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# INTEGRATING ARTIFICIAL INTELLIGENCE IN THE CIRCULAR ECONOMY: A STANDARDISED FRAMEWORK

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**ABSTRACT**

The integration of Artificial Intelligence (AI) into Circular Economy (CE) practices presents significant potential for enhancing sustainability and resource utilization. This study aims to develop a comprehensive framework for implementing AI and CE, based on the systematic literature review (SLR) and expert validation using the Delphi method. The Slayer was conducted following the PRISMA guidelines utilising Web of Science, Scopus and ScienceDirect databases to identify key attributes relevant to AI-CE integration. The Delphi method was employed to achieve expert consensus, with agreement validation through percentage agreement analysis. The proposed framework consist of five core components: **Data Management, AI Model Selection**, **System Integration, Performance Monitoring** and **Governance & Ethics**. Expert feedback was incorporated, ensuring the frameworks relevance and applicability. This study contributes to existing research by providing a structured approach to AI-driven CE processes while maintaining efficiency, ethical considerations, and regulatory compliance. The framework serve as a guideline for researchers, policy makers, and in industry stakeholders, supporting sustainable development goals through responsible AI applications.

**Keywords:** Artificial Intelligence, Circular Economy, Delphi Method, Sustainability, Framework.

## Introduction:

### Circular Economy:

The circular economy (CE) aims to achieve economic expansion without relying on the use of limited resources and therefore decoupling the need for expansion with resource utilization (Nobre &Tavares, 2017). In order to develop this new economic structure, the problem of reliance on a single linear system based on the traditional take-make-dispose in which raw resources are harvested, then used to manufacture items and eventually discarded as waste must be addressed first (Murray et al., 2017). It contrasts with the circular economy which strives to extend the lifetime of materials through bypassing the dispose end of the consumable loop and supporting its regeneration through processes of recycling, reusing, or repair throughout the lifecycle of the item (Blomsma & Brennan, 2017; Carrillo-Hermosilla et al., 2010; Witjes & Lozano, 2016).

The previous perception has reversed and a need has arisen to establish strategies that are geared towards the promotion of a circular economy, thanks to the concerns caused by the linear economic model. All these activities result in a palpable impact to the environment as the rate of resource related activities reached a saturation point, deforestation, pollution and landfill sites issues are exacerbating (Ali, 2023). There is also a societal aspect at play, the majority of the Earth's populace ration commences at the urban level and that in turn leads to a spike in the growth of consumption and thereby waste. The globe is known to produce an estimated 2.01 billion tons of municipal solid waste every year, this figure is likely to rise further due to factors of population and urbanization (Geng & Doberstein, 2008; Jabbouret al., 2019; Su et al., 2013). Furthermore, more than 90% of the world's resources are utilized just once before being discarded, resulting in serious environmental consequences and resource depletion (Gordan et al., 2023).

In response to these issues, the concept of circular economy has been developed and has been increasingly embraced. It has emerged as a central notion of sustainable development as it promotes the effective management of resources, decreases waste production and enhances environmental quality (Ghisellini et al., 2016). To this end, the paradigms of CEs try to address the issue of 'take, make, dispose' economy by ensuring that the materials input into the production of products should be replenished or increased in the same way by for example repairing or recycling instead of throwing away and incinerating. This action not only addresses the problems raised by the international community with regard to environmental sustainability, but also creates new forms of economic value and new possibilities. (Sehnem et al., 2019; Sell et al., 2023). A circular economy facilitates elimination of waste thereby enhancing the usefulness of resources, reducing dependence on raw materials, cutting down emissions, and eventually fostering a strong and sustainable economy development (Ellen Mac Arthur Foundation & McKinsey Centre for Business and Environment, 2015).

One of the most apparent driving forces for the development of the ideas of circular economy is the increasing pressure over the governments, the companies as well as the consumers to act in a more sustainable way (Blomsma & Brennan, 2017;Carrillo-Hermosilla et al., 2010; Witjes & Lozano, 2016). The European Union, for instance, has fixed ambitious targets for its Circular Economy Action Plan which emphasizes waste prevention, increase in recycling and changes in product design.(Berbenni-Rehm, 2022). Alignment with concepts of circular economy in member states is essential to legislate, satisfy consumers' respect for green products, and save costs in the future (Ellen Macarthur Foundation, 2019).

