AI-Enabled Pathways For Circular Economy Transition In Steel Industry To Foster Reuse And Recycle

SHUBHAM AGARWAL, SHWETA LOONKAR,
KARISHMA DESAI

Abstract: *This research aims to adopt CE strategies within the steel industry to mitigate greenhouse gas emissions and resource waste; therefore, we will examine the potential of AI in supporting CE practices throughout the entire lifecycle of steel products (including both pre-and post-manufactured products). This research paper presents a review of qualitative case studies aligned to the research questions and a systematic literature review, following the PRISMA Guidelines, of 31 research articles from the past ten years to determine how AI applications, technological enablement, and performance improvements can enhance the economic viability and sustainable performance of steel manufacturing operations. We have found that by integrating machine learning, deep learning, and predictive analytics into their processes, companies can increase the amount of recycled material used and decrease their reliance on virgin resource content; hence, AI applications allow steel producers to become more environmentally and financially sustainable. The steel industry faces several challenges to become more circular, including the presence of heterogeneous materials, fragmented lifecycle data, and very little integration of AI and other digital devices (D/E/S) into the supply chain. To facilitate a better understanding of how to implement AI to create a sustainable, closed-loop steel supply chain, a conceptual framework has been developed, which provides practical guidance on successfully implementing sustainable steel production processes. Future research in this area should continue to explore the feasibility of using AI technology in conjunction with digital twins, multi-modal modelling merging data stream from multiple sectors, and enhanced cross-sectoral collaboration in creating a fully closed-loop steel supply chain.*

Keywords: AI, Circular Economy (CE), Steel Industry, Digital Twins (DTs), Reverse Logistics.

Shubham Agarwal (agarwalshbham2005@gmail.com) St Xavier's College, Kolkata, India
Shweta Loonkar (shwetaloonkar@gmail.com) MPSTME, NMIMS Deemed to be University, Mumbai,
Karishma Desai (karishmamihirdesai@gmail.com) S. P Jain Global School OF Mgmt, Mumbai,
https://orcid.org/0009-0009-5171-9588

Introduction

The steel industry is at the heart of the sustainability challenge because of its essential role in both infrastructure and economic growth, and this is along with the amount of impact the steel industry has on the environment. Steel production accounts for about 7 to 9 percent of total worldwide CO2 (carbon dioxide emissions), and it is one of the most energy and resource intensive industries in the world. Therefore, it is also vital to global net-zero and climate change mitigation strategies [14] [11] [19]. The growing number of regulations, the tightening of carbon emissions markets, and the demand from society for businesses to operate in an environmentally sustainable manner has created a pressure to identify and implement transformative pathways to separate steel production from environmental degradation[2].The introduction of the circular economy (CE) to address the inherent inefficiencies of the traditional linear (take–make–dispose) model has led to the development of a systemic paradigm that can be applied to various industries. By applying the principles of resource efficiency, reuse, recycling, and lifecycle optimization to facilitate minimal waste generation and increased material lifecycles, CE offers a means of reducing overall reliance on virgin resources, which is crucial for industries that produce large quantities of materials, such as steel manufacturing [13]. Circular strategies such as closed-loop material flows, scrap-based steelmaking, and industrial symbiosis are increasingly viewed as essential components to the transition towards low carbon steel and the long-term resilience of industry[16] [21].

Figure 1: Macro-level sustainability pressures driving systemic transformation in the global steel industry.

The transition of the steel industry at a global level is being shaped shown in Fig. 1 which indicates the increasing level of international commitments to reducing greenhouse gas emissions including net-zero emission targets under the Paris Agreement as well as the Sustainable Development Goals (SDGs). The steel industry also has an exceptionally large environmental impact and, according to various reports, the industry contributes between 7%-9% of total global carbon dioxide (CO_2) emissions. The downward flow indicates that there is an urgent need for the systemic transformation of steel manufacturing and the associated value-created throughout the steel manufacturing value chain to effectively address the critical importance of global decarbonization and sustainability.

Even though there is widespread acceptance of the advantages of adopting a circular economy (CE) model in steelmaking, scaling this practice up is difficult because there are many barriers. Some of these barriers consist of poor data availability, little or no access to real-time lifecycle visibility on products through scattered supply chains, and inefficient decision-making processes across the lengthy and complicated value chain. The use of AI has emerged as one of the major enablers of circularity because it supports all aspects of the life cycle including; design, source materials, produce, recover waste and manage end-of-life. Empirical evidence indicates that the implementation of AI-based supply chain intelligence, digital twins and data-driven automation greatly increases resource and energy efficiency, predictive maintenance and recycling and remanufacturing potential in high energy intensive sectors. These technologies have decreased the level of scrap, emissions intensity and operational inefficiencies. Consequently, AI is not just an incremental efficiency increasing tool; it is also a strategic capability with the potential to fundamentally redesign industrial systems. For the steel industry particularly, this is of utmost importance since steel production accounts for approximately 7-9% of the CO_2 emissions associated with fossil fuels on a global scale due in large part to energy-intensive processes associated with primary ironmaking. The potential for reducing GHG emissions in the secondary steel manufacturing process is tremendous but due to the following issues; variability in scrap quality, contamination, lack of efficient reverse logistics systems and limited material traceability throughout a fragmented supply chain, it will not be maximized at this time.

