Innovative Computing Perspectives

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Review

AI-Enabled Sensors and Analytical Chemistry for Resource Recovery: Trends and Frontiers in the Circular Economy

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Abstract

Shifting to a circular economy requires new ways to recover materials from waste. Waste must be reimagined as a source of value. The core of this change is analytical chemistry, sensor technologies, which detect, quantify and characterise critical resources in a variety of waste streams. Artificial intelligence or AI has become a transformative enabler recently to provide sophisticated solutions for data-driven modelling, predictive analytics, and process optimisation. This review describes the AI-based sensor and analytical chemistry techniques applications in water and wastewater treatment, energy recovery, recovery of critical materials, plastics recycling and biomass valorization. Focus on spectroscopy, chromatography, electroanalysis, and hybrid techniques boosted by machine learning. AI-based sensors development for real-time monitoring and classification also will be discussed and showcased. In addition, the authors point out that digitalization, automation and smart platforms (i.e., IoT integration, cloud-based analytics, digital twins) can lead to fully autonomous recovery systems. It critically examines data quality, reproducibility and standardization, and AI's energy demand sustainability paradox. In the future, scientists will have next-generation AI models, autonomous laboratories, and quantum computing that will speed up analytical chemistry for resource recovery. This work integrates chemistry, engineering, data science, and policy to support the idea that AI can facilitate a circular economy as well as sustainable resource use and global environmental accountability.

Keywords

Artificial intelligence, Sensors, Analytical chemistry, Resource recovery, Circular economy, Digitalization, Sustainable technologies

Article History

Received: 1 October 2025 Revised: 26 November 2025

Accepted: 8 January 2026 Available Online: 9 January 2026

1. Introduction

The collaboration of Artificial Intelligence (AI) and the implementation of innovative sensor technologies and the latest analytical chemistry is transforming the environment of the resource recovery in the framework of the circular economy. The classic paradigm of linear production that can be referred to as take-make-dispose has become more unsustainable with the rising level of waste production, shortage of resources, and environmental deterioration. Circular systems, in turn, focus on the flow of materials, minimization of waste, and optimized use of resources. A major facilitator of this shift is AI, which will improve the accuracy, speed, and intelligence of material recovery processes in industrial, agricultural, and environmental settings [1,2]. AI-based systems enhance environmental footprints and sustainable industrial practices through predictive analytics, optimization algorithms, and real-time monitoring, which enhance the identification, classification, and transformation of the waste streams into valuable secondary resources.

Recently, further advances in Green AI architecture have further accelerated the use of computational intelligence on the recovery of resources. Green AI focuses on the design of algorithms with low energy requirements, lesser records of the carbon footprint of computations, and eco-friendly hardware settings and still remains highly effective in the processing of large datasets in the context of data processing [3]. The current global economic model, characterized by extensive resource extraction, high consumption rates, and escalating waste generation, is increasingly recognized as environmentally unsustainable and a major driver of ecological degradation [4]. This prevailing linear paradigm often described as the "take-make-dispose" model contrasts sharply with the principles of the circular economy, which emphasize keeping resources in productive use for as long as possible, maximizing value during use, and recovering and regenerating materials at the end of their life cycles [5]. By design, the circular economy seeks to decouple economic growth from resource depletion through waste minimization, pollution reduction, and improved material efficiency, thereby conserving finite natural resources and reducing environmental burdens [6].

Within this context, AI has emerged as a pivotal technological enabler of circular economy implementation. AI-driven systems offer advanced capabilities for managing complex and dynamic resource flows, optimizing process efficiency, and supporting data-driven decision-making across industrial ecosystems [7]. Through predictive analytics, pattern recognition, and systems-level optimization, AI can enhance material recovery, improve operational efficiency, and reduce energy and resource inputs throughout production and recycling chains. As highlighted by Ranpara [6], the integration of AI into circular systems enables more adaptive, resilient, and sustainable industrial practices, positioning computational intelligence as a critical tool for accelerating the global transition toward regenerative and resource-efficient economic models.

In addition to the primary production, AI is also needed to convert agricultural and municipal wastes into renewable energy sources. The waste-to-energy (WtE) systems can optimize the process of anaerobic digestion, pyrolysis, and gasification through machine learning algorithms that predict the biogas yield, model the characteristics of the substrate, and provide stability of the operation process [8]. This improves the processes of converting organic waste into bioenergy and decreasing the emission of greenhouse gases and the use of fossil fuels. Connecting agriculture, energy production, and waste management into a circular system with AI, a symbiotic industrial relationship will be created, where a by-product of a sector transforms into the resources of another one.

Altogether, these inventions emphasize the transformative nature of AI in aiding the sustainable, data-driven decision-making in the agricultural, industrial, and energy sectors. Combining sophisticated sensors, analytical chemistry, and smart computational platforms allows creating the new generation of closed-loop resource cycles that are more efficient, less harmful to the environment, and economically resilient. With the growing pressures of the global community, be it climate change, scarcity of resources, etc., the implementation of AI-based technologies in the models of the circle of economy is a viable and scalable method to address long-term sustainability. This introduction provides the conceptual framework for the investigation of AI improving circularity in the technological, analytical, and systemic channels of production and resource recovery systems.

The purpose of the research is to critically discuss how AI, high-tech sensor devices, and modern analytical chemistry would help optimize the efficiency of resource recovery within the framework of the circular economy and, in specific cases, sustainable agriculture, waste-to-resource transformation, and environmentally friendly industrial processes. In particular, the paper will examine the workings of AI-based analytical and sensing platforms, assess their roles in material circularity and energy efficiency, and construct a conceptual framework to explain how their joint efforts can be used to achieve sustainable, data-driven, and regenerative production processes.

2. Methodology

The methodology used in this review was a narrative-systematic hybrid, which is meant to integrate systematic rigour in the identification of evidence and narrative richness in interdisciplinary synthesis. To contribute to methodological transparency, the review procedure was adapted to the PRISMA 2020 principles whereby well-specified databases, time frames, search terms, screening criteria, and selection procedures were used.

2.1 Search Strategy

To identify quality scientific evidence, a systematic and reproducible literature search was done in five major academic databases, which include Scopus, Web of Science, PubMed, ScienceDirect, and IEEE Xplore. The search included publications between 2000 and 2025, which contained both the groundbreaking works and the new developments.