Technological advancements along with the corporate's and consumers' priorities toward sustainability have advanced the circular economy. It appears that the concepts of the CE are firmly established within many firms although not all of the potential expected has been realised (Potting et al. 2017). Circular economy policies involve changes in product development, distribution, aspects of manufacturing and the way products are disposed of. Specialized creative ideas on operations, resources and product life cycle data management are necessary for companies to practice circular economy correctly. This is where artificial intelligence (AI) comes into play (Patwa et al., 2021; Vasiljevic-Shikaleskaet al., 2017) .

**The Role of AI in Facilitating Circular Economy**

Artificial intelligence (AI), which is defined as the robots' capability to mimic the human intelligence and perform tasks such as learning, solving problems, and making decisions, has become a powerful tool across various sectors (Davenport & Ronanki, 2018). Since the process of shifting towards sustainable models continues, AI can significantly enhance the efficacy of the circular economy initiatives (Das et al., 2023).

There are many ways through which AI supports the circular economy and some of them are resource management, waste minimisation, product design and recycling processes. This is because one of the major barriers of a circular economy is that it is difficult to track resources as they move through the supply chain from acquisition to use and either recycling or disposal (Schneider & Leyer, 2019). Legacy methods for retaining this information are mostly cumbersome, fallible, and incapable of processing vast datasets in real-time (Brynjolfsson & Mcafee, 2017; Davenport, 2018; Venkatraman, 2017). AI can help businesses and governments to improve the way they allocate their resources, material flows, and manage the waste due to its data processing ability and ability to identify the patterns.

**Resource Efficiency and Waste Reduction:** AI will analyse vast amounts of data from all available technologies to improve manufacturing procedures, cut down on material waste, and identify areas where energy may be saved (Tayyab, Singari, et al., 2024). Organizations can reduce waste by using machine learning algorithms to identify manufacturing inefficiencies, forecast demand trends, and improve supply networks (Hasan et al., 2023). AI-powered solutions, for example, can examine production data to spot any bottlenecks, assisting businesses in streamlining their operations to use less energy and materials. Additionally, during the production process, AI systems may track waste and byproducts to ensure that they are properly recovered or repurposed, hence aiding in resource recovery and waste reduction (Onyeaka et al., 2023).

**Optimizing Product Design:** Product design is essential in a circular economy to guarantee that items are recyclable, repairable, and reusable. With the help of AI, designers may use sophisticated computational tools to model a product's life cycle, predict its effects on the environment, and suggest design changes that extend its lifespan and make it more recyclable. For instance, generative design, an AI-driven methodology, uses algorithms to produce a number of product concepts according to preset constraints like weight, material consumption, or environmental impact (Ghoreishi & Happonen, 2020). This makes it possible for designers to create products that are more resilient, require fewer resources, and can be recycled at the end of their useful lives.

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**Advanced Recycling Technologies:** The application of artificial intelligence to enhance recycling procedures is growing quickly. Manual sorting and labor-intensive procedures are common in traditional recycling systems, and they can be inefficient and imprecise (Wilson et al., 2021). The sorting of recyclables like paper, metals, and plastics is being automated and improved by AI-powered technologies, such as robotic sorting devices using computer vision and machine learning. By precisely identifying and classifying things according to their color, shape, and composition, these systems can reduce contamination and boost recycling effectiveness (Venkatraman, 2017; Wilson & Daugherty, 2018).

**Predictive Maintenance and Extended Product Life:** The predictive maintenance of machinery and products, which enables the anticipation of when a number of components need to be repaired or replaced before they fail, can benefit from artificial intelligence's capacity to interpret data from sensors and Internet of Things devices [Fraga-Lamas et al., 2021]. This diminishes the demand for new items overall, prolongs product life, and reduces the requirement for new raw resources. One of them is the incorporation of artificial intelligence (AI) systems into industrial machinery to track performance and forecast when sections require maintenance, preventing failures and increasing the equipment's lifespan (Dutta et al., 2023).

**Supply Chain Optimization and Circular Business Models:** The circular economy depends on supply chain transparency, which artificial intelligence helps to increase (Westerman et al., 2014). From extraction through manufacturing and recycling, artificial intelligence (AI) can help trace materials along the supply chain (Bouschery et al., 2023). AI systems can improve resource flow, spot potential bottlenecks, and guarantee that resources and products are recycled or reused at the right points in the value chain by analysing supply chain data (Iansiti & Lakhani, 2020). Additionally, rather than just selling products that would eventually end up in the trash, AI can assist businesses in implementing circular business models like product-as-a-service, which enables companies to retain ownership of assets while simultaneously offering services like maintenance and updating (Bradley & O'Toole, 2016).