The most recent studies of decarbonization of steel found that utilizing hydrogen-based production, carbon capturing, using biomass as an alternative to fossil fuels, and electrolysis are just some new technological methods available to steel producers. Reducing the number of emissions throughout steel production cannot be accomplished solely through improvements in efficiency of steelworks. Systematic transformation of the entire steel production industry through circular economy actions and initiatives for green steel must occur. Additionally, there are many unanswered questions regarding how to define "green" steel, how to provide "certification," how to determine "cost competitive" products, and how to apply "green" policies across developing economies; therefore, even if green steel exists, many steel producers will be unable to adopt green steels because of these uncertainties. Regulatory incentives, executive-level commitment, and pollution control have been well-established as the three factors that enable sustainability in corporations; however, even though there are numerous studies on sustainability in literature today, they are primarily related to one geographical area or country, and limited studies are conducted to integrate emerging digital technologies with existing CE and DT frameworks for the steel sector. Recent advancements demonstrate the ability of digital twin technology (DT) and emerging technologies such as AI, internet of things (IoT), and cloud/edge computing to provide real-time data monitoring, predictive analytics, and the ability to control the entire production cycle from cradle to grave. Nonetheless, the conventional DT and CE framework is too generic, and more sector-based studies are needed to determine how best to operationalize the entire circular supply chain of steel by utilizing AI-validated DTs and predictive analytics as a means of scaling the entire steel industry's ability to transform into a competitive and sustainable circular economy.

The purpose of this study is to identify ways that AI can be applied to the steel industry in order to transition this industry from its current method of production to the more sustainable processes associated with circular economies, including re-use and recycling. This study synthesizes information from existing research and trends in the areas of AI & machine learning, predictive analytics & models, remanufacturing and digital IoT solutions, as well as the integration of these technologies into circular supply chain management (CSSC) within the steel industry (B2B). Ultimately, this study will provide firms with practical solutions for improving resource efficiency, reducing environmental impacts and enhancing sustainability performance related to both production and trade in steel products.

This paper is divided into five sections. Section 1 contains an introduction which provides an overview of the sustainability challenges faced by the steel industry and discusses how AI can support a circular economy (CE) through enabling CE transition strategies. Section 2 presents a comprehensive review of the literature on sustainable assessment methods, CE strategies and AI-based solutions and identifies gaps in existing research. Section 3 describes the research methodology employed in this study, which includes the use of a systematic literature review based on PRISMA and qualitative case study analysis to explore AI enabled circular practices. Section 4 includes an analysis of how AI can support material design, waste sorting and reverse logistics to enhance the overall circular supply chain performance. Section 5 is comprised of the conclusion and future scope and summarizes the main findings of the research presented, and describes directions for developing scalable and AI enabled circular steel systems.

Literature Review

Circular Economy, AI, and Sustainability in the Steel Industry

The increase in industrial sustainability measures is due to the impact of the depletion of natural resources, climate change, and environmental degradation. As a result, the circular economy (CE) has become the primary framework through which companies are looking to shift from the traditional way of producing and consuming products to a more sustainable and resource efficient method. In the CE paradigm, all aspects of producing and consuming goods will follow a closed-loop system in which waste is eliminated as much as possible and all resources utilized to produce goods and services will be reused, recycled, and retained throughout the entire lifecycle of a product [46]. The circular economy model for manufacturing, however, goes beyond just recycling, and includes other practices, such as eco-design, industrial symbiosis, extended product life cycles and recovery of by-products; thus, redefining the entire value chain rather than individual processes [52]. As the CE practices develop, AI will play a key role in supporting sustainable manufacturing through the use of big data, predictive analytics, and automated intelligent manufacturing. Machine learning, computer vision, and advanced data analytics through AI have increased the accuracy of demand forecasts; optimised the flow of energy and material; Enhanced the efficiency of maintenance and Predictive maintenance; and enhanced the efficiency of Processes and Resources. AI represents a significant reduction in Resource Intensity over time and protects the Resources used in making AI Decisions across complex Industrial systems [36]. Historically, the adoption of AI within the heavy industries has been primarily driven by cost savings and increased productivity, but there now exists a strategic alignment with the objectives of the CE, thereby enabling AI as a Vehicle for Transformative change in the creation of sustainable outcomes within the Industrial System, and beyond.

Fig. 2. shows that circular economy (CE) is based on three core concepts: Reduce, Reuse, and Recycle, but a strong emphasis has been placed on resource efficiency and ecological effectiveness. A circular production system seeks to minimize waste while maximizing retained material value. The downward curve illustrates how the CE will present trouble in applying CE concepts successfully, at a practical scale, and hence large-scale implementation in steel.

Figure 2: Core circular economy principles underpinning sustainable steel production

The steel industry is an ideal candidate for developing Circular Economy (CE) and AI strategies because of its extremely high environmental impact and its significance as a driver of global economic growth. The iron and steel industry is an energy intensive sector that uses one-third of the total energy consumed by the manufacturing sector and is responsible for approximately 7% of global anthropogenic CO2 emissions [32] via the use of fossil fuels in the energy intensive blast furnace-basic oxygen furnace (BF-BOF) process. In the context of projecting a 25-30% increase in global steel demand by 2050 [32] [19], there is increasing concern about the environmental impacts of continuing to rely on traditional steelmaking methods, including those associated with greenhouse gases, securing energy, water scarcity and waste [32] [19]. These pressures exist throughout the entire steel value chain, which spans raw material extraction and primary ironmaking (the primary forms of iron production) to the finishing manufacturing processes, and end-of-life activities, which create increased regulatory pressures and increased public demands for greater sustainability performance. In life cycle assessment (LCA) studies, primary ironmaking emerges as the dominant environmental "hotspot" with respect to total energy and emissions relative to global warming potential, human toxicity, and natural resource depletion. As a result, this area of the value chain needs substantial innovation in technology development, improvements in process efficiencies, and increased use of secondary raw materials [38].

Improvements in energy efficiency over time will decrease GHG emissions from 15% to 20% of current levels, but meeting long-term climate change goals requires more than just those improvement measures; it requires a shift from fossil fuels to alternative technologies including hydrogen, carbon capture, utilization, and storage (CCUS) [32]. Furthermore, estimated increases in scrap metal supply potentially 50% (of input materials) by 2050 emphasize the critical importance of CE recycling, which creates value from by-products, throughout the steel supply chain. This transition will be praised as a successful application of circular economics for all materials and channels of value in the steel production chain, as CE will influence the way materials and their value flows through the ecosystem and how the two concepts will help reduce complexity of closed-loop and data-driven production systems with predictive analytics delivered by AI. While both CE and AI are currently established independently as innovative frameworks, they have been historically considered individually without consideration for their collective use in creating sustainable systems of production; therefore, there remains a significant knowledge gap between how these two concepts can work together to promote the creation of sustainable steel production methods.