Grey literature policy documents, industrial reports, technical briefs of UNEP, OECD, EU Circular Economy Initiatives, and national sustainability agencies were also filtered to expand the coverage of materials outside of the traditional academic sources.

The search strings were designed with the help of Boolean operators (AND, OR) and were adjusted to each database. Search query by a representative:

(Artificial Intelligence or AI) AND (Sensors or Spectroscopy) AND (Resource Recovery or Waste Valorization or Circular Economy) AND (Analytical Chemistry or Sustainable Materials or Environmental Monitoring).

This was a strategy to provide a transparent and comprehensive search of the literature that addressed the field of AI-driven analytical chemistry, sustainable material development, and circular economy systems.

2.2 Inclusion and Exclusion Criteria

In order to deal further with the expectations of the reviewers on the aspect of transparency, clear criteria were used:

Inclusion Criteria:

Policy papers, book chapters, peer-reviewed research articles, and reviews.

Publications from 2000 to 2025.

Articles about the use of AI in analytical chemistry, sustainable materials, resource recovery, circular economy, bioplastics made with seaweed, or environmental monitoring.

Publications written in English, in full text.

Exclusion Criteria:

Newspaper articles, commentaries, conference papers, or non-scholarly articles.

Research did not mention any other AI applications (e.g., robotics, cybersecurity) alone.

Redundant ones, lost full texts, or papers with poor methodology.

2.3 Process of Screening and Extraction of Data

All the records that were retrieved were loaded to a reference management system to eliminate duplicates. There were three steps in screening, namely:

Title screening to relevant thematics.

Abstract screening according to inclusion criteria.

Two reviewers carried out a full-text assessment to minimize bias.

The difference was solved by consensus negotiation. Extracted data included:

Study objectives:

Research design and tools of analysis.

Algorithms or methods of AI used.

Applications of sustainable chemistry/material science.

This policy has technological implications and key results.

The systematization of the narrative approach with a focus on the systematic method is justified by the following reasons:

The systematic review was done in a purely systematic way because the topic of the research was rather broad and cross-disciplinary. The hybrid approach allowed:

Organized methodology in determining, screening, and recording evidence.

Policy trend, technological curve, and conceptual development integration.

Adaptability to integrate various areas (AI, analytical chemistry, circular economy, seaweed biopolymers) that cannot be easily synthesized with a more rigid systematic-only design.

3. Conceptual Framework

3.1 Circular Economy and Resource Recovery

The circular economy is founded on the core principles of reducing, reusing, recycling, and recovering materials to keep them in productive use for as long as possible [9,10]. Resource recovery is a critical component of this framework, as it enables the extraction of valuable compounds and materials from waste streams, thereby minimizing environmental burdens and reducing dependence on virgin resources. Key examples include nutrient recovery from wastewater through anaerobic digestion and the reclamation of essential raw materials such as lithium and rare-earth elements from electronic waste [11]. This approach is crucial for optimizing environmental outcomes and reintroducing high-value materials back into the economic cycle, thereby supporting long-term sustainability and resource efficiency [12].

Other processes like chemical transformation of plastic waste into polymer feedstocks also contribute to lessening reliance on virgin petrochemical feeds and contribute to regenerative production systems [11]. Altogether, they reduce environmental impacts, increase the resilience of industries, and correspond to the international sustainability goals, which constitute the conceptual base of the resource recovery models built around the idea of the circular economy [9, 10].

3.2 Uses of Analytical Chemistry in Recovery of Resources

Analytical chemistry is the science that offers the scientific foundation to determine, measure, and characterize recoverable materials in a wide variety of environmental and industrial matrices. Conventional analytical techniques, such as atomic absorption, ICP-OES, and ICP-MS spectroscopy, and chromatographic methods, such as Chromatography (HPLC), Gas Chromatography (GC), and Ion Chromatography (IC), have conventionally been utilized in the characterization of complex samples with high accuracy.

Recently, advancements in the miniaturization of instruments, high-throughput systems, and hybrid analytical platforms have enhanced selectivity, sensitivity, and field portability, while remaining compatible with the principles of green chemistry [13,14]. These innovations facilitate real-time monitoring of waste composition, improve the efficiency of resource recovery processes, and ensure compliance with environmental regulations. This focus on sustainable analytical practices is critical for environmental protection, social cohesion, and economic development, addressing the legacy of pollution from past industrial activities [13]. A combination of sustainable and AI-supported analytical procedures is increasingly becoming a defining trend in contemporary resource recovery practices [14].

3.3 Sensors and Analytical Chemistry AI

The modern measurement science has been focusing on AI, especially sensor technologies and analysis processes. Some of the tasks that are improved using machine learning (ML) and deep learning (DL) algorithms include spectral deconvolution, pattern recognition, noise filtering, and predictive modeling [14,15].

A system based on AI may analyze large data sets provided by sensors in the environment and industry and respond adaptively to the changes in waste composition and operational conditions [12]. Combining AI with traditional methods of analytical chemistry, the efficiency of recovery will be increased, the process will become more circular, and it will also make industrial activities more sustainable [14-16].

This theoretical perspective is the premise of the interpretation of the interaction of sensing technologies, analytical science, and AI-based tools to speed up the process of resource recovery on the basis of the circular economy.

4. Resource Recovery Sensors and Analytical Chemistry Methods

4.1 Types of Sensors in Resource Recovery

The contemporary sensor technologies aid in the environmental surveillance and restoration of resources by identifying the pollutants and valuable analytes in real-time matrices.

Electrochemical sensors, which are extensively utilized in the detection of heavy metals, nutrients, and redox-active species, are appreciated because they are highly sensitive, inexpensive, and can be made easily. Recent studies by [17] emphasize the importance of nanostructured electrodes and novel geometry in improving the performance.

Rapid detection of trace analytes can be done by optical sensors such as fluorescence-based systems and surface-enhanced Raman scattering (SERS) instruments without labeling. Fiber-optic SERS systems have enhanced sensitivity, miniaturization, and field sensitivity with nanostructured plasmonic materials and flexible substrates [18].

The aptamer-, enzyme-, or microbe-based biosensors are highly selective and friendly to the environment. Innovations in aptamer screening and nanomaterial-mediated signal transduction, graphene quantum dots (GQDs), and metal-organic frameworks (MOFs) have also enhanced detection properties to a greater extent [19].

Collectively, these sensor platforms can create a fundamental technological basis of sustainable environmental monitoring and recovery systems that are efficient with regard to resources.

