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The Role of Artificial Intelligence (AI) in Circular Economy in a Bid to Ameliorate Global Waste Crises

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Abstract
The accelerating global waste crisis - driven by rising consumption, short product lifespans, and uneven waste-management capacity - demands transformative solutions. This paper examines how advances in Artificial Intelligence (AI) can catalyze the transition from a linear "take-make-waste" model to a Circular Economy (CE) that designs out waste, keeps products and materials in use, and regenerates natural systems. The paper synthesises recent evidence and examples across waste prevention, product design, wastes sorting and recycling, resource recovery and policy enforcement. It further identifies technical, social and governance challenges; and proposes actionable policy and operational recommendations for governments, industry and research actors. The paper concludes that AI is an enabling technology for CE at scale, but real impact requires systemic integration, data-sharing architectures, human-centred governance and targeted investment.

Keywords: Circular Economy, Artificial Intelliegence, Waste disposal, Global wastes crises

1. Introduction

Municipal Solid Waste (MSW) and hazardous waste streams (notably plastics and electronic waste) are growing faster than global capacity to manage them. The United Nation Environment Project (UNEP) projects that MSW could rise from ~2.1 billion tonnes per year in 2023 to roughly 3.8 billion tonnes per year by 2050, with annual direct costs already in the hundreds of billions of USD and total external costs much higher (Global Waste Management Outlook, 2024).

Global waste volumes and hazardous waste streams (notably plastics and e-waste) continue to grow faster than infrastructure and policy can manage. Recent global assessments and monitoring reports highlight both the magnitude and the unequal distribution of the burden: millions of tonnes of plastic leak into aquatic ecosystems annually, and e-waste collection and recycling rates remain low, even as device volumes soar. These patterns create environmental, health and socioeconomic harms that disproportionally affect lower-income regions (E-Waste Monitor by Cornelis, *et. al*., 2024). Consider the UNEP's Projected Global Municipal Solid Waste Growth (2023 to 2050) depicted in Figure 1.

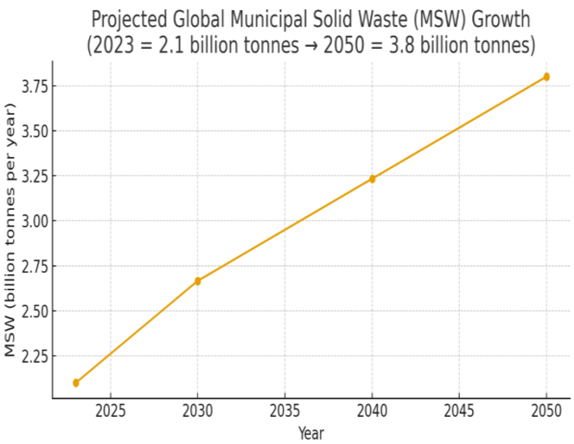

Figure 1: Projected Global Municipal Solid Waste Growth (2023 - 2050).
Source: UNEP Global Waste Management Outlook 2024; derived interpolation. (https://www.unep.org/ietc/resources/report/global-waste-management-outlook-2024?utm_source=chatgpt.com)

The circular economy (CE) offers a pathway out of the linear "take-make-waste" model by:
(a) designing out waste and pollution,
(b) keeping products and materials in use (reuse, repair, remanufacture), and
(c) regenerating natural systems.

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Yet CE is a system's transition that requires coordination across design, business models, logistics, recovery infrastructure and markets. AI is emerging as a critical enabler across this system - but its promise depends on governance, data, and equitable deployment (ellenmacarthurfoundation.org, https://www.youtube.com/watch?v=NBEvJwTxs4wandt=62s).

Before we continue our discussion on this discourse, let's have some basic understanding of the major important concepts in the theme of this conference: Artificial Intelligence Revolution and Circular Economy: The Synergy to Curb Global Waste Crises.

1.1 Concept of Waste

Waste refers to any material, substance, or object that is no longer useful or needed and is discarded after its primary purpose has been served. It includes items that are unwanted, defective, or no longer fit for use. From an environmental perspective, waste is anything that pollutes the environment or disrupts ecological balance when not properly managed. Types of waste include:

(i) Solid wastes (e.g., plastics, paper, food scraps)
(ii) Liquid wastes (e.g., wastewater, industrial effluents)
(iii) Gaseous wastes (e.g., carbon emissions)
(iv) Hazardous wastes (e.g., chemicals, medical waste)
(v) E-wastes (e.g. electronic gadgets, bad batteries, etc)

In essence, waste is the by-product of human activities that must be handled responsibly to prevent harm to human health and the environment.

1.2 Concept of Electronic Waste (E-Waste)

Electronic waste, commonly called e-waste, refers to discarded electrical or electronic devices and their components that are no longer functional or wanted. It includes items like old computers, mobile phones, televisions, printers, refrigerators and batteries.

E-waste is a growing global concern because it often contains toxic substances such as lead, mercury, cadmium, and brominated flame retardants, which can pollute soil, water, and air if not properly recycled or disposed of.

