

21st Century Challenge: How Can We Effectively Recycle the 60+ Million Tons of Electronic Waste Produced Every Year?

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ABSTRACT: Electronic waste (e-waste), as defined by the United Nations, is any discarded electric or electronic equipment, including all components and subassemblies, that are part of the equipment when it becomes waste, ranging from dead smartphones to broken washing machines. As the technology industry and global consumption increase, the volume of e-waste has surged, yet the systems for reprocessing are still disconnected, inefficient, and most of all, hazardous. To address these challenges, this study investigates the potential of digital platforms to resolve inefficiencies in e-waste disassembly and recycling. Researchers have applied robotics, AI modeling, platform analysis, and past studies to achieve this goal. While some studies explored e-waste logistics systems with multiple suppliers, others used deep learning to identify components in circuit boards. This study examines the applications of artificial intelligence, the impact of chain digitization, and sustainable resource management in e-waste recycling from various research sources. By combining automation, data exchange, and disassembly procedures, this paper contributes to clarifying digital platform requirements for e-waste recycling and its benefits. Because current solutions tend to focus on individual e-waste products, a more unified model is needed that connects these works, which could cover the vast e-waste architectures.

KEYWORDS: Recycling and Waste Management, Machine Learning, E-waste, Automated Dismantling, Architecture.

■ Introduction

Electronic waste is the fastest-growing waste stream in history, generating over 60 million metric tons annually, of which only 17% is properly collected and recycled.¹ According to the Global E-waste Monitor, the average annual growth rate (AAGR) of e-waste grew by roughly 5.15% annually between 2010 and 2022. This growth is expected to increase by another 32% by 2030. Due to their limited underground supply, valuable materials like gold, copper, platinum, and other rare earth elements (REEs) are already in short supply and are found in the majority of these products. E-waste recycling procedures are still expensive, time-consuming, and fragmented despite this trend. Current models have limitations on supply chains, rely heavily on manual labor, and have little mechanization.¹ As a result, in the last ten years, researchers in this field have started to investigate the use of automation, robotics, and artificial intelligence (AI) to enhance e-waste object identification, sorting, and dismantling.² Additionally, several studies show how digital platforms can be used to improve circular economies and expedite disassembly processes.³ Despite some advancements in robotics and AI applications in the stream, the dismantling step remains the most hazardous, laborious, and costly step. Yoshida discusses the challenges in large-scale automation, due to manual disassembly still being common because of how variable device architecture can be.⁴ Chen and Bhardwaj point out that although AI-based innovations are growing, they are frequently disjointed and incompatible.^{3,5} The primary gap in this field, which includes scalability issues and recycling process bottlenecks, is made clear by the absence of a centralized framework or platform that links these tools for global-scale dismantling workflows.

Preliminary methods of managing e-waste are unrefined and pose a risk to both the environment and human health. To recover valuable metals, discarded electronics are often exported and burned outdoors in developing nations.⁶ Areas like Guiyu, China, and Agbogbloshie, Ghana, are notable hotspots for unofficial recycling practices, where workers, even minors, handle electronics disassembly without safety gear, exposing them to toxins like cadmium, lead, and mercury.⁷ Although there are some values recovered, these practices contaminate nearby rivers and are responsible for the majority of premature deaths. Modern systems for recycling e-waste have shifted toward automated procedures. Devices are broken down into smaller pieces using industrial shredders. The particular materials are then recovered by manual sorting.⁸ To extract metals, many current facilities commonly use hydrometallurgy, pyrometallurgy, chemical leaching, and bioleaching.⁹ Though easier to implement, these approaches have significant drawbacks, especially when it comes to global scalability. The systems only focus on REE extraction, meaning any non-valuable components are still landfilled. They also still show low recovery rates, pose toxic exposure risks, and are very expensive to operate.¹⁰ Complex dismantling procedures also primarily depend on human labor, which slows output and raises worker risk even more.⁵

To overcome these obstacles, researchers have begun studies on automated AI-based classification and disassembly systems. Robots plan disassembly sequences through certain models that use machine learning (ML) and deep learning (DL) to identify device models from vast image data.² Convolutional neural networks (CNNs) are often used in other systems with sensor data to recognize different kinds of materials like glass, metal, and plastic.⁸ Despite these emerging solutions, ML and DL technologies for e-waste disassembly are still in the

experimental stage and are often restricted to specific device categories.⁵

AI approaches offer several potential ways to improve the safety and scalability of e-waste recycling. One approach uses DL to identify devices; these models, trained on small datasets, can determine features on smartphone backs and set predictions on the steps involved in its disassembly.² To maximize the recovery of rare earth metals or plastics, AI algorithms are also used in maintenance and sorting, where they can predict failure points or material fatigue in products.^{5,9} A more advanced idea is the use of AI-controlled robotic arms. By combining visual data, weight sensing, and metal detection, they can take apart devices on their own with minimal human intervention.^{2,5} These systems cut down on hazardous manual work, speed up material recovery, and increase accuracy. These solutions' need for more training data, generalization, and system integration, however, is the main reason they are not widely used in general e-waste recycling. These AI solutions are still uncommon in full-scale industry practice, with the majority being limited to pilot projects or research labs. They are still limited and dispersed because large-scale e-waste facilities around the world still mostly use manual or semi-mechanical processes.

This paper proposes a first-of-a-kind, centralized AI system that integrates current advancements into a single, flexible workflow to address the above disparity issue. The system would integrate robotic controls to carry out dismantling tasks, predictive algorithms to identify the best disassembly sequences, and various sensing (visual, infrared, and X-ray) for device and material identification. The discord observed in current AI prototypes would be resolved since all parts would share a common database of device build-ups. This allows for information exchange and adaptation to new products without the need for constant manual reprogramming. This review will investigate the potential of AI-driven tools in the e-waste industry, blending them into a single digital platform that enables safer, more efficient, and scalable dismantling of electronic waste. By integrating advances in machine vision, automation, and platform design, the proposed solution aims to overcome limitations in conventional recycling and present a path toward sustainable e-waste recovery.

