Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/BA08.20250191
Published: December 20, 2025

Project and Supply Chain Optimization to Enhance Sustainability in AI-driven Industry 4.0: A Review of Recent Trends

Afia Saiara Akhi, Mustakim Jahan and Shamima Shammay
Undergraduate Student in Industrial and Production Engineering
National Institute of Textile Engineering and Research (NITER), Dhaka, Bangladesh
afiasaiaraakhi@gmail.com, mustakim.official96@gmail.com, shammishamima72@gmail.com

Proma Acharjee
Faculty in Industrial and Production Engineering
National Institute of Textile Engineering and Research
(NITER), Dhaka, Bangladesh
pacharjee@niter.edu.bd

Abstract

The growth toward Industry 4.0 has transformed global industrial ecosystems, compelling organizations to embrace artificial intelligence (AI) as a core driver of sustainable competitiveness. The integration of digitalization, automation, and intelligent analytics now defines how projects and supply chains are optimized to achieve both operational efficiency and environmental responsibility. This paper presents a systematic review of recent global research that explores AI-driven optimization techniques for sustainable project and supply chain management. It synthesizes advancements in predictive analytics, machine learning, digital twin technology, and multi-objective optimization that enable data-driven decision-making across production planning, logistics, and maintenance. The findings highlight a clear global trend: industries are increasingly integrating AI models to minimize carbon emissions, enhance energy efficiency, and improve transparency across interconnected supply networks. However, challenges persist regarding data interoperability, explainable AI, and the alignment of digital transformation with circular economy goals. This study provides an integrated conceptual framework summarizing the state-of-the-art approaches and identifies emerging research directions that emphasize ethical, resilient, and sustainable industrial ecosystems. The insights from this review contribute to bridging the gap between technological innovation and sustainable operations, offering strategic guidance to academia, practitioners and policymakers in advancing AI-empowered sustainable industrial operations globally.

Keywords
Artificial Intelligence, Project Optimization, Sustainability, Digital Twin, Predictive Analytics.

1. Introduction

1.1 Background

The global industrial scene is also maturing fast, going through a profound digital transformation powered by the combination of various emerging technologies, such as AI, CPS, IOt, and big data analytics systems. All these technologies combine to form the industrial technologies that will lead us into the Fourth Industrial Revolution (Industry 4.0), where intelligent automation and interconnectivity across the production systems will provide enhanced visibility, flexibility, and a better decision-making capability of the operation (Kagermann, et al., 2013; Lee, et al., 2015; Tirkolaee et al., 2021). Industries have gradually transitioned from labor- and resource-intensive processes to data-driven, knowledge-driven processes in the last 10 years. Consequently, these changes are reshaping traditional production and supply chain paradigms and call for computational tools capable of handling complex databases, providing predictions of performance trends, and optimizing resources (Xu et al., 2018) in a sustainable way. Simultaneously, rising environmental regulations, resource scarcity, and societal demand for sustainable practices have pressured organizations to reconcile economic growth with environmental stewardship (Sarkis 2020; Seuring, & Müller 2008). As a result, production systems should emit less waste, throw less waste, and be more energy efficient so that all industrial systems can compete in global markets. Here, the use of AI with Industry 4.0 technologies is not only an evolution in technology but also a strategy to adopt for sustainability and resilience in the long run (Sony, M., & Naik, S. 2020).

1.2 The Industrial Revolution 4.0 and the Rise of AI

Industry 4.0, the fourth industrial revolution, embodies the notion of smart manufacturing and the framework for real-time connectivity of machines, humans, and digital platforms (Lasi, H et al., 2014). At the core of this transformation is AI, which allows predictive analytics, self-learning systems, and autonomous decisions to be made across industrial ecosystems (Ivanov, D et al., 2019). Algorithms such as machine learning (ML), deep learning (DL), and reinforcement learning (RL) allow industries to identify latent patterns in the discreet attributes of operations data and convert them into actionable insights (Jordan, M. I., & Mitchell, T. M. 2015). Although the recent hype around AI has centered on automation in manufacturing, its potential is wider. Among them, predictive maintenance, quality control, logistics optimization, and demand forecasting (Baryannis, G et al., 2019; Wuest, T., Weimer, D et al.,2016) are provided. With the aid of AI for industrial enterprises, intelligent factories that autonomously self-diagnose inefficiencies and adjust autonomously by responding to fluctuations in production through automated adjustments in the manufacturing process are possible. An example of such an enabler is the digital twin technology that creates virtual replicas of physical assets, which can then be used to simulate, analyze, and optimize the behavior of systems in real time (Kritzinger, W et al., 2018). These changes have allowed project and supply chain management to evolve from reactive to proactive management systems, and as a result data driven intelligence enables more accurate forecasting, reduced operational risk as well as improved sustainability during product life cycles (Zhang, Y et al.,2017). However, high-impact identification of AI opportunities requires quality data, cross-functional collaboration, and a strong digital backbone, all of which remain challenging for many industries (Kamble, S. S et al,.2018).

