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Research Article

# Analytical assessment of green AI architectures for advancing sustainable resource use in circular economies

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**ABSTRACT**

This We present a concise analytical write-up focusing on green AI architectures and sustainable resource use in circular economies. Two chenges in the transition to a circular economy are insufficient resource efficiency and sustainability assessment of decisions affecting resource use. AI-enabled solutions can contribute positively but often with energy and emissions costs that undermine their ecological value. The analytical lens examines green AI architectures that avoid, minimize or counterbalance adverse energy, data, and life-cycle sustainability impacts.

The idea behind the circular economy is to use as few resources as possible and keep and recover as many materials as possible in socio-technical systems. It works by using closed-loop systems, product designs that make it easy to take things apart, and service models that make products last longer. The end goal is to separate economic growth from the use and depletion of natural resources. Encouraging the effective use of resources makes it easier to put circular economy ideas into action and speeds up the shift to fully circular production systems. The main goal of resource circularity is to close the material loop by efficiently getting valuable resources back through processes like extraction, collection, recovery, recycling, reproduction, and remanufacturing. Even though AI doesn't directly help, its impact on these processes is both big and life-changing.

## 1. INTRODUCTION

Currently, the discourse regarding sustainability-driven artificial intelligence and its connection to the circular economy predominantly exists within a conceptual and theoretical context. Even though this is still a new idea, using AI in circular economy projects has a lot of potential for future growth and new ideas. The move toward a circular economy model requires complicated, systemic changes that are meant to greatly improve how well resources are used[2]. These changes include a wide range of practices that affect how materials are used and how energy and water are used in all areas. This change needs more than just cutting down on consumption; it also needs finding new ways to do things and coming up with new ideas that can take the place of old systems[3].

These kinds of changes put a lot of stress on AI-enabled information and management systems. They require changes to current industrial and organizational practices to fit with new economic and environmental models. Numerous case studies provide empirical evidence of the vital and transformative role of green AI in enhancing material and energy efficiency in industries directly associated with circular economy principles[4]. These studies show real progress, such as AI-enhanced recovery and sorting of construction materials that encourage reuse and cut down on waste, the use of smart manufacturing systems that improve production forecasts and operational performance while cutting down on lifecycle waste, and the creation of advanced strategies that make it easier to reuse water and raw materials across supply chains. These applications demonstrate how technology-driven strategies can be effectively utilized to achieve sustainability outcomes aligned with the objectives of the circular economy[5][6].

### 1.1. Research Problem and Gap

While scholarly and professional interest in sustainable artificial intelligence has been progressively growing, current research predominantly focuses on discrete elements, such as improving algorithmic efficiency, minimizing computational

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energy consumption, or tackling ethical dilemmas. There are only a few studies that have tried to create a comprehensive analytical framework that links green AI architectures to measurable outcomes of the circular economy, such as resource circularity, lifecycle performance, and the connections between data and energy use. Moreover, sustainability indicators are frequently regarded as ancillary factors rather than being integrated into the core design of AI systems.

This disjointed view makes it hard to fully understand how certain architectural setups, like energy-efficient models, data-efficient learning paradigms, and designs that focus on the whole lifecycle, can all work together to make materials and resources more circular. The primary research problem examined in this paper pertains to the absence of a cohesive analytical framework that evaluates how various green AI architectures promote sustainable resource utilization within circular economic systems. To address this gap, the study suggests a systematic mapping of essential architectural patterns, assesses their inherent trade-offs, and recognizes their potential synergies with the principles of the circular economy.

## 1.2 Research Methodology and Scope

This study employs a conceptual-analytical review methodology that amalgamates a critical analysis of current literature with thematic synthesis to investigate how the development of Green AI architectures improves resource efficiency and sustainability in circular economy (CE) systems. The methodological design comprises three interrelated stages:

Conceptual Mapping: figuring out what the main types of Green AI are and putting them into groups. These types are energy-aware, data-efficient, lifecycle-integrated, and explainable architectures.

Comparative Evaluation: examining the trade-offs, interconnections, and sustainability consequences of these paradigms in the context of Circular Economy principles, including resource circularity, lifecycle optimization, and waste minimization.