4.2 AI Cases in Sensor Development and Monitoring

Modern sensing systems have been redesigned and reconfigured through AI. Acting as part of sensor networks, AI allows interpreting multidimensional data two to three times faster, helping to detect faults faster, predict better, and optimize the system performance in industrial and environmental conditions [20].

In the manufacturing industry, AI sensors detect defects and anticipate failures in the system based on integrated past and real-time data [21]. Edge AI processes data immediately at the sensory device, leading to lower latency, reduced energy consumption, and real-time adaptability in environmental systems [22]. For example, Wang et al. [22] demonstrated that edge-enabled sensing platforms facilitate the management of water and air quality in smart cities. Predictive maintenance systems and remote diagnostics have been further reinforced with cloud-based AI systems, which integrate distributed sensor networks through a unified decision-making framework [21,23]. These innovations align with Industry 4.0 principles and enable cleaner, more efficient, and sustainable resource recovery processes.

4.3 Analytical Chemistry Techniques in the Recovery of Resources

Analytical chemistry offers the necessary instruments for determining the amount of materials that can be recovered, analyzing the purity, and regulating compliance with the regulations in the resource recovery systems. The classical methods of analytic analysis, such as chromatography, mass spectrometry, and molecular spectroscopy, are still being improved in terms of being smaller and more sustainable [24].

The overall use of AI and ML can be used to improve analytical processes by automation of pattern recognition, optimization of method development, and dynamically adjusting parameters in view of variability in samples. The new generation of hybrid analytical systems can now offer precise determination of the recoverable materials in multifaceted waste samples and help to adopt the principles of the circular economy by achieving higher accuracy and efficiency [14,25].

4.4 Spectroscopic, Chromatographic, and Electroanalytical Methods

4.4.1 Spectroscopic Techniques

The most common spectroscopic methods employed for multi-element analysis with high precision in environmental and industrial matrices include inductively coupled plasma optical emission spectrometry (ICP-OES) and inductively coupled plasma mass spectrometry (ICP-MS), both of which enable simultaneous determination of a broad range of elements with high sensitivity and dynamic range, laser-induced breakdown spectroscopy (LIBS), which offers rapid in situ elemental analysis with minimal sample preparation, and X-ray fluorescence (XRF), a nondestructive technique widely used for rapid screening of elemental composition in solids such as soils, sediments, and industrial materials [26,27]. They have the advantages that they have low limits of detection, they can detect more than one element at a time, and they can be used on complex matrices. Nonetheless, the maturity and practical implementation are quite dissimilar: ICP-based approaches are strongly standardized and widely tested in laboratories, which is why they can be trusted to ensure regulatory compliance and quality control in industries. Conversely, LIBS and portable XRF are novel technologies that have yet to be overcome, such as the effects of matrices, the stability of calibration, and the operation in the field that may have different environmental conditions.

The cost, training of the operator, and complexity in interpreting the results of the data are currently limiting the adoption of LIBS in industries and portable XRF. Although such methods have the potential to minimize time spent in the preparation of samples and sample analysis, their sensitivity and accuracy are not as high as they need to be to enable them to support regulatory monitoring or high-stakes industrial decision-making. Case study: Portable XRF has been used in mining operations to on-site screen metal ores rapidly so that on-site decisions can be made on ore blending, but ultimately final assays are verified using ICP-MS. This technology has been implemented successfully [27].

AI-based models (convolutional neural networks, CNNs, and recurrent neural networks, RNNs) can be used to enhance spectroscopic analysis through spectral deconvolution in noisy conditions, signal overlap correction, signal spectrum stabilization, and real-time heterogeneous sample classification [28,29]. This integration makes the tools of spectroscopy more applicable to field scenarios that can be divided into high throughput but has not yet been widely available due to the infrastructural requirements of the computation and due to the necessity of trained sets of data.

4.4.2 Chromatographic Methodologies

Chromatographic techniques such as High- Performance Liquid HPLC, GC, and IC are essential for the separation, identification, and quantification of organic and inorganic analytes [30]. These methods are highly selective and capable of resolving structurally similar compounds, making them indispensable across pharmaceutical, environmental, and food analytical settings. However, traditional chromatographic method development is inherently time- consuming, often involving extensive sample preparation, iterative optimization of mobile phases and gradients, and multiple experimental runs to achieve desired resolution and selectivity. These factors, combined with high solvent consumption and manual tuning, limit the scalability of chromatographic workflows in high- throughput industrial processes and circular- economy applications [31].

To address these challenges, AI and ML tools are increasingly being explored to enhance and streamline chromatographic workflows. AI approaches can significantly improve method development by predicting retention times, optimizing gradient conditions, deconvoluting overlapping peaks, and supporting automated parameter selection, thereby reducing the need for labor- intensive trial- and- error experimentation [32].

One promising application of AI in chromatography is the prediction of retention behavior. ML models, including quantitative structure- retention relationship (QSRR) models, neural networks, and other supervised learning frameworks, can associate molecular features with chromatographic outcomes such as retention time based on training data from historical experiments. These models enable rapid in silico evaluation of chromatographic conditions before empirical testing, reducing experimental runs and solvent usage[33].

Beyond retention prediction, AI- assisted methods can automate peak detection and integration, even in complex or noisy chromatograms. Traditional peak identification often relies on manual setting of thresholds and baseline corrections, but ML- driven peak algorithms can decompose overlapping signals and maintain consistency across large datasets. This is particularly valuable in high- throughput environments such as pharmaceutical quality control, where manual processing becomes infeasible[34].

AI tools also enable multi- objective optimization, where models balance trade- offs between analysis speed, resolution, solvent consumption, and sensitivity to produce chromatographic conditions tailored to specific application goals. These tools can iteratively propose optimized mobile phase compositions, flow rates, and temperature settings based on defined performance criteria, substantially accelerating method development cycles and reducing resource inputs [34].

Despite these advantages, real- time in situ chromatographic monitoring remains a technical challenge. Many industrial and decentralized settings require portable and robust instrumentation with minimal maintenance burden. The integration of AI into real- time control systems for chromatography such as dynamic adjustment of gradients or inline quality assessment faces hurdles related to computational complexity, data acquisition rates, and instrument integration costs. Nevertheless, advances in digital chromatographic data systems and AI- enabled signal processing point to increasing feasibility in the near future [35].