1.3 Sustainability and The Optimization Imperative

Sustainability has become a key focus for industries owing to current issues such as global warming, pollution, and depletion of resources (Geissdoerfer, M et al.,2017). Sustainability is a key metric because modern supply chains contribute to the amount of carbon emissions and energy used (Dubey, R et al.,2017). To overcome these obstacles, optimization approaches are being increasingly implemented to create resource-efficient production systems in line with circular economic ideals (Nikolaou, I., & Tsalis, T. 2021). Under this setting, the optimization consists of a trade-off between economic, environmental, and social objectives, known as the "triple bottom line" (Elkington, J. 1998). Therefore, conventional optimization models are restricted by static assumptions and linear correspondences that are ineffectively fit to the dynamic and uncertain characteristics of contemporary industrial systems (Govindan, K., & Hasanagic, M. 2018). On the other hand, optimization created through AI utilizes algorithms that can learn from historical data and adjust in real time. Machine learning models, for example, can be used to predict demand more accurately, thereby reducing overproduction and waste due to inventory (Hofmann, E. 2019). Reinforcement learning approaches have been proposed to alter logistics routes dynamically to protract transportation costs and emissions (Gendreau, M., & Potvin, J.-Y. 2010), and multi-objective evolutionary algorithms facilitate decision-makers in determining the trade-offs among conflicting sustainability objectives (Deb, K. 2001). It allows AI to be embedded within optimization frameworks to enable major advances in energy use, waste, and process visibility in industries (Chae, B. K. 2019).

1.4 Project Management

Industry 4.0 drives innovation in project management by highlighting the importance of sustainability and supply chain optimization through integration of artificial intelligence (AI) and digital technologies. The paper argues that artificial intelligence models machine learning (ML), deep learning (DL), reinforcement learning (RL), etc. have become indispensable tools in achieving operational efficiency and sustainability goals. By predicting disruptions, effectively utilizing resources, and simplifying decision making, these AI models can play a crucial role in increasing the sustainability of projects (Jordan & Mitchell, 2015; Baryannis et al., 2019). Digital twin technology enables project managers to simulate the real time status, working conditions, and production properties of physical assets and processes, allowing for the optimization of resource allocation and carbon emission reduction prior to the execution of actual processes (Kritzinger et al., 2018; Ivanov & Dolgui, 2021). It allows decisions to be made before any physical changes are made, which reduces waste and increases sustainability through greater operational efficiency of the systems (Wuest et al., 2016). In addition, the traditional method of managing supply chains has changed significantly with the help of AI. The paper cites that predictive analytics and optimization models are applied to reduce lead times, improve logistical flows, and minimize environmental drawbacks, including energy use and waste (Queiroz et al., 2020; Gendreau & Potvin, 2010). In addition, this study highlights the importance of applying a multi-objective optimization framework to reflect the trade-offs between economic, environmental, and social sustainability objectives to realize a circular economy in supply chains (Deb, 2001; You & Grossmann, 2008). Therefore, project management will enable sustainable projects to be carried out through the utilization of AI and Industry 4.0 technologies to sustain the operations of supply chains per human and environmental sustainability.

1.5 AI Adoption in Project and Supply Chain Management

Real-time data integration and intelligent decision support are emphasized in the management of projects and supply chains in Industry 4.0 (Ivanov, D., & Dolgui, A. 2021). From the supplier to the end consumer, nodes in the supply chain are now digitally connected, and AI technologies are replacing conventional supply chains towards smart supply networks (Queiroz, M. M et al., 2020). With this integration of the supply chain, organizations could enjoy predictive visibility, that is, they would be able to identify potential disruptions, predict lead time, and manage risk with ease (Bai, C., & Sarkis, J. 2020). AI improves the precision of planning, resource allocation, and risk mitigation in project management. Before experiencing project delays, cost overruns, or performance deviations, predictive analytics can identify them (Han, S. J., & Lee, H. 2021). Likewise, planning the labor, materials, and time in the most sustainable manner is obtained using an AI-driven optimization model (Cook, D. J., & Das, S. K. 2007). SCM includes AI applications such as supplier choice and segmentation, demand prediction, production scheduling, and distribution optimization (You, F., & Grossmann, I. E. 2008; Min, H. 2019; Ivanov, D., & Dolgui, A. 2020). Deep learning models, for instance, have been used to identify outlier behaviors in logistics networks, whereas digital twins permit the simulation of supply chain scenarios under different market conditions (Wilts, H et al., 2021). AI-empowered SCM can also promote the transformation of SCM from traditional supply chains to circular supply chains (i.e., reuse, recycling, and remanufacturing) (Sharma, R et al., 2020). All these technologies complement each other to create a data-centric environment that continuously enhances efficiency and minimizes the environmental footprint (Tseng, M.-L et al., 2018). Even so, many sectors have full adoption of AI at the leadership stage for 2022, but barriers still prevent many industries from reaching this level, such as data silos, interoperability, and the inability of AI to explain their decision-making processes (Wright, C. S., & Schultz, R. 2022).

