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CRITICAL REVIEW

State of the art of automatic disassembly of WEEE and perspective towards intelligent recycling in the era of Industry 4.0

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Abstract
Disassembly of e-waste has received significant attention over the past decades to extract value-added parts or components for recovery or reuse. It is imperative to develop automatic disassembly to replace human workers thus safeguarding them against the hazardous environment. Most scholars investigate the disassembly of e-waste from a technical perspective on laboratory scale. Few types of research related to its development track and scaled application are completed. This paper attempts to fill this gap by analyzing the disassembly of Waste Electrical and Electronic Equipment (WEEE) in a strategic perspective from manual operation, (semi)-automation to intelligent disassembly through a systematic literature review. The main barriers to automating the recycling industry lie in the high complexity and uncertainty of end-of-life (EOL) products that perplex the automatic handling and planning. Intelligent systems integrated in cognitive robots are helpful to handle the uncertainty through learning and revision processes. This work has three objectives: first, to map out what research has been carried out in the field of WEEE disassembly and the necessity for disassembly automation; second, to conduct a systematic literature review for the state of the art of automatic disassembly and discuss the barriers to its industrial application; third, to propose a perspective for integrating Industry 4.0 technologies with disassembly automation to promote flexibility and efficiency, providing a new scheme for future treatment of WEEE.

Keywords Waste from electrical and electronic equipment · Disassembly automation · Recycling · Intelligent dismantling · Industry 4.0

1 Introduction

It is estimated that the global municipal solid waste generation level is approximately 1.3 billion tons/year, and this figure is anticipated to rise to around 2.2 billion tons/year by 2025 and 3.4 billion tons/year by 2050 [1]. The Waste Electrical and Electronic Equipment (WEEE) sector stands out as the fastest-growing segment, encompassing a wide range of products from small cell phones to televisions, all of which contain valuable and potentially hazardous materials [2]. Annually, 30 million computers and 100 million phones are retired and disposed of in the USA and Europe [3]. End-of-life (EOL) products should not mark the end of their life cycle. A shift from a linear model of material flow to the circulation of functional parts or elements is necessary. This transition is supported by the implementation of financial circuits aimed at minimizing the consumption of finite resources. Such an approach aligns with the principles of the circular economy (CE) [4]. The CE concept is enabled through the implementation of the 3R principles: reuse, recycle, and recover, depending on the hierarchy level of material in an aspect of economic value, as shown in Fig. 1 [5]. The closed loop of material cyclic utilization offers a viable solution to the supply chain by providing an alternative source of raw materials, thereby reducing the environmental impact of mining, production, and disposal of materials used in electrical and electronic equipment [6, 7]. Unfortunately, the current global recycling rate for Waste Electrical and Electronic Equipment

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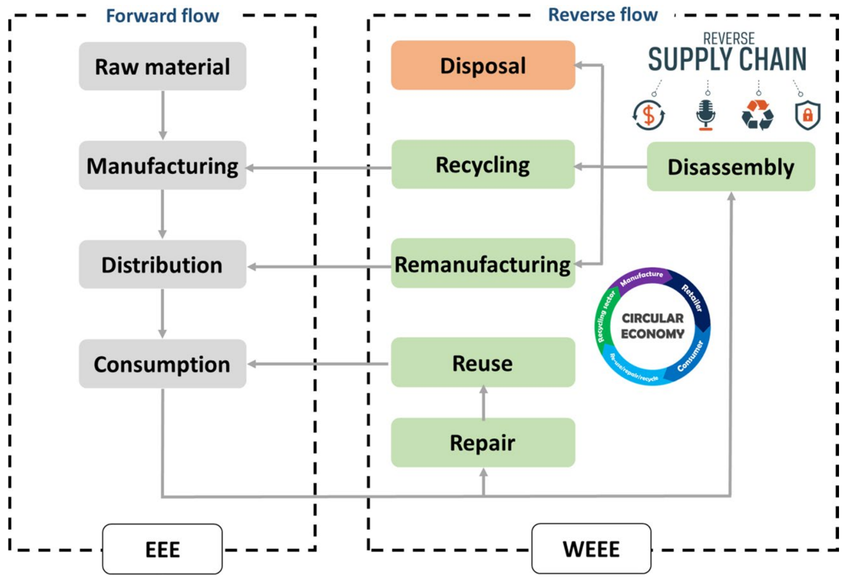

Fig. 1 Closed-loop lifecycle of EEE/WEEE in material flow [9]

(WEEE) stands at only 20%, as reported by the World Economic Forum in support of the United Nations E-waste Coalition [8]. Therefore, it becomes imperative to study the existing facilities and enhance WEEE recycling efforts.

The e-waste recycling process involves four main steps: collection, sorting and disassembly to mechanical and chemical processing, finally, to the recovery of raw materials [10]. Disassembly plays a crucial role in identifying potential resources in end-of-life (EOL) products and preserving their technical and economic value [9]. However, the current disassembly practices are often carried out under harsh conditions, leading to issues like dust and noise pollution, even in modern recycling facilities [11]. It is important to not compromise the health and well-being of workers in the pursuit of CE and sustainable remanufacturing. This is why the industry is increasingly investing in automation, including the limited but growing use of robotics [12]. Previous researchers have explored various approaches to WEEE disassembly, such as the design of versatile tools, collaborative disassembly stations, and automated equipment. Notably, these solutions are suitable for handling dangerous, repetitive, or heavy-duty tasks, reducing the workload on laborers. Full automation of e-waste dismantling that gets rid of dependence on people is still in infancy, especially for highly complex products. Technical gaps exist that the disassembly system is required to be capable of recognizing, self-learning, and planning to cope with the tanglesome e-waste, instead of performing the predefined repetitive actions. Furthermore, the learning process is time consuming for cognitive robots with high capital investment, leading to the concern of practicality in industrial recycling. In general, challenges and gaps of existing literatures on automatic disassembly are summarized as follows:

- Existing studies investigate the disassembly operations or devices for designed specific e-waste and lack analysis from a strategic perspective to handle unstandardized WEEE with inconsistent parts or components. WEEE is collected in various brands or models, leading to manifold structure design or material usage. Meanwhile, the complicated scenarios of WEEE with different degrees of damage or deformation should be considered.
- The majority of the existing studies focus on the innovative method for WEEE disassembly but only in laboratory scale. The actual application in the recycling industry for volume treatment of e-waste remains to be studied. The review on disassembly systems exploiting AI combined with various sensing and machine vision technologies to overcome the barriers of WEEE uncertainty is still absent.
- Current studies have investigated the application of Industry 4.0 technologies in smart manufacturing. But literature combining the intelligent technologies of In4.0 with the WEEE disassembly process is in lacking. Higher flexibility for handling the WEEE leads to higher costs and a slower operation pace. An intelligent solution is needed to achieve interaction and information sharing to improve the efficiency and lower the cost.

To address these limitations, this paper takes a strategic approach by combining a thorough review with a forward-looking perspective to bridge the research gaps. First, it is necessary to develop a comprehensive dismantling solution suitable for different types and degrees of WEEE from a strategic perspective: using advanced technologies such as artificial intelligence and deep learning, develop algorithms and tools that can autonomously identify and classify different WEEEs. Establish a nationwide waste management network and strengthen the supervision and management of WEEE collection, treatment, and recycling, thereby improving disassembly efficiency and reducing disassembly costs, improving resource utilization and environmental awareness. Second, we try to develop and evaluate an intelligent WEEE disassembly system based on artificial intelligence and machine vision. Develop an intelligent WEEE disassembly system using modern technologies such as artificial intelligence and machine vision, and then evaluate it in the laboratory and actual environment to determine its performance and reliability. Third, in order to achieve intelligent solutions, devices are needed to collaborate and share information with each other. We need to develop technologies that can enable interaction and information sharing between devices, such as IoT technology and cloud computing technology. The key advantages of Industry 4.0 intelligent solutions are flexibility, efficiency, adaptability, and a high degree of automation. These advantages can be used to solve the problems of high cost and low efficiency encountered in the WEEE disassembly process.

The structure of this paper is organized as follows: The background of WEEE disassembly and recycling is illustrated in Section 1. Section 2 describes the research method of this paper. The necessity and the state of the art of disassembly automation are reviewed from equipment, semi-automation, to intelligent full automation in Section 3. To better handle the e-waste dismantling in industrial applications, technical barriers and potential solutions are discussed in Section 4. A perspective of the intelligent disassembly system, which combines the emerging technologies in Industry 4.0, is proposed to promote the flexibility and efficiency of the disassembly process, providing a new scheme for the future treatment of WEEE.

2 Results

2.1 Research method

This research is based on the process of a systematic literature review according to Denyer and Tranfield guidelines [13]. The aims of this review work are as follows: systematically explore the development track of WEEE disassembly and map out what research has already been carried out in this field; address the necessity of upgrading manual dismantling to automation; and discuss the gaps or barriers of applying automatic disassembly in industrial scale as well as the potential solutions with the emerging technologies in the era of Industry 4.0.

This review work focuses on the disassembly action of WEEE and the related fields of publications, including journal papers, scientific reports, and books. Google Scholar and Web of Science are used as reference databases due to their powerful capability of retrieval. Only literature published between 2000 and 2021 and written in English are reviewed. Different searching strings are attempted to search literature for review. As this paper is to discuss the automatic disassembly of WEEE, the example string "WEEE AND disassembly" since 2000 is searched. One hundred seventy results are found in Web of Science while 6610 results are found in Google Scholar with a more diverse background. When the searching string is changed to "WEEE AND automatic AND disassembly," 2420 results are presented in Google Scholar but only 6 results in Web of Science. The search scope would be extended if the string is modified to "robot AND disassembly." About 14,000 results can be found in Google Scholar while 1963 results are found in Web of Science. English is used as the primary language in the literature review since it is the lingua franca of academic communication. The output publications are classified by checking the relevance between the content and the objective of this paper. At first, the title or abstract is reviewed to determine if the literature searched introduces the topic related to dismantling action on WEEE management, including but not limited to the disassembly equipment, robotic disassembly, and sequence planning. If yes, a further browse would be conducted on full text to judge if the content is effective information for this review. The experimental study or innovative device for WEEE disassembly is preferred. In addition, the development and the concerns in aspects of economy and environment are also reviewed.

2.2 Literature review

In the process of recycling e-waste, certain types of ex-service electric appliances are collected, classified, and transported to recycling facilities. Components such as plastic casings, wires, Printed Circuit Board (PCB), and other main parts are separated through dismantling and sorting [14]. Advanced disassembly is required to separate out the value-embedded components and keep materials on the highest economic value hierarchy level. Variations in WEEE bring about more difficulties in classifying and dismantling; a large amount of human operators are employed by recyclers to handle the tasks [15]. Dismantled parts will be transported to subsequent facilities for reuse or recycling, depending on their reusability. The purpose is to extract the residual value or convert them into useful materials for manufacturing with minimum cost, achieving the accurate recovery of WEEE.