A contemporary case study from pharmaceutical manufacturing illustrates practical AI usage in HPLC workflows. AI- enhanced HPLC systems have been deployed as continuous quality control tools to minimize solvent use and detect impurities early in production lines. These solutions demonstrate that even though the initial cost and integration complexity can be high, industrial applications benefit from increased process efficiency, reduced waste, and improved compliance with quality standards, underscoring the relevance of AI- assisted chromatographic optimization in modern manufacturing environments [36].

In summary, while traditional chromatographic methods provide high selectivity and structural resolution, their optimization is resource- intensive. AI and ML tools offer promising pathways to streamline these workflows by accelerating method development, enhancing data analysis, and reducing solvent and time demands. Continued advances in AI- driven prediction and automation are likely to make chromatographic techniques more scalable, sustainable, and adaptable particularly in industrial and high- throughput settings where efficiency and cost- effectiveness are paramount [37,38].

4.4.3 Electroanalytical Methods

Modern battery technologies depend on electrochemical storage systems. However, the performance of such systems is limited by complicated multi-scale processes. These processes include transport of ions, interfacial reactions, and degradation [39]. The electroanalytical techniques, including potentiometry, voltammetry, and electrochemical impedance spectroscopy, are relatively inexpensive, portable, fast, and appropriate in monitoring redox-active species and trace metals in situ [36,40,41]. They tend to be more field-ready than spectroscopy or chromatography, but there are still difficulties: electrode fouling, low selectivity in complicated matrices, and they usually have to recalibrate.

Pattern recognition using electroanalytical techniques can be enhanced with AI because the impedance spectra and voltammetric signals can be analyzed and are predictive of degradation, and degradation can be implemented with adaptive calibration to operate over a long duration. Although these have these benefits, large-scale adoption of sensors is limited by their lifetime, reproducibility, and data infrastructure requirements. Example: Electrochemical sensors combined with machine-learning algorithms have been tested to detect heavy metal that is present in industrial effluents and have shown to be fast in making decisions and necessitate routine maintenance and calibration in hostile condition

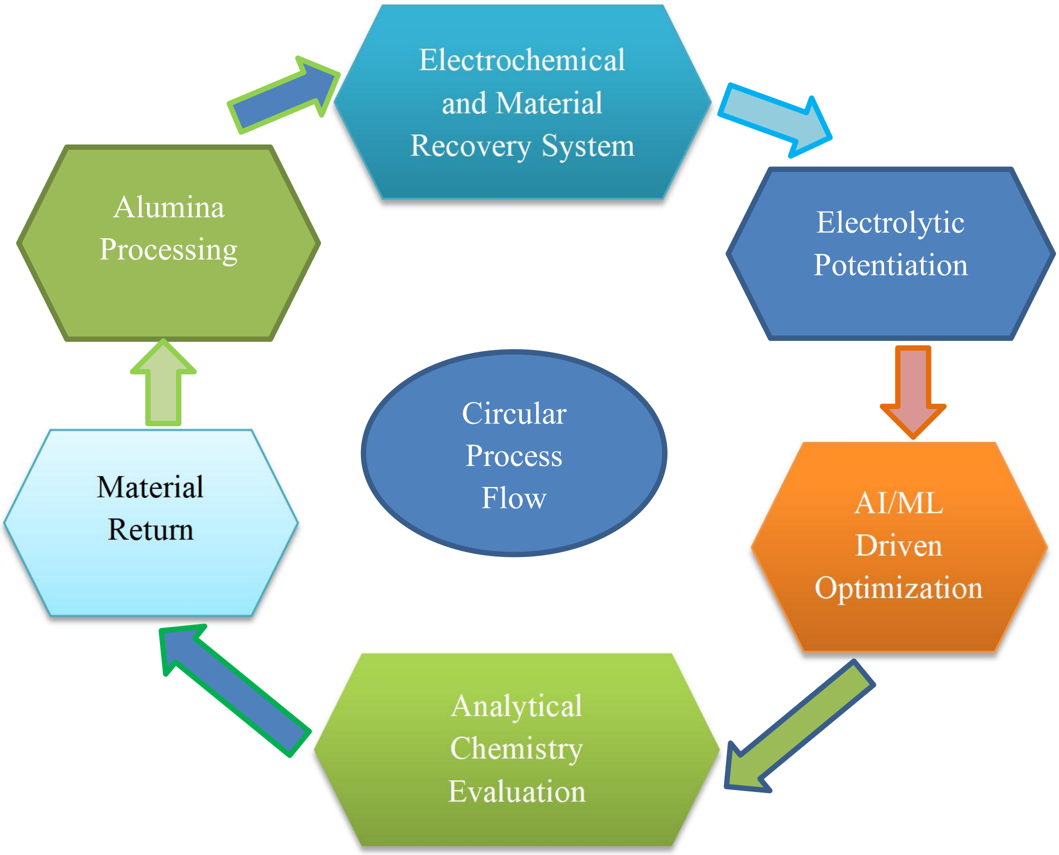

Figure 1. Circular process flow for electrochemical and material recovery systems.

This diagram illustrates the cyclic workflow involving alumina/nepheline processing, electrolytic potentiation, AI/ML-driven optimization, material return, and analytical chemistry evaluation.

4.5 Hybrid Analytical Systems and In Situ Monitoring

Hybrid systems: Hybrid systems include LC-ICP-MS, LIBS-GC-MS workflows, portable MS systems, as well as multi-sensor arrays to exploit complementary strengths of analysis [42,43]. Hybrid methods provide the selectivity of chromatography, the sensitivity of ICP-MS, and the speed of prescreening of LIBS or XRF.

Nonetheless, it has serious obstacles to industrial implementation. LC-ICP-MS is a highly advanced laboratory-based technique, which is costly, necessitates a skilled staff, and is not very portable in the field. Portable MS and combined LIBS-GC-MS systems are novel, and they have some technological challenges such as power consumption, calibration, and resistance to fluctuating environmental factors.

Integrating edge AI into sensor networks enables real-time tuning of sensing parameters, spectral/data fusion, anomaly prediction, and decentralized decision-making, effectively closing the gap between laboratory accuracy and practical field use[44,45]. For example, multi-sensor AI systems have been applied in municipal waste and e-waste sorting, where on-site automated decision-making enables higher throughput and reduced human effort compared with manual processes. However, the cost and complexity of these systems remain significant barriers to large-scale industrial adoption. Robust datasets, high-performance sensing hardware, and advanced edge computing units are required to sustain such performance in real environments, which can limit uptake in smaller or resource-constrained facilities [46,47]. Chromatography is accurate but slow and less mobile; AI can enhance partial automation but not scale constraints entirely.