The remainder of the paper is organized into the following sections: The Discussion will cover the current and past recycling methods with an emphasis on the main drawbacks of today's procedures, followed by the main issue at hand. It will then introduce the digital unified platform concept, combining robotics, AI, and training datasets. The remainder will explore this platform through three lenses: safety, efficiency, and scalability. We will conclude by discussing the future potential of these systems in creating a circular economy and reducing environmental harm.

■ Discussion

Problem Definition:

Three main problems continue to affect e-waste recycling, despite advancements in mechanization and early AI integration:

(1) Health and safety hazards

(2) Ineffective recovery procedures

(3) Lack of scalability

Even in regulated facilities, workers are still exposed to hazardous materials, recovery rates for critical materials are still below economically feasible thresholds, and the solutions that are currently available are fragmented and context-specific.^{5,8} Without extensive innovation, the global e-waste problem is predicted to reach 74 million metric tons by 2030, more than doubling the current recycling capacity. Instead of making tiny, gradual changes, a platform-level approach that simultaneously integrates safety, efficiency, and adaptability is essential to address these problems. Several nations are experimenting with extended producer responsibility (EPR) systems, which require manufacturers to legally take back and recycle their products at the end of their useful lives, in addition to official recycling facilities. Effective EPR systems can lower landfill waste and encourage manufacturers to create more recyclable products, according to studies, though adoption varies.¹¹ Another tactic that has been successful in raising awareness but struggles to sustain long-term behavior change is consumer-level education campaigns. Despite these developments, recycling rates remain low worldwide, highlighting the need for solutions that integrate technological innovation, policy, and infrastructure.¹

Past and Current Methods:

A. Early Methods of E-waste Disposal:

In the 1990s and early 2000s, the initial step in recycling e-waste was mostly unregulated and dangerous. People in developing countries often take part in disassembling electronic products manually without proper safety gear or regulations.⁶ Communities in Guiyu and Agbogbloshe burned plastics and circuit boards in open-air environments to extract copper and other rare earth metals, which in turn released dioxins and heavy metals into the air, soil, and water.⁷ Despite its harm, these methods continued to generate income by selling scrap metals and therefore continued. With this being an ongoing issue even today, the pollution prompted environmental damage and long-term health defects like neurological damage, respiratory illness, and even cancer.¹² Worker injury rates have remained high, averaging 46% and even rising to 70% in severe regions.¹³ Richer countries export large amounts of used electronics under the semblance of "second-hand goods", knowing that they would frequently wind up in hazardous recycling facilities.¹⁴ In the absence of official infrastructure, informal recyclers created their own methods, which, despite their rudimentary nature, were crucial for survival in economies, especially with limited options. As a result, toxic practices were established in the socioeconomic communities where dangerous methods were normalized as "work" rather than "exposure".

B. Transition to Mechanized Recycling:

Recycling in developed countries has moved away from these informal methods and toward mechanized systems. Today, high-powered industrial shredders are used to break down electronics into smaller pieces, with regulations now enforced in some regions.⁸ To retrieve valuable parts such as gold, palla-

dium, and copper, these shredded materials are sorted by their physical/chemical properties. This can be done by hand or with sensor machines. Techniques like hydrometallurgy, pyrometallurgy, and chemical leaching are then used to further refine the products. However, each method possesses certain drawbacks. For example, hydrometallurgy, which involves the use of strong acids (e.g., sulfuric, hydrochloric, nitric, aqua regia) and agents like cyanide, thiosulfate, and halides in large volumes, they contribute greatly to soil and groundwater contamination. In southern coast districts in China, child blood lead levels were found to be 54% higher than average in some areas. Chemical leaching also utilizes considerable amounts of chemicals and creates toxic waste streams. Studies show that open burning and leaching can lead to soil contamination of up to 18,125 ppm, compared to the US EPA play-area standard of 400 ppm. Pyrometallurgy, or the use of high heat to facilitate metal recovery, requires up to 2000 kilowatt-hours of energy per ton of e-waste and can allow explosive organic compounds to escape.^{9,10} Though they perform better than traditional sorting by hand, recovery rates remain far from desirable levels and allow non-valuable fractions such as flame-retardant plastics to be landfilled.⁵ Furthermore, these processes frequently externalize costs. Consumers often see the “green” in marketing, while the hidden energy requirements and chemical waste remain significant.

C. Labor Dependency and Safety Risks:

Human labor continues to play a significant role in the dismantling process. It is frequently challenging for machines to completely automate disassembly because of the complex architectures and non-standardized device layouts of e-waste.⁴ When removing batteries, capacitors, and display screens, workers are often susceptible to chemical and physical risks. The psychological effects on employees who are continuously exposed to dangerous substances despite protective regulations are another aspect that is often undervalued. Research has shown that employees in mechanized recycling plants have higher levels of stress and fatigue, implying that these “safer” facilities may not always be safe.³ Electronic device variability makes standardization and automation even more difficult because different models can call for specific disassembly techniques.³

D. Preliminary AI Integration:

Researchers are investigating DL and ML systems to improve device identification and disassembly sequencing. Using CNNs, early AI-based systems have shown that they can classify devices based on image data. This allows systems to identify phone models and properly predict the disassembly procedures.² To improve material classification even more, some platforms incorporate sensor data as well as weight and surface resistance.⁸ Narrow training datasets and hardware limitations still affect these systems, though. In addition, these pilot projects represent a change from “damage control” to “predictive control,” where AI aims to predict risks as opposed to just reacting to them. This change is similar to advancements in other areas, like autonomous driving, where

error margins are decreased by the use of predictive algorithms. However, the recycling industry faces the risk of creating limited AI solutions that are unable to generalize across global streams without larger datasets containing multiple device families. Additionally, current implementations lack scalability and are frequently restricted to particular device types or recycling facilities.^{2,5}

Proposed Platform:

This section makes the case that an integrated platform is necessary due to the shortcomings of the existing e-waste tools, such as fragmented architectures, device-specific designs, and uneven safety controls. This is addressed by the proposed E-waste Recycling Automation Operating System (ERAOS), which offers a unified API layer that connects robotic disassembly, hazard-alert systems, and object detection into a single modular, scalable workflow.