**Circular Economy and AI Synergies:** The combination of AI and circular economy principles results in a virtuous loop. AI's ability to handle vast amounts of data, find inefficiencies, and optimize processes has the potential to expedite the shift to circular models by allowing organizations to employ smarter, more efficient practices (Js & Mahesh, 2023). CE, on the other hand, provides a sustainable environment for AI applications, guaranteeing that AI-driven breakthroughs are leveraged for societal benefit, such as waste reduction, resource conservation, and industry-wide promotion of sustainable behaviours (Suboyin et al., 2023; Pallavi & Singh, 2021).

The increased need to address global environmental challenges is reflected in the growth of the circular economy as a transformative model for sustainable development (Bag et al., 2021). AI provides the technological means for enterprises to transition to more sustainable practices. AI is essential to supporting a circular economy, from improving resource efficiency and product design to advancing recycling technologies and encouraging circular business models (Borges et al., 2021). In order to address pressing problems like waste, resource depletion, and environmental degradation, the combination of AI with CE holds great promise for creating a more resilient and sustainable future (Agrawal et al. 2021).

## Methodology:

A systematic literature review (SLR), the Delphi method, and expert validation were the components of this study's mixed-methods approach (Buer et al., 2018; Macke & Genari, 2019; Parmentola et al., 2022). a plan to create, assess, and verify a model or structure for repurposing AI in the circular economy. To attain a comprehensive theoretical understanding that is mutually referenced, expert consensus, and practical validation, the study strategy is implemented in several phases.

### 2.1. Systematic Literature Review (SLR) on AI in Circular Economy

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were adhered to by the systematic literature review (Tranfield et al., 2003; Tutore et al., 2024). In order to extract and synthesize relevant material, the review approach involved intense content analysis, the application of inclusion and exclusion criteria, and comprehensive database searches (Moher et al., 2015; Palmatier et al., 2018).

#### 2.1.1. Database Selection and Search Strategy

Three primary academic databases—Web of Science, Scopus, and ScienceDirect—were thoroughly searched (Alvarez Jaramillo et al., 2019). The search terms used to find pertinent publications on artificial intelligence and the circular economy are displayed in Figure 1.

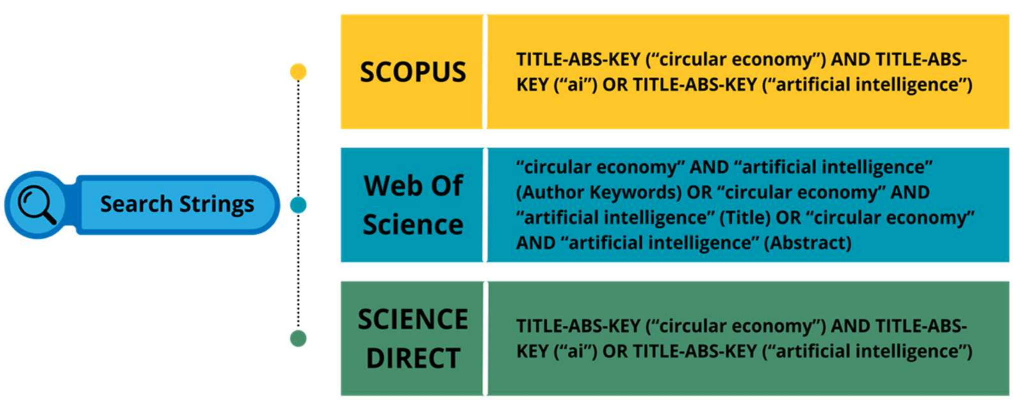


**Figure 1:** Search Strings Used in Systematic Literature Review.

#### 2.1.2. Screening and Selection Process

A total of 1023 articles were found in the first search of the pertinent databases, including 342 from Web of Science, 396 from Scopus, and 285 from ScienceDirect. Using Zotero reference management software, duplicates were found and eliminated to expedite the collection, yielding 678 unique articles in total.

To guarantee their quality and applicability, the chosen studies were subsequently put through a rigorous inclusion and exclusion process. Peer-reviewed articles that concentrate on the relationship between AI and the circular economy, are published within the last ten years (2013–2023), are available in full-text, and are written in English are required. On the other hand, research with missing data or access issues, papers published before 2013, publications that were not in English, and publications that had nothing to do with AI in the circular economy were also disqualified.