Electroanalytical instruments are portable and suffer selectivity and maintenance problems.

Hybrid systems have complementary benefits but are hindered by cost, power, and calibration.

Practical implementations are in existence but point out trade-offs in terms of precision, throughput, and complexity of operation.

Table 1. Comparative synthesis of sensors, analytical methods, and AI algorithms.

Sensor / Method	Detection Target	AI Algorithm	Strengths	Limitations	Maturity / Readiness Level	Scalability
Plasmonic-based Raman Sensor	Pharmaceutical residues, pollutants	ML for signal analysis	Ultra-sensitive, fast detection, label-free	High cost, requires trained personnel	Experimental / Early adoption	Moderate (requires specialized equipment)
Electrochemical Sensors	Heavy metals, toxins	ML / Pattern Recognition	Portable, low cost, real-time	Limited selectivity, interference-prone	Pilot / Field trials	High (can be mass-produced)
Vibrational Spectroscopy (IR, NIR, Raman)	Mycotoxins, food contaminants	DL, Chemometrics	Non-destructive, multi-analyte capability	Requires large datasets, complex preprocessing	Mature / Commercial	Moderate to High
Chromatography coupled with MS (LC-MS, GC-MS)	Broad chemical targets	AI for peak deconvolution, predictive modeling	Highly accurate, widely accepted	Expensive, time-consuming, lab-bound	Mature / Standard	Low to Moderate (lab-dependent)
Biosensors (enzymatic, immuno-based)	Pathogens, toxins, metabolites	ML / DL for pattern recognition	High specificity, rapid response	Limited shelf-life, environmental sensitivity	Pilot / Early adoption	Moderate

Recent advances in sensor technologies have broadened the toolkit available for chemical and environmental detection, each with distinct advantages and limitations that influence their suitability for specific analyte targets and operational contexts.

Surface-enhanced Raman spectroscopy (SERS) and related plasmonic Raman sensors offer ultra-sensitive, label-free detection by amplifying Raman scattering signals at plasmonic nanostructures. These sensors can detect molecular fingerprints with exceptional sensitivity, making them highly effective in laboratory analyses of trace analytes and pathogens. However, the requirement for precisely engineered plasmonic substrates and specialized instrumentation typically limits their widespread, field-based deployment due to high cost and the need for expert operation [46].

Electrochemical sensors provide a low-cost, portable, and real-time monitoring solution for heavy metals, toxins, and other analytes in environmental matrices. These devices (e.g., voltammetric and potentiometric platforms) can quickly quantify target species with minimal sample preparation, and advanced nanomaterial-modified electrodes substantially improve sensitivity and lower detection limits. Real-time electrochemical monitoring of heavy metal ions in water has been demonstrated with limits of detection in the low µM to fM range, demonstrating their utility for field applications. However, in complex environmental matrices, selectivity can be compromised by interfering species [47].

Vibrational spectroscopy techniques such as mid-infrared (IR), near-infrared (NIR), and Raman spectroscopy enable non-destructive, multi-analyte analysis. These methods can characterize complex chemical mixtures without extensive sample preparation, and their analytical performance is increasingly enhanced by DL and chemometric algorithms that improve spectral interpretation, deconvolution, and classification. Advances in AI-assisted spectral analysis are expanding the scalability and robustness of vibrational techniques across food safety, environmental monitoring, and pharmaceutical quality assessment [48].

Chromatography coupled with mass spectrometry (LC-MS, GC-MS) remains the gold standard for broad-spectrum chemical detection due to its unmatched accuracy, reproducibility, and ability to separate complex mixtures. Techniques such as LC-MS and GC-MS can quantify diverse organic and inorganic compounds at trace levels with high confidence, and are central to regulatory compliance and forensic analyses. However, these systems are inherently laboratory-based, time-intensive, and resource-heavy, requiring careful sample preparation, skilled operators, and lengthy analytical runs [49].

Biosensors leverage biological recognition elements (e.g., enzymes, antibodies, aptamers) to detect pathogens, metabolites, and environmental toxins with high specificity and rapid response. Their integration with signal transduction mechanisms (electrochemical, optical, or piezoelectric) enables sensitive detection in minutes, and AI algorithms can further enhance specificity and interpretive performance. Still, biosensors often suffer from environmental sensitivity, limited shelf life, and stability issues, especially under variable field conditions [50].

In summary, while ultra-sensitive Raman and plasmonic sensors excel in laboratory settings and chromatography–MS provides the highest analytical rigor, electrochemical and vibrational spectroscopy platforms offer portability and rapid response with evolving AI support. Biosensors bring fast, specific detection but require improved durability for widespread environmental applications. Choosing the most appropriate analytical method depends critically on target analyte, required sensitivity, throughput demands, environmental complexity, and operational constraints, emphasizing that no single technology is universally superior across all contexts.

5. AI-based Resource Recovery Application

Since the time when AI was considered a theoretical tool, it is no longer that but the game-changer within the realm of resource recovery and circular economy. The combination of ML, DL, and sensor data fusion makes AI more efficient, selective, and scalable in terms of water and wastewater treatment, energy conversion, critical material recycling, polymer recovery, and biomass valorization, among others. The integration of these technologies makes convergence possible to optimize in real time predictive maintenance and data-driven sustainability in the recovery process across the multiple processes.

5.1 Lost Nutrients Rehydration

Restoration of key nutrients, especially nitrogen and phosphorus, is crucial to sustaining the global nutrient cycle and reducing the chance of eutrophication. Combining AI with high-frequency sensors will result in precise real-time monitoring of nutrient loads and active optimization of recovery mechanisms, including increased biological phosphorus removal and struvite precipitation, and reduced chemical utilization and operation costs [50].

Predictive models based on AI also enhance the forecasting of micropollutant loads, which allows optimizing processes and increasing their efficiency [51]. This integration of Raman and FTIR spectroscopy and ML enables accurate detection of heavy metals and microplastics, lowering the occurrence of false positives and enabling the diversion of contaminated effluents to hydrometallurgical extraction on time [52]. The combination of these methods makes the wastewater treatment systems better in terms of nutrient cycling and environmental protection.