A. Use of Current Tools:

Although current tools are specialized and usually limited to particular applications, AI has already demonstrated measurable advantages in automating the processing of e-waste.¹⁵ As an example, AMP Robotics sorts recyclables with a high accuracy rate of ~99% using computer vision and deep learning, compared to the average of 85% for manual sorting.^{8,16} However, AMP systems are designed for commodity streams (e.g., bottles, cardboard) and rely on training sets that use homogeneous visual classes. This limits transferability to the heterogeneous component shapes of e-waste (PCBs, battery packs, adhesive-sealed modules, motherboards). ERAOS responds to this limitation by integrating multi-modal sensing (RGB + IR + X-ray) to reduce blind spots, and enforcing a modular dataset standard, thus classifiers can be retrained and shared across sites. This reduces the fragility that currently prevents AMP classifiers from generalizing across the diverse e-waste streams.

Advanced object-detection networks, such as the YOLO (You Only Look Once) algorithm, can process 45 frames per second and achieve detection accuracies of 90% on datasets in object detection research.¹⁷ In the context of recycling, this speed translates into the real-time identification of printed circuit board (PCB) components. Manual inspection can take five to ten minutes per board, depending on how complicated the process is. As found in laboratory tests, specialized models like PCBNet can further improve detection capabilities and reach accuracies above 95%. This is done by focusing on high-value components (e.g., rare-earth magnets, gold-plated connectors).¹⁸ Such accuracy is important because, according to Forti *et al.*, a mere 1% increase in recovery from the world's e-waste could result in an extra 20 tonnes of gold annually.¹⁸ These approaches work well on lab datasets, but they often rely on small collections of data and lack consistent uncertainty analysis when confronted with new device models and degraded parts. ERAOS mitigates this by taking advantage of confidence reports sent from the classifiers, sending low-confidence cases to a planner or human-in-the-loop flow. This

design reduces false negatives for hazards and provides a clear safety metric available for evaluations.

On the mechanical side, robots today can achieve high throughput. For example, in the case of Apple's Daisy, the robot can disassemble 200 iPhones per hour with 95% material-recovery purity. Though Daisy's outputs double those of manual dismantling, they are only applicable to iPhones, which makes them incapable of handling the much larger e-waste ecosystem. In order to combat the severe lack of dismantling versatility, ERAOS is outlined with modularity and reconfigurability. By having standardized module interfaces, ERAOS allows task-specific modules to plug into the OS while preserving the safety and dataset frameworks. This allows performance improvements for each device without interfering with the process.

Raspberry Pi-based prototypes demonstrate that low-cost AI hardware can be integrated into small-scale sorting systems for less than \$200 in total component costs.^{19,20} These systems enable localized recycling in developing countries where recycling facilities might not be as practical, despite their slower processing speeds (1-2 items per minute). Even though these tools outperform conventional techniques in terms of speed and accuracy, their lack of integration and standardization ultimately keeps them from growing on a global scale. The ERAOS model addresses these challenges by defining a standard application interface and a fallback safe mode that implements verification of safety before modules are allowed to execute in production. This allows for low-cost operations while maintaining worker safety.

Table 1: Quantitative comparison of traditional, mechanized, early AI, and projected ERAOS systems across efficiency, safety, scalability, and performance indicators.

Approach Type	Examples	Recovery Efficiency	Safety Profile	Scalability / Throughput
Traditional (manual/ open burning)	Hand sorting; open burning	High variability; unmeasured; material loss of 40-60%. ⁵	High exposure to Pb, dioxins, PBDEs; toxicity rates of 15-20%. ²⁴	Not scalable; throughput of 10-20 kg/hr per worker. ²
Mechanized	Industrial shredders; pyro/hydro-metallurgy	Most recovery possible; 15-20% loss. ³¹ ; large losses in multi-material streams	Safer than manual; toxic effluents persist; increases soil contamination by 10x-45x. ⁴	High throughput (0.5-5 tons/hr) ²⁹ but high capital cost. ⁶ ; requires constant energy.
AI-Assisted (early tools)	YOLO object detectors, PCBNet, AMP Robotics	Detection accuracy: 90-95% for common components; weak on rare parts/hazard items. ⁷	Reduces worker exposure; classification errors of 5-10%; risk of handling errors persists. ³	Currently limited by dataset size & product specific training; throughput of 40-160 kg/hr for 2D-sorting systems. ³¹
ERAOS (Projected)	Unified OS with module "puzzle pieces": sensor fusion, component classifier, toxicity detector, robotic arm driver	Projected: 88-94% recovery on modular disassembly lines; based on recognition and adaptive sequencing. ^{3,7}	Hazard detection integrated; expected to reduce risk within validated operating limits. ^{13,21} ; fail-safe triggers stop actuators during toxic-gas or thermal anomalies	Modular installation suited for low-power sites; By integrating with existing systems, projected throughput 0.3-5.0 tons/hr depending on hardware. ^{20,29}

As shown in Table 1, recycling approaches vary greatly in efficiency, safety, and scalability. Traditional informal recycling, while widespread, is characterized by severe health hazards, uncontrolled emissions, and material losses approaching 50%. Mechanized recycling offers higher throughput and improved recovery of metals such as gold, copper, and palladium, but remains energy-intensive, costly, and dependent on trained operators. Although early AI tools show definite benefits in speed and accuracy, lowering worker exposure and attaining component detection accuracies above 90%, these systems are still limited by device specificity and dataset constraints. However, our suggested platform unifies these disparate innovations into a modular ecosystem. It overcomes the limitations of current approaches by fusing flexible hardware modules with clever software for operator integration, safety monitoring, and disassembly. It is made to work dependably in a variety of resource situations, in addition to scaling across facilities of various sizes. This contrast demonstrates the revolutionary potential of an integrated platform in advancing e-waste management from dispersed solutions to a single, globally scalable system.