These criteria were strictly adhered to, and the final list included 73 publications deemed suitable for in-depth examination. The screening and selection procedure is depicted in figure 2. The foundation for developing a standardized framework for integrating artificial intelligence into circular economy operations is this extensive collection of articles.


**Figure 2:** Flow diagram of the screening and selection process.

### 2.2. Content Analysis

A research method for methodically examining textual, visual, or auditory material in order to find themes, patterns, or meanings is called content analysis (Kiet al. 2020; Dasanayaka et al. 2022). In this study, pertinent material about the incorporation of AI into the circular economy is extracted and synthesized from selected articles using content analysis. The content analysis procedure used in this study is summed up in the following steps:

### 2.2.1. Data Extraction

Data extraction entails identifying and gathering important information from selected publications. This stage guarantees that all relevant data for AI applications in the circular economy is acquired and analysed.

***Identification of Relevant Sections:***

The abstracts, introductions, techniques, results, and discussions of the articles were analysed to identify portions on AI applications in CE. Key topics covered included data management, AI model selection, system integration, performance monitoring, and governance. Extracted data was documented in an organized fashion, usually on a spreadsheet. This includes information about the study's focus, procedures, AI techniques, and CE outcomes.

***Key Attributes Extracted:***

1. **Data Management:** Understanding data collection, quality control, and sharing in AI and CE.
2. **AI Model Selection:** Identifying applicable AI models for CE applications, such as machine learning and predictive analytics.
3. **System Integration:** Investigating ways to integrate AI into CE systems (e.g. supply chain and recycling processes).
4. **Performance Monitoring:** Measuring AI's efficacy by set indicators, such as resource optimization and waste reduction.
5. **Governance:** Addressing ethical and regulatory concerns and involving stakeholders in AI adoption.

### 2.2.2. Initial Coding

Coding entails organizing the retrieved data into meaningful groups or themes. During the initial coding, broad categories are formed to organize the data. Following an initial evaluation of the papers, a codebook was developed. This codebook included a list of prospective codes for several areas of AI in CE, including "data collection," "machine learning algorithms," and "ethical AI deployment." Each segment of the retrieved data received a starting code. For example, a paragraph detailing the use of machine learning to optimize recycling processes was labelled "machine learning algorithms."

### 2.2.3. Thematic Coding

Thematic coding refines the initial codes to create more precise themes. This approach entails recognizing patterns and relationships in the data to create comprehensive themes that represent the essential characteristics of AI applications in CE. The initial codes were examined and adjusted to ensure they appropriately represented the data. Redundant or overlapping codes were combined, and new codes were generated as needed. The revised codes were organized into large categories.

Table 1 shows how codes such as "data collection" and "data sharing and transparency" were classified under the theme "Data Management".

**Themes Identified:**

1. **Data Management:** Emphasis on protocols and methods for handling CE-related data.
2. **AI Model Selection:** The emphasis was on selecting the appropriate AI algorithms to handle CE challenges such as waste reduction and resource optimisation.
3. **System Integration:** Emphasized the smooth integration of AI into current CE activities.
4. **Performance monitoring**: focuses on creating KPIs (Key Performance Indicators) and methodologies for evaluating AI contributions.
5. **Governance:** Investigated issues such as legal compliance, ethics, and stakeholder involvement.

**Table 1:** Final Thematic Coding Summary:

| **Themes** | **Codes** |
|---|---|
| **Theme 1: Data Management** | Code 1.1: Data Collection |
| | Code 1.2: Data Sharing and Transparency |
| | |
| **Theme 2: AI Model Selection** | Code 2.1: Machine Learning Algorithms |
| | Code 2.2: AI for Optimization |
| | |
| **Theme 3: System Integration** | Code 3.1: Interoperability |
| | Code 3.2: Integration with IoT |
| | |
| **Theme 4: Performance Monitoring** | Code 4.1: AI Evaluation Metrics |
| | Code 4.2: Feedback Loops for Continuous Improvement |
| | |
| **Theme 5: Governance and Ethics** | Code 5.1: Ethical AI Deployment |
| | Code 5.2: Regulatory Compliance |

### 2.2.4. Synthesis of Findings

Synthesis entails bringing together the identified themes to form a cohesive understanding of the research topic. This stage brings the topics together into a coherent framework that shows how AI can be effectively integrated into the circular economy. The relationships between themes were examined to better understand how various parts of AI and CE interact. For example, consider how data management techniques impact the efficacy of AI models. A uniform framework was developed based on the identified themes and their interrelationships. This framework defines best practices and recommendations for incorporating AI into CE, covering topics such as data management, model selection, system integration, performance monitoring, and governance.

