulation reflects this need, mandating battery labelling and the creation of battery passports to facilitate information flow [43]. However, the current lack of standardisation in design remains a significant barrier to automating battery disassembly [44]. Additionally, the uncertain conditions of end-of-life or damaged EVBs add to the complexity of executing the disassembly process effectively. It is well known that the current void of battery design regulation created a heterogeneous ensemble of design solutions that represent a challenge to automatic disassembly [45].

New EU battery regulation [19] defines requirements on sustainability, safety, labelling and information on the batteries marketed and put on service in the EU. The scope of the new regulation is for all batteries except those used by military and space exploration.

Carbon footprint information is required for batteries with a capacity greater than 2 kWh after the 18th of February 2025. The information includes the manufacturer, battery model, geographic location of the manufacturing plant, the carbon footprint as kilogrammes per kWh over the expected lifecycle, detailed carbon footprint according to lifecycle states, EU declaration of conformity number, and a web link to the public version of the carbon footprint calculation. The batteries have a legible label indicating the carbon footprint, and the technical documentation demonstrates that the lifecycle carbon footprint is below the set threshold.

Manufacturers are obliged to report the utilisation of recycled raw materials and to increase the percentage of recycled materials. In the first phase, after 18th of August 2028, the manufacturers start including the percentage information on the recycled content. The obligation concerns batteries containing cobalt, lithium or nickel in active materials. In the second phase, the minimum levels for the utilisation of recycled materials become effective after 18th of August 2031 and the battery manufacturers are required to utilise at least 16%, 85%, 6%, and 6% of recycled cobalt, lead, lithium, and nickel, respectively, in the manufacturing process of new batteries. Finally, after 18th of August 2036, the demand for the percentage of recycled materials rises to 26% cobalt, 85% lead, 12% lithium and 12% nickel.

[1] The acronym derives from the French "appareils destinés à être utilisés en ATmosphère EXplosive" equivalent to "equipment intended for use in explosive atmospheres".

Manufacturers are obliged to provide a free-of-charge take-back system for the EVBs without obligation for the customer to buy a new battery, regardless of condition, brand, or origin. EVBs are collected at the end-of-life vehicle treatment facilities and from the end-users. Manufacturers are responsible for the transportation of the EVBs to the processing facilities.

Labelling batteries with general capacity and carbon footprint information on the battery is required after 18th of February 2027. In addition, a quick-response (QR) code is required to provide information on the battery content and recycling information and identify the individual battery unit to interact with the upcoming digital battery passport. Digital battery passports have been proposed by the EC to validate the authenticity of the repurposed, remanufactured and recycled EVBs [20]. The digital passport enables the circular economy stakeholders to verify all the transactions of the battery packs down to the origins of the raw material supply used to assemble the pack. The proposed digital passport is planned to utilise *Electronic exchange system* described as an accessible online system.

The publically accessible information contained in the battery passport information on the materials and chemistry, carbon footprint, responsible sourcing of materials, recycled content, renewable content, capacity, voltage, expected lifetime, allowed operating temperature, warranty, internal resistance, declaration of conformity, and EoL management. The professionals working in the service and recycling sectors are provided with information on the material composition, part numbers for the components, exploded diagrams, disassembly sequence, types of fastening methods, tools required for disassembly, safety measures, state-of-X (SoX), risks and amount of cells.

The obligation for the manufacturers to provide detailed information on the disassembly sequence, fastening methods, and SoX enables overcoming the lack of information from the original equipment manufacturers (OEMs) regarding battery disassembly [46].

In addition to EC, Ford Motor Company (Dearborn, Michigan, USA) plans to initiate a Battery passport with Everledger.io (London, UK). The tracking of the EVB is initiated by attaching a unique identification tag to each EVB and all the modules during manufacturing [47]. The passport contains information on the chemistry, usage, service, updating, remanufacturing and recycling of the EVB.

By adopting the passport concept, Ford aims to have comprehensive information on the EVB to decide whether the pack or modules can be reused as a remanufactured part, repurposed as a building energy storage, or recycled after the EV is decommissioned. Using the battery passport, the chemical composition of the battery modules and the raw materials used during manufacturing are known for repurposing, remanufacturing and recycling. The proposed solution utilises blockchain technology as a secure and decentralised information database.

3.5. Health assessment and lifetime prediction of EVB

This section reviews the non-destructive testing methods to predict the state of health and remaining useful life of EVBs and approaches to utilising robots to inspect and test the EVBs. To define the SoX of the EVBs, direct assessment, statistical and data-driven approaches are used. Fig. 6 presents the categorisation of the approaches to screen the EVBs before disassembling.

Research exploring EVB health estimation advancements underscores the dynamic roles of machine learning (ML) and neural network (NN) models. In [49], authors explore diverse neural network models for precise SoH and RUL predictions, demonstrating a broad application of ML techniques for battery health assessment. The work [50] focuses on back-propagation neural networks to evaluate retired EVB's SoH for second-life applications, emphasising the reusability aspect of battery technology. Meanwhile, [51] delves into deep learning models to manage complex datasets effectively, showcasing advanced ML frameworks for accurate EVB health diagnostics. These studies reveal a comprehensive strategy for enhancing EVB assessments, integrating traditional and advanced neural networks to forecast SoH and RUL, thereby contributing significantly to sustainable automotive technologies.

One notable approach involves deep neural networks (DNNs), where a collection of trained DNNs estimates the SoH in a target domain [52]. This method, notable for its robustness and adaptability to real-world scenarios, involves averaging estimations from selected DNNs to produce final, reliable estimates. This process effectively handles the uncertainties inherent in training, and it is particularly adept at leveraging data from various commercial LiB cells, each with its distinct cathode material and manufacturing technique.

In the evolving field of EVB health assessment, integrating neural network models has shown significant advancements. The exploration of real-time applications of these models in battery health assessment [53] adds to our understanding of practical challenges and solutions. This integration of advanced machine learning techniques complements existing methods, such as data-driven approaches [54] for optimising fast-charging protocols, highlighting the comprehensive scope of AI in battery health assessment. Additionally, ensemble learning and random forest regression are explored for monitoring the SoH of LiBs. These methods are particularly effective in handling complex, large datasets, making them suitable for online capacity estimation and real-time health monitoring of batteries [49,55,56].

Further, techniques such as Gaussian process regression and support vector machine-based approaches have been applied to SoH estimation. These methods often focus on specific operational data segments of the battery, such as partial charging segments or incremental capacity curves, to derive precise health estimates [57,58].

Each method contributes a unique perspective to estimating the SoH and RUL of EVBs. As the demand for reliable and efficient EVBs increases, the advancements in neural network modelling and data analysis become increasingly vital, ensuring the longevity and safety of battery systems.

4. Literature review

The use of robotics and autonomous systems for the disassembly of EoL products is considered one of the most promising solutions by several works [15,17,59–62] to overcome the current limitation of manual disassembly in terms of workers safety and process efficiency. The study in [62] highlighted that with the increasing Level of Automation, it is challenging to address and manage uncertain external factors in the disassembly system of an EoL product. The automated disassembly system requires either HRC, AI, perception systems or a combination of these to address external factors and reach the required flexibility effectively [38].

The level of disassembly was studied [63] to identify the "stopping point" making a partial disassembly or the disassembly of sub-modules to maximise the economic profit and the environmental impact. Similarly, in [64], the system acquires information on the device to autonomously predict the value of regained components or recyclable materials, predicting the optimal level of disassembly. In [65], authors interviewed experts from various sectors along the value chain of EVB. In the interview, the experts were asked to provide the potential degree of automation for the 3R scenario: Reuse, Remanufacturing, and Recycling. The highest potential of automation was for a recycling use case with an average of 74.2%; this result was motivated by the fact that recycling does not necessarily need non-destructive disassembly. However, all the experts agreed that a fully automated disassembly process is yet to be feasible due to the current battery design and structure.