Integrative Synthesis: developing a cohesive analytical framework that reveals the synergies between AI architectural design and the resource loops intrinsic to circular economic models.

The study predominantly analyzes peer-reviewed publications and technical reports published from 2021 to 2025, emphasizing recent advancements in energy-efficient machine learning, federated and distributed learning systems, AI-driven lifecycle assessment, and transparent circular supply chain management. Instead of concentrating on empirical experimentation, the review methodically examines theoretical foundations, architectural advancements, and their extensive ramifications for sustainability.

This methodological framework seeks to offer a comprehensive insight into how design choices in AI architectures can promote or obstruct the creation of circular resource flows. This establishes a foundation for subsequent frameworks that implement Green AI within the framework of circular economies, as depicted in Figure 1

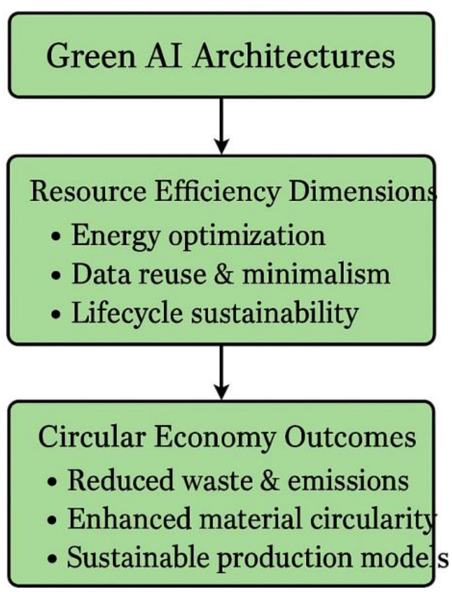


Fig. 1. Conceptual integration framework linking Green AI architectures with Circular Economy principles

Figure 1 shows how the proposed conceptual framework shows how Green AI architectures interact with important aspects of resource efficiency to create real results in the circular economy. This framework serves as a fundamental reference for the ensuing analytical discourse, directing the interpretation and integration of subsequent findings.

## 2. THEORETICAL FOUNDATIONS OF GREEN AI AND CIRCULAR ECONOMY

Green AI is a group of strategies and practices that aim to reduce the negative effects of AI systems on the environment. The main goal is to make AI models more energy- and data-efficient while taking into account the entire process of development, deployment, and operation. The circular economy is a promising way to make things without harming the environment even more, as the climate crisis and digital expansion put more pressure on global resources. Because extracting materials and making things are two of the most important ecological limits, sustainable progress needs not only better circularity but also more efficiency in non-circular material flows. Despite the increasing popularity of the idea of circularity, it is still not fully understood and is still not fully formed. In this context, AI can greatly improve how efficiently resources are used, making it a key part of circularity [6]. So, it's both timely and necessary to pay close attention to the link between Green AI and material circularity.

The main idea behind a circular economy is to keep resources and materials moving around all the time. Circular models, on the other hand, try to get rid of waste by recovering, regenerating, and reintegrating materials into the value chain. This keeps resource loops going. Resource circularity refers to the continuous recirculation of materials, whereas material or product circularity pertains specifically to the persistent flow of physical goods within economic systems. In this context, the European Union taxonomy provides definitions and objectives for environmentally sustainable activities, while new paradigms focus on separating economic growth from resource use by improving ways to reuse and recover resources [5].

Different architectural styles that help with sustainability can be grouped into three main areas of resource efficiency: energy, data, and product lifecycle. Every category is important for reaching circularity and encouraging sustainable technological progress [7].

Machine learning that focuses on sustainability stresses making model architectures that use less computing power and energy. This is an important step in separating AI innovation from increasing resource use. To balance system performance with environmental cost, research, training, and deployment all focus on low-energy setups. Designers can use hardware-software co-optimization strategies by looking at energy profiles during both the training and inference phases. This lets them build sustainability constraints directly into model development. A lot of different optimization methods have been suggested to make models more energy efficient, including pruning, quantization, and lightweight architecture design [8].