Life Cycle Assessment and Emissions Dynamics in the Iron and Steel Industry

Many studies on sustainability and circular economy practices in the steel industry utilise Life Cycle Assessment (LCA) to estimate energy usage, emissions and resources used throughout the various stages of steel making. Earlier studies predominantly utilised long and short form product based LCAs where functional units included 1 tonne of steel, or 1 kilogram of refined steel, and environmental impact categories typically assessed included global warming potential, energy use, and solid waste produced [37]. In subsequent studies, the LCA model was expanded to include comparisons of multiple types of steel products e.g., slabs, hot-rolled, cold-rolled, and galvalume steel, and included additional environmental impact categories e.g., fossil fuel depletion, ecotoxicity, mineral depletion, cancerous effects, and air emissions [33]. Some studies, like [53] have highlighted the water-related impacts of steel production and have shown that steel production poses a significant threat to water systems at a local and regional level and therefore should be viewed within the framework of sustainable water stewardship. In an attempt to fill the product-level data gaps of traditional long form and short form LCAs, process-based LCAs have evaluated the greenhouse gas and fossil fuel impacts of the different methods of producing steel; for example, Burchart-Korol evaluated various routes and found that blast furnaces were the most harmful, both in terms of greenhouse gases and fossil fuel consumption, while sintering operations led to the greatest number of respiratory illnesses linked to steel manufacture. Although both product and process based LCAs are limited by narrowly defined system boundaries, location specific inventories, and a lack of methods that standardize how LCAs are done, these limitations have implications for comparability and generalizability between different areas. Most recently, many researchers have placed steel LCAs in relation to overall decarbonization and circular economy movements, especially in countries like China where steelmaking is an important part of the country's total emissions [16].

Sustainability Assessment Frameworks for the Steel Industry: Focus on China and Integrated Methodologies

The steel industry of China continues to be a major part of the discussion about sustainability globally. In 2022 alone, it produced approximately 1,340 million metric tons of crude steel (almost 54% of the world's production), which is a significant contributor to the Greenhouse gas emissions Tax (GHG), waste water, and industrial waste generated by any country's economy 20. The large volume of production has allowed for rapid growth and development using this resource, but there also exists an unpredictable level of environmental pressures placed on the country due to the overall amount of steel produced there. As a result, China will provide a valuable opportunity for research and investigation of different ways to achieve industrial and economic growth with a reduction of the energy consumed, depletion of resources, and pollution associated with manufacturing steel. A significant body of literature has been created on strategies that could achieve this goal, which include sustainable/smart manufacturing, green/sustainable supply chain management, and technologies that leverage big data, remanufacturing, and lifecycle-based tools [39]. Emergy Analysis (EMA) is a tool that has developed to work alongside the two traditional approaches of analysing environmental impact, i.e., Life Cycle Assessment (LCA) and 'Carbon Footprints'. These two assessment methods assess the environmental impact of all phases of the life cycle of steel products from 'cradle to grave'. As a result, they assess not only emissions but also resource efficiency and exergy flows. Therefore, by converting all resource inputs into a common solar emergy unit, EMA has enabled researchers to also analyse the overall interaction (i.e., ecological, economic and social) of all resource inputs. This is very significant since many of the reports produced today by academia and the steel industry provide some insight into emissions, resource efficiency and exergy flows, and although many of these reports do not provide a comprehensive view of the environmental impact of a specific technology or process, most of the literature generated in the steel industry focuses on 'how do I recycle this?' rather than 'how do I fashion my resources together?'.

Steel Industry Challenges and Resource Efficiency in the Context of Circular Economy

Numerous challenges continue to impede the steel sector's ability to apply circular economy (CE) principles due to the vast reliance on energy and raw materials, as well as high levels of greenhouse gas emissions, solid waste, and wastewater generated from steel production, thereby driving ongoing improvements in resource efficiency and advanced recycling and reuse practices throughout the steel industry [16]. Current sustainability assessment tools (Life Cycle Assessment (LCA), Emergy analysis, and Carbon Footprinting) are suggesting systemic deficiencies taking place in material use, energy consumption and waste management throughout the entire life cycle of steel production, severely restricting and limiting CE practices [42]. While Electric Arc Furnace (EAF) recycling methods greatly improve upon energy efficiency compared with traditional blast furnace production methods (approximately 65.7 % efficiency versus 29.1 % energy efficiency), Closed Loop Systems (CLS) of steel production continue to be hindered due to end-of-life (EOL) problems related to inadequate collection of EOL products, lengthy longevity of EOL steel products and material losses due to product contamination and metallurgical constraints associated with steel production [43]. Such material losses are keeping the steel sector reliant on primary iron ore, especially in high-volume producing countries such as China where steelmaking is contributing disproportionately to the carbon and water footprint of production systems [40]. Therefore, combining optimized supply chains, enhanced EOL recovery systems (EOL = end of life), carbon pricing models and AI-based process optimization will also be increasingly acknowledged as necessary for establishing sustainable competitiveness for steel manufacturers as well as to help reduce environmental impacts created by steel production.

Figure 1: Industry-specific barriers to circular economy adoption in the steel sector.