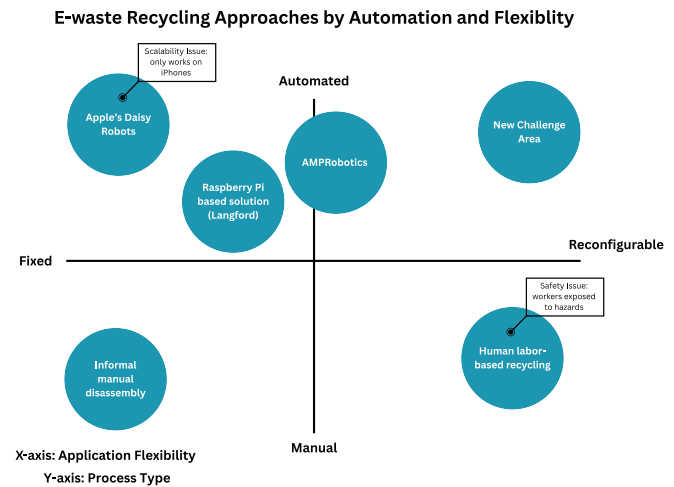


Figure 1: Comparison of e-waste recycling methods according to application flexibility (horizontal axis) and automation level (vertical axis). Informal disassembly occupies the low-flexibility, low-automation quadrant, while advanced systems like AMP Robotics are located in the high-automation, moderate-flexibility area.

The way that these tools are positioned in regard to automation and application flexibility helps to further define them. The degree of automation is represented by the vertical axis in Figure 1, with fully automated processes at the top and manual methods at the bottom. Flexibility is represented by the horizontal axis, which has fixed applications on the left and reconfigurable ones on the right. Plotting informal manual disassembly in the bottom-left quadrant of this figure shows low automation and fixed applicability. Recycling that depends on human labor is in the lower-right quadrant because it is still manual and presents significant safety risks, even though it can be tailored to different device types. On the other hand, because it is limited to iPhones, Apple's Daisy robot exhibits a significant scalability limitation. Raspberry Pi-based prototypes, which have limited processing speed but partial automation, occupy a similar fixed space. Located in the upper middle quadrant, AMP Robotics exhibits advanced automation

and moderate adaptability, making it one of the most scalable systems on the market today. However, because its design is primarily focused on the components of a single company, it lacks standardized interfaces. Finally, the gap in demand for systems that combine high automation and reconfigurability is highlighted by the "new challenge area" quadrant. The figure highlights the necessity of developing a single AI-driven platform that closes these gaps by integrating current solutions and shows how current approaches are fragmented.

B. Proposed Solution: A Unified AI-Driven Dismantling Platform:

i. System Architecture and Data Flow:

Although AI-based recycling technologies have advanced quickly, the industry is still essentially divided. The majority of systems do not use shared interfaces, rely on unique control pipelines, and are constructed around specific device categories. These limitations make it challenging to guarantee consistent safety communication, reuse algorithms, and generalize models across devices. The ERAOS platform is built as a layered architecture that uses a common application programming interface (API) to link hardware drivers, software modules, and operational tasks in order to overcome these constraints.

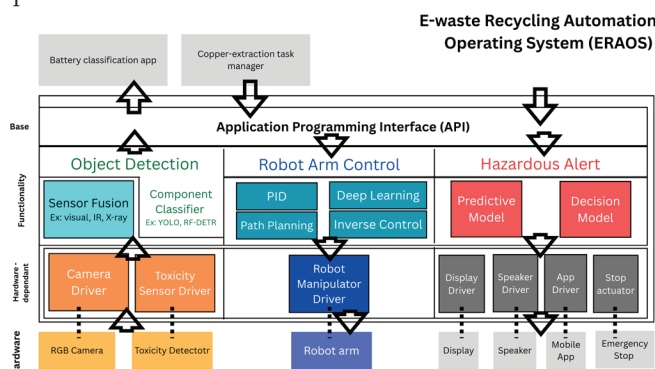


Figure 2: Concept diagram of the unified AI-driven system (ERAOS) in an application programming interface architecture.

Lightweight applications, like a battery-classification tool or a copper-extraction sequence manager, send requests through the API from the top, as illustrated in Figure 2. These apps give users device-specific instructions, hazard alerts, and real-time supervision. The central coordination layer of the API sits beneath them. ERAOS oversees three main subsystem groups: Object Detection, Robot Arm Control, and Hazardous Alert, as opposed to previous prototype designs that directly embedded modules in a rigid structure.

Sensor-fusion pipelines and component classifiers (e.g., RGB, IR, or X-ray inputs combined with models like YOLO or RF-DETR) are used in object-detection functionality to identify components and dangerous features on devices. Route planning, PID loops, and deep reinforcement learning policies that convert detection outputs into control mechanisms are all part of the robot-arm control subgroup. The hazard-alert subsystem gathers risk signals from other modules, evaluates them using system safety rules, and notifies the hardware actuators and the operator.

Hardware-specific drivers connect the software to hardware tools beneath the functionality layer. Modules can remain portable and compatible across facilities thanks to camera drivers, toxicity-sensor drivers, robot-manipulator drivers, and alert-device drivers. This enables the use of new hardware without necessitating significant upper-level software reengineering. Sensors and actuators, such as cameras, toxicity detectors, displays, emergency stops, and robotic arms, perform tasks specified by the platform at the bottom layer.

Data moves through this architecture in three parallel streams: object-detection data, control signals for the robot, and hazard-alert messages. The platform is designed to prioritize any safety alert by routing it through a channel with low latency, ensuring that hazardous-item misclassification or dangerous chemical signatures trigger operator notification or automatic intervention.²⁵ Because of this structure, ERAOS can manage edge cases anywhere from unexpected gas emissions to short-circuit risks to structural instability by prioritizing risk signals without delaying the flow.