## 3. DATA-EFFICIENT LEARNING AND FEDERATED APPROACHES

Sustainable AI promotes the minimization of data collection and storage, aligned with circularity objectives. Continual learning allows further adaptation without retraining on existing data. Privacy-preserving federated learning addresses confidentiality concerns by keeping data on-site, and transferability generates reasonable models across different environments with minimal new data [9].

Lifecycle assessment and explainability

The incorporation of life-cycle assessment (LCA) with model training assists in measuring, visualizing, and optimizing AI system sustainability, supporting the transition to circularity. Sustainability-oriented AI requires a clear explanation of how optimization contributes to sustainability, enabling informed decision-making at each iteration and fostering accountability, transparency, and trustworthiness [10].

### 3. 1 Energy-aware model design

Two approaches contribute to delivery efficiency in hardware-level design: low-energy architecture and hardware-software co-design. Enabling core energy-efficient architectures—such as intermittent, voltage-scaling, and dynamic-reconfiguration circuits—for long inference time within a given energy budget, model choices such as compact model over-provisioning or AI accelerators support energy-efficient inferences [8]. Supporting an understanding of training/inference energy profiles facilitate the establishment of explicit optimization objectives. Such awareness permits dedicated architectural adaptations and selection of training objectives that address energy consumption [7].

Interoperability at the hardware-software boundary advances effective channel utilization during AI workloads and supports frameworks for energy-management techniques balancing accuracy and energy consumption. Energy-efficiency trade-offs between training techniques, e.g. pruning, quantization, and cluster learning, for temporal-coherence or sparsity already feature in end-to-end frameworks but are not yet connected to actual energy-consumption estimation.

### 3. 2 Data-efficient learning and federated approaches

In artificial intelligence (AI), the need for large datasets and effective, condition-agnostic model updates makes data efficiency a major objective. In the real world, there are often only a few samples available, which leads to the use of data minimization methods like semi-supervised learning. AI systems also get data on a regular basis, which means they can keep learning without being held back by what they already know. The study of data-efficient AI is progressing rapidly, highlighting its interaction with alternative architectural paradigms [11].

Federated learning is especially important because it tries to improve models while keeping data private, or, more generally, not knowing anything about the dataset. Interest in this area has grown a lot, especially when it comes to apps for mobile phones. Transferring data usually needs a lot of bandwidth, and in many cases, it's even impossible to transfer a model update. So, federated approaches not only help protect privacy, but they also cut down on data exchanges. Transferable updates take these ideas even further by letting people use knowledge in ways that are harmful to others at work or on their devices [12].

Substantial effort has concentrated on federated and continual learning frameworks, which often accommodate transfer learning. The move towards decentralised data designs responds to the complexity of modern datasets, especially at large scales. AI deployment grammars can now encompass multi-context systems that model information at different levels or values across different locations [13].

Specific materials circularity outcomes, including the invisible configuration, traceability of components along supply chains, order fulfilment across geographic distributions, and patient recruitment, lend themselves to federated and ongoing updates. Research already exists that optimises distribution-scale deliveries across countries while transferring knowledge from one customer base to another, an approach that also contributes to the resource allotment of brands and logistics.

## 3. 3 Lifecycle assessment and explainability

Lifecycle assessment (LCA) should be integrated into model development to ensure that resource consumption and environmental impacts beyond mere task performance are considered. An LCA quantifies the overall resource use and emissions associated with the creation and operation of a model and helps to identify the best trade-offs, potentially leading to an improved sustainability profile of all products and services that rely on the model. Explainability requirements should also incorporate a sustainable-development aspect to capture whether and how the use of the model contributes to the longer-term sustainability of individual products/services and society at large. Explanations of model predictions should provide insights into how and why a model influences the consumption of critical resources, energy use, waste generation, and pollutant emissions; such insights, in turn, enable improved decision-making throughout product/service lifecycles [14].