The typical flow for automated dismantling is data acquisition on the device, capturing 2D/3D images, detecting components, identifying components, determining components' positions, defining a disassembly plan, and removing the components. All these tasks involve several

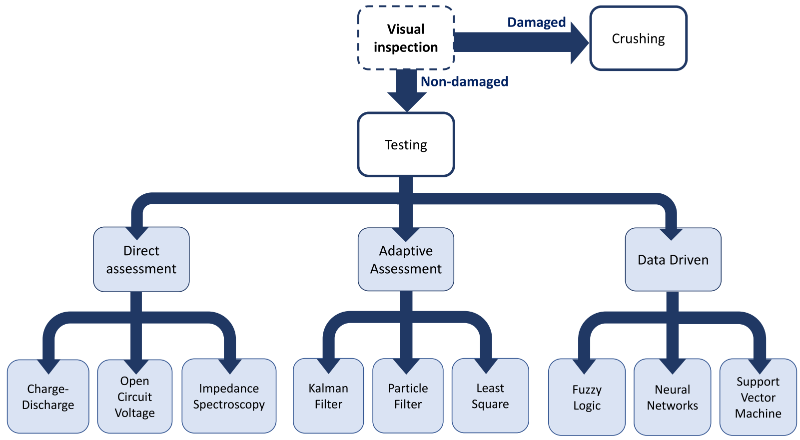

Fig. 6. Screening methods to define the health of the EVB.
Source: Adapted from [48].

research areas such as battery testing, MV, ML, Robot Programming (RP), Disassembly Sequence Planning (DSP) and Task Planning (TP), HRC and Safety. The following sections group the revised papers by topic, reporting the main contribution of each single work.

4.1. Advanced robotics for EVB disassembly

Due to the variation of the EVBs, the autonomous and semi-autonomous disassembly of EVBs requires more advanced robotics than the manufacturing of new products. The approaches to cope with unpredictability utilising advanced programming techniques, disassembly sequence planning, and HRC are reviewed in this section.

4.1.1. Robot programming

Traditional programming methods for industrial robots are point-by-point teaching using teach pendant and offline programming. When production batches are known, the methods mentioned are efficient for creating repetitive programmes for assembling new products manufactured in batches. For the disassembly of EVBs, traditional programming methods are inefficient, and higher-level control capable of adapting to product variation is required.

Robots for disassembly impose a long programming time that can constitute a significant obstacle to robot adoption, particularly with the high variability of battery pack design. The robot programming methods are a heritage of the past, without standardised languages or tools. The research community investigated new programming methods to save time, trying to bring robotics closer to non-expert users. In [66], authors proposed using a six Degree of Freedom SpaceMouse to programme the robot, avoiding using the robot Teach Pendant during the robot online programming. Regarding the offline programming methods, using the information in the computer-aided design (CAD) model, the robot part programme can be generated drastically, reducing the programming, as described in [67].

The use of task-oriented programming, instead of robot-oriented programming, is poorly adopted, but it was demonstrated that it could be quickly introduced, with the support of an intuitive user interface, to workers without any robotic expertise [68]. The authors demonstrated that the above methods significantly reduce programming time, helping spread robotic solutions to non-expert users.

4.1.2. Disassembly sequence planning and task planning

A crucial aspect of complex device disassembly is generating the optimal disassembly sequence, minimising multiple factors such as the cycle time or the energy consumption. The complexity of the components imposes the design of multiple disassembly stations, which even increases the disassembly sequence generation complexity [69]. Pioneering work of [70] analysed the disassembly sequence, proposing using a disassembly matrix and the disassembly priority graph to describe the connection and the priority relationships, precedence constraints, between components. The extraction of the disassembly sequence from the CAD model is also a viable solution evaluated in [44]. In this work, the authors highlighted the lack of a standard to share the disassembly information; they proposed using the STEP data exchange format (ISO 10303-21) as a possible solution, defining all the necessary information that the STEP model should contain for the disassembly at the EoL of the device.

Choux et al. [71] presented a task planner for the EVB disassembly. The system has a single 3D camera as an input for the task planner based on the Robot operating system framework (ROS) and an industrial robot as the mechanism for disassembly. Initially, eight pictures of the battery pack are taken in predefined locations, and You only look once (YOLO) object detection library is used to detect the components essential to disassembly. The order for the disassembly is top-down based on detecting overlapping components. The presented solution generates trajectories based on the camera input and thus does not require a digital battery pack model. While the proposed approach focuses on one specific battery pack from the Audi A3, it can be adapted to various battery packs incorporating screw joint construction. The solution presented focuses on the design of the task planner and verifying the accuracy of the planned paths; tooling for the disassembly is not included in the proposal.

Rastegarpanah et al. [16] proposed a behaviour-tree framework for a mobile grasping solution to sort the detached EVB parts. In the presented framework, the behaviour tree is divided into navigation, object pose tracking, and grasping modules. Hellmuth et al. [72] defined two indexes to support decisions while assigning tasks to the robot or the human worker. For a given disassembly graph, the two indexes consider several factors helping the evaluation of a task. Chu et al. [73] used a hybrid particle swarm optimisation with the Q-learning algorithm to find the optimal disassembly sequence planning, enabling an efficient human–robot collaborative disassembly.

Alfaro-Algaba et al. [63] propose a cost–benefit analysis using a model to compute the optimal disassembly level, optimising the trade-off between the maximum economic profit and the minimum environmental impact. The model supports the user in making decisions, providing the proper disassembly plan based on the state of modules with profit maximisation.

Zhang et al. [61,74] presented a self-directed learning disassembly planning system utilising NeuroSymbolic task and motion planning. This architecture accommodates planning in an unstructured and dynamically evolving environment. The researchers introduced neural predicates, employing probabilistic learning techniques to derive discrete symbols from continuous visual inputs. These symbols describe states relevant to the disassembly task. By abstracting the planning problem, the authors transformed task planning into pursuing optimal action plans within symbolic space.

The work [75] proposes a disassembly task planning method based on an ontology model and partial destructive rules. The ontology model supports decisions for case/rule reasoning. Then, the authors proposed a set of partial destructive disassembly rules and disassembly tool selection to solve the problem of parts that cannot be disassembled with non-destructive tasks. Finally, an iterative generation method of parallel disassembly sequence is used to infer feasible planning schemes from the rules and eliminate unrealistic disassembly sequences.

The use of cloud-based disassembly architecture [76] and the concept of cloud robotic disassembly [77] was introduced, proposing a cloud infrastructure to control multiple disassembly robotic cells. The cloud infrastructure is responsible for high-level task scheduling, data collection, storage and elaboration, providing disassembly services to multiple robotic cells. This study [78] provides insights into the experimental disassembly process of EVBs, focusing on time and cost analysis. While not directly linked to cloud-based disassembly, its data analysis could support future cloud integration for optimising disassembly processes.

On the other hand, [79] emphasises optimising disassembly strategies through adaptive planning, potentially complementing cloud-based approaches by enabling enhanced decision-making and automation within a cloud framework. These studies suggest a move towards data-driven, optimised disassembly processes, hinting at the synergy between direct experimental methodologies and cloud-based technological advancements for electric vehicle battery recycling.

4.1.3. Robotics cell layout and automation architecture

Some authors propose studies for robotic cell layout [80] involving multiple robots to cope with heterogeneous battery design. In [81], authors proposed the design of an infrastructure based on information-driven robotic disassembly. The architecture follows the principle of an intelligent agent to allow adaptive behaviour and target-oriented implementation. Several interconnected modules can analyse the battery pack and, thanks to AI-based algorithms, make decisions on the EoL of the battery for further disassembly actions. Then, a perception unit, such as a vision system, acquires data, produces information, and stores it in a cloud for the execution unit, for example, a robot. Finally, an intuitive human-machine interface presents the relevant information.

4.1.4. Robot tool design

The tool design is crucial in robotic disassembly [80], particularly for battery disassembly. The disassembly process sets special requirements, such as high voltage isolation and the capability to operate in a potentially explosive atmosphere for the tools. The requirements impose the design of special solutions [82] to improve the components available on the market. In [83], authors identified the four mandatory tasks: handling, separation, clamping, and monitoring to pursue the disassembly of the battery pack into modules. The robot needs at least one tool for each listed task. Several works analysed the disassembly, proposing the design of specific disassembly tools. In [61], authors designed a passive and compliant pneumatic torque actuator to loosen fasteners. The device embeds a camera to detect the fastener and guide the robot on the target, being able to compensate for the depth error measurement given by the fastener localisation and prevent the collision of the tool during the loosening of the screw. In [84,85], authors designed a dedicated tool for cutting covers and plates and an optimised fast-responding two-finger gripper to manipulate parts. A genetic algorithm was used to support the tool selection for a specific task in HRC disassembly in [86].