This diagram describes the fundamental structural and operational obstacles that inhibit circular economy implementation in the Steel Sector. Examples would be the high amount of material waste produced through the linear production processes of Steel; variable quality that leads to an inability to recycle effectively; the amount of energy consumed to produce steel through the use of blast furnaces; the existence of fragmented and opaque supply chains; and, lastly, the increasing amount of regulatory pressure associated with initiatives such as the EU Green Deal, the carbon pricing system, and sustainability initiatives in developing countries like India. The downward pointing arrow at the bottom signifies the critical need for enabling technologies, regulatory frameworks, and organizational structures to help to address the barriers to circular economy transformation.

AI Applications in Circular Economy for the Steel Industry

Integration of AI with Industry 4.0 technologies (e.g., the Internet of Things, big data analytics, and blockchain) can fundamentally change steel production from its traditional linear model to a circular and Sustainable model by allowing for real-time monitoring, predictive optimization, and collaboration of decisions across the entire value chain [41]. In terms of material design and alloy optimization, AI applications will reduce experimental cycles, raw material usage & energy consumption and improve the recyclability & performance of steel products [48]. In addition, by improving the quality of scrap, reducing lost materials, and providing the capability to plan recovery effectively, AI-generated digital waste management, scrap sorting capabilities, and the capability for predictive reverse logistics will increase secondary uses of steel. AI-generated digital capabilities also provide increased operational efficiencies, regulatory compliance, and productivity through intelligent automation leading to less waste of resources and reduced environmental impact [18] There are many examples of empirical evidence demonstrating AI digital ecosystems that lead to improved economic, environmental, and social performance through inter-company collaboration and waste reductions like that found in the case study of the Feralpi Group [49].

Pathways and Research Gaps in AI-Enabled Circular Economy for the Steel Industry

Low-carbon steelmaking technologies have made great strides recently in producing low-carbon steel using hydrogen, integrating renewable energies, and increasing the use of scrap steel. We have also improved resource efficiency through these technological advancements. However, even with all of the advances we have made in low-carbon steel production, there are still many areas where we can do a better job of achieving an end-to-end circular economy of steel [44]. Therefore, it is critical that we take advantage of the benefits that will be provided by AI to improve our understanding of the entire life cycle of steel products. Currently, both the primary (blast furnace-basic oxygen furnace) and secondary (electric arc furnace) production methods are technically feasible; however, the cost of production, scalability issues, and the limited amount of integration between systems throughout the entire system (production to consumer to waste) are preventing both technologies from being widely adopted. AI is being researched as one means of overcoming these barriers, as the use of AI can provide insight into the flow of material, energy, and information throughout the value chain of steel products. Recent research is starting to demonstrate that the integration of AI with blockchain and the Internet of Things (IoT) will improve real-time scrap traceability, demand forecasting, emissions monitoring, and closed-loop recycling decision-making [41]. The recent development of multimodal AI and Large Language Models such as SteelBERT brings an opportunity for accelerated optimisation and analysis of alloys and processes where experimental data is constrained and have been placed outside the parameters of conventional ML. However, there are still significant research gaps with regards to the development of AI Benchmarking Standards, Limitations on Interoperability, and Lack of Integration of AI Across the Lifecycle of Circular Steel Systems.

TABLE 1. Literature Review On Ai-Enabled Circular Economy Transition In The Steel Industry

References	Key Findings	AI Technology	Sustainability Focus	Research Gap
[23]	AI optimizes scrap sorting efficiency	Computer Vision, ML	Material reuse, waste reduction	Limited real-time industrial validation
[11]	Predictive AI reduces blast furnace emissions	Predictive Analytics, ANN	Carbon footprint reduction	Poor integration with circular KPIs

[47]	AI enables lifecycle steel quality tracking	Digital Twins, IoT	Resource efficiency	Fragmented lifecycle data models
[48]	ML improves secondary steel yield rates	Supervised ML	Recycling efficiency	Lack of cross-plant learning models
[43]	AI enhances energy efficiency in EAFs	Reinforcement Learning	Energy sustainability	High computational costs
[1]	Smart AI systems reduce material losses	Optimization Algorithms	Waste minimization	Minimal reuse pathway modelling
[41]	AI supports circular supply chain planning	AI-based Forecasting	Sustainable logistics	Weak reverse logistics modelling
[50]	NLP extracts insights from sustainability reports	NLP, Text Mining	ESG transparency	Limited domain-specific ontologies

Key findings on AI-enabled circular economy transitions in steel are synthesized in Table 1, showing specific AI technologies mapped to specific sustainability objectives along with unresolved research gaps. AI has shown great potential to support recycling, energy efficiency and supply chain circularity; however, there is limited industrial validation at scale and integrated life cycle implementation of AI.

Research Questions

1. What collaborative functions do predictive analytics and Machine Learning Models in Material Design play to improve waste sorting and Reverse Logistics within the context of the Circular Economy of Steel Manufacturing?
2. How does the combination of the AI-IoT and RFID-enabled Blockchain improve the processes of monitoring and creating remanufactured products for reusing steel?

3. What sustainable outcomes, including but not limited to reduced CO2 emissions and increased Circularity within Supply Chains, result from the adoption of AI in Steel?

Hypotheses:
H1. The use of AI-based Machine Learning to optimize alloys results in increased steel recycling rates due to increased reusability of materials and lower manufacturing waste.
H2. The utilization of Real-Time AI-IoT technology within the CSSCM creates greater resource efficiency and lowers environmental emissions than traditional steel supply chain methods.
H3. The combination of RFID-Blockchain enabled AI framework provides increased transparency and collaboration between stakeholders, resulting in improved sustainability performance in the B2B steel market.