Examples of e-wastes:

(i) Computers, laptops, and accessories
(ii) Mobile phones and chargers
(iii) Televisions and radios
(iv) Refrigerators, air conditioners, and microwaves
(v) Batteries and circuit boards

1.3 Concept of Circular Economy

Circular Economy (CE) is an economic model designed to minimize waste and make the most efficient use of resources. It replaces the traditional *linear economy* ("take, make, use, and dispose") with a system that keeps products, materials, and resources in use for as long as possible through reuse, repair, remanufacture, recycling and regeneration.

The goal of the circular economy is to eliminate waste and pollution, circulate products and materials, and regenerate natural systems, creating sustainable growth that benefits businesses, society and the environment.

From the above, it could be inferred that the circular economy is a system where materials never become waste and nature is regenerated. In a circular economy, products and materials are kept in circulation through processes like maintenance, reuse, refurbishment, remanufacture, recycling and composting. The circular economy tackles climate change and other global challenges, like biodiversity loss, waste, and pollution, by decoupling economic activity from the consumption of finite resources. The Circular Economy (CE) depicts systems and business models that keep products, components and materials at high utility and value (Refuse → Rethink → Reduce → Reuse → Repair → Refurbish → Remanufacture → Repurpose → Recycle → Recover).

The circular economy is based on three principles, driven by design:

(i) Eliminate waste and pollution;
(ii) Circulate products and materials (at their highest value); and
(iii) Regenerate nature

Underpinned by a transition to renewable energy and materials, the circular economy is a resilient system that is good for business, people and the environment.

1.4 Concept of Artificial Intelligence (AI)

Artificial Intelligence (AI) refers to the branch of Computer Science that focuses on creating machines and systems capable of performing tasks that typically require human intelligence. These tasks include learning from experience, reasoning, problem-solving, understanding natural language, recognizing patterns and making decisions. AI systems are designed to perceive their environment, analyze data and act autonomously or semi-autonomously to achieve specific goals.

The key components of AI include:

(i) Machine Learning (ML): This component enables systems to learn from data and improve over time without being explicitly programmed.
(ii) Natural Language Processing (NLP): This allows machines to understand and communicate using human language.
(iii) Computer Vision: This enables systems to interpret and process visual information from the world.
(iv) Robotics: This involves designing intelligent machines that can perform physical tasks.
(v) Expert Systems: This mimics human decision-making based on a set of predefined rules and knowledge.

In essence, AI seeks to simulate human cognitive functions to enhance efficiency, accuracy, and innovation across diverse fields such as healthcare, manufacturing, education, security and environmental management.

For this paper, AI includes:

(i) *perception* (computer vision, hyperspectral identification);
(ii) *prediction* (remaining useful life, contamination likelihood);
(iii) *optimization* (routing, scheduling, pricing),
(iv) *generation* (design and material substitution); and
(v) *coordination* (marketplace matching, incentive mechanisms).

Proper management of e-waste through recycling, reuse and safe disposal is essential to protect human health and promote environmental sustainability. This discussion paper examines how advances in Artificial Intelligence (AI) can catalyze the transition from a linear "take-make-waste" model to a circular economy (CE) that designs out waste, keeps products and materials in use and regenerates natural systems. The paper synthesise recent evidence and examples across waste prevention, product design, sorting and recycling, resource recovery, and policy enforcement; identify technical, social, and governance challenges; and propose actionable policy and operational recommendations for governments, industry and research actors.

In essence, the paper aims to:
(a) synthesize peer-reviewed and high-quality grey literature on AI contributions to CE;
(b) identify evidence of impact across CE stages; and
(c) propose policy, technical and research recommendations.

2. Why the Circular Economy - A Brief Conceptual Framing

Globally in the current economy, we take materials from the Earth, make products from them, and eventually throw them away as waste. This process is linear in nature. However, in a circular economy, the wastes being produced are stopped in the first place. The Circular Economy (CE) reframes economic activity to keep materials in productive use (through design for durability, reuse, remanufacture, and recycling) and regenerate natural systems. The CE is not a single technology but a systems transition: product design, new business models (product-as-a-service, take-back schemes), reverse logistics, and supportive policy are all required to eliminate "waste" as an outcome of economic activity. (ellenmacarthurfoundation.org).

The circular economy gives us the tools to tackle climate change and biodiversity loss together, while addressing important social needs. It gives us the power to grow prosperity, jobs, and resilience while cutting greenhouse gas emissions, waste, and pollution.

3. Where AI plugs into the CE: Capabilities and Functions

(a) **Problem:** Nigeria generates over 32 million tonnes of solid waste annually, of which only about 20–30% is collected, and less than 10% recycled. ECOWAS States face similar trends, with e-waste, plastics, and construction debris rising rapidly due to urbanization, industrialization, and population growth. Linear "take-make-waste" models externalize environmental and health costs and overwhelm municipal systems.

(b) **Opportunity:** AI can drastically improve prevention, transparency, and recovery by sensing material flows, predicting failure and contamination, optimizing collection and logistics, automating sorting, and matching secondary materials to demand. In Nigeria and West Africa, AI could complement existing waste-to-wealth policies and support continental frameworks like the African Circular Economy Alliance (ACEA).