4.1.5. Human–robot collaborative disassembly

Although using human–robot collaborative applications is quite common for assembly tasks, it is less frequent to find applications in disassembly [81,87]. One reason behind this is that battery design considers specific techniques to fix parts together, e.g. glue, that benefits assembly and performance at the cost of hindering its disassembly. On the other hand, EoL products might present the effects of tear and wear in their components, so prior additional operations or a different disassembly procedure should be performed. Hence, using human–robot collaborative disassembly (HRCD) cells where humans and robots coexist is a viable solution for disassembling components at their EoL [59,70]. Besides HRC techniques, cells themselves need to be designed to consider their application in natural environments, mainly ensuring operator safety from the risks associated with the different disassembly operations of EVBs as performed in [82]. In [88], a strategy for optimising the disassembly of EVBs through human-machine collaboration is presented. It focuses on improving efficiency and safety by leveraging neural network algorithms to guide the disassembly tasks, emphasising the synergy between human skills and robotic precision in recycling and remanufacturing processes. Yuan et al. [89] explore the efficiency and security of HRCD processes for spent LiBs. It introduces a resilience assessment model utilising stability, redundancy, efficiency, and adaptability metrics, evaluated through fuzzy Bayesian fusion and analytical network process methods. This novel approach demonstrates flexibility in complex disassembly tasks, systematically optimising HRCD for battery recycling and enhancing decision-making and operational efficiency.

Hellmuth et al. [72] presented criteria to assess the automation potential of the dismantling of electric vehicles, presenting updated criteria to evaluate the necessity and technology ability for automation of each process and comparing it against existing assessments. This work highlights the necessity of HRCD and states which operations should and could be automated, with unscrewing operations at the top of the list. This conclusion was also drawn by the pioneering work of Wegener et al. [17,70], which considers the design of an HRCD cell for all the processes involved in the different unscrewing tasks. Particularly, in [90], they present an approach to avoid relying on specific tool-changing solutions and instead change between socket wrench bits to unscrew all the different threaded fasteners in EVBs, also including a Learning-from-demonstration phase for their position and the approach strategy.

Duan et al. [91] studied increasing the safety and efficiency of HRCD by using mixed reality. The proposed framework comprises the physical HRCD cell for battery disassembly and its digital twin. A 3D camera percepts the physical twin to detect the poses of the human worker and the positions of objects; combined with DSP, this information enables AI to recognise the disassembly phases. The augmented reality headset lets the human worker visualise the disassembly sequence and virtually disassemble the EVB. An experimental setup enabled the authors to compare time, success, and collision rates to a pre-programmed HRC solution not featuring perception, AI, and mixed reality to increase adaptability. The experimental results show that the time consumed working increases, and the time consumed waiting decreases for both the human worker and the robot.

To exploit the concurrence of human and robot actions such that costs are reduced compared to manual operations, task sequence must be distributed between both agents. Uneven distribution is tackled in [73] considering the processing of multiple batteries between multiple disassembly cells, also introducing into the problem the associated risk to each process from the level of deformation of the battery components. Wu et al. [92] defined a mathematical model to optimise four objectives: number of workstations, workstation idle time, number of workers, and disassembly cost in a human–robot disassembly line. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is used to solve the multi-objective optimisation problem efficiently.

The disassembly of a battery module presented in [93] showcases an approach that considers combining task scheduling using multi-agent RL with 2D robot path optimisation using Q-learning. Later [94] proposed a model based on the discrete squirrel search algorithm to solve the complex problems associated with two-sided disassembly lines, focusing on balancing efficiency and human–robot interaction.

The reference standards for robotic safety are ISO 10218-1 [95] and ISO 10218-2 [96]. ISO/TS 15066:2016 [97] was later introduced to supplement the requirements and guidance on collaborative industrial robot operation provided in ISO 10218-1 and 10218-2. The risk assessment and corresponding operational scenario should identify the relevant safety principle. Furthermore, the risk assessment must outline the specific technical safety requirements. The safety system requirements vary based on the application and the collaboration mode between the robot and the human operator. The standards distinguish between four different types of collaborative robot operation: *safety-rated monitored stop*, *hand guiding*, *power and force limiting* and *speed and separation monitoring*. Looking at a disassembly task, where the operator's intervention is supposed to be frequent, and where tasks can be cooperative tasks instead of collaborative, the most promising approach is speed and separation monitoring (SSM), which avoids unnecessary stops with a reduced impact on productivity [98]. In SSM, any contact between the robot is prohibited. The robot has to maintain a protective separation distance from the operator, which is computed considering several human and robot factors. The distance between the robot and the operator is constantly measured. The robot's speed is adjusted dynamically based on the distance to the operator; the robot stops when the distance to the operator is unsafe. For example, the robot can work at the nominal speed even if the safety constraints are respected, *i.e.,* the operator is in a different part of the workspace, and a safe distance remains between the two. Since contact is not allowed, the SSM can be applied to standard industrial robots, enabling collaboration and cooperation [99]; the current limitation is the availability of a certified sensor to track the operator in real-time.

Of the new upcoming standards, the updated ISO 10218 standard incorporates collaborative robot system safety functions from ISO/TS 15066. Combining the two provides a standard for collaborative and industrial robots, integrating technical requirements for collaborative functions, end effectors, loading stations, and force testing.

4.2. Machine vision and machine learning EVB disassembly

The comprehensive review [45] demonstrated how battery disassembly could benefit from AI and ML in all the disassembly steps: sorting, testing, safety monitoring, decision-making, disassembly target detection (*i.e.,* machine vision to identify disassembly targets), parts separation and handling. Despite the vast potential, the data collection for AI model training remains the main obstacle to their wide usage. The authors analysed part of the revised solution from the Technology Readiness Level (TRL), and it emerges that the highest TRL reached by such solutions is five, meaning that the current literature proposes prototype solutions validated in the laboratory.

Machine vision techniques in disassembly are mainly dedicated to object localisation and classification. Deng et al. [100] demonstrated their approach of optimising camera exposure with the help of deep learning in the use case of screw removal of EVB. Quan et al. [101] proposed a two-stage framework to detect screws during EVB disassembly. The first stage is to use a trained feature regression model to detect the regions, including screws, and the second stage uses the regions to be analysed further to detect possible false detections that occurred during the first stage. The detection accuracy of the proposed approach compared to methods based on YOLO, Soar, ResNet, and R-CNN is improved when a similar amount of images is used for the dataset.

Al Assadi et al. [102] studied utilising ML to detect faulty and intact Torx, Phillips and hexagon screws. This work used approaches based on CNN and ML to compare their accuracy in monitoring the unscrewing process by comparing the actual screwdriver torque curve to reference curves. The rotation angle-torque curves were collected utilising an industrial screwdriver featuring controllable inputs for speed and torque and output for torque curves. By utilising a dataset consisting of over a thousand angle-torque curves of intact and faulty screws, it was possible to detect the unscrewing process reliably. Rastegarpanah et al. [103] proposed a concept to unscrew hexagon head bolts utilising a two-finger gripper to grasp the bolt and the sixth joint of the robot to unscrew the bolt. In this approach, the robot is used to explore the surface of the EVB to detect the screws; sensing is based on the force sensors integrated into the robot arm.

The presence of multiple types of screws imposes the use of autonomous classification systems in [17] to choose the proper unscrewing tool. A depth camera was used in [61,104] to detect the position of fasteners by combining MV techniques and machine learning algorithms (*i.e.,* YOLOv5). In [105], authors proposed what they called *"Active Screw Detection"*, an adaptive method to detect and precisely locate screws and bolts. The two-stage approach consists of the use of a depth camera to roughly localise the screw using depth and RGB images processed by a modified YOLOX model. Then the robot, thanks to an eye-in-hand camera setup, moves the camera on the closest screw to acquire other depth and 2D images from an optimal snapping position. The final accurate screw detection is obtained by processing the images acquired in the second stage with the modified YOLOX model. This approach optimises the final detection position, which strongly affects the final localisation accuracy.

In [23], authors used a depth camera to acquire an RGB point cloud. In the first step, using only the red, green, and blue (RGB) colour model information and an instance segmentation network, the instances of each component were identified, making a pixel-wise classification. In the second step, an accurate component localisation is obtained, registering the segmented point cloud with a point cloud of the component previously created in a known coordinate system.

Gerlitz et al. [42] used 3D image registration between imaged battery modules and CAD images to compensate robot trajectories to possible deformations. In [106], authors used point cloud semantic segmentation to detect wires and flexible elements using model-free algorithms; model-based algorithms may fail in detecting flexible elements that can easily differ from the nominal shape.