1.6 Research Gaps and Challenges

While the separate application of AI, machine learning, and optimization technologies in industrial systems has been well documented in prior scholarly literature, the synthesis of these technologies into one compilation of systems extensions focusing on sustainable projects and operations is needed (Bousdekis, A et al., 2019). Most of the existing literature is dispersed, focusing only on either technical model advancement (Wright, C. S., & Schultz, R. 2022; Bousdekis, A et al., 2019) or the environmental assessment approach (Tseng, M.-L et al., 2018), without combining the two views (Baryannis, G., Dani, S et al., 2020).
Key challenges include (Figure 1):

- Interoperability and quality of industrial data: Industrial data are usually heterogeneous, inconsistent, and distributed on multiple platforms, making the task of training AI models more challenging (Papadonikolaki, E., & Wamelink, J. W. 2017).
- Interpretability and transparency: Many AI algorithms, especially deep learning algorithms, are black boxes and do not allow inference of conclusions from the glow of the outcomes (Adadi, A., & Berrada, M. 2018).
- Weak Alignment With Global Sustainability Goals: The alignment of AI-driven optimization with global sustainability targets, such as carbon neutrality and circular economy, has received little attention from researchers (Dantas, T. E., et al. 2021).
- Ethical and governance issues: AI led to challenges related to data privacy, algorithmic bias, and the replacement of human labor (Floridi, L., & Cowls, J. 2019).

Furthermore, although AI-based optimization has shown great potential, its use is still limited to developing countries and SMEs owing to cost and infrastructure limitations (Tortorella, G., et al. 2021). Thus, the inability of existing digital transformation frameworks to address the need (Baryannis, G et al., 2020) for inclusive and sustainable digital transformation highlights the urgent need to develop holistic frameworks that align technological innovation with policy and management (Dalenogare, L. S et al., 2018).

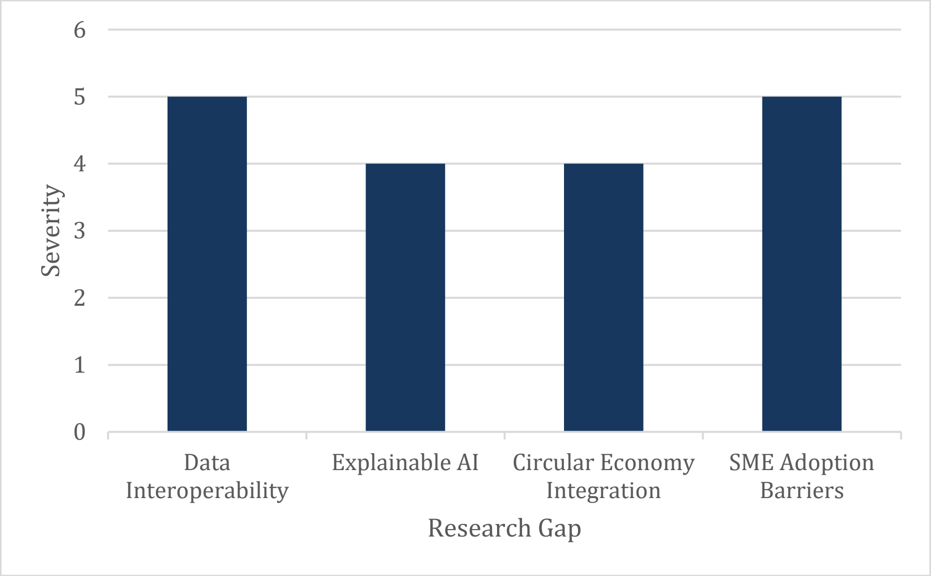

Figure 1**.** Research Gap Analysis

1.7 Research Problem, Aim, and Objectives of the Study

Motivated by these trends and the identified challenges, this paper aims to systematically review and summarize recent world research on AI-based optimization methods for sustainable projects and supply chain management from the lens of Industry 4.0 (Tirkolaee, E. B. et al. 2021).