AI for improving resource efficiency in circular-economy concepts and processes is increasingly prominent, with growing evidence supporting the emerging discourse. A collection of green-AI architectural patterns promotes this application domain by improving resource sustainability, supporting circular-economy principles like closing loops, lowering overall demand, and speeding up service delivery for products and services. Still, it's important to carefully think about the trade-offs between performance, energy use, data use, and environmental impact. Evaluating and tackling these issues earlier in the architecture-design process—preferably during the model-design phase—will facilitate the pursuit of circular-economy resource-efficiency goals in conjunction with conventional performance targets, thereby enhancing sustainability outcomes [4].

Adding AI to material-recovery processes has a big and positive effect on getting back a lot of materials, like plastics and metals. On the other hand, AI helps close loops and reduce resource use and the environmental effects that come with it by making it possible to track and improve the management of circular supply chains. AI-enabled smart-manufacturing processes and production-scheduling methods that accurately forecast product demand are increasingly demonstrating their potential for circular-economy applications especially when efficiently allocating resources and limiting undesirable impacts such as production waste [4]. As shown in figure 2.

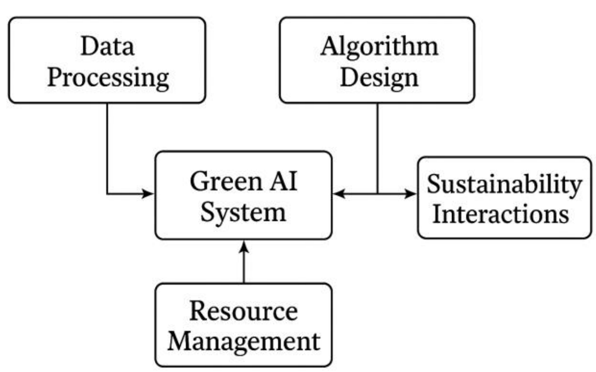


Fig. 2. Core architectural components and sustainability interactions in Green AI systems

The interconnections among core architectural components in Green AI systems are visualized in Figure 2. The figure highlights how data processing, algorithm design, resource management, and sustainability interactions collectively shape an environmentally responsible AI framework.

## 4. GREEN AI IN RESOURCE CIRCULARITY: CASE STUDIES

The potential of artificial intelligence (AI) as a supporting technology to achieve the transition towards a circular economy has gained much attention recently [5]. Circular economy principles aim to restore and regenerate products, components, and materials back to the productive economy and preserve their value for as long as possible [15]. Therefore, the analysis highlights three case studies of green AI architectures explicitly focusing on resource efficiency, in line with the objectives of the international consensus on the circular economy.

AI-enabled material recovery and sorting facilitate high electro-optical sorting for construction and demolition waste, which helps to increase the recovery rate significantly from the current 5% to better than 50% and improves the energy efficiency. AI systems for production scheduling based on machine-learning-enabled demand forecasting support a smart manufacturing initiative to reduce excess production and improve schedule accuracy. However, a trade-off between forecast accuracy and model energy consumption has to be dealt with to keep the over energy-kilogram saved ratio above 0.25 for continuous energy management over seven days. AI-enabled traceability and transparency for products and materials within circular supply chains support logistics operations by optimizing inventory and routing. Simulation results indicate that the inventory optimization has a capacity of 40% space reduction and that the optimized routing is approximately three times shorter than the baseline solution; performance within the large-scale scenario remains similar.

TABLE I. COMPARATIVE ANALYSIS OF GREEN AI ARCHITECTURAL APPROACHES AND THEIR CONTRIBUTIONS TO CIRCULAR ECONOMY PRINCIPLES