As depicted in Figure 2, AI contributes to CE objectives across five mutually reinforcing functions:

1. **Design intelligence**: AI-enabled design tools can optimise materials usage and enable modular, repairable, and recyclable products via generative design, lifecycle modelling and material substitution simulations. This reduces embedded waste before a product is manufactured (Bang-Ning, et. al. 2025).

2. **Predictive logistics and consumption management**: ML models optimise collection routes, match reverse-logistics capacity to return patterns, forecast product-end dates, and enable circular business models (predictive maintenance and reuse). These reduce transport emissions and costs while improving reuse rates (David *et. al*, 2024).

3. **Smart sorting and automated recycling:** Computer vision, robotics, and sensor fusion allow high-speed identification and physical separation of mixed waste streams (e.g., plastics by polymer type, complex packaging, textile blends), improving recovery yields and purity. Recent commercial deployments show meaningful gains in throughput and lower contamination. (Isaac Avilucea, 2025).

4. **Material intelligence and resource matching**: AI can map material flows, predict secondary-material availability, and automate matching between waste suppliers and manufacturers seeking feedstock, thereby facilitating industrial symbiosis (Yuekuan Zhou, 2025).

5. **Policy, enforcement and consumer engagement:** Natural language processing and data analytics support monitoring of compliance (e.g., traceability of waste exports), detect anomalies in flows, and personalise consumer nudges to improve sorting behaviour. Ethical, transparent AI can help align behaviour with circular goals (Iryna Bashynska, 2025).

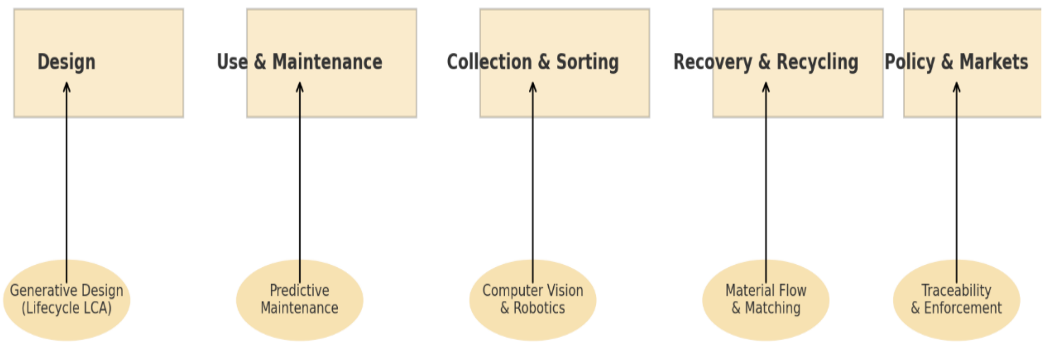

Figure 2: Conceptual mapping: AI functionalities → Circular Economy stages.

Each of the above AI contributions is already being prototyped or deployed in pilot-scale operations; the growing body of literature shows both promise and caveats (Juan *et. al. 2025)*.

3.1 AI Technologies Relevant to CE (Reviews and Synthesized Findings)

Several systematic reviews and empirical papers identify core AI techniques relevant to CE: computer vision and deep learning for optical recognition of materials; robotic manipulation for high-speed pick-and-place; predictive analytics for product life extension and logistics; optimisation and matching algorithms for material flows; and NLP/analytics for monitoring policies and market signals. Key recent reviews: Acerbi et al. (2021) on AI in circular manufacturing; Roberts et al. (2022/2024) on ethical and governance issues; and Ramos et al. (2024) on ML for plastic detection/classification.

3.1.1 Computer Vision and Robotic Sorting

Deep learning models (ResNet variants, YOLO, custom CNNs) have been trained on waste imagery datasets to classify plastics by polymer type, separate paper/cardboard, and identify contaminant items. Combined with high-speed robotic pickers, these systems increase throughput and purity relative to manual sorting in pilot and commercial deployments. News and deployment reports (e.g., AMP Robotics) document real world rollouts and scaling efforts (Edgar Ramos *et. al.,* 2024).

3.1.2 Predictive maintenance and life-extension

AI for Prognostics and Health Management (PHM) supports predictive maintenance for complex products (electronics, appliances), enabling reuse and remanufacturing. These techniques extend useful life and reduce early disposal. Reviews show this is a promising area though empirical scaling remains limited (Muhammad *et. al*, 2023).

3.1.3 Material flow analysis, matching and markets

AI/ML can analyze supply-side waste generation patterns, forecast secondary feedstock availability, and match suppliers to manufacturers needing recovered materials, improving industrial symbiosis. Still, the literature stresses data fragmentation and the need for common data standards (Pattarapol and Pokpong, 2024).

3.1.4 Smart collection and logistics (IoT + ML)

IoT sensors on bins and ML route optimization reduce collection costs and emissions; municipal pilots show reduced empty-truck runs and fuel use. However, equity concerns are raised for under-resourced municipalities that cannot adopt these systems without financing.

3.2 Evidence of Impact: What the Literature Shows

3.2.1 Waste Sorting and Recovery Yields

Empirical pilot studies and early commercial deployments report increases in sorting accuracy and purity that can translate into higher recycling yields and less contamination. Reported benefits vary by material and context but include faster throughput, higher recovery, and lower downstream processing costs. For instance, automated optical/robotic systems demonstrate higher correct identification rates for common packaging streams versus manual sorting under controlled conditions (Edgar Ramos *et. al.,* 2024**).**

3.2.2 Logistics and Cost Savings

Smart routing and fill-level forecasting using IoT + ML can cut collection frequency, reduce fuel consumption, and lower operational costs. Case studies show notable percentage reductions in collection costs and emissions where pilots have been deployed.