X-ray fluorescence hand-spectrometer was used in [23] to determine the composition of the disassembled components. The technology was suitable for detecting some materials, such as metal alloys, while not working on polymers. The high cycle time and the presence of coatings on the material surfaces are obstacles to adopting this technology.

4.3. Enhancing safety in EVB testing and disassembly

The hazards remain in the EVB disassembly area despite the trained professionals, protective suits, and isolated tools. While the risks are lowered, the high voltage and chemical composition of the EVB still expose the human worker to chemical, electrical, and fire risks. In addition to hazards related to the EVB itself, the solvents, freezing air, hot air and cutting used to separate glues and adhesives generate chemical and physical hazards to the human worker. Only complete physical isolation of the worker from the disassembly process enables overcoming safety issues related to EVB disassembly.

In the innovative field of EVB testing, the incorporation of robotics marks a significant leap forward. Robots, guided by advanced techniques like visual servoing, are increasingly employed to perform intricate tasks such as Electrochemical Impedance Spectroscopy tests on LiBs [107]. This automation enhances precision in battery health assessment and streamlines the process, catering to the growing demands in the EVB sector. Using robots for such intricate tasks exemplifies the blend of robotics and battery technology, paving the way for more efficient and reliable battery testing methods.

A robotised testing approach based on visual inspection was proposed by Rodriguez et al. [108] for pre-sorting damaged and non-damaged battery modules to avoid passing damaged modules to the human worker at the voltage testing station. The presented approach improves the safety of human workers by passing only non-damaged battery modules for further testing and processing by human workers. After the pre-inspection, the open-circuit voltage (OCV) test defines the SoH of the non-damaged batteries.

Efficient battery voltage and health testing solutions integrated into the robot gripper have been presented by [59,109]. The grippers feature electrically isolated and dynamic fingers for handling components and testing OCV and internal resistance of the modules during disassembly. In addition to multi-functionality, the distance between the gripper fingers adapts to the size of the handled components in the approach presented by Tan et al.

During the comprehensive literature review, only one publication proposing telerobotics for the EVB disassembly was found. Hathaway et al. [110] proposed and validated two approaches to using teleoperation in the dismantling and sorting of EVBs. In the first approach, a haptic control device with six degrees of freedom was used to teleoperate a seven-degrees-of-freedom collaborative robot arm, and in the second setup, master and slave devices were identical robot arms. In the proposed approach, the human worker dismantling the battery is isolated from the processing area and becomes the teleoperator of the dismantling and sorting robot.

The study aimed to compare the success rate and the completion times between the two slave devices in cutting, handling, sorting and screwing operations during the EVB processing. It was noted that the identical mapping of the master and slave devices is more significant in improving the completion times, and the haptic feedback contributes to the improved success rate.

4.4. Battery design for disassembly

Many authors agree that a fundamental aspect of improving the performance and the reliability of automatic/robotic disassembly is the application of the paradigm: "Intelligent design for disassembly" [45, 111], or the more advanced concept of Design for remanufacturing or recycling using non-destructive and easy dismantling solutions. Avoiding permanent joints, such as welding, glueing, and adhesive joints, is the first fundamental step for a practical disassembly [80] and designing the device to enable the disassembly along the vertical axis [59]. The circular economy paradigm generally benefits from devices designed considering their EoL [112].

Lander et al. [111] made a systematic techno-economic analysis of the manual disassembly of six commercially available EVB packs, computing the cost of the process. The results highlight a considerable heterogeneity in battery design, providing quite different disassembly costs on the base of the battery pack manufacturer. In the work, the author estimated that the disassembly cost can drastically decrease by adopting semi-automatic (human–robot disassembly) and fully automatic disassembly. Despite this, many authors conclude that a complete automatic disassembly is unfeasible due to the high variably of battery design [15,61,65,73,80,87,92,93,109], even if most of the battery packs require the same tasks to be disassembled [17,61,63,82,85]. Obviously, DfD would be the way to reduce the disassembly costs and improve the use of robotics and automation in the future [45,65, 111]. The non-destructive disassembly would be preferable for reuse and remanufacturing, but with the current battery design preferring permanent joints such as weld or glue [40], destructive disassembly methods are required to separate the components [15,75]. DfD has been actively studied during the last five years, and most reviewed publications reviewed in this section were published between 2022 and 2023.

4.5. Previous review publications

In the bibliographic research, some reviews emerged, their focus being primarily on chemistry and material recycling. At the same time, automation and robotics for battery pack disassembly were addressed only in two reviews.

In the case of [14], authors discussed robotic disassembly concisely. In contrast, in [21], the authors extensively reviewed works using robotics and automation for battery disassembly, deeply focusing on robotic control, robotic autonomy and HRC applications. Both reviews addressed multidisciplinary topics that strongly impact the robotised battery disassembly, such as the DSP and TP, the HRC, the AI, and the MV. The work [109] revised the state-of-the-art battery disassembly framework, also looking at the literature to disassemble generic mechatronic devices to propose a human–robot hybrid disassembly workstation equipped with custom flexible tools.

In [15], authors made a global revision of all the relevant topics related to the battery EoL, also discussing robotic disassembly and the limits of robot adoption caused by the lack of standards design and the limited number of information on spent batteries.

The review [81] is dedicated to revising the state-of-the-art in robotic disassembly. The application is general and not strictly dedicated to battery; in the context of circular economy, authors evaluate the application of Industry 4.0 technologies to disassembly, highlighting that the use of robotics in this application is relatively recent. Over the years, the focus of the revised papers moved from the concept of fully automatic solutions to the broader use of HRC applications. As a critical remark, disassembly is not strictly a reverse assembly but a completely different task due to devices not yet designed to be disassembled.

In robotic battery disassembly, the review [87] offers pivotal insights. It emphasises the critical role of HRC, which is crucial for addressing the complexities in battery disassembly. The paper's detailed exploration of safety standards and collaborative operation modes directly applies to developing efficient, safe robotic systems for battery handling. Additionally, its analysis of communication interfaces and identification of technical challenges serve as a guide for creating advanced, reliable robotic solutions that contribute significantly to the sustainability and efficiency of the battery recycling process.

The review [45] explores AI applications in disassembling EVBs. It suggests using machine learning for process optimisation and decision-making, specifically recommending reinforcement learning for determining efficient disassembly sequences. Additionally, the paper discusses the potential of MV for identifying and classifying battery components. These AI methods aim to enhance the precision and adaptability of robotic disassembly, addressing challenges like varying battery conditions and compositions and thereby improving the safety and efficiency of the process.

The review [113] underscores the role of de-manufacturing in the circular economy, highlighting the necessity of incorporating circular economy principles right from the design stage. This perspective is crucial for designing robotic systems for battery disassembly, as it advocates for an integrated approach where end-of-life considerations are embedded in the initial design. Such an approach could lead to more sustainable and efficient disassembly processes, aligning with the goals of a circular economy in battery recycling.

Zhang et al. [114] reviewed the central and local policies on processing and repurposing used EVBs in China. The authors utilised a two-dimensional analysis to review the basic policies and the industrial chain, which consists of the collection, storage, transportation, testing, disassembly, and repurposing of the EVBs. The policies set by local and central authorities affect each subsection of the industrial chain; for example, fire safety and technical building regulations define the requirements for the storage infrastructure of the used EVBs. The authorities focus on setting policies for the utilisation, testing, sorting, and disassembly of EVBs, indicating authorities' priority on the research and development of the technology. The number of policies for storage collection and transportation phases represents only 10% of policies set.

In [112], authors revised papers discussing circular business models for EVBs and white goods, concluding that the device design needs to be evolved to facilitate the adoption of circular economy models.

The bibliographic research also brought to the reviews [115–117], which focus on the battery's chemistry, the materials supply chain, and the material recycling techniques. Although these topics are fundamental, they are not relevant to the contents of this review.

Table 1
Table of reviewed publications.