5.2 Energy Recovery and Conversion

The use of AI has taken center stage in biogenous energy generation, particularly in predicting and optimizing outputs such as biogas, hydrogen, and biodiesel. Advanced ML methods including artificial neural networks (ANNs), ensemble learning, and recurrent architectures have been shown to outperform traditional regression models in forecasting methane yields and co-digestion performance in anaerobic digestion systems. For example, AI models achieve higher predictive accuracy by capturing nonlinear interactions among operational variables, enabling more reliable estimation of methane production and early detection of process instabilities, which enhances both stability and conversion efficiency [53]. Coupled with digital twin frameworks, these AI models integrate real-time sensor data (e.g., pH, oxidation–reduction potential (ORP), and gas composition) to enable dynamic optimization and predictive maintenance of anaerobic digesters, minimizing downtime and improving overall process resilience [54].

In the biodiesel production process, AI and statistical learning tools are increasingly used to screen catalysts, model complex reaction pathways, and optimize key process parameters such as methanol-to-oil ratio, temperature, and catalyst concentration. Such AI-assisted optimization approaches have demonstrated significant gains in process efficiency and product yields in recent studies, leading to improved biodiesel conversion with reduced experimental overhead and energy inputs [55]. These applications illustrate how AI can play a pivotal role in advancing renewable energy systems by improving process predictability, enhancing operational efficiency, and helping to minimize the carbon footprint of biochemical energy production.

5.3 Extraction of Vital Substances and Metals

E-waste and second-hand batteries, which are major priorities in meeting the aims of a circular economy, are being recycled using AI-driven technologies and are now used to retrieve rare-earth elements (REEs) and strategic metals. Machine-learning-based models automate the characterization of feedstock with speed and precision by combining X-ray fluorescence (XRF) images and multisensor readings, which reduces processing times and enhances classification success of high-value materials more than tenfold [56].

Explainable AI (XAI) is used to predict leaching efficiency in hydrometallurgical extraction depending on the surface characteristics of the particles, including the presence of binders and morphology, enhancing scalability and compliance with regulations [57]. In addition, AI-assisted computational screening supports the identification of selective extractants used in the separation of REE to enhance recovery performance and reduce the amount of waste reagents [58]. These developments increase the economic and environmental sustainability of metal recovery pathways.

5.4 Recycling Plastic and Polymer

AI has dramatically transformed the processing of plastic waste by automating polymer identification and sorting. Techniques such as near-infrared (NIR) and hyperspectral imaging, often combined with deep convolutional neural networks (CNNs) or other machine-learning models, can classify and separate different polymer types with high accuracy, significantly reducing contamination and increasing the purity of the recyclate stream in recycling operations [59].

AI-enhanced spectroscopic methods are increasingly capable of identifying and quantifying microplastics (MPs) and nanoplastics (NPs) in aquatic environments, enabling early environmental diagnostics and more effective pollution monitoring. For example, ML models applied to Raman spectroscopy data have achieved high accuracy in distinguishing nanoplastics from other particles in water samples, demonstrating the potential of AI-assisted spectroscopy for environmental monitoring of plastic pollution [60]. Such smart sorting and detection systems can assist with data-driven remediation approaches and can also promote closed-loop recycling models to minimize plastic accumulation in the natural ecosystems.

5.5 Food Systems, Agriculture, and Biomass Valorization

AI-aided feedstock characterization and bioprocess optimization continue to become more and more instrumental in the valorization of biomass and agricultural residues into high-value bio-products proteins, lipids, phenolics, etc. The machine-learning algorithms determine the best microbial strains and enzyme systems to use in their fermentation process, and biosensors coupled with the soft-sensor models determine the concentrations of metabolites in real time [61].

Digital twins optimize and simulate biorefinery pathways, which shorten the time-to-market of bio-based products and processes by means of decentralization in line with the principles of the circular economy [62]. In the agricultural field, AI-empowered decision support systems can be used to monitor nutrients in soil and crops in real time to enhance precision in fertilizer and irrigation management, improving productivity while minimizing eutrophication and soil erosion [63,64]. These compound applications underscore the importance of AI in ensuring the existence of nutrient loops and sustainable agri-food bioenergy systems.

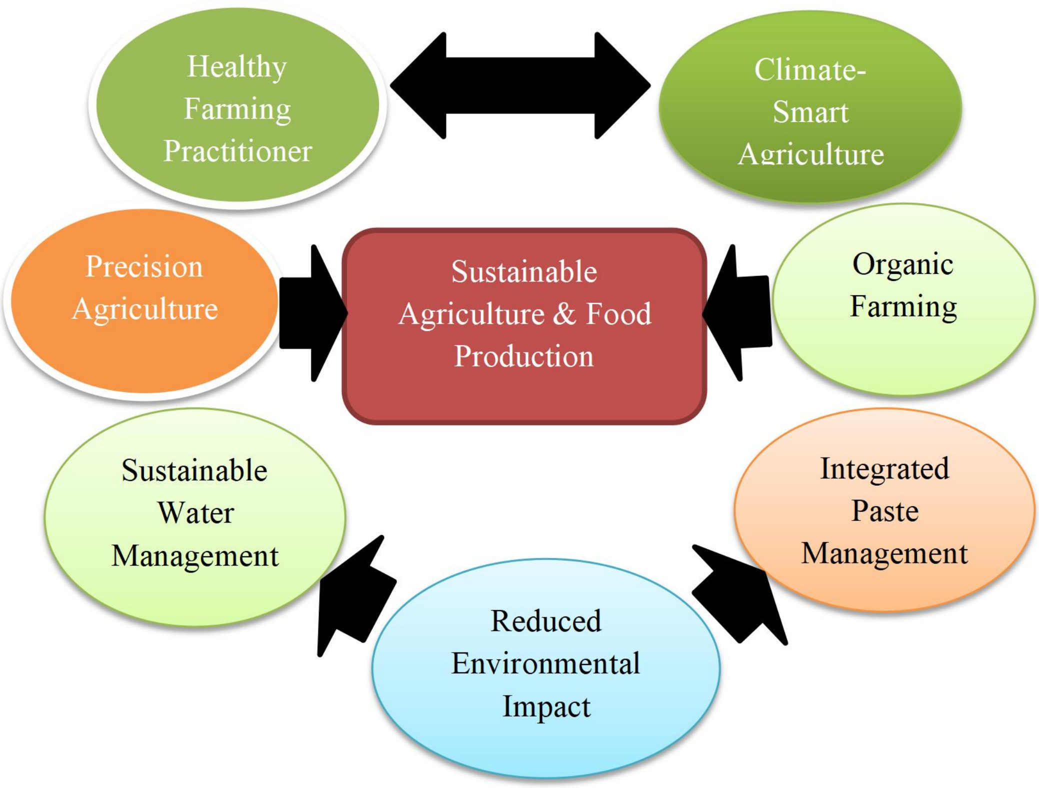

Figure 2. Integrated approaches in sustainable agriculture and food production.