3.2.3 Design and Lifecycle Optimization

Generative design combined with lifecycle assessment (LCA) models supports material substitution and product architecture changes for reparability and recyclability. Studies show potential reductions in embodied material use and lifecycle emissions when optimization is applied early in product design. However, industry adoption depends on procurement incentives and regulatory standards (Acerbi, *et. al.* 2021).

4. Practical Case Studies and Illustrative Deployments

(i) **Automated sorting robots**: Several companies have commercialised AI-driven robotic pickers that scan mixed waste on conveyor belts and physically pick items at high rates. Deployments in municipal and commercial recycling facilities report higher recovery rates and lower contamination versus manual sorting. (News coverage of recent rollouts underscores rapid real-world adoption) (Alayna Alvarez, 2025).

(ii) **Smart bins and IoT-enabled collection**: Trials with sensors and ML-based fill-level forecasting reduce collection frequency for underused routes and prioritise overloaded bins, lowering fuel use and operational costs while improving service.

(iii) **AI for e-waste identification and refurbishment**: AI inspection tools (visual and diagnostic) can triage returned electronics for refurbishability or material recovery, increasing reuse lifetimes and reducing hazardous recycling burdens. Recent monitoring reports emphasise the urgency of scaling such solutions to improve low e-waste recycling rates (Global e-waste Monitor, 2025).

(iv) A Pennsylvania waste management company will start using AI-powered robots to sort through trash at one of the largest recycling plants in the Northeast (Isaac Avilucea, 2025).

Why it matters: Penn Waste says the robots can more efficiently sort through the hundreds of tons of recycling the plant processes each year.

The big picture: The robots, created by Amazon-backed startup Glacier, are already being deployed in cities like San Francisco, Seattle and Detroit, but this is the first time they're being used in Pennsylvania.

Driving the news: Penn Waste officials will demo the robots during an event and facility tour at the company's plant in York, about 100 miles west of Philly.

How it works: The robots utilize advanced computer vision to identify and sort through dozens of materials, ranging from synthetic fibers to toothpaste tubes, at about 45 picks per minute, company representatives tell Axios.

5. Opportunities - Quantified Impact Pathways

AI enables reductions in landfill and leakage through:

(a) higher recycling yields via accurate sorting,
(b) increased reuse through predictive maintenance and refurbishment triage, and
(c) upstream waste prevention via design optimisation.

Global waste assessments find that systemic CE adoption - supported by digital and AI tools - could substantially lower lifecycle emissions and raw-material demand compared to business-as-usual scenarios. However, these impacts depend on policy, infrastructure, and market signals aligning to capture recovered value (UNEP, Global Waste Management Outlook, 2024).

6. Challenges, Risks, Limitations and Failure Modes

6.1 Technical and data challenges

(i) **Data gaps and interoperability**: Effective AI requires labelled datasets (waste imagery, material properties, lifecycle data). Data are fragmented across municipalities, manufacturers, and recyclers, hampering model generalisability.

(ii) **Edge cases and contamination**: AI models struggle with rare materials, composite products, and contaminated streams; performance in controlled pilots may degrade in messy real-world facilities (Edgar Ramos *et. al.*, 2024).

6.2 Data and Generalisability

AI models require labeled data from real waste streams. Models trained in one geography/facility often degrade when transferred to different waste mixes, lighting, or contamination levels. Public, FAIR datasets and transfer learning approaches are needed (Edgar Ramos *et. al.*, 2024).

6.3 Capital intensity and deployment inequality:

Advanced AI/robotic systems require investment that may be out of reach for low-income countries and small operators, risking tech-driven divergence in waste management quality.

Sophisticated AI+robotics systems are capital-intensive. Without concessional finance and targeted procurement, deployment risk accentuating a two-track world: high-income regions gain efficient recovery while lower-income regions remain dependent on informal, hazardous recycling or open dumping (UNEP, Global waste Management Outlook, 2024).

6.4 Labour and Social Impacts Workforce transition:

Automation changes job roles in waste sorting and processing / logistics. Ethical deployment should prioritise augmentation (improving safety and pay) and fund reskilling programs rather than replacement. Case evidence suggests human-in-the-loop configurations maintain employment and retraining pathways while improving productivity (Huw Roberts *et. al*, 2022).

6.5 Governance, Ethics, and Environmental Justice

AI could enable more efficient routing of exports - including harmful waste flows - unless traceability and trade rules are strengthened. Governance must ensure that AI doesn't become a tool for outsourcing environmental harm.

(i) **Algorithmic transparency and accountability**: Decisions (e.g., which materials to prioritise for recycling) should be explainable to stakeholders.

(ii) **Waste trade and global justice**: AI can optimise export routes and flows, which risks enabling continued export of problematic waste to countries with weaker enforcement - governance must prevent "waste imperialism." Recent trade data show surges in plastic exports to lower-income nations, underscoring the governance gap (Karen McVeigh, 2025).