Tag	Publications
AI	[16,17,23,45,61,71,74,88,100–102,104–106]
Business model	[63,111]
Cell layout	[17,70,80,83,98]
Cutting	[84,85]
Design	[15,40,44,60,65,80,111]
Detection	[23,71,101–103,105,108]
DSP	[44,61,63,68–75,77–79,86,88]
Framework	[16,76,77,81]
Grasp	[84,85,110]
HRC	[17,38,59,70,72,73,82,88–94,98,108,109]
Legislation	[114]
Machine vision	[17,23,42,45,61,71,81,98,100,103–106,108]
Unscrew	[17,61,98,100,102–105,110]
Recycling	[62,64,81]
Review	[14,15,21,45,62,81,87,112,113,115–117]
Robot programming	[66,67,98]
Safety	[80,95–99]
Separation	[109]
Sorting	[16,23]
Teleoperation	[110]
Testing	[59,107–109]

5. Discussion

This section discusses the comprehensive review results presented in Section 4. Table 1 categorises the reviewed robotised EVB disassembly publications according to the authors' primary focus. Section 5.1 summarises and discusses the automated EVB disassembly tasks and the utilisation of AI in those tasks. The following subsections discuss the tasks remaining manual and the challenges in automating those tasks.

5.1. Current level of autonomy in EVB disassembly

The seven tasks addressed in the reviewed publications are separation, testing, sorting, cutting, grasping, detecting, and unscrewing. The plot in Fig. 7 reports the number of papers found in the review for a specific disassembly task. The presented graph answers the first research question *Which disassembly and sorting tasks are automated?*

The automation of unscrewing the screws attaching various EVB components to the battery frame was studied in nine of the reviewed publications, and it is the most widely researched task of robotised EVB disassembly. The attention to the topic is motivated by the extensive usage of screws and bolts in the current EVB construction as non-permanent joint connections.Worth mentioning is that 36% of the tasks were automated using methods other than AI.

None of the presented publications presented a solution to detect the thread pitch of the screws. Matching the linear speed of the robot with the rotation speed of the screws is essential to effective unscrewing. The absence of solutions for detecting the thread pitch indicates the immaturity of the research on the topic on a practical level, leaving the focus on identifying and locating the screws rather than on the unscrewing action. Machine vision is the most popular method to identify and locate the EVB components, while force-feedback-based surface exploration [103] has also been utilised to locate the screws. Detecting the screw types and locations was studied in four out of seven publications presenting approaches for detection. Two publications considered detecting other EVB components, such as BMS, modules and mounting brackets, and in one publication, machine vision was used to detect damaged batteries before the disassembly. Cameras capable of percepting two- and three-dimensions were used to detect the components.

Grasping and sorting the EVB components using a proven vacuum technology gripper was proposed and tested to pick and place the battery modules from the battery pack into a container in one of the publications. A custom two-finger gripper design utilising force feedback and 3D-printed fingers was presented for handling the EVB modules during module-to-cell level disassembly [84,85]. The authors concluded that the latency of the force feedback was too slow, and the fingers printed of polylactide were too fragile for reliable handling of the modules. In addition, the authors used a 4 kg payload industrial robot capable of handling only the weight of 3D-printed mockups instead of actual battery modules. The challenges in robotised handling of EVB components are the varying dimensions and surfaces of the EVB internal components, requiring either adaptive or multi-functional grippers. Sorting of the EVB components was studied only in two of the reviewed publications [16,23].

Robotised testing and pre-sorting of damaged and non-damaged battery modules have the potential to increase safety by passing only intact batteries for further processing. Especially in cases of HRC and manual dismantling of the batteries, the worker's safety is increased by rejecting leaking and mechanically defective batteries, posing fire or chemical risks. An approach for robotised visual inspection was proposed in one of the reviewed publications to pre-sorting, and a multi-functional gripper was proposed in two publications to directly assess the OCV and internal resistance of the EVB modules to define the state-of-charge and state-of-risk of the modules. Combining the visual inspection and direct measurement capabilities of the two approaches would enable a robotised solution for battery pre-sorting and testing of the EVB, which is a critical step in ensuring safe disassembly for the EVB.

Cutting the module connection tabs and fasteners was proposed in two reviewed publications [84,85]. In the presented approaches, a rotating wheel cutter tool was used to cut 3D-printed plastic mockups of the battery modules. The described setups avoided the problems of generating sparks during the cutting process, potentially causing fire, explosion and eye injury risks. None of the revised papers discussed issues related to cutting metals close in an environment with the possible presence of explosive gas, such as leakage of the cells due to thermal runaway; the problem was studied in [82] arguing that cutting must be avoided due to the possible generation of sparks.

Separation of the glued joints was proposed only in one of the reviewed publications [109]. The solution is a pneumatically activated tool to separate the adhesive joint securing the battery cover from the frame. The presented solution remains conceptual and relies on the linear force the pneumatic cylinder provides and the mechanical leverage. Since the empirical data is absent, the functionality of the proposed tool remains untested. In addition to applying force, freezing the adhesive below - 115 degrees Celsius has decreased the required separation force [118]. More research work is required to gain knowledge on the topic.

The tasks that remain manual are separating spot welds, disconnecting connectors, and removing electrical wire assemblies. The remaining manual tasks are required in module-to-cell level disassembly; over 90% of the reviewed publications focus on pack-to-module level disassembly. In addition, research on robotising grasping, cutting, sorting, separation and testing tasks in EVB disassembly could be researched more intensively to enable fully autonomous EVB disassembly approaches for both pack-to-module and module-to-cell level disassembly. None of the reviewed publications presented approaches to connect the robotised dismantling to the battery passport, for example, by reading radio frequency identification (RFID) tags or labelling the disassembled components to interact with the upcoming battery passport.

5.2. HRC disassembly

Several papers foresee the possibility of HRC disassembly. In many cases, the disassembly tasks are not strictly collaborative but rather cooperative tasks; improperly using the term collaborative instead of cooperative is frequent. In most cases, works suggest HRC as a solution to address the current variability of EVB, leaving humans in charge of

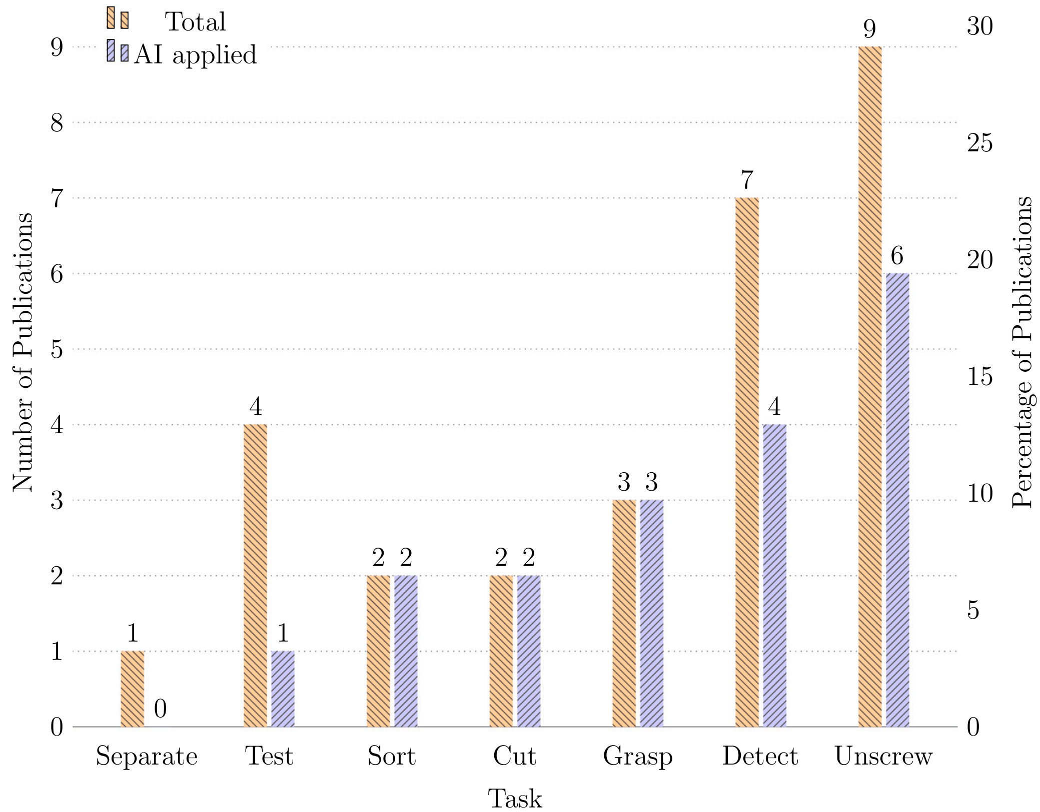

Fig. 7. Summary of robotised tasks.

the most complex activities, such as the removal of connectors and flexible object manipulation. The adaptability, flexibility and dexterity of a disassembly robot does not exceed the capabilities of the human worker in the mentioned tasks. Detaching electric connectors is a paradigmatic example of high variability leading to uneconomic automation and robotics solutions. The high variability of connectors requires custom tools, high dexterity, and diverse disassembly strategies. Connectors are frequently placed in a dense layout, and other components can occlude them, limiting the use of optical sensors. On the contrary, an operator with cognitive capabilities can quickly address the detaching task requiring decision-making, dexterity, vision, and tactile skills.