| **Architectural Approach** | **Core Principles** | **Strengths** | **Limitations / Trade-offs** | **Contribution to Circular Economy (CE)** | **Key References** |
|---|---|---|---|---|---|
| **Energy-aware model design** | Focuses on minimizing power consumption through efficient architectures, hardware–software co-design, and low-energy inference. | Reduces carbon footprint; enhances computational efficiency; compatible with existing AI pipelines. | May sacrifice accuracy or performance; requires costly hardware adaptation. | Promotes *energy circularity* by decoupling AI growth from energy use. | [7], [8] |
| **Data-efficient learning** | Employs semi-supervised, continual, and federated learning to minimize data collection and storage. | Reduces data redundancy; enhances privacy; lowers bandwidth and storage demands. | Potential loss of model generalization; high initial coordination cost. | Supports *information circularity* by optimizing data reuse and minimizing waste. | [9], [12], [13] |
| **Federated and decentralized learning** | Enables distributed training without centralizing data, improving data sovereignty and local resource use. | Increases user privacy; reduces data transfer; supports localized optimization. | Energy costs per node can be high; synchronization overhead. | Facilitates *distributed resource optimization* and localized circular processes. | [12], [13] |
| **Lifecycle assessment (LCA)–integrated models** | Embeds LCA into AI design and evaluation to measure environmental impact over the model's lifecycle. | Offers holistic sustainability insight; ensures transparency and accountability. | Data-intensive; lacks standardized metrics; complex to apply universally. | Enables *closed-loop evaluation* and environmentally responsible AI lifecycle management. | [10], [14] |
| **Explainable and accountable AI (XAI)** | Enhances interpretability of sustainability impacts and decision processes. | Improves trust, transparency, and decision quality; aligns AI with ethical CE values. | Complexity in modeling; may slow deployment. | Strengthens *ethical circularity* by linking accountability with resource governance. | [14], [15], [21] |
| **Smart manufacturing & demand forecasting models** | Integrates AI for predictive production and logistics optimization. | Reduces waste; improves material flow efficiency; supports agile circular supply chains. | Energy-intensive training; requires precise demand data. | Reinforces *material circularity* by optimizing production and reducing surplus. | [16], [17], [18] |
| **AI-enabled traceability and supply-chain transparency** | Uses AI to track materials and products through the entire lifecycle. | Increases visibility; supports reuse and recycling; reduces inefficiencies. | Implementation costs; interoperability challenges. | Promotes *loop closure* and resource recovery efficiency. | [4], [5] |

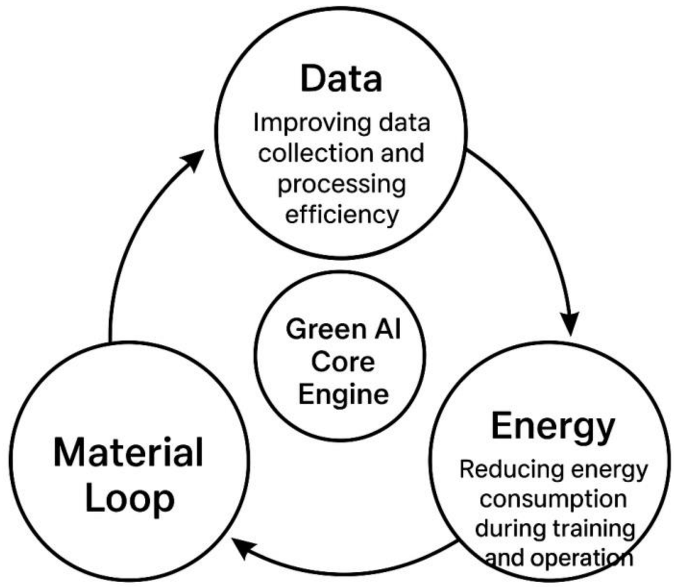


Fig. 3. AI-enabled circular resource flow integrating material, data, and energy loops

Figure 3 illustrates the AI-enabled circular resource flow that integrates material, data, and energy loops. The central "Green AI Core Engine" serves as the operational nexus driving sustainable resource optimization across all loops, forming the conceptual foundation for the subsequent case studies.

### 4.1 Material recovery and optimization

Most materials used by society today are non-renewable resources and their demand is expected to almost double by 2060 [16]. Implementing a circular economy based on reduction, re-use, repair, and recycling can mitigate looming supply shortages by extending the use of materials and recirculating output flows [5]. The global healthcare sector generates considerable amounts of waste—up to 25 percent of costs could be eliminated by removing it altogether—yet little attention is paid to waste eviation. Robotic disassembly, intelligent material sorting, and machine-learning-guided visual control play an important role in bolstering material recovery.