Research Methodology

A mixed-method and multi-stage research design was used for this study to address the three research questions about AI-enabled circular economy transitions in the steel industry. Scholarly literature was sourced only using Scopus, Web of Science, and IEEE Xplore to ensure a high-quality peer-reviewed body of evidence. The two above-mentioned data sources [35] were used to triangulate the empirical findings from the industry and add credibility to the data set's robustness. Research Question #1 utilised the PRISMA systematic review protocol. This consisted of structured search strategy identification, screening and assessment for eligibility, and then synthesis of the studies relevant to Machine Learning based on Material Design, Waste Sorting, and Reverse Logistics aspects of Steel Circularity. A Comparative Study methodology was adopted for Research Questions #2 & #3 and used to analyse and compare two of the world's leading manufacturers of steel and to compare the recycling ecosystems and how those ecosystems leverage the Integrated AI/Internet of Things (AIoT) in their operations through RFID Block Chain enabled systems and Digital Monitoring Systems. This methodology enabled an in-depth review of their real-time remanufacturing, reuse processes, and sustainability performance. The Cross-Case Synthesis methodology was used to identify the common motifs associated with the technologies employed, operational methods employed, and sustainability achievements realised including reductions in CO_2 emissions, increased energy efficiency, and improved supply chain circularity. The integration of evidence obtained through the use of systematic reviews with evidence obtained through the study of real-world cases provides the greatest methodological credibility; supports an in-depth analysis of the related fields; and has the greatest degree of generalizability.

PRISMA Phase I: Identification

• Data Sources: To source comprehensive literature, a systematic literature review was conducted over four major peer-reviewed academic databases: Scopus, Web of Science (Core), IEEE XPLore and Science Direct (by Elsevier) because of their comprehensive coverage of manufacturing engineering and AI; circular economy research, and Industrial Sustainability. In conjunction with the above academic databases, these databases provide a high degree of coverage for studies of metallurgical and manufacturing engineering, and AI application, and machine learning application, and circular economy frameworks; supply chain and logistics optimization, thereby minimizing the risk of selection bias based on database selection.

• Search Strategy: To achieve a balanced approach to capturing interdisciplinary contributions related to AI-enabled circularity in steel supply chains, this research utilized an iterative Boolean search approach to optimise both recall and precision. Searches were broken into three separate topic areas: (1) Circular Economy & Steel Manufacturing; (2) AI & Data-Driven Analytic; and (3) Waste Management, Recycling, and Reverse Logistics. An example of a potential search string is: ("circular economy" AND "steel industry") AND ("predictive analytics" OR "machine learning" OR "AI") AND ("reverse logistics" OR "waste sorting" OR "scrap recycling"). All searches focused on the title, abstract, and author keywords of each record in order to identify relevant contributions. Once the entire collection of records was identified, they were transferred to a reference management programme, where duplicate entries were identified by an automated process before being manually verified in accordance with the recommendations outlined in systematic review literature [31].

PRISMA Phase II: Screening

• The subsequent title/abstract screening was performed for all remaining records after duplicate removal and focus was exclusively directed towards studies that addressed the steel/metal manufacturing sector; recycling/reuse as one way to implement circular economy pathways; and implementation of AI, machine learning, and/or predictive analytics. Studies were excluded during this stage if they addressed only a specific non-metal industry with no transferable relevance to metals; presented purely as conceptual sustainability discussions that did not employ data-driven methodologies; or were editorial/non-peer-reviewed publications. This screening process dramatically reduced conceptual noise from our results while permitting the retention of studies that may hold potential relevance to our full text assessment.

PRISMA Phase III: Eligibility

• The methodological rigour and thematic congruence of articles published in the period from 2015 to 2025 were assessed according to criteria pre-defined for

RQ1. Articles were excluded from consideration if they did not specify an application of AI in manufacturing to circular economy principles; focused exclusively on energy efficiency without considering material flows or recycling; provided insufficient transparency regarding methodology; or were based solely on simulation-based methods and could not be demonstrated to be relevant for industrial purposes. Eligible articles were assessed through a comprehensive set of criteria established for quality appraisals regarding methodological rigour; industrial applicability to steel value chains; alignment with circular economy objectives; technical rigour of AI methods employed; and strength of empirical evidence used. Only articles that satisfied all five categories of the quality appraisal were eligible for synthesis.

PRISMA Phase IV: Inclusion

- The final phase of the PRISMA review resulted in the inclusion of 124 studies in both the qualitative and thematic–conceptual synthesis. These studies provide consolidated evidence on how AI enables circular economy practices in the steel industry. The included literature primarily focuses on four key areas: AI-driven material design and alloy optimization to improve recyclability and performance; predictive analytics for scrap classification and waste sorting to enhance secondary steelmaking efficiency; machine learning applications supporting reverse logistics and closed-loop supply chain coordination; and integrated AI–IoT systems for remanufacturing and real-time process monitoring across the steel lifecycle. Collectively, these studies offer a robust empirical and conceptual foundation for understanding the role of AI in operationalizing circular supply chains and advancing sustainable steel manufacturing.

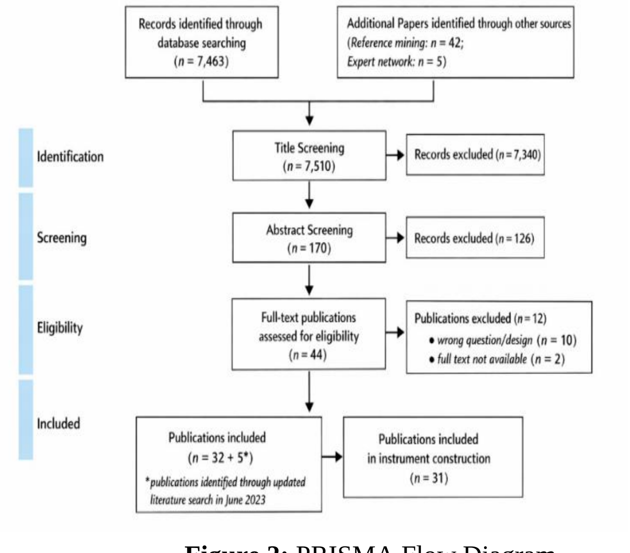

Figure 2: PRISMA Flow Diagram

The PRISMA Flowchart given in Fig 4. indicates each of four stages conducted during the identification, screening, eligibility, and inclusion of the final studies selected for qualitative, thematic, and conceptual synthesis as follows: Stage 1: Identification - a combination of Scopus, Web of Science, IEEE, ScienceDirect, and other peer-reviewed research databases; Stage 2: Screening - the removal of duplicates and rejection of titles/abstracts that were irrelevant to this review; Stage 3: Eligibility - full-text articles were assessed and subsequently excluded, but reasons for exclusion were well documented; Stage 4: Inclusion - the total number of studies (n =31) that met all criteria is exactly equal to the total number of peer-reviewed articles listed at the end of the research paper.