With its design, ERAOS replaces the fragmented challenge of current systems with a unified architecture that standardizes interfaces, separates hardware from software, and ensures safety communication across all modules.

ii. Modular Integration and Scalability:

ERAOS's modular design allows the system to adapt to the diversity of modern electronics. Each module can be "slotted in" or replaced digitally through the API. This lets you assemble configurations fitted to specific devices. For example, sensor-fusion modules can be used to support X-ray imaging in addition to camera sensors for battery-dense devices, while specialized classifiers can be added for rare-earth extraction or PCB component detection. With only ten of these module types, the design will be able to generate over 3.6 million configurations, allowing sites of different scales to build their own workflows.²⁶

All the modules can take advantage of hazard-reporting rules built into the platform. Therefore, applications do not need to implement their own hazardous alert systems. Unlike existing systems, ERAOS embeds hazard reporting directly into its system. This greatly minimizes delays, increases awareness, and reduces human-error risks.

The modular design of this platform also allows it to adapt to e-waste variations from each operation's data. ERAOS's detection, path-planning, and hazard-identification models get better as it manages more devices, and it can switch components to adapt to new rules or waste designs. By facilitating generalization across various electronics, this system resolves one of the primary issues with early AI dismantling.

Mean-time-between-failures (MTBF) can be tracked through driver-hardware interactions; misclassification probabilities for hazardous items can be measured across datasets; recovery yield can be evaluated through material purity and recovery rates; and throughput can be quantified as completed disassembly operations per hour per layout. Researchers can monitor the system's performance and find new bottlenecks

to enhance the model thanks to the system's capacity to record and provide these measurements.

ERAOS's design treats each component as an interchangeable module that follows the same rules, enabling it to scale. This architecture allows the platform to expand without having to be redesigned, accommodate new device types, and enable quantifiable performance gains.

Safety:

This section focuses on both the physical risks faced by recycling employees and the systemic risks introduced by automated disassembly. The suggested platform aims to create a safer environment while keeping high efficiency through safety in both hardware and software contexts.

A. Human Safety:

Workers who manually disassemble e-waste are exposed to high concentrations of acid fumes, flame retardants, and heavy metals. Lead concentrations in dismantling workshops in Guiyu, China, for instance, were found to be 371 $\mu\text{g}/\text{m}^3$, which is almost 37 times greater than the 10 $\mu\text{g}/\text{m}^3$ OSHA limit in the United States.²⁷ Polybrominated diphenyl ethers (PBDEs), which can interfere with endocrine function, are also released when cables are burned openly. In recycling workers, PBDE levels have been found to reach 200 ng/g lipid weight in blood serum, whereas in the general population, they range from 5 to 10 ng/g.^{18,28}

By automating hazardous disassembly tasks with AI-driven robotics, direct human contact with these toxins can be reduced. For instance, Kim describes robotic arms that can safely disassemble smartphones by accurately identifying and handling hazardous components.² This improves the standard of material recovery while also protecting workers by reducing unintentional damage. Additionally, fewer workplace accidents involving manual dismantling procedures result from less human involvement, which may improve the recycling environment's safety. These advancements could lower the industry's occupational health risks as automation increases.

Manual dismantling is particularly prevalent in regions with informal recycling economies, such as Southeast Asia and Africa. Workers are frequently exposed to dangerous fumes and heavy metals that can cause long-term health issues because they do not wear safety gear.²⁹ In addition to the health risks, manual dismantling's scalability is severely constrained by how labor-intensive and time-consuming it is, which prevents it from keeping up with the exponential growth of e-waste worldwide.¹ However, this method is still widely employed due to the recovery of valuable materials like copper and gold, requiring minimal technological investment.

B. AI Safety:

When incorporating AI into dismantling workflows, there are problems with error management and system dependability. A safety risk could arise from improper handling of hazardous materials due to AI errors or misclassifications.⁵ To solve these problems, ongoing sensor-based monitoring is required. Sharma describes how AI and real-time safety sensors can be used

to spot irregularities or dangerous situations and notify human operators so they can take the necessary action.⁹ Furthermore, human supervision and the creation of strong fail-safes guarantee the safe operation of AI systems. Testing must be done before deployment in order to reduce errors in AI-driven disassembly. AI safety in the specific OS necessitates that modules share their risks before execution, in addition to algorithms.¹⁷ By serving as a kind of fail-safe, this safety channel incorporates hazard warnings into the regular process rather than making them an optional feature.

To address safety within the proposed open-source platform, a standardized framework that mandates peer-reviewed validation of each AI module or dismantling algorithm before integration can be implemented. This model not only increases transparency but also enables the greater scientific community to identify and correct errors in the tools prior to their use in real facilities. It is possible to implement platform-level safety measures, such as automated fail-safe triggers that integrate with different AI tools. Because these safeguards are built into the system rather than being optional add-ons, even smaller recycling facilities using the technology will benefit from consistent and reliable safety standards.

C. Functional Safety:

Functional safety, which addresses a system's ability to function dependably in both typical and unusual circumstances, is a field that goes beyond human and AI safety. This means making sure that robotic arms, shredders, and chemical handling modules malfunction safely rather than disastrously when it comes to recycling. Recycling platforms can adopt functional safety standards like ISO 26262, which are frequently used in automotive AI.²⁴ This calls for redundancy in crucial subsystems like actuator controls and vision sensors.¹⁷ Backup sensors, like thermal or chemical detectors, should catch the error before it leads to dangerous disassembly, for instance, if an object detection algorithm incorrectly classifies a lithium-ion battery as inert plastic. By using multi-layered redundancies, worker safety and material quality are maintained by preventing a single failure from leading to more serious incidents.