7. Policy and implementation recommendations

To maximise AI's contribution to a global CE while minimising harms, the following are recommended:

(i) **Establish open, labeled data commons and standards** - public-private partnerships should develop open labelled datasets for waste imagery, material signatures or properties, anonymised waste flow records and product lifecycles; adopt common data schemas and APIs for interoperability, transferability and to accelerate model training Muhammad Salman Pathan *et. al.*, 2023).

(ii) **Targeted financing and procurement** - governments and multilateral development banks should subsidise pilot deployments in resource-constrained settings and use green public procurement to create demand for secondary materials and refurbished products (UNEP, 2025).

(iii) **Mandate traceability and strengthen export controls**: Combine AI-enabled tracing / tracking with stricter export controls policy to prevent diversion of hazardous waste to low-capacity recyclers. Use digital tracking standards for EoL flows (Cornelis *et.al.*, 2024).

(iv) **Human-centred automation and workforce policies** - require human-in-the-loop systems, mandate company-funded reskilling programs, and incentivise local employment models that integrate AI tools for augmentation, not wholesale replacement. Regulations or funding conditions should favor human-in-the-loop system designs and mandate reskilling/upskilling programs for affected workers.

(v) **RandD for hard-to-recycle materials (composites, multi-layer packaging)** - support translational research that pairs AI classification with novel separation technologies, chemical recycling pathways and material-recovery technologies for composites and multi-layer packaging.

(vi) **Ethical governance frameworks** - develop sector-specific AI governance for transparency, bias audits, privacy safeguards and environmental justice tailored to waste management and CE contexts.

8. Research Agenda and Knowledge Gaps

Priority research questions on Circular Economy should include:

(i) How to create robust, privacy-preserving shared datasets that generalise across geographies and facility conditions? That is, how to build robust, privacy-preserving, generalisable datasets for waste recognition and material properties?

(ii) What governance models best prevent AI-enabled waste flows from reinforcing global inequities? That is, which governance models prevent AI-enabled optimization from reinforcing waste export and environmental injustice?

(iii) How to measure lifecycle environmental benefits of AI interventions reliably? That is, what are standardized metrics to measure lifecycle benefits of AI interventions (beyond facility Key Performance Indicators, KPIs)?

(iv) What are effective human-AI work designs in waste sorting facilities that maximise safety, dignity, and productivity?

(v) Which business models (cooperatives, public-private partnerships) create inclusive, local jobs while leveraging AI for efficiency?

Filling these gaps requires interdisciplinary researches, combining AI, materials science, industrial ecology, labour studies, public policy and international collaboration on dataset sharing and standards.

9. Implementation Roadmap (Priority, Actions and Pilots)

Phase I (0–12 months): Foundations and pilots

(i) Establish a Circular-AI Taskforce (government, producers, recyclers, academia, informal sector reps).

(ii) Pilot AI-assisted Materials Recovery Facilities (MRF) upgrades in a major metropolitan city (e.g., Lagos or Abuja). A Materials Recovery Facility (MRF) is a specialized plant tha**t** receives, separates and prepares recyclable materials for further processing or sale to manufacturers. There are two main types:

a) **Clean MRF:** Handles pre-sorted recyclables (e.g., from households that separate waste).

b) **Dirty MRF:** Handles mixed solid waste (unsorted waste that includes recyclables and non-recyclables).

Traditional MRFs rely on:

a) Conveyor belts
b) Manual pickers (human workers)
c) Magnets (for metals)
d) Air jets (for lightweight plastics)
e) Mechanical screens (for paper and glass separation)

An AI-assisted MRF uses machine learning, computer vision, robotics and sensor-based systems to automate and optimize waste sorting and recycling operations. Developed countries have implemented MRFs. For example, we have:

(a) **AMP Robotics (USA)**: This uses AI-powered vision systems and robotic arms to sort recyclables with >90% accuracy.

(b) **ZenRobotics (Finland)**: This employs AI-guided robots to pick metals, wood, and plastics from mixed construction waste.

The AI helps by analyzing visual or sensor data to recognize materials, for example:

a) **Cameras and sensors** scan items on a conveyor belt.

b) **AI algorithms** identify each item by shape, color, barcode or texture.
c) **Robotic arms or air jets** automatically sort items into correct bins (plastic, paper, aluminum, glass, etc.).

For a developing country like Nigeria, AI-assisted MRFs can:
(a) Help formalize waste management by integrating informal recyclers.
(b) Support data-driven recycling policies and traceable waste flows.
(c) Create green jobs in technology-supported waste processing.
(d) Reduce landfill burden and pollution by improving recovery rates.
(e) Serve as digital infrastructure for Circular Economy initiatives (e.g., linked with Digital Product Passports).