Part of the work mentions that HRC makes general descriptions and preliminary studies of possible disassembly workstations in which humans and robots share the workspace. Another part of the works study HRC mainly from the point of view of DSP/TP; only one of the publications utilised HRC in practice to aid the human worker by handling necessary tools and holding objects in place to ease the disassembly of the battery modules [91]. In most cases, HRC disassembly is used as a complex use case to demonstrate the effectiveness of the DSP/TP task allocation algorithm with an uncontrollable agent as a human. Such works support their results through simulations, addressing the problem from the theoretical point of view without real-world experimental validation.

The theoretical approach to HRC in most reviewed publications reveals the complexity of applying HRC to EVB processing in practice due to safety-related issues. In addition to cost savings, the reason to automate the EVB processing is the isolation of the worker from the hazardous phases of the process. However, HRC does not improve safety if the battery modules are present while the human worker conducts the disassembly tasks. In the reviewed publications, HRC is proposed to avoid facing the challenge of developing autonomous solutions for complex disassembly tasks.

5.3. Utilisation and limitations of artificial intelligence

As reported in the review [45] AI has great potential in all the battery disassembly phases, such as sorting, testing, safety monitoring, decision-making, disassembly target detection (*i.e.,* machine vision to identify disassembly targets), parts separation and handling. As shown in Fig. 7, AI is already pervasive in all the disassembly tasks, and in some cases, such as sorting, cutting, and grasping all the revised papers made some use of AI to address the task. AI has been utilised to identify the EVB components, select the correct tools, locate the components for disassembly, create a sequence plan, and test the EVB. The role of AI is essential in defining the SoX and RUL of the EVB and applying various methods that have been researched on the topic. However, as this review focuses on the robotised processing of EVBs, publications focusing on AI algorithms to define the state of the batteries were not included.

The combination of MV and AI is the most frequent, using DL to process images and locate and classify elements to be disassembled. The publications on detecting objects during disassembly focus mainly on detecting screw types and locations. AI was utilised in seven unscrewing approaches to identify and/or locate the screw heads. YOLO is the most popular library for the task, while OpenCV [119] was utilised in one of the approaches. Detection of connectors, BMS, attachment plates and battery modules, in addition to screws, were presented in [16,71]. The detection of the screws is a transfer of technology from previous applications to the EVB disassembly, and datasets of screw types are available. Instead, the datasets dedicated to classifying EVB components to detect EVB-specific components still need to be included. Creating and sharing public datasets to identify the EVB-specific components enables more research on the topic. AI was also used to detect the correct insertion of the socket to the screw head by developing an algorithm utilising linear force detection as in [61],

Table 2
Robots utilised in the reviewed publications.

Robot make	Model	Type	Payload [Publication]
ABB	IRB 140 IRB 4400	Industrial Industrial	6 kg [99] 60 kg [71]
COMAU	NJ 220	Industrial	220 kg [82]
Fanuc	LR-Mate 200iD/4S	Industrial	4 kg [85]
Franka Emika	Panda	Collaborative	3 kg [110]
Kuka	KR 16 KR 50 LBR LWR	Industrial Industrial Collaborative Collaborative	16 kg [102] 50 kg [82] 14 kg [81] 7 kg [17,98,109]
Techman	TM 14	Collaborative	14 kg [82,100]
UR	10e	Collaborative	10 kg [61,68,104,105]

while in [102] authors utilised AI/ML for analysing an angle-torque curve to detect faulty screws during disassembly.

In addition to identifying and locating components, AI is utilised in DSP. AI was used in three publications to plan the sequence for unscrewing; AI was applied to plan the complete disassembly of the pack in one publication.

5.3.1. *Utilisation of robot types*

Articulated arm robots featuring six degrees of freedom were used in all reviewed publications. Most revised papers tested the proposed methodologies with laboratory setups and prototypes, such as 3D-printed tools installed on low-payload collaborative robots. Collaborative robots are utilised in research due to their advanced safety features, making working areas restricted by safety devices obsolete. However, the tradeoff in utilising collaborative robots is their limited payload capacity and reduced operational speed. It is worth remembering that some disassembly tasks require manipulating heavy objects, such as modules weighing a few tens of kilogrammes, and handling requires medium or high-payload robots. The separation of glued or sealed plates, which is frequent in the current EVB design, imposes high forces that are unavailable with collaborative robots. Robots for heavy tasks are also suitable for relieving operators of unhealthy activities. Table 2 summarises the robots utilised in the reviewed publications.

The handling capacity of the robot exceeded 15 kg in two out of seventeen publications. Experiments with industrial setups rarely appeared in literature, demonstrating a significant gap between the current state of the art and real industrial applications. As the laboratories presented lack the required safety monitoring and fire prevention systems, and the utilised hardware is not industrial grade, the presented solutions remain between TRLs 2–4.

5.3.2. *Documented battery packs and available datasets*

Table 3 presents the publications providing extensive information on the EVB disassembly, such as bill of materials or disassembly sequence flowcharts. The table is sorted by the vehicle make and model.

In addition to information on the EVB disassembly, links to open datasets for AI training are listed in Table 4. In addition to the datasets listed, many reviewed publications state that datasets are available upon request.

6. Research perspectives

This section presents the actions the authors of this review propose to robotise the remaining manual EVB disassembly tasks. This section answers the second research question *What are the challenges and opportunities in applying robotics to automate the remaining manual tasks?*.

Table 3
Publications containing extensive information of EVBs.

Vehicle make	Model [Publication]
Audi	Q5 Hybrid [17,70] e-tron 50 [23]
BAIC	BJEV EU5 [111]
BYD	Han EV [111]
Chevrolet	Bolt EV [72]
Fiat	500e [82]
Nissan	Leaf 2011 [110] Leaf 2018 [111]
Peugeot	e208 [111]
Renault	Zoe R135 [111]
Tesla	Model 3 [111] Model S [75]

Table 4
Publications sharing open datasets.

Publication	Link to dataset
Semi-Autonomous Behaviour Tree-Based Framework for Sorting Electric Vehicle Batteries Components [16]	[120]
Machine learning based screw drive state detection for unfastening screw connections [102]	[121]
Point cloud instance segmentation for automatic electric vehicle battery disassembly [106]	[122]
Deep learning to estimate LIB state of health without additional degradation experiments [52]	[123]

6.1. *Removal of connectors and wires assemblies*

A robotised solution for detaching electrical connectors and wire assemblies would enable safety during EVB processing. The wire assembly removal is a hazardous disassembly phase; the high voltages are present in the wiring assembly, contactor-fuse unit and battery modules until the wiring assembly is removed. After the wiring has been carefully removed, the high voltages are isolated to the module packs only. Cutting off the wires is not an option since it could short-circuit the battery cells, causing damage to the cells and the wiring assembly. Short circuits are also one of the causes of thermal runaway.

Due to the complexity of removing the flexible wire assemblies, research work and approaches for detaching the wiring connectors and the wire assemblies are absent. The challenges in detaching the connectors include the variety of connector physical dimensions, orientations and latching mechanisms, dense layout of the connectors and locations behind obstacles. For example, the Ford Transit EVB wiring assembly consists of fourteen different-sized physical connectors, including two different latching mechanisms. The orientation of the connectors is vertical or horizontal, and a few of the connectors are located behind another component, or the wire assembly blocks the access to the latching mechanism of the connector.

The unmanned removal of the wire assembly is essential to ensuring safety during EVB processing, and approaches to overcome the challenges should be proposed. Challenges are related to the dexterity required to release the locking mechanisms to detach the connectors and the flexible wiring assemblies installed in tight spaces. The variety of connector types and sizes requires a selection of tools, and the variety of connector orientations requires machine vision and AI to adapt. Fig. 8 presents a conceptual example of setup with an Automatic Tool Changer (ATC), a gripper, and a 3D camera.