Speed is one of the biggest benefits of mechanical shredding since it allows for the quick processing of large numbers of devices. However, the process is destructive by nature, frequently combining valuable metals with plastics and other materials, making downstream separation more difficult. For instance, rare earth elements that could otherwise be recovered through manual disassembly may be lost when printed circuit boards are shredded. This trade-off between recovery efficiency and throughput emphasizes the need for hybrid approaches and the risks of mechanical methods alone.³⁰

Efficiency:

Efficiency in e-waste recycling is measured not only by speed but also by adaptability, material recovery yield, and workflow optimization. This section explores how AI-enhanced disassembly, visual recognition, and simulation tools improve operational throughput while integrating seamlessly with the proposed ERAOS for both performance and safety.

A. Faster Disassembly:

The complexity and inconsistencies of device makeups often slow down the already time-consuming disassembly process. Robotics with AI support has shown a great deal of promise in speeding up these processes. Machine learning-trained robotic systems can quickly and accurately unscrew and separate components, and they can adapt to a variety of device geometries.² Higher throughput is possible with these systems than with manual labor because they run continuously and without fatigue. According to studies, these automations could cut disassembly time by as much as 40%, allowing recycling facilities to process higher volumes more effectively and keep up with growing demands for e-waste management.

Additionally, a single platform might be used as a tool to assist recyclers in selecting the best disassembly path for a particular device. By combining data from product design files, previous disassembly experiences, and AI-driven predictions, the system could recommend whether manual, robotic, or hybrid approaches are the most practical and material-recovery efficient.^{11,30} Most importantly, this type of platform could be adapted for use in developing countries, where it is essential to streamline processes within advanced recycling facilities and maximize material yield from poor facilities because of resource constraints.¹

B. Visual Recognition:

AI-powered computer vision systems greatly improve the speed and accuracy of identifying e-waste components. These systems use advanced machine learning models, such as convolutional neural networks (CNNs), to recognize and classify components on circuit boards and other devices.^{5,28} The early detection of dangerous substances such as toxic capacitors, lithium-ion batteries, and switches containing mercury can prevent workers from the risk of contamination. This feature also makes it possible to remove toxic elements more precisely, with more time to generate dismantling.²

In addition to safety, visual recognition improves quality control by verifying correct component separation and disassembly. This can increase the effectiveness and speed of material recovery. Studies show that integrating AI vision into recycling procedures can reduce sorting errors by over 30%, speeding up processing and reducing costs.² More widespread adoption across recycling facilities globally will be made possible by these systems' increasing adaptability to new device types and operating conditions as they develop. Visual recognition components can also mark hazardous objects in real time and send alerts when used together with the hazard-aware operating system, making sure that speed does not come at the cost of security.

C. Simulation Methods:

Digital twins and other simulation tools enable the virtual modeling of disassembly procedures, providing chances to optimize workflows before actual execution. Sharma talks about how simulation predicts effective disassembly sequences, which eliminates trial-and-error. In addition to simplifying processes,

simulations can be used to model equipment wear and resource allocation.⁹ These uses are most important in aiding in facility maintenance planning and modifications. When paired with AI, these virtual models evolve via feedback loops that contrast simulation predictions with real outcomes.⁵ In the future, simulation might evolve into a predictive analytics tool for recycling flows around the world. By modeling entire e-waste supply chains instead of just individual devices, facilities could forecast which devices will dominate recycling streams in the years to come. By promoting more targeted AI model training and strategic hardware investments, this vision can ultimately turn the recycling ecosystem into a proactive one rather than a reactive one.

Scalability:

Scalability refers to the system's ability to operate across different facility sizes, regions, and budgets. This section examines how software and hardware can adapt to local conditions, how AI models improve with expanding datasets, and how deployment costs influence global accessibility.

A. Software/Hardware Adaptation:

Because of its inherent modularity, the suggested AI-driven e-waste recycling system offers flexibility in terms of both software and hardware integration. Conveyor belts, robotic arms, and shredders are examples of hardware components that can be changed to meet local requirements and purchased from industrial suppliers. On the software side, the system's recognition algorithms (like the YOLOv8 object detection models) can operate on server networks for industrial plants or on GPUs as small as the NVIDIA Jetson Xavier NX for environments with limited resources. By learning to adjust to changes in device design, robotic disassembly systems can lessen their reliance on standardized product layouts. For example, robots can more accurately detect screws, clips, and other fastening mechanisms thanks to vision-based AI, which reduces the possibility of destroying recoverable materials. Long-term advantages of such systems include lower labor requirements, enhanced worker safety, and increased recovery rates of critical minerals, despite their high initial cost. Because of this, robotic disassembly is especially desirable in areas with high labor costs or where stringent workplace safety regulations are in place.

B. AI Training Sets:

A major strength of the system is its capacity to improve through continuous training. Initial datasets can be built from open-source PCB images and expanded with photos collected during daily operations. Research in defect-detection AI shows that adding roughly 5,000 labeled images can increase classification accuracy by up to 12% for specific components.³⁰ This suggests that recycling facilities do not need entirely new models to account for regional differences in device types.

As the accuracy of material identification and disassembly sequencing improves, recovery rates rise as well. Machine learning is also increasingly used beyond robotics to optimize separation and recovery processes. Models trained on large e-waste datasets can classify metals, plastics, and hazardous

substances more precisely. Predictive algorithms can forecast future waste streams and estimate the lifespan of consumer electronics, helping both recyclers and policymakers plan infrastructure more effectively.²⁹ These capabilities position machine learning as not only a tool for present-day recycling but also a foundation for more adaptable global e-waste strategies.¹

C. Labor and deployment costs:

Labor reduction is a major factor in achieving scalability. Traditional manual dismantling accounts for up to 50% of operating costs toward labor.³¹ Automation reduces the number of specialized workers required and allows remaining staff to focus on supervision and maintenance.

In many lower-middle-income countries, dismantling a ton of e-waste per day requires about 15 workers, costing roughly \$40,000 annually. An AI-assisted workflow reduces this to about 4–5 workers per ton, lowering annual labor costs to around \$12,000. This 70% reduction lowers the break-even point and makes small facilities financially viable in developing regions. With open-source algorithms and low-power AI hardware, pilot plants could be launched for under \$50,000 as opposed to the \$250,000 needed for traditional mechanized systems.²⁵

However, global deployment must consider disparities in infrastructure. A system that operates smoothly in North America or Europe may encounter import taxes, unstable power grids, or limited internet access in Sub-Saharan Africa or South Asia. For this reason, resilience to resource constraints is as important as modularity. Local government partnerships, solar-powered hardware, and offline-capable AI models can help ensure that the system functions reliably in diverse environments without increasing technological dependence.