2.3 Manual disassembly

Manual disassembly refers to the use of hand tool and technologies to disassemble objects or equipment. Operators are required to carefully check and identify each part of the disassembled objects and the relationship between them. Manual disassembly technology needs professional training and learning and needs to master the use methods and precautions of various hand tools to ensure safe disassembly. In the WEEE dismantling industry, manual dismantling technology is widely used for dismantling and handling various types of electronic devices, such as computers, mobile phones, tablets. Technical workers manually disassemble electronic products, separating and classifying various materials from them for reuse. Although manual disassembly technology is a valuable skill, the accompanying safety and cost issues urgently need to be addressed.

2.3.1 Environment and health risk

Traditionally, WEEE was treated and recycled by individual workshops, such as Guiyu in Guangdong Province, China, which accommodated millions of tons of WEEE from all around the world per year. Due to the lack of environmental awareness as well as supervision, uncontrolled recycling and disposal of WEEE by manual dismantling/separation, open burning, and acid treatment have resulted in severe environmental contamination that endangers the health of residents [16, 17]. It is reported that the elevation of blood lead levels among children in Guiyu area is caused by the primitive e-waste recycling activities [18, 19]. Figure 2a and b illustrate the manual dismantling of waste PCB and the open burning of e-waste that creates poisonous gases. As the strict laws were enacted to ban the illegal disassembly by the family-run workshop, WEEE recycling was transferred to the scaled factories. The pipeline operation with mechanical tools, personal protective equipment (PPE), and necessary training for employees would greatly improve the efficiency and working conditions (Fig. 2c and d).

The disassembly of WEEE in factories continues to result in the emission of dangerous metals and organic compounds [31]. Those hazardous substances may be transferred from products to dust matrixes through miniaturization, direct migration, or vaporization [32]. The exposure to these toxic chemicals has a profound impact on the health of workers, leading to significant negative health effects [33]. As shown in Table 1, field monitoring data indicates that over-ranging $PM_{2.5}$, PM_{10}, and heavy metal concentrations than the air quality standards are found in the dismantling station of recycling companies. Julander et al. investigate metal concentrations in ambient air and exposure biomarkers [34]. They conclude that WEEE recycling workers undergo 10 to 30 times higher airborne exposure to toxic metals than people at the office environment. Meanwhile, substantially higher concentrations of heavy metals Co, Cr, and Pb and even rare earth metal Sb are found in biomarkers of workers [34, 35]. They are classified as carcinogenic elements, which could enter into the human body through ingestion, inhalation, or dermal contact, causing harmful health effects [36]. Therefore, it is imperative to keep human beings away from the dust environment and transfer them to engage in more advanced services.

Fig. 2 Traditional and illegal disassembly of WEEE **a** PCB baking and manually pick the valuable components [20]. **b** Firing the remaining parts in low value. Disassembly in recycling factory [21]. **c** Cathode-ray tube (CRT) TV manual dismantling in recycling line [22]. **d** Compressor punching using drill [23]

Table 1 Mass concentrations of Cr, Ni, Cu, Cd, and Pb in two workshops (mg/g) [33]

	Mechanical workshop			Manual dismantling workshop		
	PM_{10}	$PM_{2.5}$	$PM_{2.5}/PM_{10}$	PM_{10}	$PM_{2.5}$	$PM_{2.5}/PM_{10}$
Cr	0.554	1.202	2.17	0.436	2.875	2.182
Ni	0.472	0.744	1.58	0.459	1.148	2.499
Cu	27.76	3.753	0.14	31.8	1.205	0.038
Cd	0.108	0.033	0.31	0.398	0.094	0.104
Pb	12.34	20.46	1.66	2.043	6.935	3.394

2.3.2 Escalating cost of manual disassembly

Apart from the health issue, the safety of workers cannot be neglected. Katrina et al. conduct a survey on injuries among e-waste recycling workers. Four hundred twenty-six injuries in total are reported in the prior 6 months for 46 participants. Of the injuries, 65.2% are lacerations while the most common injury location is hand (45.7%) [37]. According to statistics from Occupational Safety & Health Department (OSHD), more than 30% of European manufacturing workers are affected by lower back pain, bringing about extra social and economic costs [38]. The Raise the Wage Act of 2021 (H.R. 603) in the USA states that the federal minimum wage will increase from \$7.25 to \$15 by 2025 [39]. In addition, the aging of workforce is a non-negligible fact that brings potential risk, incurring higher labor cost due to the unbalance between shortage of young workers and increasing amount of e-wastes [40]. Meanwhile, statistic results indicate that 50 s or older workers are more likely to suffer injuries due to the decline of their physical abilities with age and weak mental stress related to aged auditory or vision [41]. Therefore, it is necessary to improve the recycling technology to reduce reliance on labor; thus, it protects human labor from danger and reduces cost.

2.4 Disassembly automation

Automation has become a competitive solution in the manufacturing world, which allows for mass production at outstanding speeds and with great repeatability or quality [42]. The discussion of intelligent manufacturing systems towards Industry 4.0 era is illustrated in SM. Due to the uncertainties of EOL products that increase the complexity of planning and operation, automatic disassembly of e-waste is in limited use in the recycling industry [43]. It refers to some disassembly stations that can imitate human workers to achieve the key steps of dismantling. WEEE Disassembly has been implemented to some extent under the following scenarios [44]:

- Disassembly automation is a fully automated disassembly method that primarily utilizes automated equipment and robot operations, with no or limited human involvement required. Disassembly automation has the advantages of high efficiency, high safety, good repeatability, and high precision.
- The semi-automated operation is also referred to as hybrid disassembly, in which some of the dangerous, repetitive, or heavy-duty tasks are handled by designed automation. Operators need to monitor the automatic devices while manually dismantling other parts. It combines the advancements of operators' flexibility and robots' efficiency.
- Intelligent disassembly is a more advanced disassembly method, in which artificial intelligence is used to improve the overall efficiency and accuracy of the disassembly process. This method uses advanced algorithms and machine learning to analyze and identify individual components and determine the best method to disassemble them.

2.4.1 Disassembly equipment

For the disassembly of EOL products, it is desired to perform non-destructive disassembly so that the embedded value of parts can be fully reused. However, the real scenario of WEEE is full of deteriorations, such as wear and corrosion of components and joints. With primitive tools including screwdriver, pliers, saw, drill, and cutters, well-trained operators are able to efficiently detach various fasteners. The logical selection of potential removal operations can be based on an understanding of the components' condition and drawing on past experiences [45]. Advanced equipment is expected to accommodate different types of fasteners in various geometries, resulting in the concept of almighty end-effector tools (Fig. 3). Seliger et al. have developed a highly versatile tool for unscrewing different types of screws, even those with damaged heads [46]. This tool utilizes a pneumatic impact unit to create slots on the screw head, which serve as new active surfaces for torque transmission. As a result, it enables the unscrewing operation regardless of the screw's shape or type [44]. To make the disassembly process simplifier, the modular Disassembly Toolkit (DTK) has been developed, which can support easy adaption to multi-purposed applications by changing modules of the same kind. Highly integrated DTK apparatus makes it efficient to dismantle connectors and then liberate the parts in the module level. Compared to reconfiguration of the applied modules, it consumes less time when plenty of tools are required for one disassembly process.

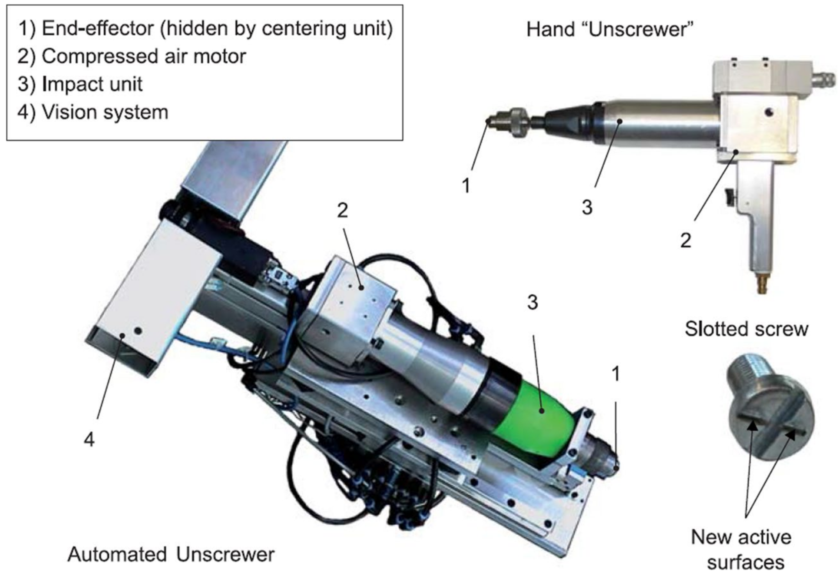

Fig. 3 Automatic unscrewer works by cutting a slot used as a new acting surface [44]

The disassembly system is made of multiple parts. Robot arms are generally employed as a manipulator, which realizes the movement following the designed trajectory to take along the equipment for the disassembly task [47]. The degree of freedom (DOF), armspread, and payload of robots are planned according to the task requirement and local conditions. The SCARA, Cartesian, and gantry robots with 3–4 DOF are applied in pick-and-place tasks while articulated and delta robots with 4–6 DOF are sufficient for more complex handling of disassembly tools. Six or more DOF robots can achieve the arbitrary position and orientation [48]. While the manipulator carries the disassembly tools to operate the dismantling action, the object to be disassembled requires handling devices to transport and fasten at the designed place. Motion control during the disassembly is executed by logistics systems. Fixtures and grippers are used to securely stabilize the object, giving convenience to disassembly operation with high accuracy. The fixture is not necessarily the fixed device, instead, the moving fixture that can be actuated is also available, such as the robot arm [49]. Based on the real scenario of execution, it is necessary to adjust the fixtures or grippers at different disassembly stages, such as the flip table applied in the robotic disassembly of LCD screens [50]. Handling devices should be flexible enough to handle various product models but should not interfere with the removal of product components. Figure 4 demonstrates cases applying adjustable or flexible grippers for WEEE disassembly.

2.4.2 (Semi)-automatic disassembly

Semi-automatic disassembly, also referred as hybrid disassembly, means that the disassembly task is partly shared by automatic workstations to reduce the load of people and improve the efficiency. Figure 5 illustrates four degrees of interaction, in which capsulation indicates no interaction at all, and collaboration allows humans and robots to work simultaneously on the same workstation [53]. Coexistence means humans and robots can work on different tasks in the same area. At the cooperation level, human operator can load materials and supervise the robots to work.