In addition, cognitive capabilities are required to plan the approach direction of the detaching tool and to adapt to the wiring's random position, angle and exit direction. If the wire assembly is blocking access to the latching mechanism, the wire assembly must be relocated before approaching the connector for disconnection. In general, the

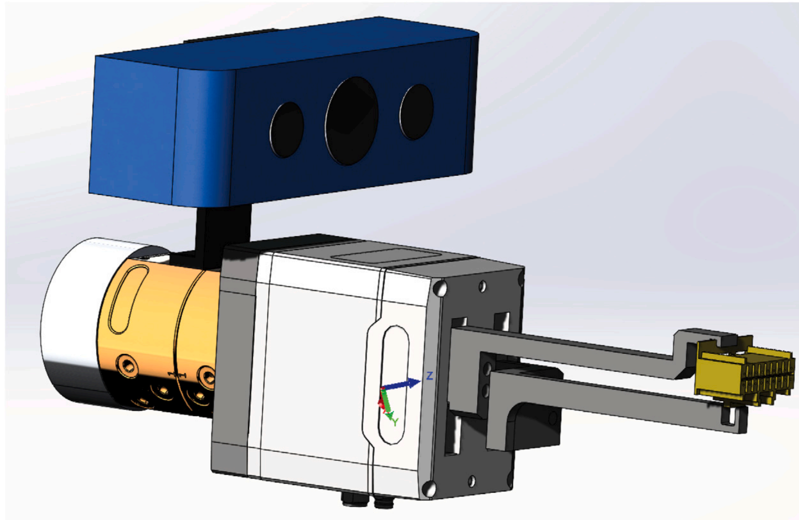

Fig. 8. Conceptual drawing of custom gripper consisting of ATC, camera, and gripper to detach wiring connectors (Centria University of Applied Sciences).

level of autonomy of the state-of-the-art disassembly application is still far from being applied to a real industrial plant for these activities.

6.2. Battery passport and the digital twin

The battery passports proposed by industrial stakeholders and the EC enable the digital twins (DT) of the EVBs. The physical twins are identified by tags such as RFID or a QR code, which connects to the digital identity of the EVB and enables efficient repurposing, remanufacturing and recycling. Introducing the DT concept presented by Grieves [124] as an ideal for product lifecycle management to the battery passport would enable comprehensive testing, planning, and design for the remanufacturing and repurposing of the EVB. As the product life cycle evolves, recycling is accompanied by repurposing, remanufacturing, and reusing products.

By utilising DT, the manufacturer has the information on battery health to decide whether it can be reused as a replacement part, repurposed as a building energy storage, or recycled after the vehicle is decommissioned. In addition, the chemical composition of the battery modules and the amount of various metal types are known for recycling.

Grieves presents two reasons for updating the DT during the disposal phase of the physical twin: to increase knowledge to build better systems in the future and to register the possible hazardous materials during disposal to minimise or avoid using similar materials in the following versions. The market for EVs is expanding, not only for electric cars but also for electric trucks and vans. The methods for repurposing and recycling the batteries are required to reduce the need for the mining of materials to manufacture new batteries. Preut et al. [125] identified the following beneficial stakeholders of EoL product DTs: OEM, distributor, user, servicer, re-user, re-manufacturer, recycler, logistics provider, and regulatory actors. In addition to the EoL phase, re-users and recyclers benefit from the DT even after the EoL phase. Fig. 9 presents the information flow between the physical and digital twins of an EVB during the lifecycle.

If modules of the EVB are repurposed or remanufactured, the data collected during previous utilisation can be transferred to the DT of the resulting product. For example, if EVB modules are repurposed as building energy storage, the information of the previous service is transferred to the DT of the new product. During the design phase of repurposing, DT can be used to model the original product components and behaviour to explore alternative uses and configurations. The battery passport supports the circularity of the product life cycle, which is a transformation; traditional recycling is evolving into repurposing and reusing products. Repurposing and reusing save environmental resources and energy more efficiently than recycling the EVB to raw materials.

The digital version of the product may remain after the disposal of the physical product. The data and knowledge collected during the creation, manufacturing, sustainment, and disposal phases can benefit the iterative design of new products. Utilising the data can avoid repeating prior mistakes and miscalculations during the product lifecycle phases. In addition, if sub-components of the product are repurposed in a new product, the data collected during previous utilisation can be transferred to the new DT. The BMS monitors the cells since they are assembled in the factory. The BMS monitors each charging and discharging cycle of the cells and registers the temperature, overcharging and undercharging tendencies and the SoH of the EVB.

This section covers the third research question *What are the benefits of upcoming EU battery regulation and the battery passport proposal for the EVB disassembly?*.

6.3. Increased flexibility and adaptability

The disassembly process of the EVB requires multiple methods and tools. Only a few reviewed publications presented an ATC to enable the robot to adapt to the tasks required during disassembly. The considerable variability of battery design and models imposes the use of a wide range of disassembly devices, demanding extreme flexibility.

Integrating a specific range of robot tools and multi-functional tools is mandatory. Multi-functional tools can deal with multiple tasks, such as grippers equipped with cameras to locate parts or voltage/resistance measurement systems to check the state of the modules. This approach requires a seamless integration of the perception systems with external controllers and the robot to address complex tasks such as unscrewing. Harnessing the AI to utilise various perception sources enables the amount of control during the processing of EVB. Fig. 10 illustrates utilising multimodal inputs and AI for the unscrewing task.

In addition to unscrewing, AI can be utilised to automate various disassembly tasks. For example, to apply AI for the wiring connector detaching task, the inputs of linear gripping force and the relative gripper jaw distance replace the inputs for rotation, torque, and speed to detect the successful unlatching and detaching actions. The adapted outputs for speed and position are complemented by adding an output for linear gripping force. In addition to inputs and output parameters, the approaching strategy differs between the two applications; connector detaching requires avoiding collision with the wiring assembly curving from the connector during the approach. These are two examples of applying AI to automate EVB disassembly tasks, and the presented method can be utilised to automate the remaining tasks.

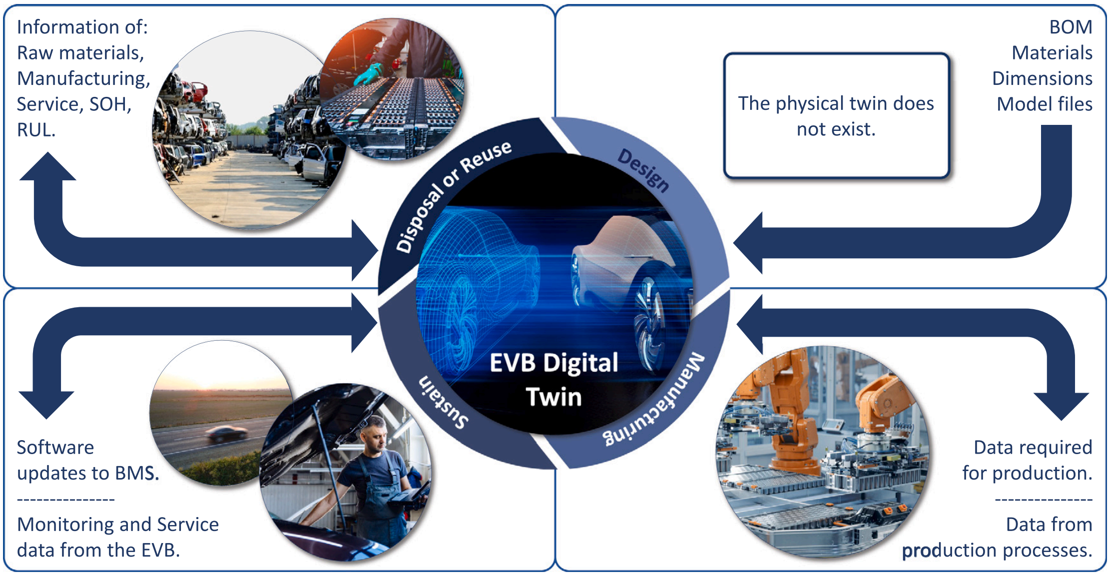

Fig. 9. The lifecycle of an EVB in design, manufacturing, sustain and recycle or reuse phases.