(iii) Launch Digital Product Passports (DPP) Pilot / Test for batteries and selected products like phones and consumer appliances in a bilateral corridor (e.g., Nigeria–Ghana). A Digital Product Passport (DPP) is an electronic record that stores key information about a product's origin, composition, environmental footprint, ownership history and end-of-life management. It uses digital technologies (like blockchain, QR codes or RFID tags) to make this data accessible throughout the product's lifecycle - from production to disposal or recycling. For example, a DPP for a battery might include:

a) Manufacturer details
b) Date and location of production
c) Material composition (e.g., lithium, cobalt)
d) Energy efficiency and carbon footprint
e) Repair and recycling instructions
f) Traceability of raw materials
g) Ownership and warranty history

The DPP concept is central to the Circular Economy, as it helps track materials, encourage reuse and improve recycling. Launching such a DPP pilot in the Nigeria - Ghana corridor can:
a) Support ECOWAS and AfCFTA goals for green trade and digital transformation.
b) Reduce illegal e-waste dumping and promote responsible recycling.
c) Attract foreign investment in sustainable manufacturing and battery recovery industries.
d) Strengthen regulatory cooperation between two key West African economies

(iv) Rapid food-waste analytics pilots in hospitals/universities/hotels.

Phase II (12–36 months): Scale and Market Building
(i) Expand certified waste sorting capacity and match secondary material offtake via public procurement and private contracts.
(ii) Implement Extended Producer Responsibility (EPR) fee modulation to reward product circularity. Extended Producer Responsibility (EPR) is an environmental policy approach that makes producers (manufacturers, importers, or brand owners) financially and/or physically responsible for the entire lifecycle of their products — especially when those products become waste. In simple terms:

"If you make it, you must take responsibility for what happens to it after use."

Under EPR, producers are required to:
(a) Collect or finance the collection of used products (e.g., packaging, electronics, batteries).
(b) Ensure recycling, reuse, or proper disposal.
(c) Report waste management data to regulators.

Examples:
(a) Electronics manufacturers funding e-waste recycling programs.
(b) Beverage companies paying for bottle collection and recycling systems.
(c) Battery producers supporting safe collection points and recycling facilities.

In essence, to implement Extended Producer Responsibility (EPR) fee modulation to reward product circularity means setting up an EPR system where producers pay different fees based on how eco-friendly and circular their products are - encouraging sustainable design and discouraging wasteful production.

Let's take plastic packaging as an example in Table 1.

Table 1: Plastic Packaging Example

Product Type	Circularity Feature	EPR Fee (per kg)
Single-use plastic wrapper	Hard to recycle	₦300
Multi-layer film (partially recyclable)	Some recyclability	₦200
100% recyclable PET bottle (with recycled content)	Fully recyclable	₦100
Refillable bottle system	Reusable and circular	₦50

This fee differentiation would motivate producers to:

(a) Use recyclable materials,
(b) Design refillable or reusable packaging, and
(c) Invest in sustainable product innovation.

Implementing EPR fee modulation can:

(a) Encourage local industries to adopt circular product design.
(b) Reduce importation of non-recyclable goods.
(c) Support job creation in recycling and repair sectors.
(d) Build data-driven waste financing systems for sustainable cities.
(e) Complement Digital Product Passport (DPP) initiatives by linking design data to EPR compliance.

Phase III (36–60 months): Systems integration
Integrate National Material Flow Accounts (MFA) dashboards, cross-border compliance for hazardous streams, embedding circular KPIs into municipal budgeting.

Material Flow Accounts (MFA) are systematic national datasets that track the flow of materials, such as biomass, minerals, metals and fossil fuels, through an economy. They measure how much raw material a country:

(a) Extracts from its own environment,
(b) Imports from other countries,
(c) Consumes domestically (for production and consumption), and
(d) Exports or discards as waste or emissions.

In simple terms, MFA helps a country answer: "Where do our materials come from, how do we use them, and where do they go after use?"

A National Material Flow Accounts (MFA) Dashboard is a digital platform or data visualization tool that presents a country's MFA data in an interactive, easy-to-understand format. It acts as a monitoring and Decision Support System (DSS) showing key indicators of resource use, efficiency and circularity. So, instead of having raw data buried in statistical reports, a dashboard turns it into visual insights with charts, maps and trend analyses.

The MFA dashboard tracks national-level indicators of material use and circular economy performance, such as in Table 2:

Table 2: National Level Indicators

Indicator	Meaning / What it Shows
Domestic Material Extraction (DME)	Amount of raw materials extracted within the country (e.g., mining, forestry, agriculture).
Imports and Exports of Materials	Physical trade flows in tonnes per year.
Domestic Material Consumption (DMC)	DME + Imports − Exports → total materials used domestically.
Material Productivity	GDP divided by DMC (economic output per unit of material used).
Circular Material Use Rate (CMU)	Percentage of materials recycled or reused in the economy.
Waste Generation per Capita	Amount of waste produced per person.
Carbon/Environmental Footprint	Material use linked to CO_2 emissions and environmental impact.

National MFA dashboards are used for:
(a) Tracking national resource efficiency and sustainability goals.
(b) Informing circular economy and green growth policies.
(c) Comparing trends across sectors (construction, agriculture, manufacturing, etc.).
(d) Monitoring progress toward UN SDGs (especially SDG 8, 12, and 13).
(e) Supporting industrial policy by identifying high-impact or waste-intensive sectors.