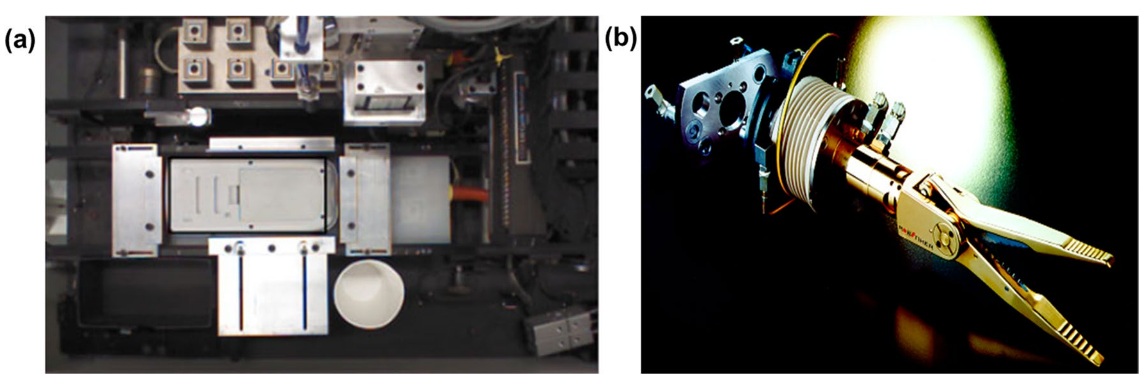

Fig. 4 **a** Adjustable vice with kinetic system to fasten electronic devices [51]. **b** Pneumatic cutting tool with shock absorber [52]

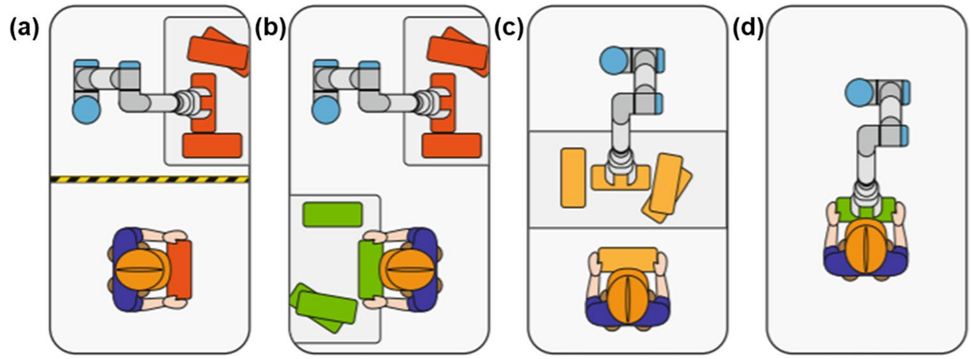

Fig. 5 Four degrees of interaction between a human and a robot. **a** Encapsulation. **b** Coexistence. **c** Cooperation. **d** Collaboration [53]

Normally, operators take over more responsibility in decision-making and process control, while the automatic station focuses on repetitive or more dangerous tasks. For example, Wegener et al. proposed a concept for battery disassembly workstation where a human is assisted by a robot [54, 55]. The operator would perform more complex tasks such as prying apart components joined with snap fits or (to a limited extent) glue, and pulling out or cutting cables, while the robot would help with unfastening screws and bolts. Meanwhile, the bit changing is achieved automatically through camera-based detection. In addition, Esther et al. proposed collaborative robots to perform disassembly tasks [56]. It is able to learn from the operator through the hand or finger gestures. Additional spoken instructions can also be combined to supervise the robot where to cut, unscrew, or manipulate a component and where to discard it [57]. Semi-automated PCB disassembly station is also proposed by Galparoli et al. to desolder the waste PCB with the assistance from cobot [58]. However, semi-automation cannot be the optimal choice in WEEE recycling since the exposure to the hazardous environment has not been resolved [59]. Hence, much effort has been paid for full automation, which can be classified into predefined automation and cognitive automation. The former is the predefined process, in which the automation and robots are employed for the fixed scenes, executing preprogrammed repetitive actions. For example, automatic disassembly of PCB to separate out the electronic components has been studied by several researchers. Automatic apparatus designed using heating with vibration [60], heating with a centrifuge [61], or physical scrapping [62] has been confirmed to be effective for detaching parts from baseboard. It is suitable for products in high volumes and comes with large capital investment. The other type of automation is the cognitive automation, which can accommodate different types of e-waste and achieve flexible disassembly.

2.4.3 Intelligent disassembly

The concept of "Cognitive robotics" is applied by emulating human behavior and providing cognitive-level functionality in the disassembly process. It employs vision or other sensors for reasoning and monitoring the disassembly operation. This method is definitely more intelligent and applicable for WEEE treatment due to the complexity of EOL products. As shown in Fig. 6, the system consists of three modules: (1) the vision system (VS), (2) the cognitive robotics (CR), and (3) the disassembly operation (DO). VS is used to recognize the critical components and determine their location. Slight variation among different products is tolerable with the guidance of computer vision. In the disassembly operation, real-time information is collected by VS and transmitted to CR for reasoning and planning. Pre-trained model and algorithm could quickly unscramble the image information to capture critical components and their features. Knowledge base (KB), which obtains data and information from learning and revision processes, will be invoked by Cognitive Robotic Agent (CRA) for reasoning and monitoring [63, 64]. In addition, the existing KB can be revised to make it more efficient if the disassembly scenario faced is out of the scope. During the disassembly process, DO is carried by CR which will follow the designed trajectory to conduct the disassembly behavior.

The disassembling behaviors of the system are illustrated in Fig. 7. If the object is determined to be a known model, disassembly behaviors will be conducted following instructions in KB. Otherwise, the learning and revision process will be performed to enrich the KB through trial and error. Based on the detection of an object and analysis of its disassembly requirements, disassembly plans and rules are generated. For example, the disassembly techniques (non-/ semi-/ full-destructive) are selected according to the types of main components as well as connections. Meanwhile, the damage or no-damage condition and toxicity of materials also need to be considered [66]. When the disassembly domain as well as plan is determined, such as the physical behaviors like gripping, cutting, or unscrewing, its feasibility will be verified by tentative removing operation. VS and the image processing algorithm are critical parts for intelligent disassembly, allowing the tolerance for the uncertainty, complexity, and diversity

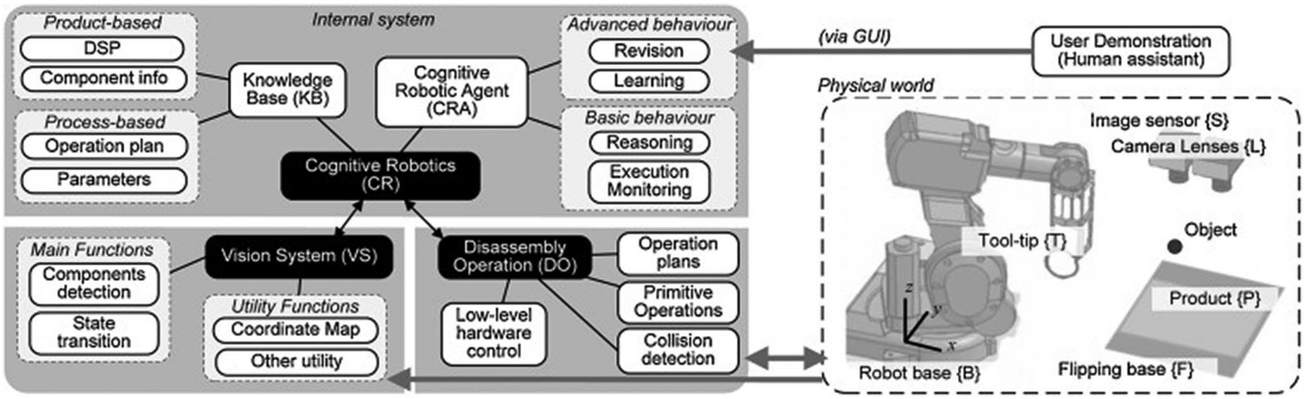

Fig. 6 The system architecture of cognitive robot for disassembly [65]

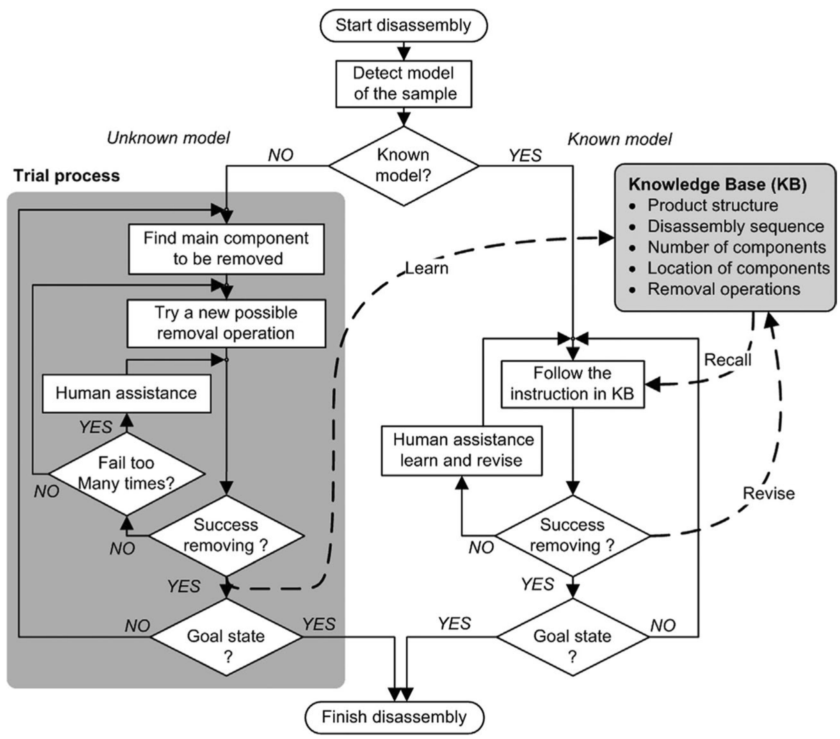

Fig. 7 Behavior of the CRA for the known and unknown models [72]

of e-wastes. Various deep learning algorithms, such as convolutional neural network (CNN), region-based CNN (R-CNN), and other classification methods like multi-layer perceptron (MLP) or support vector machine (SVM), have demonstrated high efficacy in detecting complex objects [67, 68]. However, their application in waste segregation is limited due to their slow computing capabilities and time delays. In contrast, the YOLO (You Only Look Once) network tackles this issue by transforming the problem of target classification and localization into a regression problem, resulting in improved detection speed compared to other CNN models [69]. It achieves prominent detection accuracy and speed, especially for small objects [70]. VS is also used for execution monitoring to judge the degree of completion and evaluate each disassembly step. Human assistance is required when one operation fails too many times. Apart from this, other advanced sensing technologies in robotic applications are of great importance. In combination with tactile sensors, the accuracy of VS can be improved to satisfy the requirements [71]. Schumacher et al. propose specific tooling concepts which are combined with sensorial features for active disassembly [51].

Several researchers focus on autonomous disassembly based on cognitive robots. Bdiwi et al. propose a robotized workstation for motor dismantling [73]. The connecting screws are detected through a novel image processing algorithm, and screws as well as hexagonal bolts are removed by tools carried on the robot station. Similarly, crosshead screws on different types of TVs can be detected by computer vision method even though in different orientations [74]. Marconi et al. design an automatic system containing a wave soldering machine, a two-axis manipulator equipped with a suction cup, and a central control unit for dismantling spent PCB nondestructively [75]. The desoldering is achieved by laser cutting to detach the electronic components from PCB for remanufacturing. It can be concluded that these platforms can perform specific actions for a single step of e-waste disassembly, allowing variations to some extent. In the real recycling industry, more robust and efficient solutions are required to execute the disassembly of the whole device:

LCD disassembly Liquid crystal display (LCD) is now sharing the biggest market among all types of TVs. The potential and recycling strategies for LCD panels from WEEE are discussed in the SM. The works of Vongbunyong et al. are based on the industrial environment of LCD-monitor dismantling [45, 65, 72, 76]. Their concept of an agent-based system using cognitive robotics (reasoning, execution monitoring, and learning) with agents on three different control levels can be regarded as a milestone in the development towards an autonomous robotic disassembly system, in which the main components can be disassembled following the sequence: back cover → PCB cover → PCBs → carrier → LCD module. The edge detection and contour geometry are shown in Fig. 8(a)–(j), the color and depth image of each state in LCD disassembly are illustrated [76]. The object is detected by a vision system, and the cutting operation is performed by the robotic arm around the contour of electronic parts.