To support intelligent disassembly, automated and semi-automated sorting, and real-time visual inspection for disassembly and sorting, novel Embedded Visions Systems (EVS) are developed and incorporated into Flexible Robotic Cells (FRC) provided with TI-DNN compliant data sets. The formulation of a flexible robotic-based disassembly system is presented and its study framing is set, outlining the process's main requirements. The implementation of a hierarchical decision-level strategy combined with a Set-Input-Output-Place Petri Net graphical representation reflects the desired global functionality of the system and helps classify both hardware and software building blocks, also indicating their interconnections.

### 4.2 Smart manufacturing and demand forecasting

Smart manufacturing and demand forecasting present promising opportunities for improving resource efficiency in circular economies through AI-enabled systems. The ever-increasing demand for customization and reduced lead times has made it critical for manufacturing companies to fine-tune their production and inventory planning. Statistical-forecasting methods are often unable to cope with the short life cycles of Industrial Internet of Things products, while deep-learning models have the potential to extract value from historical data by integrating heterogeneous time series at multiple time scales. However, deep-learning methods typical have high associated energy costs, with deep-learning models consuming 8.5 times more energy for a 22% higher operational performance compared to traditional macro-models [17].

In materials recovery facilities and waste-to-resource scenarios, machine-learning-based production scheduling can bring substantial improvements to waste reduction and the circular economy. Scheduling decisions require a plant-wide view to align with demand while reducing work-in-process inventory waste. Hybrid modeling can provide greater accuracy for short-term scheduling; illustrate the trade-offs between energy, additional accuracy, and model complexity; and enable diverse modeling strategies within a single structure with fewer state variables. Such models can then be combined with reinforcement learning and an accelerator algorithm to improve solution quality and convergence speed. [18]

### 4.3 Circular supply chains and logistics optimization

The increasing virtualization of supply chain systems provides new opportunities for circular supply chains, enabling process optimization and end-of-life traceability, thus facilitating reverse logistics and location-based reuse. To this end, AI plays a crucial role by improving demand forecasting accuracy, assessing product lifetime for replacement and reuse, and designing environment friendly and sustainable product alternatives [5].

It is very important to use the right protocols at each supply chain node to keep the quality of the products during location-based distribution and product reuse. Due to outside forces, rules, and government authorities, circular supply chain operations are very uncertain. For this reason, a supply chain network should be built with the goal of gradually lowering the costs of the circular economy, degradation, and replenishment. AI algorithms can make these kinds of complicated systems much more resistant to unexpected problems.

## 5. TRADE-OFFS AND GOVERNANCE

Green AI represents a transformative shift towards more environmentally friendly principles and practices in artificial intelligence (AI) [15]. In urban cultures, material cycling is important for keeping healthy biophysical stocks and flows of metals, industrial materials, nutrients, and organic matter as a good replacement. The literature acknowledges green AI solutions that have both direct and indirect impacts on circularity objectives. The gradual establishment of life-cycle assessment (LCA) standards for non-functional AI attributes aligns with green AI architectures and design principles, directing data and energy-efficient circular interventions [8].

Quantifying trade-offs among various, frequently conflicting, circularity objectives facilitates more informed decision-making. Trade-offs can show, for instance, energy–data recycling, hardware–software co-design, and safety–performance. AI growth might not be linked to regular punishments, which would encourage open-source, multi-use generative applications. More horizontal ecosystems have been created, and different goals in supply and demand models lead to design choices like making accurate forecasting more understandable.

### 5.1 Environmental cost accounting in AI systems

Artificial intelligence (AI) systems have considerable, yet often disregarded, environmental costs manifesting as greenhouse gas emissions and non-renewable resource consumption. These costs arise at three distinct stages: the design and development of AI models, the use of trained models in AI applications, and ultimately the provision of AI-related products and services to end users [15]. Each of these stages generates environmental burdens that are unique to the AI field. According to Zhao et al. [7] , 70% of total AI operation costs are linked to data processing, storage, and network transmission, raising critical sustainability concerns about the responsible design of AI systems.