Standardised Framework for AI in Circular Economy

The standardised framework created in this study incorporates the important qualities identified during the systematic literature review (SLR) and confirmed using the Delphi technique. The framework lays forth best practices and standards for using AI to improve the circular economy (CE). It covers essential topics like data management, AI model selection, system integration, performance monitoring, and governance and ethics.

### 3.1. Framework Overview

The standardized framework for integrating AI into the circular economy (CE) offers a complete roadmap to using artificial intelligence to improve sustainable practices (p. 476; Sarc et al., 2019). Figure 3 illustrates how this framework is divided into five major components: data management, AI model selection, system integration, performance monitoring, and governance and ethics. Each component is critical to ensure that AI applications properly contribute to the goals of the circular economy.

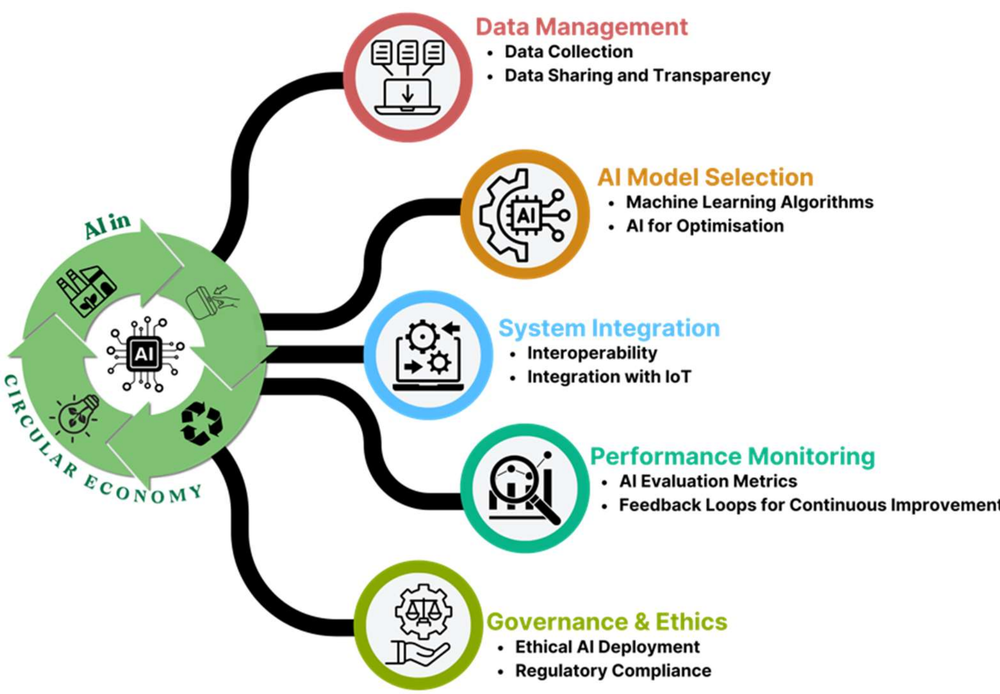


**Figure 3:** Graphical Representation of Proposed Framework.

Detailed explanation of each component and its sub-elements of the framework are given below in table 1.

**Table1:** Components and sub-elements of the proposed framework.

| Category | Subcategory | Overview | Importance/Relevance |
|---|---|---|---|
| **Data Management** | Data Collection | AI applications require accurate, comprehensive, | High-quality data is the foundation for reliable AI |

| | | | |
|---|---|---|---|
| | | and high-quality data from multiple sources such as IoT devices, sensors, and traditional databases. | models that can make accurate forecasts and optimizations. |
| | Data Sharing and Transparency | Platforms enabling data exchange and transparency improve collaboration among circular economy stakeholders. | Transparency fosters trust and enhances the efficiency of circular economy processes. |
| **AI Model Selection** | Machine Learning Algorithms | Selecting appropriate algorithms is crucial for predicting material flows, optimizing recycling, and improving resource recovery. | AI effectiveness in CE depends on using suitable algorithms for specific applications. |
| | AI for Optimization | AI-driven optimization models can improve efficiencies in processes like supply chain logistics and material sorting automation. | Optimization reduces waste and enhances resource utilization, aligning with circular economy principles. |
| **System Integration** | Interoperability | AI solutions must seamlessly integrate with existing systems in industries such as waste management and manufacturing. | Compatibility increases AI value and minimizes operational disruptions. |
| | Integration with IoT | AI integration with IoT enables real-time tracking and monitoring of waste streams, resource usage, and critical processes. | Real-time data enhances decision-making and operational efficiency, essential for circular economy success. |
| **Performance Monitoring** | AI Evaluation Metrics | Precise metrics, including energy efficiency, recycling efficiency, resource recovery rates, and environmental | Metrics help evaluate AI effectiveness and identify areas for improvement. |