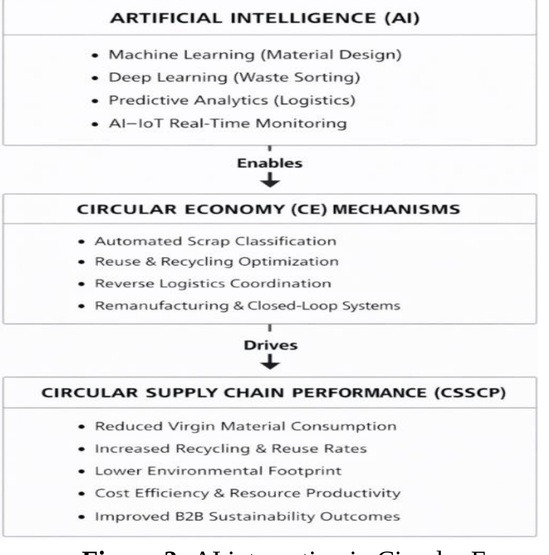

Figure 3: AI integration in Circular Economy

Figure 5 shows a new conceptual framework will describe how circular economy processes in the steel industry are enabled and facilitated through AI technologies. AI technologies include machine learning for producing the most suitable combination of materials and determining what alloy would work best; Deep Learning, which allows for the analysis of large quantities of data using Computer Vision to provide precise results on scrap classification; and Predictive Analytics that together with AI–IoT systems provide real-time insights and facilitate better decision-making across the entire steel value chain (when combined).These AI technologies allow for the process of converting a traditional linear production system into a closed-loop production model, through the application of automated waste sorting to purify raw materials; Predictive Logistics to optimize reverse material flow; and the continuous monitoring of materials to support the reuse and remanufacturing decisions of suppliers. Collectively, these mechanisms allow steel supply chains to fully implement the principles of reuse, recycling, and manufacturing. Measuring the results for the framework's outcomes layer includes results such as: less dependency on virgin materials; increased rates of recycling and reuse; decreased environmental impact and emissions; improved cost efficiency/resource productivity; improved business-to-business sustainable performance. The framework provides a clear pathway for measuring the relationship between AI technologies, CE mechanisms, and measurable supply chain outcomes which explicitly answers the research questions on the role of machine learning and predictive analytics in enabling waste sorting/reverse logistics to support areas that will lead to more sustainable and efficient circular steel supply chains.

A Case Study Design

The steel industry has significant barriers to attaining circularity, mainly due to fragmented visibility into production, inconsistent quality control, high scrap values, and poor traceability through reverse logistics systems [34] [28]. The classic cut-and-bend/rebar making processes are still mostly manual, creating waste and delays when making decisions, and adding CO2 emissions. Therefore, this study employs an integrated AI/IoT and RFID-based blockchain approach to explore real-time monitoring and predictive decision-making concerning remanufacturing optimization for reuse, which identifies the primary goal of RQ2. The methodological approach employs various elements of Industry 4.0, including sensor-based real-time acquisition of data, machine learning data analytics, and blockchain-based traceability to develop a closed-loop circular steel production process [29] [32]. This research consists of a multiple-site case study design exploring the use of AI-driven sustainable automation in India-based steel service centres by combining two industry-specific applications of these technologies:

(i) Smart manufacturing through a Blockchain-AI-IOT architecture focusing on fault identification and diagnosis, quality assurance/control, and secure data governance.

(ii) The implementation of an AI-based sustainability automation initiative for optimizing scrap reduction of various offcuts and managing inventory.

The aim of this research will be to create a model for the practical use of these technologies to increase material circularity, reduce waste, and increase overall process effectiveness while maintaining affordability.

B. System Architecture

The circular manufacturing ecosystem has been designed with four distinct technology layers.

- Internet of Things (IoT): Environmental and machine-health sensors that are effectively connected to legacy and modern steel processing machines record real-time data, such as the temperature, vibration, energy consumption, the usage of the machinery, and the flow of materials. RFID tags that are attached to steel billets, rebars, and other scrap steel will allow for tracking through the entire value chain (production, storage, transportation, and remanufacturing).
- AI and Analytics: Machine learning models (predictive maintenance, maintenance fault diagnosis, quality inspection and demand forecasting) utilize a

combination of hybrid and non-linear solutions to accomplish these tasks, and in turn help to make cut-length decisions (reducing the scrap generated) as well as help predict machine failures and improve machinery use.

- Big Data: The structured operational data is stored in a relational database (such as Amazon Aurora) that can be expanded based on the amount of data being recorded, whereas the unstructured data from sensors and images are stored and processed within large distributed frameworks (such as Amazon S3 & AWS Auto Scaling) that provide the ability to create large amounts of analytics across multiple sites.
- Blockchain Technology: A private Hyperledger Fabric network captures machine events, provenance information, availability of offcuts, and transactions related to reusing the offcuts. In addition, through the use of smart contracts, the validation of quality, eligibility for reuse, and the processes of remanufacturing will be automated, thereby facilitating coordination and cooperation among all stakeholders in a secure and transparent manner.