The paragon of intelligent disassembly of LCD in industry is Veolia in the UK. Dubbed RoboTele system has been built for dismantling up to 500,000 flat screens per year [77]. In this system, the speakers, plugs, and accessories of LCDs are removed manually. It can be observed in Fig. 9a and b that the first robot will load the LCD on the flip table. The four corners of the LCD would be fastened, and the scraper underneath removes the frame case without damaging the screen. Then, the top layer of the LCD display can be easily removed, while the back portion is sent to a second robot. This

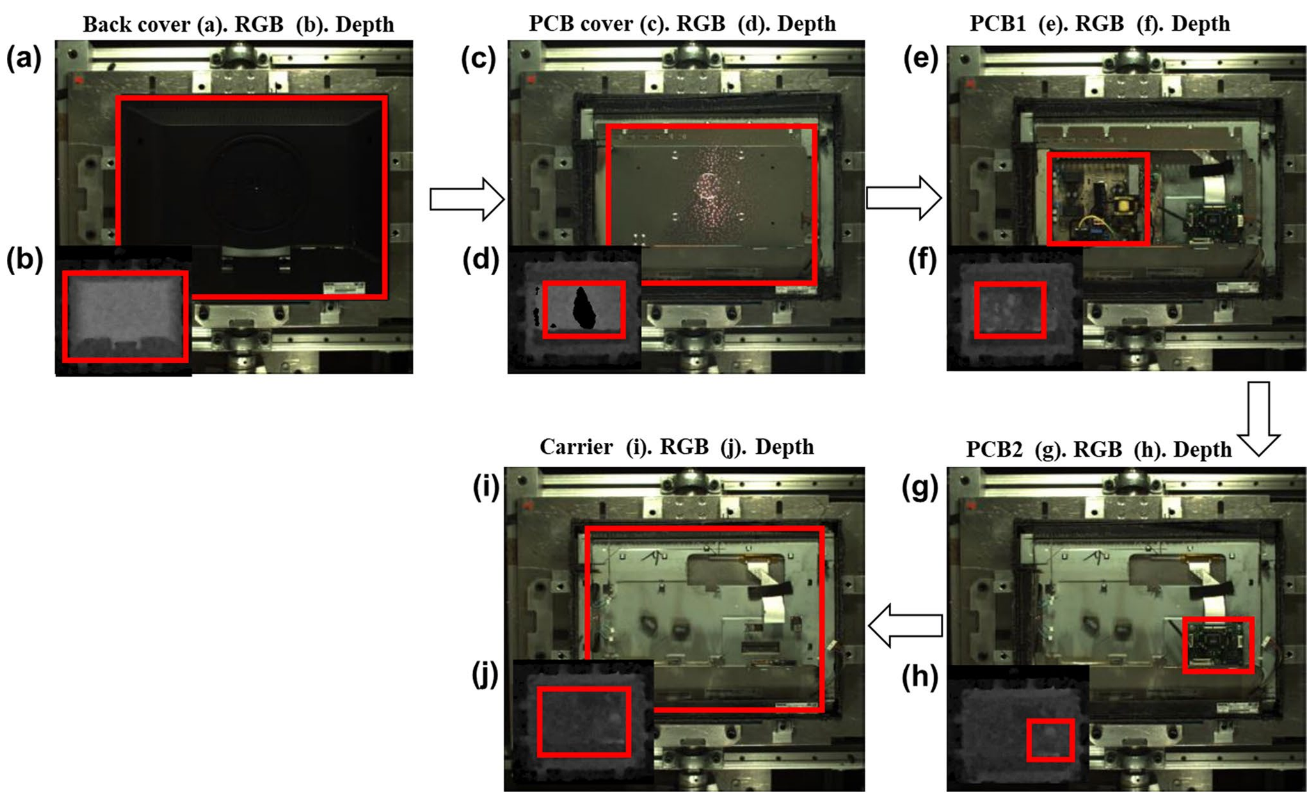

Fig. 8 Disassembly states of LCD in RGB and depth image. Back cover (**a**) RGB, (**b**) depth; PCB cover (**c**) RGB, (**d**) depth; PCB1 (**e**) RGB, (**f**) depth; PCB2 (**g**) RGB, (**f**) depth; carrier (**i**) RGB, (**j**) depth. [72]

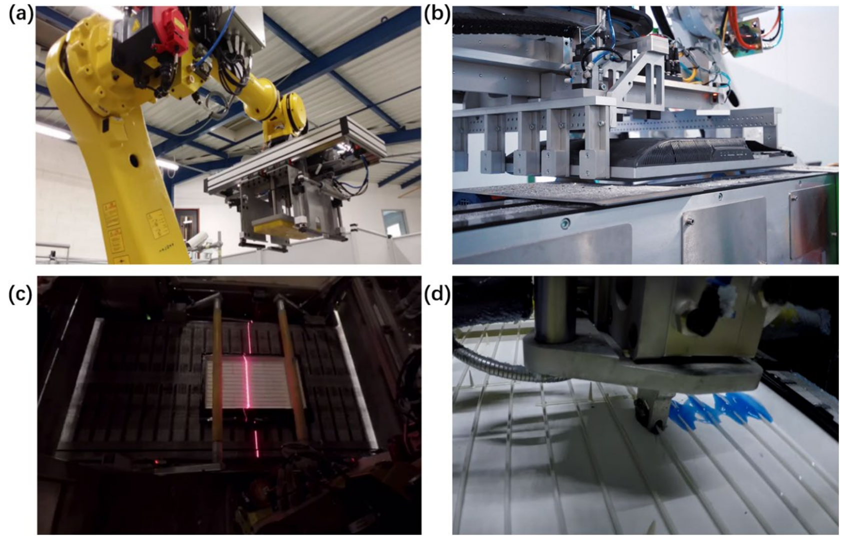

Fig. 9 Intelligent disassembly of LCD flat TVs. **a** Overview of the LCD disassembly station. **b** Loading LCD with the robot arm. **c** Linear sweeping to localize the backlit tube. **d** Incise the backlit tube meanwhile release the wax to protect the toxic material from leak

robot will cut the mercury backlight tube and inject a wax mixture to prevent the release of mercury. Figure 9c demonstrates linear sweeping using the 3D camera for localizing the backlit tubes, and Fig. 9d introduces the cutting and wax injection process on backlit tubes. The broken tubes could be safely removed and collected by operators while the remaining back case will be shredded for material recovery.

Mobile phone disassembly Mobile phones have one of the shortest lifespans among consumer electronic products, with approximately 1.46 billion units being sold worldwide annually. While some phones are resold, a significant number end up being discarded [78]. The EOL mobile phone treatment is of great significance to reutilizing the critical materials inside. Apple ushered the Liam robotic system which is capable of disassembling 1.2 million iPhone 6 units per year in 2016 [79]. Its upgraded version dubbed Daisy was unveiled later, which can dismantle 15 different versions of the iPhone, at a rate of 200/h in 2019 [80]. Due to the limited types of products, the models of spent iPhones can be recognized through a vision system. The display is removed by jamming the robot's prongs into the crease between the display and the body (Fig. 10a). In order to detach the battery, which is adhered in place, a jet of ultra-cold air at – 80 °C is directed towards it, causing it to freeze along with the adhesive. Following this, a tool is used to dislodge the battery from its position. As illustrated in Fig. 10c and d, screws holding the logic board are punched out followed by removing cameras, speakers, and other bits. The remaining aluminum shell is carted off for recycling [81]. Table 2 lists the materials reclaimed from iPhone disassembly.

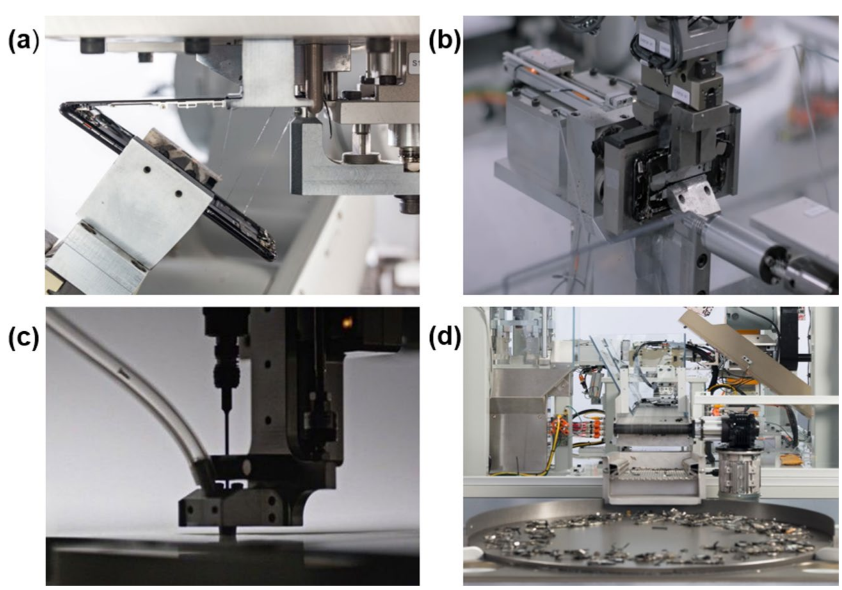

Fig. 10 **a** Separation of display and the iPhone body. **b** Dismantling the main board. **c** Transportation of disassembled parts from iPhone. **d** Collection of recovered metal materials [82]

2.4.4 Economic feasibility

When popularizing the automation in remanufacturing industry, cost effectiveness of take-back and product recovery is to be considered. To analyze the economic effectiveness of the automatic disassembly, several researchers have quantified the benefits through the calculation of treatment costs and material revenues of the different EOL treatment options [83]. These calculations are used to evaluate the EOL treatment options based on the profitability, leading to the design improvements [84]. Renteria et al. proposed a new methodology to achieve the optimized recycling process for TV sets [85]. The simulation software Robcad, which allows quick and agile changes in process parameters, is used to provide information about cycle times, productivity, and machine usage under three scenarios: full automation, half automation, and full manual operation. Detailed views of the automatic implementation and simulation are described in Fig. 11. Previous experience of the recyclers indicates the relationship between the level of material separation and unit cost of treatment with the level of automation. The higher the degree of automation, the lower the processing cost, but the worse the material separation of e-waste. To quantify the recycler's profit and evaluate the recycling process design, the objective function is proposed as revenues (sale of obtained materials) minus the treatment cost for each disassembled appliance, as shown in Eq. (1). For CRT recycling line, five most important materials ranked by weight content are included: glass, plastic, iron, aluminum, and copper.