They provide evidence-based insights for policymakers, researchers, and businesses. Let’s take a look on how a Dashboard works: A country like Nigeria might have a National MFA Dashboard that shows:
(a) **Imports:** 10 million tonnes of refined petroleum, 2 million tonnes of plastics.
(b) **Domestic Extraction:** 120 million tonnes of limestone, 50 million tonnes of agricultural biomass.
(c) **Exports:** 20 million tonnes of crude oil, 5 million tonnes of cement.
(d) **Waste Generated:** 35 million tonnes per year.
(e) **Recycling Rate:** 10%.
(f) **Circular Material Use Rate:** 5%.

The dashboard will visualize these in graphs, allowing policymakers to see:
(a) Which sectors use the most raw materials.
(b) Where recycling investments are needed.
(c) How material use relates to GDP or emissions.

The MFA dashboard typically uses the following technologies and data:
(a) **Data sources:** National statistics, customs, trade data, mining/agriculture records and waste management reports.
(b) **Analytical tools:** Input-output modeling, life-cycle accounting and environmental-economic integration.
(c) **Software platforms:** Power BI, Tableau, or web-based open data portals.
(d) **AI and automation (in advanced systems):** For predictive modeling and trend forecasting.

The MFA dashboard is a backbone tool for Circular Economy policymaking**.** It shows how efficiently a country is:
(a) Using natural resources,
(b) Recovering secondary materials,
(c) Reducing waste generation, and
(d) Closing material loops through recycling, repair, or reuse.

If we integrate MFA with Digital Product Passports (DPP)**,** EPR schemes**,** and AI-assisted waste recovery**,** Nigeria can achieve data-driven circular economy systems**.** Creating National MFA Dashboards in Nigeria, and by extension Africa, would:

a) provide baseline data for circular economy and waste policy development.
b) help governments track material imports, exports, and waste leakages.
c) support regional harmonization under AfCFTA for sustainable production and trade.
d) attract green investments by showing transparency in resource use.
e) link with AI-assisted MRFs and Digital Product Passports to create a smart circular economy ecosystem.

10. Measurement, verification and evaluation
Core outcome metrics: diversion rate; contamination/purity (MRF infeed vs output); Material Circularity Indicator (MCI); economic indicators (opex/ton, revenue per ton secondary); social indicators (formalization, wage changes, safety incidents); and AI model KPIs (precision/recall, robustness, energy per inference). Independent third-party verification and open, anonymized datasets accelerate learning (UNEP - UN Environment Programme)

11. Conclusion
AI is a powerful enabler for the circular economy: it improves design, augments sorting and recovery, optimises logistics and supports enforcement and consumer engagement. Evidence shows real gains in recovery yield and operational efficiency, but benefits are conditional on data availability, finance, governance, and human-centred design to curb the global waste crises sustainably and equitably. Yet AI alone will not solve the

global waste crisis. Meaningful impact requires systemic action. AI must be paired with open data, regulatory guardrails, equitable financing, public procurement, reskilling programs (workforce transition planning), and strong traceability, export controls and cross-sector collaboration. With deliberate governance and targeted investment, AI can accelerate the CE transition and help curb the environmental and social harms of today's growing waste flows according to UNEP (2024).

References

Acerbi, Dai, Andrew Forterre and Marco Taisch (2021). Role of Artificial Intelligence in Circular Manufacturing: A Systematic Literature Review. *Procedia Manufacturing / Politecnico di Milano repository (preprint)*. Retrieved in October 2025 from: https://re.public.polimi.it/bitstream/11311/1204215/1/Paper%20revised%20version%20FINAL.pdf.

Alayna Alvarez (2025). Colorado's trash-sorting robot makes Time's top inventions list, https://www.axios.com/local/denver/2025/10/10/amp-robotics-recycler-time-best-inventions?utm_source=chatgpt.com, Accessed, October 2025.

Bang-Ning Hwang, Pittinun Puntha, Siriprapha Jitanugoon (2025). AI-Driven Circular Transformation: Unlocking Sustainable Startup Success Through Co-Creation Dynamics in Circular Economy Ecosystems, Willey Online Library, https://doi.org/10.1002/sd.70001

Bashynska, I. (2025) Ethical aspects of AI use in the circular economy. *AI and Soc* https://doi.org/10.1007/s00146-025-02436-1 Accessed, October 2025

Cornelis P. Baldé, Ruediger Kuehr, Tales Yamamoto, Rosie McDonald, Elena D'Angelo, Shahana Althaf, Garam Bel, Otmar Deubzer, Elena Fernandez-Cubillo, Vanessa Forti, Vanessa Gray, Sunil Herat, Shunichi Honda, Giulia Iattoni, Deepali S. Khetriwal, Vittoria Luda di Cortemiglia, Yuliya Lobuntsova, Innocent Nnorom, Noémie Pralat, Michelle Wagner (2024). The Global E-waste Monitor, *International Telecommunication Union (ITU) and United Nations Institute for Training and Research* (UNITAR). Geneva/Bonn.