| | | | |
|---|---|---|---|
| | | impact, are essential for AI performance assessment. | |
| | Feedback Loops for Continuous Improvement | AI systems can learn from operational data and adapt to changing circumstances through feedback loops. | Continuous improvement ensures AI applications remain effective and adaptable to new challenges in the circular economy. |
| **Governance and Ethics** | Ethical AI Deployment | Addressing algorithmic bias, data privacy, and equitable AI access ensures ethical AI implementation. | Ethical guidelines ensure AI benefits both society and the environment while maintaining public trust. |
| | Regulatory Compliance | AI applications must comply with industrial standards and environmental regulations. | Compliance ensures legal responsibility and aligns AI applications with broader sustainability goals. |

Figure 4 is a visually representation of how AI models interact within the circular economy, showcasing the integration of AI-Driven decision-making in resource management, waste reduction, and recycling processes.

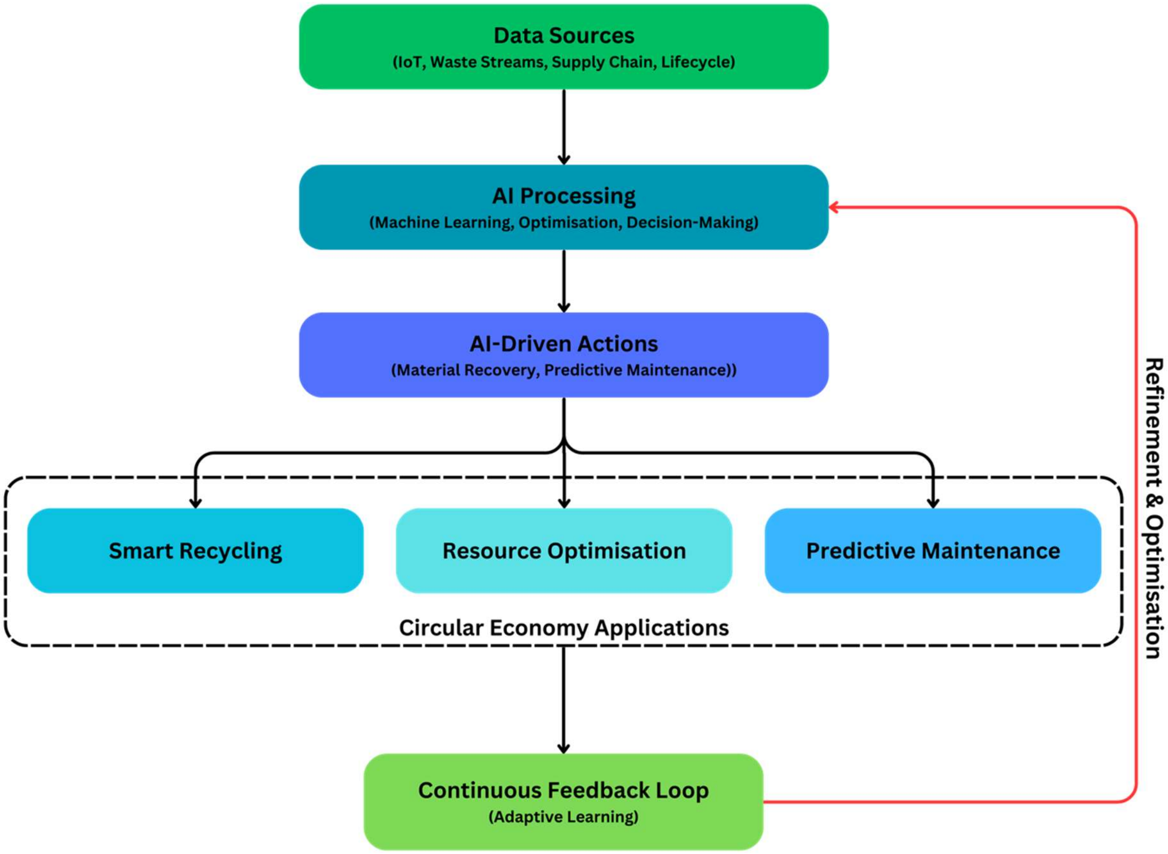


**Figure 4:** AI-CE Interaction Diagram

### 3.2. Framework Validation

The Delphi approach was used to validate the standardized framework, which involved numerous rounds of 23 expert consultations to reach agreement on the essential qualities and best practices. The percentage agreement approach was used to determine the level of agreement among 23 experts. High levels of agreement were obtained, validating the framework components' relevance and application. Validation results are provided in Figure 5 below.