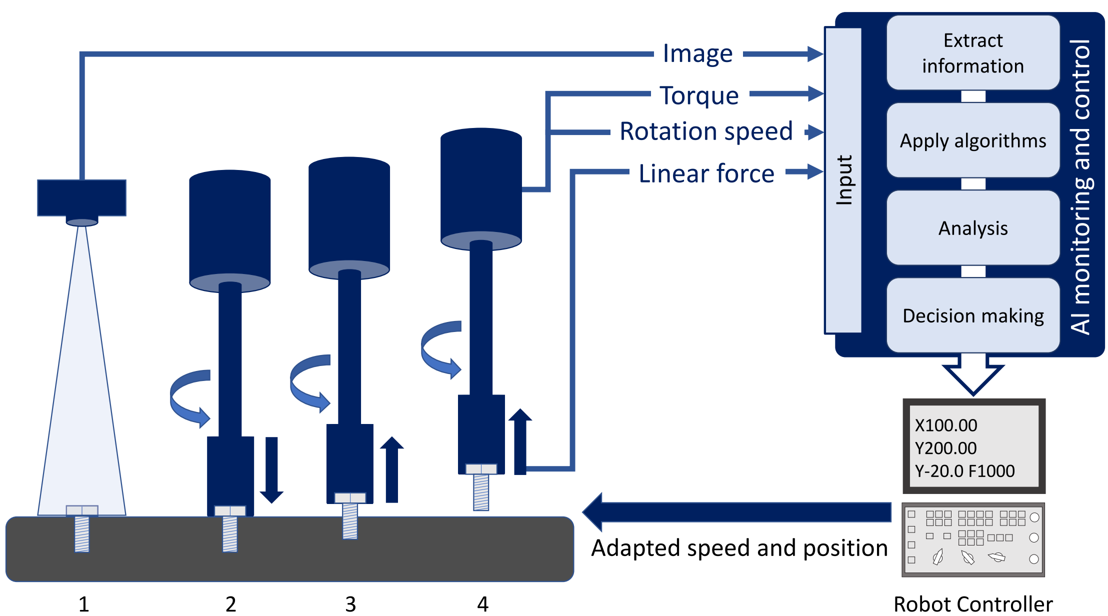

Fig. 10. (1) Locate and identify the screw, (2) Detect socket and screw alignment, (3) Detect loosening and match linear speed to thread pitch (5) Detect complete exit of the screw.

6.4. Teleoperation from other applications

Teleoperation has great potential to improve operators' safety. A location isolated from the EVB processing area enables creating safe control over the dismantling process from a distant location to the operator. In the review, only one work proposed teleoperation for EV disassembly, while robotic teleoperation is widely adopted in risky tasks such as radioactive decommissioning. As proposed in [126], EVB disassembly can benefit from using head-mounted devices to provide the augmented reality user interface and to capture the user's gestures to control the remote manipulator. The system features a multimodal interaction user interface, enabling position, eye, hand tracking, and voice command inputs to control two remote manipulators. The system can enable multi-user operation in the virtual space.

The teleoperation would benefit from a high-level extended reality user interface and a DT of the dismantling cell. As in [127], DT can be used for trainees to control physical robots utilising digital twins from distant locations. In addition to the robots, the virtual environment can include stationary elements such as walls, tables, and the workpieces required for the training, enabling location and time-independent access to the physical robotics lab for the trainees. The DTs validate the trajectories created by the trainees to avoid collisions between the robot mechanics and stationary objects.

Applying the proposed approach for the EVB processing enables the teleoperator to programme the dismantling cell during the processing of EVBs by using the digital twin to create and validate the programme for upcoming battery types. In addition, the DT of the dismantling cell enables realistic training of the operators in a safe environment. The collision avoidance functionality of the DT ensures risk-free teleoperation and training for the dismantling cell. Fig. 11 presents an example of a virtual factory for teleoperation and training of the EVB disassembly.

Fig. 11. Virtual training factory for EVB processing (Centria University of Applied Sciences).

6.5. Disassembly safety improvements

Processing only non-damaged batteries is essential in securing the safety of EVB disassembly. Automating the pre-sorting phase removes human workers around potentially hazardous batteries; damaged EVBs are recycled by crushing complete units [34]. Defining the state of risk of the EVB by visual inspection and measuring the internal resistance has been proposed in the reviewed publications. Adding a thermal camera and gas sensors to detect gas leaks and thermal runaway of the batteries would improve the capability to detect and cancel out unsafe, damaged battery packs. In addition, extracting the data from the BMS provides insights into the module temperatures and SoX of the battery pack.

Concerning HRC disassembly, a step forward in the productivity and effectiveness of industrial applications will be using standard industrial robots exploiting the SSM operational mode. Unfortunately, the current state-of-the-art of perception technology (*i.e.,* sensors for human tracking with safety certification) does not allow the release of such solutions in industrial environments.

6.6. A comprehensive database of electric vehicle battery types

The reviewed studies included comprehensive information on twelve different EVBs. We propose creating a comprehensive database of all the EVBs, including technical information, AI datasets, images, and sequences for disassembling. The database will benefit researchers and SMEs developing manual and robotised disassembling and sorting applications for EVBs. When the Battery passport proposal is complete, the collected information benefits EVB stakeholders.

Available information, such as dimensions, weights, and material compositions of the EVBs, benefit the logistics chain responsible for delivering the EVBs from dismantlers to 3R facilities and planning safe and efficient transportation of the EVBs. For the disassembly and sorting facilities outside the OEM information network, the technical information of the various EVBs enables efficient production and disassembly sequence planning. For the regulatory actors, the database enables comparison of EVB designs to guide the OEMs in manufacturing standardised EVBs designed for disassembly.

6.7. Aiming towards advanced human–robot collaboration

In addition to EVB disassembly, HRC has been applied in disassembly operations of electronic devices [128], and some of the methods developed for those applications can benefit EVB dismantling. For example, in [129,130], the focus is on the disassembly of pressed-fitted parts, introducing the use of force sensing and active compliance for robot control such that they can identify task execution and support human operations when working on the same piece. However, developing improved methods for HRC could help the dismantling process to be scalable, increasing the LoA.

In [131], an approach to utilise integrated sensor platform to extract high-level disassembly plans considering the required tools at each stage and execute movements with them. Authors in [132] propose a preliminary design of a general disassembly framework for mechatronics devices, which includes the use of multiple stations for specific tasks where collaborative robots work with humans; the extraction of disassembly features is supposed to be acquired from the device under the supervision of the operator, while a cloud control system stores information and creates the task scheduling for all the workstations.

7. Conclusions

In this study, we conducted a systematic and comprehensive review of the robotic processing of EVBs. Initially, we explored the necessity for automation and the development of robotic methods. This discussion encompassed establishing a typical disassembly sequence, the challenges related to safety, and the absence of unified design standards and regulations. Subsequently, we examined the existing body of work on various facets of EVB processing. This examination covered testing, machine vision, machine learning, robot programming, disassembly sequencing and task planning, HRC and control, and safety measures. Additionally, the review addressed the design considerations for EVBs to facilitate robotic processing and highlighted previous literature in this domain.

Given the anticipated surge in the volume of used electric vehicles over the next decade, developing tools and methods for repurposing, recycling, and remanufacturing EVBs is imperative. The findings from our review indicate a need for more comprehensive robotic solutions for battery processing. Moreover, not all components of the disassembly process are currently automated; the necessary tools and approaches remain in the nascent stages of research and development, underscoring the need for further methodological advancements.

HRC has not been utilised to its fullest potential in this context. The present design and architecture of EVBs necessitate human intervention, a requirement partly attributed to the limitations of current AI technologies. The industry would benefit from stringent regulations and guidelines encouraging manufacturers to adopt designs more conducive to efficient robotic and automated processing.

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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.

Appendix

See Table A.5.

Table A.5
List of tags used to sort the publications during the literature review.

Tag	Description
ADH	Adhesives
AI	Artificial Intelligence
ARCH	Software architecture/framework for disassembly
BC	Blockchain
BM	Business Model
CUT	Cutting
DES	Design of battery
DET	Detection
DSP	Disassembly Sequence Planning, Task Planning & Scheduling
FUT	Examples of technologies from other domains to be applied in EVB disassembly in the future
GEN	General, disassembly method also applied to other mechatronic devices
GRASP	Grasping
HRC	Human-Robot Collaboration
INT	Articles suitable for the Introduction and Background.
LCA	Life Cycle Assessment
LEG	Legislation
MV	Machine Vision
RCL	Robotic Cell Layout
RP	Robot Programming
RE	Reuse, recycling
REV	Review
SAF	Safety for the workers
SCR	Unscrew
ST	Skill Transfer
TEST	Testing state of X
TELE	Teleoperation

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