Table 2 Materials recovered every 1000 iPhones disassembled [81]

Material	Quantity (kg)
Aluminum	190
Copper	80
Gold	0.13
Sliver	0.7
Tin	5.5
Platinum	0.04
Rare earth elements	2.4

$$PF = \sum_{i=1}^{5} (Mi \times PR_i) - ((\sum_{j=1}^{n} AE_j + GE)/P) \tag{1}$$

The PF means the Profit, i represents each material while j is for each disassembly machine. M_i and PR_i indicate the amount of material i obtained in the recycling process and its selling price. AE_j and GE are corresponding to the annual depreciation of disassembling machine j and the operation cost, while P means the annual production or number of disassembled units. In addition, the economic objective associated with the investment on advanced automated technology has also been evaluated by net present valuE (NPV), internal rate of return (IRR), and pay-back period (PB). Data inputs of parameters are from previous expertise of recycling facilities and applicable regulations or national standards. Some of the datasets are assumed based on experience.

The formula for calculating NPV value is illustrated in Eq. (2). It can be explained as the desired value of an unrealized gain from the investment. NPV is the discounted cash flow to time zero; its positive value indicates the recommendation of this project:

$$\mathrm{NPV} = -II + \sum_{1}^{t} \left[\frac{OCF}{(1+r)^t} \right] + \left[\frac{TCF}{(1+r)^n} \right] \tag{2}$$

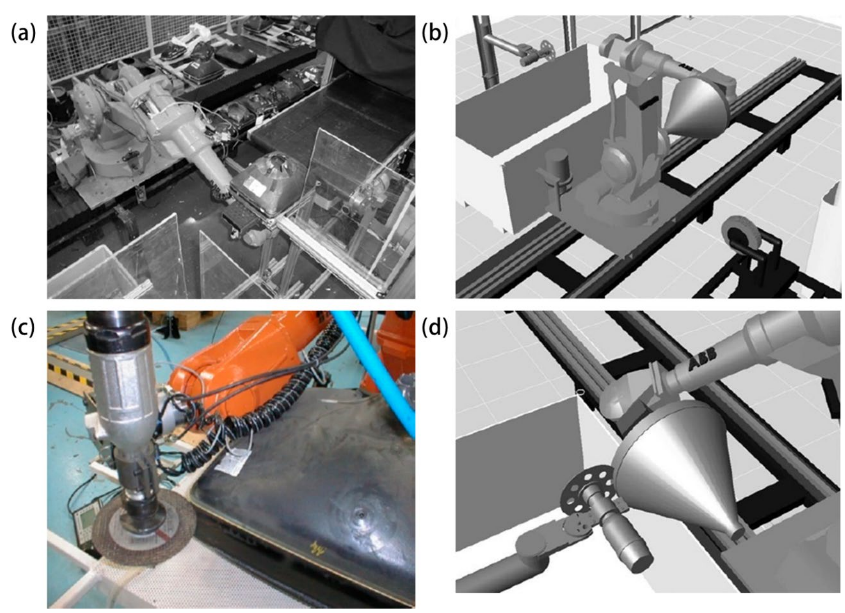

Fig. 11 Examples of automatic recycling plants of CRT disassembly: **a** CRT loading with robot. **b** simulation of robotic loading. **c** Automatic cutting of CRT [86]. **d** Simulation of CRT cutting procedure [85]

The *II* indicates the initial investment, OCF is the operating cash flow in year *t*, and TCF means the termination cash flow. *n* and *r* present the life span of the project and the project required rate of return respectively. In this study, the lifespan is set as 5 years with 15% project required rate of return. The datasets are chosen from assumptions based on working experience, which makes it convenient for profit calculation.

IRR is the discount rate that returns NPV to zero, and the project is expected to be acceptable when IRR is higher than a selected hurdle rate. It only can be found by trial and error instead of calculation through the mathematical method.

1. PB period means the shortest time needed to earn back the initial investment. The time value of money is neglected.
2. Capital back (CB) aims to free up flexible investments by alleviating the strict requirements of a short pay-back period. It is compatible with the flexibility of the automation components that constitute the recycling installation. This CB index takes into account the initial investment in flexible machines (robots, handling devices, sensors, load/unload machines, computers, etc.) and the risky investment in inflexible components (grippers, specific fixing systems, specific dismantling tools, etc.).

$$\mathrm{CB} = \frac{IInf}{OCF - (IIf - (IIf * Annuity(n, r))} \quad (3)$$

IIf is the initial investment on flexible components while *IInf* means the initial investment on non-flexible components. OCF presents cash flow in year *t* life span (in years) of the project while *r*, *IIf*Annuity(n,r)* indicates the project required rate of return and annual cost for the flexible part of the investment, respectively.

The economic analysis of the proposed recycling plant is presented in Table 3, providing a comprehensive overview of the economic feasibility and investment viability of the proposed recycling line. The PB method emphasizes on the short-term planning with more uncertainty, while index CB is applicable for flexible investments that may lead to wrong decisions, as the unpredictability is focused on the total investment. These indicators aim to evaluate the economic objective related to the investment in advanced automated technology. The values obtained from these four indicators indicate that the proposed dismantling plant solution was indeed profitable.

In summary, the literature review reveals that the technology of WEEE disassembly has been evolving for several decades, from household manual operation to assembly work in scaled factories, leading to well-organized recycling and sorting of waste components by workers.

Table 3 Economic analysis of the proposed recycling plant of CRT [85]

Parameter	Value	Units
Capacity of CRT treatment plant	50,000	CRT/year
Labor required	4	worker
Required investment	273,000	€
Annual operating cost	123,680	€
Annual revenue from recovered material	284,886	€
Recycling percentage (in weight)	82	%
Results of main financial indicators (5 years of lifespan, 15% discount rate)		
Pay-back (PB)	1.69	years
Net present value (NPV)	425,986	€
Internal rate of return (IRR)	49.7	%
Modified internal rate of return (MIRR)	24.03	%
Capital back (CB)	0.98	Years
Profitability Index (PI)	1.69	

Currently, disassembly automation is being investigated to prevent the human from hazardous environment of recycling factories and also to reduce the labor cost. In order to handle the complex structure and inconsistent fasteners of WEEE, full-feature tools such as DTK are designed to achieve efficient detachment. Collaborative robots in semi-automatic system would focus on repetitive and heavy-duty tasks for reducing the intensity of labor. Economic analysis proves the feasibility of upgrading the manual disassembly station to automatic devices. The capital investment could be paid back in the near future due to the reduced labor cost. To fully liberate the laborers from a toxic environment, the intelligent disassembly containing vision system, cognitive robots, and a disassembly operation system is developed with the capability of learning and revision to make decisions by itself. It deserves further study to make it more adaptable although the high time consumption and capital investment impede the application. For the perspective of industrial application, the disassembly strategy would be distributed to more detailed procedures to reduce the difficulty of each station with certain types of e-waste to be treated. For example, advanced application of automatic apparatus, such as Daisy robots developed by Apple, requires the presorting of fixed models or versions of iPhone that can be accommodated.

3 Discussion

To summarize the findings of this study, the development track of WEEE disassembly is illustrated in Fig. 12. The time series of manual disassembly, automatic disassembly, intelligent disassembly, and intelligent circular economy are mapped out.

3.1 Barriers of applying intelligent disassembly in industry

The developing trend of automatic disassembly is aimed toward highly autonomous systems. The use of vision technologies as well as advanced sensors helps perceive the disassembly environment. Notably, the amount of research is still small in comparison to robotic assembly and other industrial sectors since the complex condition of e-waste impedes the automatic handling and planning, resulting in a longer period for calculation and a slower operation pace. From industrial applications, it is found that 100% automation in WEEE disassembly without human assistance is still unfulfillable. Furthermore, learning and revision processes executed by cognitive robots, are pretty costly and time-consuming when the scenarios of e-waste are beyond the scope of KB. To make the disassembly task more adaptable for automation, the disassembly strategy would be distributed to more procedures based on the planned sequence, thus reducing the difficulty of each procedure. Although the complexity of each station would be reduced, larger amounts of working apparatus or hardware are required, leading to much higher costs. Meanwhile, more preparatory work is needed by operators to ensure the smoothness of disassembly line. Previous economic analysis proves that automation is better at handling the repetitive processes than human workers [87]. It is believed that cognitive robots are bound to be helpful in replacing human-beings on disassembly processes, but it is unclear when and what it costs to achieve it. Referring to the successful case in Daisy system for iPhone recycling, the models of iPhones are fixed in certain types, which gives convenience to the subsequent disassembly. Meanwhile the recycler is what produces it, indicating that the components are unsecretive and easy to be tracked. Hence, it is desired to achieve the product tracking and pre-sorting ahead of the automatic disassembly. The robots can be efficient when they are handling the dismantling task with standardized input.

It is also challenging that the disassembly by cognitive robots would be time-consuming, especially for unfamiliar models, which require a long period of learning process. Essentially, KB in cognitive robots seeks more information models to enhance the capability of handling WEEE under various conditions. To build a more powerful KB, executing the learning process through remote control or referring from KB in other machines can be efficient solutions. In this way, the involvement of human workers in person can be avoided; meanwhile, the sharing of mature models could greatly save time for learning or revision. Therefore, it is imperative to create a cohesive system of devices and applications able to share the data of KB seamlessly across machines and enterprise peers to help them optimize production and discover new cost-saving opportunities [88].

3.2 Opportunities in the era of Industry 4.0

Industrial landscape now is under the 4th revolution, being transformed with the rise of autonomous robots, contemporary automation, cyber-physical systems, the internet of things, and so on [89]. It can bring about clear benefits,

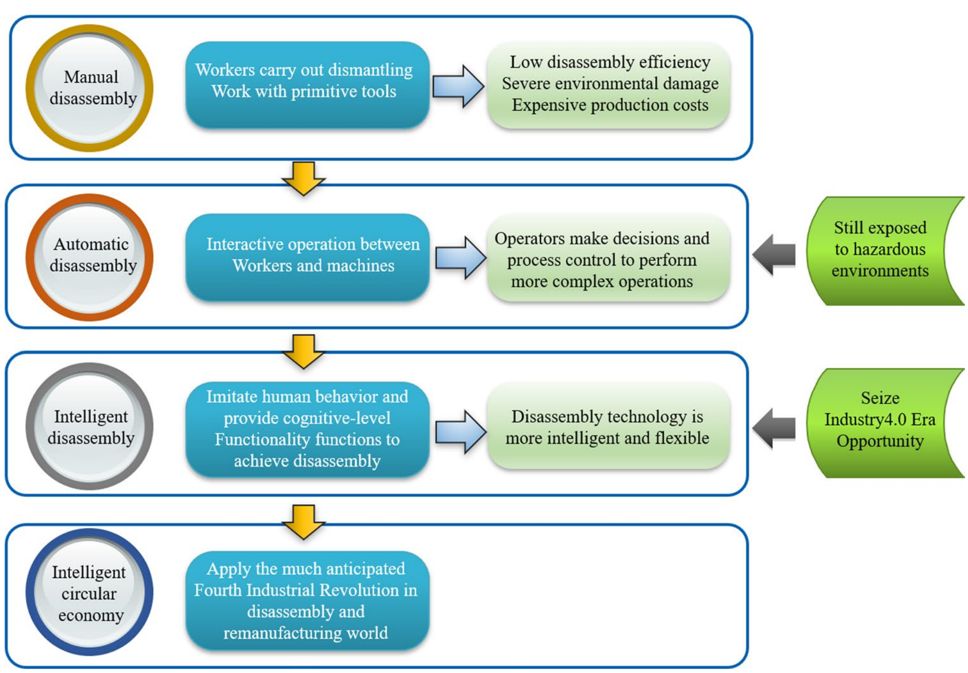

Fig. 12 Schematic illustration of the development track of WEEE disassembly

such as the increased information visibility, higher operation flexibility, lower time delay, and improved efficiency and productivity [90]. It is expected that disassembly and remanufacturing systems can be enhanced by cutting-edge technologies in Industry 4.0 to perform efficiently in recycling of WEEE for achieving the concept of CE [91]. Furthermore, the Extended Producer Responsibility (EPR) policy makes for the responsibility extension of electronic manufacturers to standardize the product, making it more convenient and efficient to be dismantled. The detailed impacts of fund policy EPR on WEEE dismantling are discussed in SM.