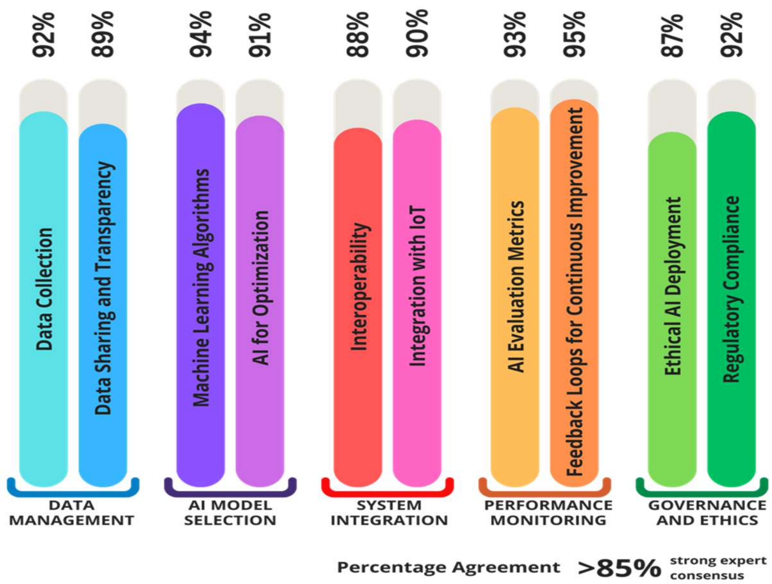


**Figure 5:** Framework attributes and their validation results:

The standardized framework for AI in the circular economy serves as a comprehensive resource for researchers, practitioners, and policymakers. It identifies the critical components and best practices for successfully incorporating AI into CE operations (Nowakowski et al. 2020). By using this approach, stakeholders can improve the sustainability, efficiency, and ethical standards of their AI-powered CE activities, resulting in a more sustainable future.

## Results and Discussion

In this section, we describe the important findings from the systematic literature review (SLR) and Delphi method validation, followed by a detailed discussion of their implications for AI applications in the circular economy (CE).

### 4.1. Results

The systematic literature review (SLR) identified important themes and features required for successful AI integration into the circular economy. The publications reviewed gave a complete overview of AI's function in different elements of CE, such as data management, AI model selection, system integration, performance monitoring, governance, and ethics.

**Key Findings from the SLR:**

**Data Management:** AI applications in CE necessitate strong data management standards, with a focus on reliable data gathering, transparency, and data exchange among stakeholders. The most popular AI data sources in CE are IoT devices, sensors, and industrial databases.

**AI Model Selection:** Machine learning algorithms and optimization models were recognized as the most common AI techniques utilized in CE. These models are commonly used in fields including material recovery, recycling optimization, and supply chain efficiency.

**System Integration:** The integration of AI into current systems was seen as a major difficulty. Interoperability between AI and legacy systems, as well as interaction with IoT devices, have been identified as critical considerations for effective AI adoption in CE.
**Performance Monitoring:** AI systems in CE are frequently assessed using performance indicators such as resource recovery rates, recycling throughput, and environmental effect. Feedback loops that enable continual learning and adaptation were also identified as critical to long-term success.
**Governance and Ethics:** The research highlighted ethical concerns about AI deployment, notably those relating to data privacy, algorithmic bias, and equal access to AI technology. Regulatory compliance was another major concern for AI applications in CE.

The framework established using the SLR and Delphi methods addresses these crucial areas, providing stakeholders with a standardized structure for efficiently integrating AI into the circular economy.

**Delphi Method Validation Results:** The Delphi approach was used to validate the suggested framework using a panel of experts from several domains, such as AI, CE, and sustainability. The experts engaged in many rounds of feedback, and agreement was reached on the framework's essential components. The findings revealed significant levels of agreement among the experts, supporting the importance and applicability of the highlighted themes.

### 4.2. Discussion

The results of the SLR and Delphi methods imply that AI has the ability to alter the circular economy. The established paradigm underlines the importance of a comprehensive and integrated approach to ensuring the successful and ethical use of AI technologies.