C. Implementation Procedure

Methodology for integrating AI-IoT & Blockchain [34] [28]

- Data Acquisition and Preprocessing: The IoT sensors continuously gather the environmental and operational data across multiple service centers on an ongoing basis while the data preprocessing normalizes, applies error handling and aligns with machine learning requirements.
- Predictive Modelling: A ML (machine learning) algorithm will examine the real-time streams of information to identify anomalies and forecast machine degradation and recommend the best cut and reuse strategies. The predictive maintenance model is designed to reduce unplanned downtime, extend the life of the equipment.
- Material Tracking and Remanufacturing Optimization: The tracking of offcuts, grades and locations of the fragments of steel is achieved using RFID (radio-frequency identification) tag technology and secure blockchain records. AI models will recommend the best pathways to reuse steel scrap, enabling sharing and minimizing waste between service centers.
- Real-Time Monitoring and Decision Support: The dashboards combine the data from the AI prediction, IoT sensors and blockchain records to provide actionable insights, thus allowing the organisation to introduce dynamic production schedules and take immediate corrective action when required.
- Evaluation of Circular Economy Outcomes: The system performance will be assessed in terms of operational efficiency, amount of scrap created, amount of waste created, reduction of CO2 emissions and transparency of the supply chain. The results of the study will provide insight into improvements made in the yield of secondary steel and the potential for scaling circular manufacturing processes.

D. Expected Outcomes

The integrated AI-IoT-Blockchain Framework will provide significant operational and sustainability advantages:

- AI-guided cutting and reuse decisions will reduce steel scrap by as much as 10%.
- Offcut utilization efficiency improved up to 50% will support the material circular economy.
- CO2 emissions will decrease due to improved predictive maintenance, optimal inventory and purchasing practices, and improved just in time (JIT) logistics.
- Traceability and accountability through the supply chain will allow for large scale closed-loop remanufacturing activities.
- Automation of quality control and real-time monitoring will result in increased operational efficiency and consistent quality [30].

The methodology utilized is based upon case study methods within complex industrial systems, which require detailed empirical observation, performance tracking and cross-site comparison of multilayered technological interventions [45]. The combination of IoT, AI and Blockchain provides data integrity, transparency and scalability to identify/actions for both academic research and practical application within the steel sector. By addressing RQ2 directly through the research focus of real-time monitoring and remanufacturing optimisation, this will illustrate the role of digital technologies in enabling circular economy objectives within the steel sector and demonstrate tangible sustainability improvements through the research findings.

Case Study Design:

To explore Research Question 3 (RQ3) — understanding the sustainability benefits (CO_2 emission reduction and improved circularity of the supply chain), this research is framed within Sustainable Business Model Theory and Circular Economy (CE) Principles [51] Sustainable Business Model promotes the creation of Economic, Environmental and Social Value while maximizing Efficiency of Resource Use; Energy Optimization and Long-Term Organisational Resilience, whereas CE Principles (e.g., Designing-Out Waste; Encouraging Regenerative Material Flows; Enabling Eco-Effective Systems) provide a way to implement sustainability across industrial ecosystems [46]. AI technologies have been increasingly acknowledged as vital to the integration of Circular Economy (CE) practices by facilitating Real-Time Decision-Making, Industrial Symbiosis and Circular Supply Chain Management [35]. This study aims to shed light on the contribution that the adoption of AI in the Steel Manufacturing Industry and its associated Industrial Ecosystem make towards Decarbonisation, Circularity and Sustainable Value Creation.

The present Research involves using a multi-source (cross industry) case study, Synthesising the findings from

1. European / Global Decarbonisation Initiatives in the Steel Sector to demonstrate AI-enabled Process Optimisation, Predictive Maintenance and Material Flow Intelligence [35]

2. AI-driven Sustainability programmes in Manufacturing e.g. Danfoss's Zero Carbon Product programme utilizing AI-enabled Material Decarbonization, Supplier Assessment and Circular Supply Chain Strategies [35]
3. Development of Circular Supply Chain Studies / CE Implementation Frameworks in Heavy Industries which Support the Operationalization of Sustainability Reporting and Industrial Symbiosis Practices [35].

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he use of a Case Study approach allows us to triangulate the results of our quantitative Sustainability outcomes, such as CO_2 reduction, Offcut utilization rates, etc with Qualitative Insights regarding Governance, Alignment with Strategy and Integration in the Supply Chain.

Data Sources:

- The operational and sustainability performance measures provided by European steelmakers and their international business collaborators.
- Proof of the companies' use of AI for programs related to; energy optimization, predictive maintenance, material re-use, and supply chain transparency.
- Corporate Sustainability Reports (CSR) following GRI, ISSB, CDP, TCFD, Science-Based Targets Initiative (SBTi), etc.

Data Collection Methods:

- Utilization of Secondary Data Analysis through sustainability reports, company disclosures and industry case studies.
- Document Analysis of AI-enhanced circular supply chain pilot projects including decarbonization roadmaps, strategies for material substitution, and life cycle Assessment.
- Through Expert Interviews or Surveys depending on the availability of stakeholders for input regarding AI-Enabled Sustainability outcomes and Operational Issues [35].

Analytical Framework

The following are Assessment Dimensions to assess Operational Performance, Supply Chain Circularity, and Governance and Strategic Alignment of AI:

- Assessing Operational Performance related to the reduction in CO2 Emissions, increasing Energy Efficiency and improving Material Recycling for AI on historical data/predictive modelling benchmarked to decarbonisation targets.
- Supply Chain Circularity Assessment. Assessing Improvement to Offcuts Utilisation, Remanufacturing Efficiency and Industrial Symbiosis are enabled through AI material flow intelligence and Blockchain traceability.
- Governance and Strategic Alignment Evaluation. Assessing how AI adoption aligns with global reporting standards for Sustainability, Transparency of Decision-Making, and the integration of Sustainability Objectives within Procurement, Product Design and Supply Chain Governance.