David B. Olawade, Oluwaseun Fapohunda, Ojima Z. Wada, Sunday O. Usman, Abimbola O. Ige, Olawale Ajisafe and Bankole I. Oladapo (2024). Smart waste management: A paradigm shift enabled by artificial intelligence, *Waste Management Bulletin*, Volume 2, Issue 2, June 2024, Pages 244-263

Edgar Ramos, Arminda Guerra Lopes and Fábio Mendonça (2024). Application of Machine Learning in Plastic Waste Detection and Classification: A Systematic Review, *Processes*, 12(8), 1632; https://doi.org/10.3390/pr12081632

Ellen MacArthur Foundation. (n.d.). *The Circular Economy - Introduction and Model Explained*. https://www.ellenmacarthurfoundation.org/topics/circular-economy-introduction/overview. ellenmacarthurfoundation.org, Accessed in October 2025.

Ellen MacArthur Foundation. *The Circular Economy - Introduction and Deep Dive*. (CE conceptual framing and principles). https://www.ellenmacarthurfoundation.org/topics/circular-economy-introduction/overview?utm_source=chatgpt.com, Accessed in October 2025.

Global E-waste Monitor. (2024). *The Global E-waste Monitor 2024* (GEM 2024). United Nations Institute for Training and Research (UNITAR) / ITU / SCYCLE. Retrieved from https://ewastemonitor.info/wp-content/uploads/2024/03/GEM_2024_18-03_web_page_per_page_web.pdf in October 2025.

Huw Roberts, Joyce Zhang, Ben Bariach, Josh Cowls, Ben Gilburt, Prathm Juneja, Andreas Tsamados, Marta Ziosi, Mariarosaria Taddeo, Luciano Floridi (2022). Artificial intelligence in support of the circular economy: ethical considerations and a path forward, AI and Society, Volume 39, Issue 3 Pages 1451 – 1464, https://doi.org/10.1007/s00146-022-01596-8

Isaac Avilucea (2025). Penn Waste debuts AI recycling robots, Axios Philadelphia. https://www.axios.com/local/philadelphia/2025/10/08/penn-waste-ai-robots-recycling/ Accessed, October 2025

Juan Camilo Rua Hernandez, Eliana Villa-Enciso, Sebastián Cardona-Acevedo, Jackeline Valencia and Sofia Velasquez Salas (2025). Smart Innovation for a Circular Economy: A Systematic Review of Emerging Trends and the Future of AI in the Sustainable Economy, *Sustainability*, *17*(13), 5793; https://doi.org/10.3390/su17135793

Karen McVeigh (2025). UK plastic waste exports to developing countries rose 84% in a year, data shows, *The Guardian*, Wed 8 October, 2025

Muhammad Salman Pathan, Edana Richardson, Edgar Galvan and Peter Mooney (2023). The Role of Artificial Intelligence within Circular Economy Activities - A View from Ireland, *Sustainability*, 15(12), 9451; https://doi.org/10.3390/su15129451

Pattarapol Tongyodkaew and Pokpong Songmuang (2024). AI Implementations on Circular Economy: A Systematic Literature Review, *Computational Data and Social Networks: 13th International Conference*, CSoNet 2024, Bangkok, Thailand, December 16–18, 2024, Proceedings Pages 411 – 419, https://doi.org/10.1007/978-981-96-6389-7_38, Published: 07 June 2025

Ramos, E., Lopes, A. G., and Mendonça, F. (2024). Application of Machine Learning in Plastic Waste Detection and Classification: A Systematic Review. *Processes, 12*(8), 1632. https://doi.org/10.3390/pr12081632

Ramos, E., Lopes, A. G., and Mendonça, F. (2024). Application of Machine Learning in Plastic Waste Detection and Classification: A Systematic Review. *Processes, 12*(8), 1632. https://doi.org/10.3390/pr12081632.

Roberts, H., Zhang, J., Bariach, B., Cowls, J., Gilburt, B., Juneja, P., Tsamados, A., Ziosi, M., Taddeo, M., and Floridi, L. (2022). Artificial intelligence in support of the circular economy: Ethical considerations and a path forward. *AI and Society*. https://doi.org/10.1007/s00146-022-01596-8.

Roberts, H., Zhang, J., Bariach, B., Cowls, J., Gilburt, B., Juneja, P., Tsamados, A., Ziosi, M., Taddeo, M., and Floridi, L. (2022). Artificial intelligence in support of the circular economy: Ethical considerations and a path forward. *AI and Society*. https://doi.org/10.1007/s00146-022-01596-8. ACM Digital Library

The Global E-waste Monitor 2024. Electronic Waste Rising Five Times Faster than Documented E-waste Recycling: UN, https://ewastemonitor.info/the-global-e-waste-monitor-2024/ Accessed October, 2025

UNEP and ISWA. (2024). *Global Waste Management Outlook 2024: Beyond an Age of Waste*. United Nations Environment Programme. Retrieved from https://www.unep.org/resources/global-waste-management-outlook-2024. UNEP - UN Environment Programme

UNEP: Global Waste Management Outlook (2024). https://www.unep.org/ietc/resources/report/global-waste-management-outlook-2024?utm_source=chatgpt.com, Accessed, October 2025.

Yuekuan Zhou (2025). AI-driven digital circular economy with material and energy sustainability for industry 4.0, *Energy and AI*, Volume 20, May 2025, 100508

Zoumpoulis, P., *et al*. (2024). Smart bins for enhanced resource recovery and route optimisation. *Waste Management Journal / Elsevier.*