This illustrated how the various components interacts within a unified sustainability framework, Figure 2 presents an integrated conceptual model of sustainable agriculture and food production. The figure synthesizes the major approaches discussed, including agroecology, precision agriculture, climate-smart agriculture, organic farming, and circular bioeconomy strategies, showing how each contributes to resilient and environmentally responsible food systems. By visually linking these approaches, the figure provides a clearer understanding of their interconnected roles and reinforces the conceptual flow of the discussion.

5.6 AI Energy Demand Paradox

While AI-enabled chemistry and environmental monitoring offer transformative capabilities, they also introduce a significant energy demand paradox. Advanced AI models, particularly DL and large-scale predictive algorithms, require substantial computational resources, leading to increased electricity consumption and associated carbon footprints [65,66]. This creates a tension between leveraging AI for sustainability and inadvertently exacerbating environmental impacts. To mitigate this paradox, several strategies can be employed. Federated learning enables distributed model training across multiple local devices, reducing reliance on centralized, energy-intensive data centers. Low-power hardware, including application-specific integrated circuits (ASICs) and energy-efficient GPUs, can significantly lower the electricity footprint of AI computations. Additionally, Green AI architectures, which prioritize energy efficiency alongside model accuracy, allow optimization of AI workflows to reduce computational overhead [66]. Despite these strategies, trade-offs remain: reducing computational intensity may limit model complexity, predictive accuracy, or real-time capabilities, whereas maximizing model performance often increases energy consumption. Careful balancing of AI performance with sustainability goals is therefore essential, guiding the development of energy-conscious AI solutions that align with broader environmental objectives [65-67].

6. Thematic Cross-Cutting and Operational Problems

AI-enabled recovery systems in circular economy and sustainable agriculture are complex, multidimensional, and interdependent. The interplay between data systems, physical processes, and human-machine interaction introduces both opportunities and challenges that must be addressed for scalable, sustainable impact.

A visual framework illustrating these interconnections shows a farmer using digital tools to monitor crops, symbolizing data-driven and precision agriculture. In this figure, plants and livestock represent primary production, while the factory denotes agro-industrial processing and value addition. The upward arrow indicates growth in productivity, and the bowl of fruits and vegetables signifies healthier nutritional outcomes. Together, these elements highlight the integration of farming, technology, livestock management, and food processing towards achieving sustainability across the agricultural and food supply chain.

AI-enabled recovery systems are characterized by several cross-cutting and operational challenges that define their performance and long-term viability:

6.1 Real-Time Decision-Making

AI systems are increasingly capable of dynamic waste-stream rerouting, separating nutrient-rich fractions for struvite recovery or directing metal-rich flows to hydrometallurgical extraction. These adaptive systems rely on continuous sensor feedback and predictive analytics to maintain optimal process efficiency [68].

6.2 Integration of Physics-Informed and Data-Driven Models

Hybrid modelling strategies combining first-principles simulations with machine-learning models can improve the extrapolation of predictions to new or unlabelled feedstocks. This approach helps overcome data scarcity issues while retaining physical interpretability in process modelling [69].

6.3 Edge AI and Decentralization

The adoption of low-power, embedded AI systems enables localized decision-making in resource-constrained or remote environments. Edge-AI architectures enhance responsiveness by processing sensor data in real time without relying on continuous cloud connectivity, thus supporting decentralized resource recovery and autonomous plant operation [70].

6.4 Scalability, Standardization, and Interoperability

Widespread implementation of AI-driven recovery systems depends on standardized data formats, open datasets, and transfer-learning frameworks. However, current global efforts remain fragmented, with inconsistent metadata and limited cross-platform compatibility. Advancing interoperability standards and open-access databases will be crucial for ensuring transparency, replicability, and global adoption of AI-based recovery technologies [71].

Table 2. Representative experimental studies.

Application Area	Sensors / Techniques	AI Approach	Results
Water & Wastewater Treatment	Electrochemical sensors, optical probes, biosensors	Neural networks, support vector machines, DL	Enhanced detection of nitrogen and phosphorus species; automated identification of microplastics
Energy Recovery	Gas sensors, bioreactor monitoring systems	ML regression, reinforcement learning	Optimized methane and hydrogen yields; predictive control of anaerobic digestion processes
Critical Materials & Metals	LIBS, ICP-MS, XRF, electrochemical sensors	Random forests, deep convolutional networks, high-throughput AI models	Improved efficiency in recovering rare-earth elements, lithium, and cobalt from electronic waste
Plastics & Polymer Recycling	Hyperspectral imaging, FTIR sensors	Convolutional neural networks, computer vision	Automated sorting of polymers; real-time quantification of microplastics
Food, Agriculture, Biomass	Biosensors, fermentation probes, optical sensors	Bayesian ML, long short-term memory (LSTM) networks	Accurate fermentation monitoring; increased yield of proteins and bioactive compounds

Source: authors compilation

As shown in Table 2, several cross-cutting trends emerge across diverse application areas. In water and wastewater treatment, AI methods such as neural networks and SVMs significantly improve pollutant detection and microplastic profiling by enhancing the interpretive power of electrochemical and optical sensors. For energy recovery systems, machine-learning regression and reinforcement-learning models enable optimized methane and hydrogen yields through predictive control of bioreactors. Studies on critical materials leverage high-resolution analytical chemistry tools LIBS, ICP-MS, and XRF coupled with DL and high-throughput models to accelerate recovery of lithium, cobalt, and rare-earth elements. In plastic recycling, the combination of hyperspectral imaging and CNNs enables robust polymer classification and microplastic quantification in real time. Finally, AI-integrated biosensors and optical probes in food and agricultural applications demonstrate measurable gains in fermentation monitoring and bioactive compound production. Collectively, these findings highlight the central role of AI-augmented analytical chemistry in enhancing precision, scalability, and automation across circular-economy-aligned processes.

7. Challenges and Limitations

The use of AI, sensor technologies, and analytical chemistry in resource recovery activities has important transformational potential; it is coupled with various technical, environmental, and ethical issues.