■ Conclusion and Future Work

The global e-waste crisis demonstrates the importance of scalable, effective, and secure solutions that go beyond the limitations of traditional disassembly techniques. Traditional recycling has made it possible to recover some valuable materials, but it is insufficient in the face of rapidly increasing electronic consumption due to its limited scalability and dependence on risky manual processes. By automating processes, simulating disassembly, and continuously learning from operational data, AI-driven dismantling systems show potential in transforming this industry. However, the field is still in its early stages despite advancements. Early pilot studies and proof-of-concept prototypes show what is feasible, but many questions still need to be answered. AI training is limited, and model generalization across various devices is hindered by a lack of sizable, publicly accessible datasets. Policy concerns are also brought up by the introduction of such systems into current recycling chains. In order for AI-enabled recycling to benefit developing countries where e-waste accumulation is severe, accessibility issues must also be resolved.

Three main areas should be the focus of future research: building modular, affordable versions of these systems for

worldwide accessibility; integrating AI recycling into policy frameworks that incentivize innovation and sustainability; and growing collaborative datasets. To standardize evaluation across vision and planning models, near-term research should also concentrate on: (1) creating a small-scale, open benchmark dataset of 15–20 common device archetypes; (2) testing a low-cost, modular prototype that solely uses off-the-shelf components to assess real-world failure modes in community recycling centers; and (3) performing a policy and safety assessment that maps current recycling regulations to the unique requirements of AI-driven dismantling, creating a useful compliance checklist for early deployments. These practical tasks would hasten the shift from conceptual frameworks to deployable systems and offer much-needed empirical grounding.

This review explored the shortcomings of conventional recycling methods, looked into new AI-based dismantling prototypes, and discussed the potential integration of these methods into an open-source, comprehensive digital platform. In order to make e-waste dismantling safer, more efficient, and more scalable, the paper summarized recent research and demonstrated how such a platform could bring disparate solutions together. The findings demonstrate that, despite persistent problems with limited datasets, accessibility, and policy integration, open-source collaboration is crucial to ensuring that AI-driven dismantling benefits a wide range of regions and stakeholders rather than being limited to wealthier countries or private enterprises.

Beyond the realm of technology, AI-driven dismantling has profound social and environmental ramifications. In many places, recycling work is frequently performed in dangerous and low-paying environments. Automation may reduce these risks, but it may also drive out vulnerable workers if it is not combined with community support programs and retraining. More efficient recovery of precious metals and rare earths can reduce reliance on environmentally harmful mining, thereby indirectly supporting climate goals. By portraying intelligent dismantling as a social and environmental opportunity, policymakers and corporate executives can ensure that innovation enhances livelihoods while advancing global sustainability.

Concerns about governance are equally significant. If access is not equitable, AI recycling could become concentrated in the hands of a few companies or wealthy countries, leaving a significant portion of the world behind. International cooperation, fair licensing, and open-source models will be crucial to ensuring that these systems serve the public good. Ultimately, the transition to intelligent disassembly is not only a technical issue but also a chance to reconsider how people engage with electronics. Instead of encouraging a cycle of waste and inequality, we should build an intelligent, inclusive, and sustainable circular economy.

The shift to intelligent disassembly ultimately involves more than just resolving a waste management technical bottleneck. It offers a chance to rethink how people interact with electronics, shifting from a wasteful and unfair cycle to one of sustainability, inclusivity, and shared responsibility for the planet's future.

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I attest that the ideas, graphics, and writing in this paper are entirely my own.