Implementation Procedure

The steps in the process of assessing sustainability as a business outcome through the methodology are:

- Mapping the Value Chain for AI Utilization: Map all AI interventions used throughout the steel manufacturing process (material movement), for remanufacturing, energy savings, predictive maintenance and circular flow of materials [34].
- Collection and Normalization of Data: Collect operational, environmental, and product flow data from various steel producers and industrial partners. Standardize data to facilitate the comparison and quantitative assessment across cases.
- Evaluating CO_2 Emissions Impact: Use predictive and statistical models to evaluate the effect of optimizing processes through AI, removing carbon from materials, and predictive maintenance on CO_2 emissions, both operational and embodied [35].
- Assessing Circularity of Supply Chains: Evaluate initiatives related to tracking materials; reusing offcuts; industrial symbiosis; and closed loop recycling; while quantifying the increases in yield of secondary steel, and resource efficiency.
- Evaluating Designing and Reporting Processes: Review resources enabled through AI designed to create reporting or decision-support platforms and understand how they align with the GRI, ISSB, CDP, TCFD, and SBTi processes in terms of transparency, accountability, and integrating sustainability in strategic decisions.

Expected Outcomes:

The AI Sustainability Framework will provide:

- Enormous decreases in carbon dioxide emissions as a result of using energy more efficiently, using predictive maintenance tools, and decarbonizing material use.
- Greater supply chain circularity through the establishment of intelligent systems for the reuse of offcuts, creation of industrial symbiosis, and establishment of closed loop recycling systems.
- Increased governance and transparency through aligning operations with global standards for reporting and increasing confidence in investors and regulators.
- Operational and strategic insights regarding how companies can transition to a Circular Economy and embed sustainability into their core business processes [34] [35].

The systematic evaluation of the effects of AI on both environmental and operational performance will produce empirical evidence to support RQ3, which focuses on how digital technologies can support the development of decarbonizing, circular, and sustainable steel value chains.

Results and Discussions

The results of applying the PRISMA method for screening and confirming articles that meet the PRISMA criteria yielded the selection of 31 articles from journals that had been published in a minimum of 15 peer-reviewed categorizations from around the World, which covered the fields of Metallurgical Engineering, Metallurgy and Additive Manufacturing Systems (through AI), and the development of Circular Economy Research and theory in Steel and Metals. The number of peer-reviewed articles on this topic increased significantly after the year 2018, which reflects the growing attention from both an academic and industrial standpoint on AI-enabled sustainable and circular economic transitions. The results of the literature demonstrated a clear and strong consensus that AI technologies, including Machine Learning (ML), Deep Learning (DL), Predictive Analytics, and AI-Internet of Things (IoT) Systems, support the development of Circular Economy pathways through Steel Supply Chains. AI technologies and their applications, such as those described, will reduce the number of contamination incidents associated with scrap materials and help to establish better relationships between scrap and product compatibility. Additionally, AI technologies will support the generation of high-grade secondary steel, enabling higher quality products and less strain on the environment by enabling expanded usage of secondary materials. As such, AI technologies and their applications will facilitate the reuse and recycling of metal products, thus contributing to the establishment of a Circular Economy.

AI, especially using Convolutional Neural Networks, has been extensively applied to the automated sorting of scrap and waste using deep learning and computer vision techniques. Based on comparative studies, the use of AI sorting systems tends to provide greater accuracy, faster response times, and greater scalability than traditional methods. This results in improved purity rates of scrap, the ability to make real-time operational decisions, and the creation of safer recycling environments. Additionally, through the use of predictive analytics, AI allows for the optimization of reverse logistics, including the timing of collection, transportation, and remanufacturing of scrap. As a result, overall costs are lowered, the emissions of scrap are reduced, and the efficiency of the supply chain is enhanced. The application of AI throughout the entire steel lifecycle provides evidence that AI contributes to the continued sustainability of the circular economy. It is identified in the areas of recyclable material design, monitoring and managing production in real-time, and managing the recovery of scrap at the end of its life and its reverse flow. In summary, evidence supports an overall connection between AI-enabled circular practices and enhanced environmental and operational performance, including increased recycling rates, reduce reliance on virgin material, and improved cost efficiency. To maximize effectiveness, AI must be used as an integrated system capability in support of a company's circular supply chain objectives.

Conclusion and Future Scope

This research methodically surveyed AI impact on the circular economy (CE) of the steel sector by synthesizing peer-reviewed research through a PRISMA-supported evaluation; as well as reporting qualitative data from case studies. The study's analysis indicates that there are multiple system-level enabling functions of CE provided by AI applications throughout the steel supply chain (i.e., material design and fabrication via machine learning, materials recovery via deep learning-based scrap sorting, reverse logistics via predictive analytics, and real-time monitoring of supply chain activity via AI-Internet Of Things (IoT) technologies). Rather than achieving stand-alone efficiencies, AI enables the creation of integrated circular supply chains through enhanced material quality assurance, improved recycling and logistics, and decreased reliance upon virgin raw materials. Results also show that AI-driven CE practices improve environmental, operational and economic performance; hence confirming that AI promotes CE as an adaptive capacity of sustainable steel production. Nevertheless, continued challenges - i.e., data fragmentation, material non-homogeneity, difficulty in achieving full lifecycle status and varying degrees of technology adoption - impede the transformation of circular economy practices in the steel sector. Continued research is needed to create comprehensive, AI-supported circular steel supply chain models that harness digital twins, multimodal AI models, and IoT-based sensing throughout the full life cycle. Large industrial pilot tests across regions (in addition to traditional pilot tests) are required for empirical evaluation of the overall performance of AI in achieving circular outcomes and developing an accepted framework for evaluating such complex outcomes. There's great potential to combine newly available technology such as large language models and multimodal approaches (such as SteelBERT) with live production and recycling data to enable advanced alloy optimization and closed loop material flows. The use of governance, data-sharing mechanisms, and regulatory incentives will also help support scalable AI enabled circular transformations in the global steel industry.

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