AI-related emissions and resource use can be allocated between internally-used and externally-supplied components. A fair accounting approach might consider a model as a standard-one-and-zero tool. The hazards of AI designs are often visible through a knee-shaped curve in operational cost and pollution. Despite the sustainability pressure affecting the whole economy, the shadowed environmental burdens of AI persist, placing conundrums on academic intellect and enterprises.

### 5.2 Policy and standardization implications

Until recently, regulatory frameworks only covered certain areas or topics, which led to standards that weren't connected. A paradigm shift is happening, and the standards set by the International Organizations for Standardization (ISO) and the International Electrotechnical Commission (IEC) now reflect this. The European Union strategy also lists important things to do [19].

Interoperability standards are necessary for combining different solutions, but they have to deal with local use and changing data. The European Strategy pushes for a set of rules that everyone in the world can agree on for interoperable data. Policies about the data economy must make sure that users own and control their data.

Governance mechanisms are important for digital technology, but they aren't as advanced as the technology itself. Strategies for data governance have been around for a long time, but they have sped up in the last few years. The European Strategy lays out a plan for how to govern digital and AI technology [20].

## 6. EVALUATION FRAMEWORKS AND METRICS

Artificial Intelligence (AI) as it is used today needs a lot of energy, data, and other resources. We need ways to keep an eye on how these resources are being used and what effect they have on the environment. Putting sustainability metrics like energy, data, and lifecycle resource use into AI systems lets designers and modelers go for greener options [8]. Deep AI benchmarks and thorough audit trails that explain why design choices were made, how they affect usage, and what other models could be used can help make AI more environmentally friendly [15]. Creating a useful list of benchmark datasets for a wider range of application areas can help raise awareness and speed up progress. Reproducibility requirements can create shared starting points for different datasets.

### 6.1 Embedded sustainability metrics

By using resource-efficient green architectures to collect sustainability metrics, AI systems can better align with the goals of a circular economy.

To fully understand resource sustainability, you need to think about energy use, data needs, environmental effects, and costs at every stage of the process [8]. However, sustainability issues are often seen as extra or even ignored in AI research. To address this issue, we need a comprehensive approach that can identify general categories for evaluating the sustainability of architectures, methods, and systems as a whole. Green AI proposals should also include the energy footprint, data footprint, and lifecycle assessment (LCA) as part of the push to standardize metrics for responsible AI [15]. Traditional metrics look at performance, robustness, and generalization, while a holistic assessment framework combines these with measures of material intensity and other aspects of sustainability. Researchers can create frameworks that capture the energy and data needs of AI-based solutions throughout the entire training and deployment lifecycle by creating sustainability metrics alongside traditional performance metrics. These frameworks can then be linked to sustainability goals.

### 6.2. Benchmarking and auditing green AI

Governments, researchers, and industry professionals are prioritizing the enhancement of sustainability in complex technological systems, particularly artificial intelligence (AI). Because AI is so important for solving many environmental and sustainability problems [7], it is also strategically important to find and use ways to lower AI's own resource needs. "Green AI" is an important way to look at AI sustainability. It encourages people to think about how modeling choices and decisions will affect the environment in the long term and how much energy and data they will use [8]. Circular economies have become a very effective way to make many different areas more sustainable. So, it's important to look into how green AI methods and building choices can help circular economies and a more sustainable future. Some of the first specific questions to think about in this case are: What AI-powered apps help with resource efficiency and make it easier to follow circularity principles like separating growth from resource extraction and improving material flows? How can green AI techniques, such as energy-efficient machine learning models, data-efficient learning strategies, and better lifecycle assessment, help specific applications make better use of their resources? What architectural choices offer both high performance and a substantial green AI footprint to enhance understanding of trade-offs and facilitate prioritization? Lastly, which internationally accepted guidelines, frameworks, or metrics measure AI sustainability aspects like energy, data, and long-term environmental impact while still being able to work with performance?

Answering these questions helps us learn more about how green AI, circular economies, and resource efficiency are related. This is an important but rarely studied and analyzed topic. A systematic examination of the pertinent literature concerning the applicability of green AI to the advancement of circular economies, alongside associated architectural alternatives and guidance, may uncover numerous novel patterns, reveal previously unexamined interactions, and elicit considerable interest from both industrial and academic communities.