The first matter is that of reproducibility and standardization. According to Wright et al., [72], to train and validate AI models, significant, high-quality, and standardized datasets are required. However, data in chemistry and process monitoring are frequently heterogeneous, partial, or poorly described. This inconsistency compromises laboratory-to-laboratory transferability and model generalizability. Even though these issues can be alleviated by the adoption of the FAIR principles (Findable, Accessible, Interoperable, Reusable), its application in laboratories is not uniform [73].

Interpretability is another burning issue. Nguyen et al., [74] indicate that the popularity of the black-box AI models in chemical and environmental settings reduces user confidence because users cannot understand how they are internally reasoned. Neural models that combine mechanistic models with machine-learning algorithms have proven to be more interpretable and more useful in process design and monitoring.

Thirdly, there is still a concern about energy use and environmental impact. Strubell et al. [70] made the argument that the process of training large transformer-based AI models has the potential to produce carbon dioxide comparable to that of several passenger vehicles throughout their lives. Sheikh et al., [71] also noted that the high energy requirements are not only during training but also when they are in interference, especially when there is continuous industrial activity. This paradox was emphasized by [72], who used the example of AI technologies aimed at increasing sustainability but compromising environmental objectives by their computational power. The solutions suggested by [75] to reduce these energy pressures include green AI architectures, low-power inference models, and edge-computing models.

Lastly, one should not disregard ethical and governance issues. Wright et al., [72] highlights the unsettled issues of algorithm bias, privacy of data, and accountability in automated environmental decision-making. Lax regulation and a lack of governing systems increase the chances of abuse by large technology players, which could undermine the contribution of AI to sustainability transitions.

All these restrictions demand a multidisciplinary approach to come up with transparent, explainable, and energy-efficient AI systems. The creation of open-data environments, the enhancement of metadata quality, and the incorporation of human control in AI-assisted resource recovery will play a very important role in achieving sustainable technological ecosystems.

8. Future Perspectives

The AI systems of the next generation will transform the entire concept of resource recovery and analytical chemistry into a new era of unprecedented automation, accuracy, and sustainability. Recent advances in transformer-based architectures, deep generative models, and foundation models will bring to life the synthesis of multimodal data and multimodal pattern recognition in spectroscopy, chromatography, and sensor arrays [73]. Further on, the application of XAI principles will contribute to addressing the lack of transparency inherent to black-box algorithms [74,76].

Another paradigm shift is the emergence of automation and self-driving laboratories (SDLs). The AI-powered robotic systems can autonomously design the experiments, optimize the workflow, and modify the parameters of a process, as shown by [77]. Such systems, in the context of resource recovery, can transform the screening of catalytic reactions, the bioconversion of microbes, and the optimization of separation methods and radically lower time-to-insight and operation costs.

Innovation is also likely to be faster in the context of emerging paradigms of computerization, including quantum computing and edge AI. Quantum ML, which is defined by Snappet al. [78], is capable of solving complex chemical problems, such as the estimation of the adsorption energy of molecules and reaction pathways, with reduced computational efficiency. Simultaneously, edge AI will provide low-energy computations on the interface with the sense to monitor autonomously and in real time the biomass valorization, e-waste, and agroecosystem health [79].

The extension of these innovations to emerging economies is an urgent requirement. Implementation is limited by infrastructure shortages, lack of computational resources, and skilled labor. Nonetheless, the digital and AI-driven recovery platforms can be democratized, which constitutes a special chance to empower a local community, minimize environmental pollution, and tackle the problem of nutrient loss in a sustainable fashion. Finally, the AI introduction to the recovery of the resources will not only consolidate the structures of the circular economy but also provide equity, resilience, and ecological stability at the global level.

9. Policy Implications

AI-enabled chemistry offers significant opportunities to enhance regulatory compliance and environmental safety, complementing initiatives by UNEP, OECD, and the EU. For instance, AI-driven predictive models can accelerate chemical hazard assessment and support real-time monitoring, aligning with OECD guidelines on chemical risk evaluation and UNEP frameworks for sustainable chemical management [80]. However, current policies often lag behind technological advances, leaving gaps in areas such as AI transparency, data validation, and model interpretability [81,82]. Addressing these gaps through adaptive regulatory frameworks would facilitate the safe integration of AI tools while ensuring accountability and environmental protection. Incorporating AI into policy considerations also opens avenues for proactive risk mitigation and sustainable chemical design, enhancing the relevance of regulatory initiatives in a rapidly evolving technological landscape.

To fill these gaps, the future policy-making processes must introduce validation standards of AI models and formally acknowledge the use of validated AI-operated monitoring instruments and encourage adaptive, iterative policies that can adapt as technologies change. The encouragement of cross-border data-sharing efforts can also make AI models stronger and make them regulatory-relevant. The explicit incorporation of AI into the chemical and environmental regulation could enhance the state of environmental protection, create a sustainable future of chemical innovation, and ensure rigor and credibility of regulatory control.

10. Conclusion

There is a rapid shift in the use of AI in the creation of sensors and analytical chemistry in the process of recovering the resources. This has already initiated a resource endowment of processes, such as signal interpretation of insight, predictive modelling, and process optimization, that have already begun to offer unparalleled performance metrics in the nutrient, metals, polymers, and value-added biochemicals identification, tracking, and recovery. The current trend towards digitalization of laboratory and industrial systems in the spheres of spectroscopy, chromatography, and electroanalysis also contributes to that. The realization of the full potential of AI in the field involves the expertise of different disciplines. To eliminate the barriers associated with data standardization and reproducibility, chemists, engineers, data scientists, and policymakers should collaborate to do so and also guarantee that the AI-related applications meet regulatory standards. The key principle of this work is a firm position of sustainability and ethical use of data. The AI models that are powerful must have an amalgamation of domain knowledge as well as computational intelligence; the two support broader objectives of circularity, which include the production of resilient, efficient, and environmentally friendly recovery planning; sensitivity in material loops; clean production; and global sustainability platforms. More research in the field of multidisciplinary practice, along with the development of digital infrastructure and open-access platforms, is likely to positively influence the technological impacts of such innovations on the world and the planet indirectly.

Conflict of Interest

The authors declare that there are no conflicts of interest.

Generative AI Statement

The authors declare that no generative artificial intelligence (Gen AI) tools were used in the creation of this manuscript.

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