■ References

- Forti, V.; Baldé, C.; Kuehr, R.; Bel, G. The Global E-waste Monitor 2020: Quantities, Flows and the Circular Economy Potential; United Nations University (UNU)/United Nations Institute for Training and Research (UNITAR) – co-hosted SCYCLE Programme, International Telecommunication Union (ITU) & International Solid Waste Association (ISWA): Bonn/Geneva/Rotterdam, 2020.
- Kim, D.; Lee, J.; Yoon, K. AI-Based Vision System for Autonomous Smartphone Dismantling. *Rob. Comput.-Integr. Manuf.* 2023, 82, 102490.
- Chen, Y.; Li, X.; Wang, J. Advances in AI-Based E-Waste Recycling: A Review of Dismantling Technologies and Future Directions. *J. Clean. Prod.* 2024, 380, 135567.
- Yoshida, A. China's Ban of Imported Recyclable Waste and Its Impact on the Waste Plastic Recycling Industry in China and Taiwan. *J. Mater. Cycles Waste Manage.* 2022, 24, 73–82. <https://doi.org/10.1007/s10163-021-01297-2>.
- Bhardwaj, R.; Singh, P.; Gautam, D. Advancing Circular Economy through AI-Driven E-Waste Management: A Comprehensive Review. *J. Clean. Prod.* 2022, 356, 131871.
- Chi, X.; Streicher-Porte, M.; Wang, M. Y. L.; Reuter, M. A. Informal E-Waste Recycling: A Review of Current Practices, Health and Environmental Risks, and Opportunities for Improvement. *Waste Manag.* 2011, 31 (4), 731–742.
- Song, Q.; Li, J. Environmental Effects of Informal E-Waste Recycling: A Case Study of Guiyu, China. *Environ. Pollut.* 2014, 187, 36–41.
- Wang, J.; Ahmed, M.; Liu, Y. Transfer Learning-Based Method for Automated E-Waste Recycling in Smart Cities. *Comput. Environ. Urban Syst.* 2023, 97, 101947.
- Sharma, S.; Gupta, M.; Gaur, A. Smart Technology for Waste Classification and Management: A Sensor-Based Approach. *Environ. Monit. Assess.* 2023, 195 (3), 312.
- Wäger, P. A.; Hischer, R.; Eugster, M. Environmental Impacts of the Swiss Collection and Recovery Systems for Waste Electrical and Electronic Equipment (WEEE): A Follow-Up. *Sci. Total Environ.* 2012, 409 (1), 174–187.
- Li, J.; Xu, M.; Zhao, H.; Zhang, Y. A Risk-Informed Design Framework for Functional Safety System Design of Human–Robot Collaboration Applications. *Appl. Sci.* 2021, 11 (9), 3957.
- Brigden, K.; Labunska, I.; Santillo, D.; Johnston, P. Chemical Contamination at E-Waste Recycling and Disposal Sites in Accra and Korforidua, Ghana, Technical Note 10/2008; Greenpeace Research Laboratories: Exeter, U.K., 2008.
- Decharat, S.; Kiddee, P. Assessment of Knowledge, Attitude, Perceptions and Risk Assessment among Workers in E-Waste Recycling Shops, Thailand. *Environ. Anal. Health Toxicol.* 2022, 37 (1), e2022003.
- Puckett, J.; Byster, L.; Westervelt, S.; Gutierrez, S.; Davis, M.; Hussain, M.; Dutta, M. Exporting Harm: The High-Tech Trashing of Asia; Basel Action Network and Silicon Valley Toxics Coalition: Seattle, WA, 2002.
- Elkady, A. Robotics Middleware: A Comprehensive Literature Survey and Attribute-Based Bibliography. *J. Robot.* 2012, 2012, 959013.
- Shamsujjoha, M.; Lu, Q.; Zhao, D.; Zhu, L. Swiss Cheese Model for AI Safety: A Taxonomy and Reference Architecture for Multi-Layered Guardrails of Foundation Model-Based Agents. *arXiv 2024*, arXiv:2401.00000. <https://arxiv.org/abs/2401.00000>.
- Maurtua, I.; Ibaruren, A.; Kildal, J.; Susperregi, L.; Sierra, B. Human–Robot Collaboration in Industrial Applications: Safety, Interaction and Trust. *Ind. Rob.* 2017, 44 (3), 294–301.
- Zhou, X.; Kim, H.; Brahman, F.; Jiang, L.; Zhu, H.; *et al.* HA-ICOSYSTEM: An Ecosystem for Sandboxing Safety Risks in Human–AI Interactions. *arXiv 2024*, arXiv:2404.00000. <https://arxiv.org/abs/2404.00000>.
- Langford, M. A.; Cheng, B. H. C. A Modular and Composable Approach to Develop Trusted Artificial Intelligence. In *Proc. IEEE Int. Conf. Auton. Comput. Self-Syst. (ICACSS)*, 2021.
- Mihai, F.-C.; Gnoni, M. G.; Meidiana, C.; Ezeah, C.; Elia, V. Waste Electrical and Electronic Equipment (WEEE): Flows, Quantities, and Management—A Global Scenario. In *Waste Electrical and Electronic Equipment (WEEE) Handbook*, 2nd ed.; Goodship, V., Stevels, A., Eds.; Elsevier: Cambridge, U.K., 2019; pp 3–30.
- Phogat, P.; Kumar, S.; Wan, M. A Scientometrics Study of Advancing Sustainable Metal Recovery from E-Waste: Processes, Challenges, and Future Directions. *RSC Sustainability* 2025, 3, 2434. <https://doi.org/10.1039/d5su00049a>
- Apple. Apple Expands Global Recycling Programs. Apple Newsroom, 2019. <https://www.apple.com/newsroom/2019/04/apple-expands-global-recycling-programs>
- Müller, T.; Zhang, Y.; Roberts, C.; Chen, H. Mixed Reality Representation of Hazard Zones While Collaborating with a Robot: Sense of Control over Own Safety. *Virtual Real.* 2025, 29 (1), 77–91.
- International Organization for Standardization. ISO 26262:2018 — Road Vehicles—Functional Safety; ISO: Geneva, Switzerland, 2018.
- Cui, Z.; Rahman, M. A.; Tao, H.; Liu, Y.; Yaseen, Z. M. Need for Developing a Security Robot-Based Risk Management for Emerging Workplace Practices. *SAGE Open* 2021, 11 (2), 215824402110168.
- Hosmer, T.; Mutis, S.; Gheorghiu, O.; Siedler, P.; He, Z.; Erdincer, B. Autonomous Ecologies of Construction: Collaborative Modular Robotic Material Ecosystems with Deep Multi-Agent Reinforcement Learning. *Appl. Sci.* 2024, 14 (2), 615.
- Sepúlveda Lozada, A.; Schlupe, M.; Renaud, F. G.; Streicher, M.; Kuehr, R.; Hagelüken, C.; Gerecke, A. C. A Review of the Environmental Fate and Effects of Hazardous Substances Released from Electrical and Electronic Equipment During Recycling: Examples from China and India. *Environ. Impact Assess. Rev.* 2010, 30, 28–41.
- Zhang, L.; Zhang, Z.; Yu, J. Deep Learning in Robotic Disassembly: Challenges and Opportunities in E-Waste Recycling. *AI Perspect.* 2021, 3 (1), 10.
- Baldé, C. P.; Forti, V.; Gray, V.; Kuehr, R.; Stegmann, P. The Global E-waste Monitor 2017: Quantities, Flows, and Resources; United Nations University (UNU), International Telecommunication

Union (ITU) & International Solid Waste Association (ISWA):
Bonn/Geneva/Vienna, 2017.

30. Li, Z.; Han, J.; Zhao, R.; Wu, Q. An Integrated System for Perception-Driven Autonomy with Modular Robots. *Sci. Robot.* 2020, 5 (41), eabb0453.
31. World Bank. Trends in Solid Waste Management. What a Waste Data Portal. https://datatopics.worldbank.org/what-a-waste/trends_in_solid_waste_management.html (accessed Aug 17, 2025).

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