CPS Cyber-physical systems comprise smart machines, storage systems, and production facilities capable of autonomously exchanging information, triggering actions, and controlling each other independently[74]. The heterogeneous network of components links and integrates the physical world to a cyber-environment containing its virtual representation [92]. When applied in the industrial manufacturing, it is to combine the cloud-based manufacturing with hardware, making the system fit for scaling up and agile for different applications [93, 94].

Internet of Things (IoT) The "Internet-of-Things" is to extend the Web and Internet into physical things through devices, sensors with functions of sensing data collection, and processing [95]. To build a more powerful remanufacturing plant with strong structural flexibility and resilience facing marketing risk, IoT makes for mitigating the time delay between the data capture and action [96, 97]. IoT is the main enabler of cyber-physical systems (CPS) that improves productivity and efficiency. The quick and secure access to industrial robots helps react to performance-related or unexpected issues remotely [97].

Digital twin A digital twin is a virtual representation of the real world, including physical objects, relationships, behaviors, and processes, playing a key role in CPS to bridge the cyber world and physical objects [98, 99]. For WEEE disassembly, digital twin can create a coupled avatar that reflects the actual status of disassembly scenario, including robots and targeted e-wastes [89, 100].

Cloud computing Cloud computing, including servers, storage, databases, networking, software, analytics, and intelligence, is providing the industry with the improved methods of information computing and application [101, 102]. It contains several resources in one sharing platform, which allows all the identified people to get access to it based on their requirements. The shared pool of computing resources such as storage, servers, applications, and services can be utilized with minimal management effort or service provider interaction [103].

Wang et al. propose a cloud-based platform to organize recycling services [104]. The WEEE owners can scan the QR code and upload to WRCloud, in which the detailed product specifications can be quickly retrieved from Cloud Storage. Feasible suggestions will be given by Cloud Coordinator to arrange the recovery of WEEE more efficiently. In addition, a cloud-based disassembly planning approach is proposed by Xia et al. for sustainable management of WEEE [24]. Four kinds of cloud services are included: information service, disassembly modeling services, disassembly evaluation service, and disassembly optimization service, which can achieve a service-oriented environment for distributed information sharing, disassembly modeling, evaluation, and optimization.

3.3 Perspective for intelligent disassembly system

Due to the continuously decreasing prices and burgeoning case applications, robots are expected to be more popular than they already are today in the near future [25]. Meanwhile, the price for IoT sensors has dropped nearly 200% between 2004 and 2018, to an average cost of $0.44, making IoT solutions more affordable and accessible [28]. The popularizing and successful experience of intelligent manufacturing is bound to be applied in the remanufacturing field, forming an intelligent disassembly system for the future treatment of WEEE. This is consistent with the concept of CE, in which the material and financial flow lead to closed-loop supply chains or reversed supply chains, prompting the sustainability [30].

An IoT integrated architecture for the disassembly and remanufacturing of WEEE is illustrated in Fig. 13. Four main layers are contained in the architecture: physical, communication, service, and application. Physical layer is the ground floor layer, which includes the disassembly line equipped with multiple robots and sensors. The upper part is the perception part which captures real-time data during the historical production and sends the data to communication layer through field gateways. Meanwhile the control part in the physical layer will receive information from the communication layer and conduct the physical operation accordingly. In the communication layer, the goal is to transfer information from the physical layer to the internet, gathering data from IoT gateways that are connected through Ethernet or mobile networks (such as GPRS/3G/4G/NB-IoT and 5G). This layer includes field gateways that serve as interfaces between IoT gateways and transceivers, utilizing technologies like ZigBee, WiFi, Sigfox, Bluetooth, or LoRA. The information received from the communication layer is ingested and managed by the service layer. The top application layer utilizes services from the preceding layer, enabling users to perform tasks such as monitoring, control, prediction, and logistics. The cyber world acquires function data from the bottom physical layer, such as the parameters

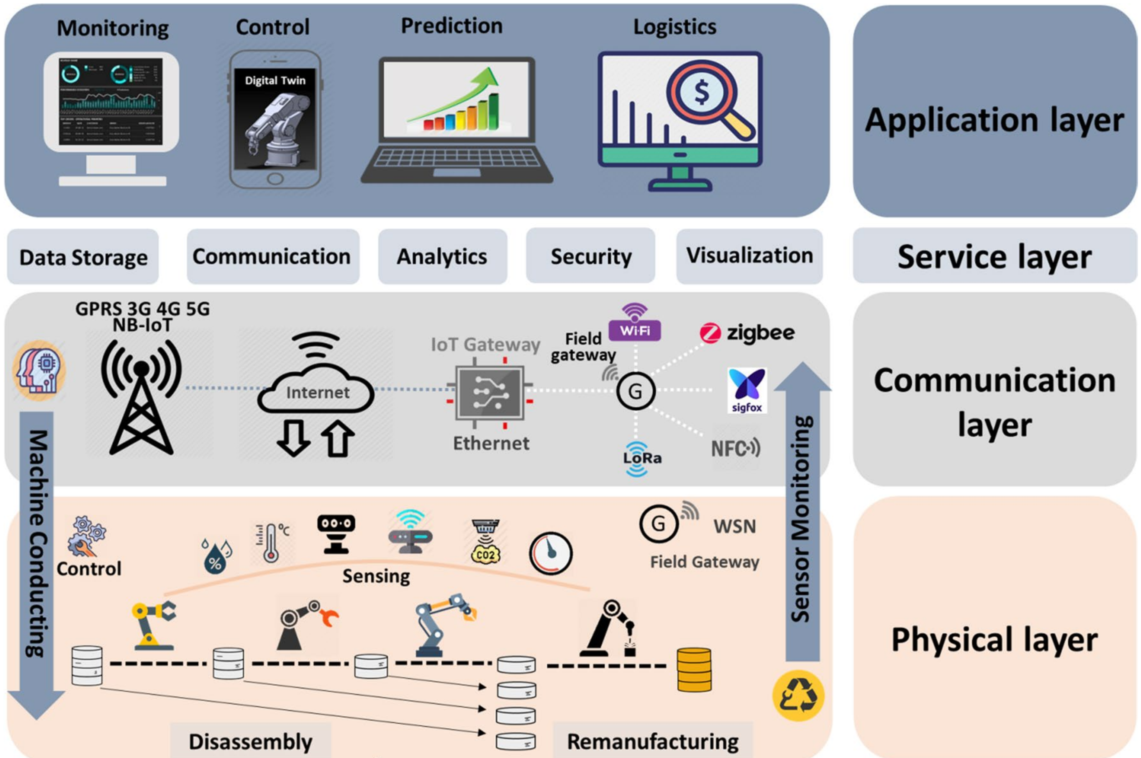

Fig. 13 The architecture of the intelligent remanufacturing system toward circular economy [29]

of robotic operation; meanwhile, it gives commands to the physical part to establish the CPS. In the service layer, data analysis through intelligent algorithms and cloud computing helps the decision making. A full-featured cloud-based remanufacturing for sustainable management of WEEE will be achieved. Real-time data is collected and transmitted through IoT infrastructure.

In this intelligent disassembly system, the cloud computing allows the sharing of disassembly operation plans and mutual data transmission. By invoking the existing WEEE model in KB from the cloud, the local robots could directly perform the disassembly operation instead of repeating the self-learning process with human assistance. In addition, the local robots can build a new model for disassembly if it cannot be found in cloud KB. Using digital twin technology, the model establishment, disassembly simulation, and trial teaching are achieved through remote control [26]. It provides service of predictive maintenance as well as early error diagnosis for physical devices. Then, the completed model would be uploaded to the cloud and shared by other users of disassembly [101, 102]. The behaviors of the cloud-based intelligent disassembly system are illustrated in Fig. 14. These advances greatly enable the smart remanufacturing, in which not only the automation is achieved, but to enable mass customization that easily fulfills the flexibility requirements, thus creating extra value [27].

In summary, disassembly automation in the recycling industry is still immature. Existing cases of disassembly automation in the recycling industry design the specific flow path for certain types of WEEE. However, it is unprofitable to design the automatic dismantling device for each model of WEEE since the electronic products are upgrading and evolving version by version, and the detailed sorting is unachievable by the current recycling facility. Cognitive robots are utilized to handle the WEEE disassembly in complicated scenarios due to their learning and revision process with powerful KB. The structure of e-waste as well as disassembly sequence could be determined by themselves for removal operations. However, the learning and revision process is pretty time consuming, resulting in a long training period for decision making. To promote the efficiency of the disassembly process, intelligent solutions in the era of Industry 4.0 are promising to achieve the interaction of entities for information transmission. Cloud-based KB provides abundant models for online robots with disassembly strategies to avoid the repetitive learning and revision processes. The cyber-enabled intelligent remanufacturing system with IoT technology uses multitudinous sensors for data collection and processing to achieve the parameter optimization. Digital twin technology enables the remote control and disassembly simulation of disassembly robots that effectively isolates workers from hazardous environments.