## 7. BARRIERS, RISKS, AND ETHICAL CONSIDERATIONS

Even though many people think that using green AI architectures is a good idea, it does come with some problems. For architectural exploration, resources are still needed; models that use less energy can sometimes be useless [15]. Federated learning usually uses less data and energy overall, but individual federated clients may not always get a lot of data reduction during their training, which can be expensive [7]. As the number of candidates increases, life cycle analysis becomes more useful for comparing models. However, creating an accurate and reliable life cycle analysis is still a big challenge. One of the many things that life cycle analysis needs to be useful with complex models is that it needs to be easy to understand.

Putting green AI architectures into practice can lead to more ethical problems. Equity is a concern because any part of society that already has limited access to data, data storage, computing power, economic revenue, or other important resources will lose even more when models need a lot of data or resources. Some types of data-aware model architectures can make this worry even worse. Transparency is still a problem because it is not as easy to decode life-cycle information from a green AI-enabled approach as it is from a traditional one. Without easy and open ways to share this information, accountability can also become unclear [21].

## 8. FUTURE PROSPECTS AND RESEARCH AGENDA

Emerging technologies herald the prospect of a new industrial revolution, driven by advances in big data and AI [7]. Key sectors agribusiness, energy, smart cities, materials, and manufacturing embark on an ambitious transition c475bb4fd-06c8-4869-9683-bc7cb4bee968ed "Green Deal" or "green product" aimed at curbing or cutting GHG and environmental footprints, increasing resource recovery, and boosting over475bb4fd-06c8-4869-9683-bc7cb4bee968 circularity [5]. Similarly, scientific works supporting "Green AI" strive for a greener world and healthier blue planet through more sustainable AIs. Despite rapid improvements in energy and carbon footprints of computational budgets and storage, AIs successfully reduce inherent emissions and resource consumption for their targeted applications [15].

Moving from AI concerned solely with efficiency of resource-use inputs—mainly energy, data, and biodiversity—to AI operating on the other sides of "circularity" is worthwhile and timely.

Illustrated blueprints proposed signify a first-and-foremost forward step towards remaining flexibility in each architectural component design and addition, and diversified space structure explorations. Each blueprint, therefore, neither prescribes a necessarily move towards yet greener set of ingredients nor confines an exclusive measure of GP. Each element articulates only one of considerably high possibilities, requires no order, and welcome adherent and integration with emerging equipment, facilities, and other trends such as Spatial-Audio or 6G. Following five deliverables are considered progressively optimal; nevertheless, advancing at least three penultimate items largely facilitates consistent evolution of the entire circularity which remains ascent.

## 9. CONCLUSION

This thorough and in-depth study shows how important and game-changing AI technologies are for not only improving resource circularity but also for making progress toward meeting important circular economy goals. The strategic use of different architectural patterns that are carefully aligned with green AI principles creates many ways for businesses to work that are specifically designed to make the most of their resources. Also, these new ideas can have a big impact on sustainability outcomes, which are becoming more important in today's world. The use of AI-enabled material recovery systems is especially helpful because it greatly improves sorting accuracy and recovery rates, which in turn makes the whole recycling process much more efficient. These advanced AI systems also improve the accuracy of demand forecasting while lowering energy use per unit. This has two benefits that help meet both economic and environmental goals. A clear and thorough understanding of these complex and interrelated relationships can help people make smarter and more strategic investments in AI technologies. This will help new green AI architectures spread more quickly and widely across many different industries and sectors. This meaningful use of AI not only makes operations more efficient, but it also puts a lot of emphasis on building a sustainable future. This method makes sure that resources are used as little as possible and that waste is handled properly. This strengthens the commitment to a circular economy model that benefits everyone involved in this effort. Organizations can lead the way in the sustainability movement by recognizing and taking advantage of these opportunities. This will open the door to new ways of using resources and dealing with waste that could change the way we do things and make the planet healthier for future generations.

### Conflicts Of Interest

The author declares no conflict of interest in relation to the research presented in the paper.

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