**Data Management:** The value of data collecting and sharing for AI in the circular economy cannot be emphasized. AI systems rely on data, and the quality and availability of data have a direct impact on AI model performance. Experts agree on the importance of transparency and collaboration in data sharing, highlighting the possibility for collective action in pushing sustainable practices in CE.

**AI Model Selection:** Machine learning algorithms and optimization models are the most used AI techniques in CE. The findings suggest that AI is especially useful for resource optimization, waste control, and process efficiency. However, the choice of AI models must be adjusted to specific applications, as not all models are appropriate for every CE process. This conclusion emphasizes the significance of a nuanced approach to AI deployment, with models chosen based on the context and goals of the CE application.

**System Integration:** The difficulty of integrating AI into current systems, particularly legacy systems, is a significant impediment to AI adoption. Interoperability and compatibility issues must be addressed so that AI technologies can be seamlessly integrated into CE processes without affecting current operations. The high level of consensus among experts on this problem emphasizes the importance of a holistic approach to system design that takes into account both emerging AI technology and existing infrastructure.

**Performance Monitoring:** The use of performance measurements and feedback loops to assess the efficiency of AI systems is critical to guaranteeing the long-term viability of AI-driven CE programs. AI systems should not be static, but rather evolve through continual learning from operational data. The experts' agreement on the need of performance monitoring strengthens the notion that AI systems must be adaptable and resilient to changing environments.

**Governance and Ethics:** Experts stress the significance of transparent, accountable, and objective AI systems, highlighting the pervasive ethical concerns surrounding AI adoption in CE. Making ensuring AI technology doesn't worsen already-existing injustices or contribute to environmental damage is a significant challenge. Since upholding environmental and data protection requirements is essential to maintaining public confidence and guaranteeing the legitimacy of AI applications, regulatory compliance was also recognized as a crucial component.

**Implications for Practice:** The study's conclusions have several real-world applications. First, creating robust data management systems that encourage openness, sharing, and cooperation should be a top priority for businesses aiming to apply AI in the circular economy (Colla et al., 2020). Second, in order to maximize the impact of AI technology, it is essential to carefully choose AI models according to their suitability for particular CE applications. Third, for AI systems to integrate seamlessly with IoT devices and legacy systems, interoperability must be considered throughout their design. Lastly, in order to preserve AI systems' long-term effectiveness and alignment with sustainability goals, ongoing monitoring, assessment, and adaptation are necessary.

The findings of this study add to our understanding of how AI can be efficiently integrated into the circular economy. The standardized framework produced through the SLR and validated using the Delphi approach serves as a comprehensive guide for parties involved in the adoption and deployment of AI in CE. This framework, which addresses critical areas such as data management, AI model selection, system integration, performance monitoring, and governance, can assist companies and governments in navigating the difficulties of AI-driven circular economy efforts, supporting sustainability and long-term success.

## Conclusion

This study developed a standardised framework for integrating artificial intelligence (AI) into the circular economy (CE), with the goal of guiding practitioners and researchers on how to use AI technology to enhance sustainable and efficient resource management (Nañez Alonso et al. 2021). Following the PRISMA protocol, we conducted a systematic literature review (SLR) to identify critical aspects of AI applications within CE, including data management, AI model selection, system integration, performance monitoring, and governance and ethics. These elements were revised and validated using the Delphi approach, with experts agreeing on their relevance and application.

The framework provides a complete structure that describes best practices and recommendations for using AI in CE operations, addressing crucial areas such as recycling process optimization, data transparency, ethical AI deployment, and performance monitoring. This framework assists in overcoming issues connected to interoperability, data sharing, and performance evaluation, all of which are critical to promoting circular economy concepts.

The validation of this framework through expert consultation (with a high percentage agreement on key components) confirms its resilience and usefulness in real-world scenarios. The suggested paradigm not only provides practical insights for increasing the efficiency and sustainability of circular economy practices, but it also underlines the necessity of ethical issues and regulatory compliance in AI deployment.

Overall, this study adds to the expanding body of knowledge about the role of AI in the circular economy and serves as a significant resource for decision-makers, researchers, and industry stakeholders seeking to drive sustainable practices with sophisticated technologies. By following the framework's criteria, stakeholders may ensure that AI integration into CE processes maximizes both environmental and economic benefits, thereby aiding the transition to a more sustainable, circular future (Mboli et al. 2020).

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