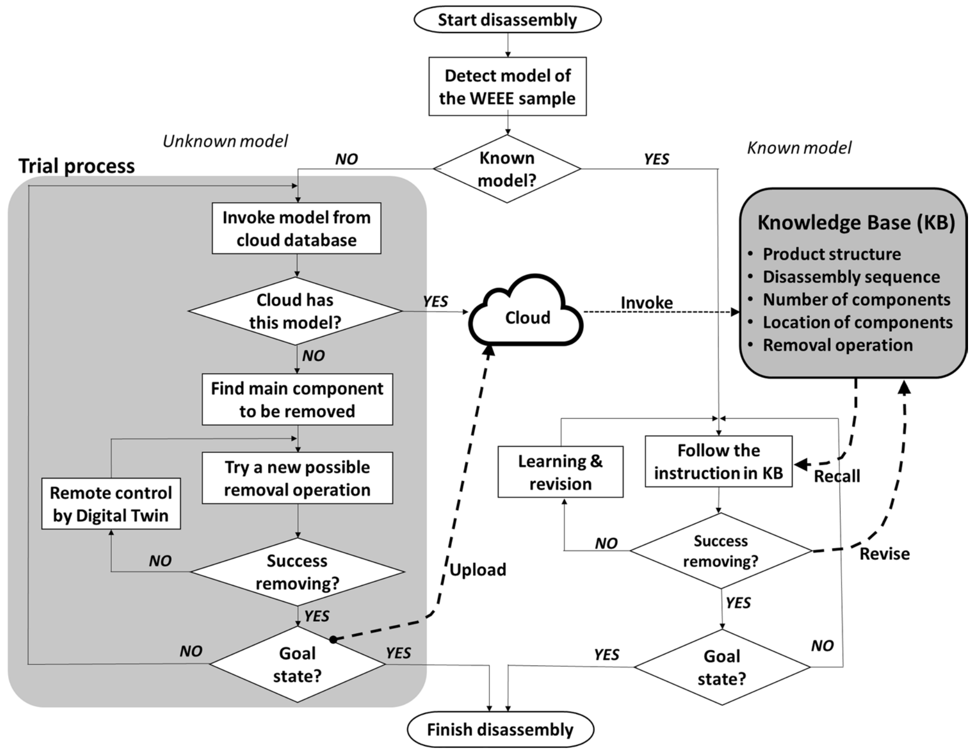

Fig. 14 Behavior of the proposed intelligent disassembly system for the known and unknown models [72]

4 Conclusion

This work reviews the state of the art of WEEE disassembly, including advanced dismantling technologies in functional tools, semi-automation, and intelligent disassembly. The almighty disassembly tools are designed to remove the fasteners while the semi-automation employs the cooperative robots for executing the repetitive or heavy-duty tasks. In-house calculation has proven the economic feasibility of upgrading the manual operation to robotic disassembly station. Short-term capital back and reduced cost of labor enable mass application of automation devices. Noticeably, full automation is only applicable in specific types of e-waste with more detailed disassembly planning. Main challenges of applying full automation in the recycling industry are the high complexity of EOL products in structure design as well as material composition. The disassembly system is required to be capable of recognizing, self-learning, and planning to cope with the complicated scenarios, instead of performing the predefined repetitive actions. Cognitive robots with vision system, disassembly operation module, and knowledge base can achieve self-adaption for the uncertainties in WEEE. To reduce the time delay from the learning and revision process and improve the operation efficiency, it is imperative to have more intelligent solutions involved to prompt remanufacturing towards a high level of digitalization and intelligence with the advent of Industry 4.0. Cloud-based platform realizes the sharing of disassembly operation plan and mutual data transmission. Local robots in factories could directly perform dismantling actions following the model-oriented strategy invoked from cloud KB instead of repeating the self-learning with human assistance. IoT technology uses multitudinous sensors for data collection and processing to achieve the parameter optimization. The use of digital twin achieves the remote control and disassembly simulation that effectively isolates workers from hazardous environments. It is our hope that this review can inform and inspire researchers and industrial practitioners to contribute in advancing the recycling industry forward. It is desired that the concepts discussed in this paper may spark new ideas in readers to apply the much-anticipated Fourth Industrial Revolution in disassembly and remanufacturing world to achieve intelligent circular economy.

Author contribution Yingqi Lu: conceptualization, methodology, writing — original draft, writing — review and editing.
Weidi Pei: writing — review and editing.
Kaiyuan Peng: writing — review and editing, funding acquisition, project administration.

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Data availability Data will be made available on request.

Declarations

Competing interests The authors declare no competing interests.

References

1. Kawai K, Tasaki T (2016) Revisiting estimates of municipal solid waste generation per capita and their reliability. J Mater Cycles Waste Manag 18(1):1–13
2. Fu J, Zhang H, Zhang A, Jiang G (2018) E-waste recycling in China: a challenging field. Environ Sci Technol 52(12):6727–6728
3. Sankhla MS, Kumari M, Nandan M, et al. (2016) Effect of electronic waste on environmental & human health-a review[J]. IOSR J. Environ. Sci. Toxicol. Food Technol 10(09):98–104.
4. Genovese A, Acquaye AA, Figueroa A, Koh SCL (2017) Sustainable supply chain management and the transition towards a circular economy: evidence and some applications. Omega 66:344–357
5. Cole C, Gnanapragasam A, Cooper T, Singh J (2019) An assessment of achievements of the WEEE Directive in promoting movement up the waste hierarchy: experiences in the UK. Waste Manag 87:417–427
6. Schäfer J, Singer R, Hofmann J, Fleischer J (2020) Challenges and solutions of automated disassembly and condition-based remanufacturing of lithium-ion battery modules for a circular economy. Procedia Manuf 43:614–619
7. Zeng X, Mathews JA, Li J (2018) Urban mining of e-waste is becoming more cost-effective than virgin mining. Environ Sci Technol 52(8):4835–4841
8. Poschmann H, Brüggemann H, Goldmann D (2020) Disassembly 4.0: a review on using robotics in disassembly tasks as a way of automation. Chemie Ingenieur Technik 92(4):341–359
9. Vanegas P, Peeters JR, Cattrysse D, Tecchio P, Ardente F, Mathieux F, Dewulf W, Duflou JR (2018) Ease of disassembly of products to support circular economy strategies. Resour Conserv Recycl 135:323–334
10. Schoch K, Liedtke C, Bienge K (2021) Designing on the Basis of Recycling-Metallurgy Possibilities: Material-Specific Rules and Standards for “Anti-dissipative” products. Resources 10(1):5
11. Papaoikonomou K, Emmanouil C, Vasilato V, Diapouli E, Grigoratos T, Zafirakou A, Kungolos A (2018) PM10 and elemental concentrations in a dismantling plant for waste of electrical and electronic equipment in Greece. Aerosol Air Qual Res 18(6):1457–1469
12. Sarc R, Curtis A, Kandlbauer L, Khodier K, Lorber K, Pomberger R (2019) Digitalisation and intelligent robotics in value chain of circular economy oriented waste management–a review. Waste Manag 95:476–492
13. Tranfield D, Denyer D, Smart P (2003) Towards a methodology for developing evidence-informed management knowledge by means of systematic review. Br J Manag 14(3):207–222
14. Matsuto T, Jung CH, Tanaka N (2004) Material and heavy metal balance in a recycling facility for home electrical appliances. Waste Manag 24(5):425–436
15. Kopacek B (2016) Intelligent disassembly of components from printed circuit boards to enable re-use and more efficient recovery of critical metals. IFAC-PapersOnLine 49(29):190–195
16. Gu Z, Feng J, Han W, Wu M, Fu J, Sheng G (2010) Characteristics of organic matter in PM2.5 from an e-waste dismantling area in Taizhou, China. Chemosphere 80(7):800–806
17. Lau WKY, Liang P, Man YB, Chung SS, Wong MH (2014) Human health risk assessment based on trace metals in suspended air particulates, surface dust, and floor dust from e-waste recycling workshops in Hong Kong, China. Environ Sci Pollut Res 21(5):3813–3825
18. Cai H, Xu X, Zhang Y, Cong X, Lu X, Huo X (2019) Elevated lead levels from e-waste exposure are linked to sensory integration difficulties in preschool children. Neurotoxicology 71:150–158
19. Huo X, Peng L, Xu X, Zheng L, Qiu B, Qi Z, Zhang B, Han D, Piao Z (2007) Elevated blood lead levels of children in Guiyu, an electronic waste recycling town in China. Environ Health Perspect 115(7):1113–1117
20. http://japanese.china.org.cn/life/2013-06/17/content_29144078_3.htm
21. https://retroworks.blogspot.com/2018/01/smokescreen-in-africa-german.html
22. http://www.kexing365.com/
23. http://news.sohu.com/a/477235476121106842
24. Chancerel P, Meskers CEM, Hagelüken C, Rotter VS (2009) Assessment of precious metal flows during preprocessing of waste electrical and electronic equipment. J Ind Ecol 13(5):791–810
25. Suzuki G, Kida A, Sakai S-I, Takigami H (2009) Existence state of bromine as an indicator of the source of brominated flame retardants in indoor dust. Environ Sci Technol 43(5):1437–1442
26. Fang W, Yang Y, Xu Z (2013) PM10 and PM2.5 and health risk assessment for heavy metals in a typical factory for cathode ray tube television recycling. Environ Sci Technol 47(21):12469–12476. Accessed 4 Dec 2022.
27. Julander A, Lundgren L, Skare L, Grandér M, Palm B, Vahter M, Lidén C (2014) Formal recycling of e-waste leads to increased exposure to toxic metals: an occupational exposure study from Sweden. Environ Int 73:243–251
28. Wang H, Han M, Yang S, Chen Y, Liu Q, Ke S (2011) Urinary heavy metal levels and relevant factors among people exposed to e-waste dismantling. Environ Int 37(1):80–85
29. Tan SY, Praveena SM, Abidin EZ, Cheema MS (2016) A review of heavy metals in indoor dust and its human health-risk implications. Rev Environ Health 31(4):447–456
30. Burns KN, Sayler SK, Neitzel RL (2019) Stress, health, noise exposures, and injuries among electronic waste recycling workers in Ghana. J Occup Med Toxicol 14(1):1
31. Cherubini A, Passama R, Crosnier A, Lasnier A, Fraisse P (2016) Collaborative manufacturing with physical human–robot interaction. Robot Comput-Integr Manuf 40:1–13
32. Sheet F (2021) The Raise the Wage Act of 2021
33. Helliwell JF, Huang H (2011) Well-being and trust in the workplace. J Happiness Stud 12(5):747–767
34. Jeong BY, Lee S, Lee JD (2016) Workplace accidents and work-related illnesses of household waste collectors. Saf Health Work 7(2):138–142
35. Low S (1988) Manufacturing automation protocol explained: the MAP report by Jack Hollingum. Published by IFS Ltd. 155pp.£ 75.00, Elsevier
36. Punkkinen H, Mroueh U-M, Wahlström M, Youhanan L, Stenmarck Å (2017) Critical metals in end-of-life products: recovery potential and opportunities for removal of bottlenecks of recycling. Nordic Council of Ministers
37. Chen SVWH (2015) Disassembly automation. Sustainable Production, Life Cycle Engineering and Management. Springer International Publishing
38. Vongbunyong S, Kara S, Pagnucco M (2013) Basic behaviour control of the vision-based cognitive robotic disassembly automation. Assem Autom 33(1):38–56
39. Seliger G, Keil T, Rebafka U, Stenzel (2001) Flexible disassembly tools. IEEE international symposium on electronics and the environment, pp 30–35
40. Ajwad SA, Iqbal J, Ullah MI, Mehmood A (2018) Optimal and robust control of multi DOF robotic manipulator: design and hardware realization. Cybern Syst 49(1):77–93

41. Seriani S, Gallina P, Scalera L, Lughi V (2018) Development of n-DoF preloaded structures for impact mitigation in cobots. J Mech Robot 10(5)
42. Büker U, Drüe S, Götze N, Hartmann G, Kalkreuter B, Stemmer R, Trapp R (2001) Vision-based control of an autonomous disassembly station. Robot Auton Syst 35(3):179–189
43. Chen WH, Foo G, Kara S, Pagnucco M (2020) Application of a multi-head tool for robotic disassembly. Procedia CIRP 90:630–635
44. Schumacher P, Jouaneh M (2013) A system for automated disassembly of snap-fit covers. Int J Adv Manuf Technol 69(9):2055–2069
45. Schmitt J, Haupt H, Kurrat M, et al. (2011) Disassembly automation for lithium-ion battery systems using a flexible gripper[C]//2011 15th International Conference on Advanced Robotics (ICAR). IEEE, 291–297.
46. Kaiser L, Schlotzhauer A, Brandstötter M (2018) Safety-related risks and opportunities of key design-aspects for Industrial Human-Robot Collaboration. Springer International Publishing, Cham
47. Wegener K, Chen WH, Dietrich F, Dröder K, Kara S (2015) Robot assisted disassembly for the recycling of electric vehicle batteries. Procedia CIRP 29:716–721
48. Wegener K, Andrew S, Raatz A, Dröder K, Herrmann C (2014) Disassembly of electric vehicle batteries using the example of the Audi Q5 hybrid system. Procedia CIRP 23:155–160
49. Alvarez-de-los-Mozos E, Renteria A (2017) Collaborative robots in e-waste management. Procedia Manuf 11:55–62
50. Megalingam RK, Bandhyopadhyay S, Vivek GV, Rahi MJ (2017) Hand gesture based wireless robotic arm control for agricultural applications. IOP Conf Ser: Mater Sci Eng 225:012204
51. Galparoli S, Caielli S, Rosa P, Terzi S (2021) Chapter 4 Semi-automated PCB disassembly Station. SpringerBriefs in Applied Sciences and Technology, P.S.T. Dr. Paolo Rosa, (ed)
52. Schluep M, Hagelüken C, Meskers C, Magalini F, Wang F, Müller E, Kuehr R, Maurer C, Sonnemann G (2009) Market potential of innovative e-waste recycling technologies in developing countries. in R'09 World Congress, Davos, Switzerland
53. Wang J, Guo J, Xu Z (2016) An environmentally friendly technology of disassembling electronic components from waste printed circuit boards. Waste Manag 53:218–224
54. Lee J, Kim Y, Lee J-C (2012) Disassembly and physical separation of electric/electronic components layered in printed circuit boards (PCB). J Hazard Mater 241–242:387–394
55. Rubin RS, de Castro MAS, Brandão D (2019) Disassembly of waste printed circuit boards using air heating and centrifugal force. Revista Eletrônica em Gestão, Educação e Tecnologia Ambiental 23:28
56. Borgida A, Mitchell T, Williamson KE (1986) Learning improved integrity constraints and schemas from exceptions in data and knowledge bases. In: Brodie ML, Mylopoulos J (eds) On Knowledge Base Management Systems: Integrating Artificial Intelligence and Database Technologies. Springer New York, New York, NY, pp 259–286
57. Zhao Y, Mooren E, Derbinsky N (2017) Reinforcement learning for modeling large-scale cognitive reasoning. in KEOD
58. Vongbunyong S, Kara S, Pagnucco M (2013) Application of cognitive robotics in disassembly of products. CIRP Ann 62(1):31–34
59. Jiang H, Yi J, Zhu X, Li Z (2018) Generating disassembly tasks for selective disassembly using ontology-based disassembly knowledge representation. Assem Autom 38(2):113–124
60. Dundar A, Jin J, Martini B, Culurciello E (2017) Embedded streaming deep neural networks accelerator with applications. IEEE Trans Neural Netw Learn Syst 28(7):1572–1583
61. Lu S, Wang B, Wang H, Chen L, Linjian M, Zhang X (2019) A real-time object detection algorithm for video. Comput Electr Eng 77:398–408
62. Redmon J, Divvala S, Girshick R, Farhadi A (2016) You only look once: unified, real-time object detection. in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)
63. Li X, Tian M, Kong S, Wu L, Yu J (2020) A modified YOLOv3 detection method for vision-based water surface garbage capture robot. Int J Adv Rob Syst 17(3):1729881420932715
64. Yamaguchi A, Atkeson CG (2019) Recent progress in tactile sensing and sensors for robotic manipulation: can we turn tactile sensing into vision? Adv Robot 33(14):661–673
65. Vongbunyong S, Kara S, Pagnucco M (2015) Learning and revision in cognitive robotics disassembly automation. Robot Comput-Integr Manuf 34:79–94
66. Bdiwi M, Rashid A, Putz M (2016) Autonomous disassembly of electric vehicle motors based on robot cognition. in 2016 IEEE International Conference on Robotics and Automation (ICRA)
67. Foo G, Kara S, Pagnucco M (2021) Screw detection for disassembly of electronic waste using reasoning and re-training of a deep learning model. Procedia CIRP 98:666–671
68. Marconi M, Palmieri G, Callegari M, Germani M (2018) Feasibility study and design of an automatic system for electronic components disassembly. J Manuf Sci Eng 141(2)
69. Supachai V, Maurice P, Sami K (2016) Vision-based execution monitoring of state transition in disassembly automation. Int J Autom Technol 10(5):708–716
70. Kirkman Richard, Voulvoulis Nikolaos (2017) The role of public communication in decision making for waste management infrastructure. Journal of environmental management 203:640–647
71. Gu F, Summers PA, Hall P (2019) Recovering materials from waste mobile phones: Recent technological developments. J Clean Prod 237:117657
72. Rujanavech C, Lessard J, Chandler S, Shannon S, Dahmus J, Guzzo R (2016) Liam - an innovation story. https://www.apple.com/environment/
73. Jackson L (2019) Environmental Progress Report. Apple: https://www.apple.com/environment/pdf/Apple_Environmental_Progress_Report_2020.pdf
74. Bogue R (2019) Robots in recycling and disassembly. Ind Robot: The Int J Robot Res Appl 46(4):461–466
75. Fulton K (2019) Apple expands global recycling programs, in Apple newsroom. https://www.apple.com/newsroom/2019/04/apple-expands-global-recycling-programs/
76. Schraft RD, Meyer C, Parlitz C, et al. Powermate-a safe and intuitive robot assistant for handling and assembly tasks[C]//Proceedings of the 2005 IEEE International Conference on Robotics and Automation. IEEE, 2005: 4074-4079.
77. Krüger J, Lien TK, Verl A (2009) Cooperation of human and machines in assembly lines. CIRP Ann 58(2):628–646
78. Renteria A, Alvarez E, Perez J (2010) A methodology to optimize the recycling process of WEEE: Case of television sets and monitors. Int J Adv Manuf Technol 54:789–800
79. Álvarez-de-los-Mozos E, Rentería-Bilbao A, Díaz-Martín F (2020) WEEE recycling and circular economy assisted by collaborative robots. Appl Sci 10(14):4800
80. Liu Q, Liu Z, Xu W, Tang Q, Zhou Z, Pham DT (2019) Human-robot collaboration in disassembly for sustainable manufacturing. Int J Prod Res 57(12):4027–4044. Accessed 2 Dec 2022.
81. Babiceanu RF, Seker R (2016) Big Data and virtualization for manufacturing cyber-physical systems: a survey of the current status and future outlook. Comput Ind 81:128–137. Accessed 2 Dec 2022.
82. Rocca R, Rosa P, Sassanelli C, Fumagalli L, Terzi S (2020) Integrating virtual reality and digital twin in circular economy practices: a laboratory application case. Sustainability 12(6):2286

83. Kerin M, Pham DT (2019) A review of emerging industry 4.0 technologies in remanufacturing. J Clean Prod 237:117805
84. Rosa P, Sassanelli C, Urbinati A, Chiaroni D, Terzi S (2020) Assessing relations between Circular Economy and Industry 4.0: a systematic literature review. Int J Prod Res 58(6):1662–1687
85. DeSmit Z, Elhabashy AE, Wells LJ, Camelio JA (2017) An approach to cyber-physical vulnerability assessment for intelligent manufacturing systems. J Manuf Syst 43:339–351
86. Monostori L, Kádár B, Bauernhansl T, Kondoh S, Kumara S, Reinhart G, Sauer O, Schuh G, Sihn W, Ueda K (2016) Cyber-physical systems in manufacturing. CIRP Ann 65(2):621–641
87. Lee J, Bagheri B, Kao H-A (2015) A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manuf Lett 3:18–23
88. Asghari P, Rahmani AM, Javadi HHS (2019) Internet of Things applications: a systematic review. Comput Netw 148:241–261
89. Miorandi D, Sicari S, De Pellegrini F, Chlamtac I (2012) Internet of Things: vision, applications and research challenges. Ad Hoc Netw 10(7):1497–1516
90. Chen Y (2012) Challenges and opportunities of Internet of Things. in 17th Asia and South Pacific Design Automation Conference
91. Xie Y, Zhang Y, Cai Y (2019) Virtual reality engine disassembly simulation with natural hand-based interaction. In: Cai Y, van Joolingen W, Walker Z (eds) VR, Simulations and Serious Games for Education. Springer Singapore, Singapore, pp 121–128
92. Wang XV, Wang L (2019) Digital twin-based WEEE recycling, recovery and remanufacturing in the background of Industry 4.0. Int J Prod Res 57(12):3892–3902
93. Bayram B, İnce G (2018) Advances in robotics in the era of Industry 4.0. In: Ustundag A, Cevikcan E (eds) Industry 4.0: Managing The Digital Transformation. Springer International Publishing, Cham, pp 187–200
94. Tadapaneni NR (2018) Cloud computing: opportunities and challenges. Available at SSRN 3563342
95. Kumar A, Shankar R, Choudhary A, Thakur LS (2016) A big data MapReduce framework for fault diagnosis in cloud-based manufacturing. Int J Prod Res 54(23):7060–7073
96. Trigueros-Preciado S, Pérez-González D, Solana-González P (2013) Cloud computing in industrial SMEs: identification of the barriers to its adoption and effects of its application. Electron Mark 23(2):105–114
97. Wang XV, Wang L (2014) From Cloud manufacturing to Cloud remanufacturing: a Cloud-based approach for WEEE recovery. Manuf Lett 2(4):91–95
98. Xia K, Gao L, Chao KM, et al. A cloud-based disassembly planning approach towards sustainable management of WEEE[C]//2015 IEEE 12th International Conference on e-Business Engineering. IEEE, 2015: 203-208.
99. Bieller S (2020) World Robotics 2020. IFR International Federation of Robotics: https://ifr.org/img/office/World_Robotics_2020_Sales_Flyer.pdf
100. Microsoft Inc., S., WA (2020) 2019 Manufacturing Trends Report. Microsoft Inc., Seattle, WA
101. Yang S, Aravind MR, Kaminski J, Pepin H (2018) Opportunities for Industry 4.0 to support remanufacturing. Appl Sci 8(7):1177
102. Talavera JM, Tobón LE, Gómez JA, Culman MA, Aranda JM, Parra DT, Quiroz LA, Hoyos A, Garreta LE (2017) Review of IoT applications in agro-industrial and environmental fields. Comput Electron Agric 142:283–297
103. Benotsmane R, Kovács G, Dudás L (2019) Economic, social impacts and operation of smart factories in Industry 4.0 focusing on simulation and artificial intelligence of collaborating robots. Soc Sci 8(5):143
104. Xia K, Gao L, Wang L, Li W, Chao K-M (2015) A semantic information services framework for sustainable WEEE management toward cloud-based remanufacturing. J Manuf Sci Eng 137(6)