The study seeks to:

- The core technical state of the art in AI applications is distilled predictive analytics, machine learning, digital twin technology, and multi-objective optimization.
- Explore how these technologies help you to be more operationally efficient, reduce your carbon footprint, and optimize your energy.
- It looks at the key roadblocks standing in the way of industrial deployment at scale, such as data management, model explainability, and regulatory alignment.
- We present a holistic conceptual framework that reviews the existing research and identifies emerging areas for future studies.

This review integrates knowledge across disciplines to help close the gap between innovations in new technologies and sustainable advancements in the industry. These results will help academics, practitioners, and policymakers formulate pragmatic policy actions to catalyze AI-enabled sustainability in global industrial ecosystems (Sharma, R., & Joshi, A. 2021).

2. Objective

This study investigates the role of artificial intelligence (AI) in sustainable project and supply chain optimization in the Industry 4.0 landscape. With industries moving into new Industry 4.0 systems, sustainability has established itself as a fundamental, pushing organizations to leverage AI technologies to help them reduce their carbon footprint in an effort to go green while increasing the bottom line. Specifically, this study examines AI-powered methods with a focus on machine learning, deep learning technologies, and digital twin technologies, with the goal of demonstrating how AI can enhance production planning, logistics, and supply chain management, as well as assist in sustainable activities such as waste minimization, and energy and carbon footprint minimization. This research is important because it can lead to concrete implications for industries, policymakers, and researchers. It also outlines the barriers for industries in implementing AI: data interoperability, explainability, and digital transformation sustainability goal alignment. This study seeks to resolve these mechanisms by providing strategies to reduce these barriers, thus enhancing the efficiency of AI integration. This study also

offers a path for industries to embrace AI technologies for circular supply chains to encourage sustainable practices. This research will offer benefits to industry leaders by providing them with a crystal-clear view of the capacity that AI has for sustainability, while also offering guidance to policymakers on how to establish frameworks conducive to the adoption of AI. Another theoretical contribution of this study lies in inspiring new interdisciplinary research on AI and sustainability topics.

3. Literature Review

3.1 Industry 4.0 and Digital Transformation

Industry 4.0 represents a fundamental shift in how modern production systems are designed, operated, and optimized. Unlike earlier industrial revolutions that focused on mechanization, mass production, or automation, Industry 4.0 emphasizes interconnectivity, digital intelligence, and autonomous decision making across industrial environments (Kagermann et al., 2013; Lee et al., 2015). This transformation is made possible through the integration of advanced enabling technologies such as artificial intelligence (AI), cyber-physical systems (CPS), Internet of Things (IoT), cloud computing, and big data analytics (Xu, L. D. et al., 2018; Sarkis, 2020). Together, these technologies allow factories to function as interconnected digital ecosystems rather than isolated production units. The digital transformation wave has reshaped traditional industrial processes by moving them away from labor-intensive, manual workflows toward data-driven, automated, and intelligent operational structures (Seuring and Müller, 2008). Real time data accessibility, smart sensors, and interconnected machines have enabled improved visibility across production networks, allowing companies to forecast disruptions, optimize resource usage, and enhance decision making (Sony and Naik, 2020). The rapid growth of digital platforms has also increased the interdependence of global supply chains, making accuracy, speed, and resilience essential requirements for sustainable industrial performance. With rising global environmental concerns, digital transformation has also become a means to enhance sustainability by promoting energy efficient operations, reducing waste, supporting circular economy practices, and enabling low carbon production systems (Dubey et al., 2017; Nikolaou and Tsalis, 2021). In this scenario, AI emerges as the backbone of smart, adaptive, and environmentally responsible industrial operations. The increasing availability of industrial data further strengthens the potential of AI to transform manufacturing and supply chain ecosystems (Elkington, 1998). Overall, the literature strongly supports the view that Industry 4.0 is not merely a technological evolution but a strategic shift toward intelligent, interconnected, and sustainable industrial ecosystems (Govindan and Hasanagic, 2018; Chae, 2019).

3.2 Applications of Artificial Intelligence in Industrial Optimization

Artificial intelligence has become one of the most transformative forces in contemporary industrial systems. Its ability to learn from data, detect hidden patterns, and adapt to dynamic conditions makes it ideal for optimizing complex industrial processes. According to Jordan and Mitchell (2015), AI-particularly machine learning (ML), deep learning (DL), and reinforcement learning (RL) is capable of translating massive datasets into actionable insights that improve decision-making and operational efficiency.

3.2.1 Machine Learning in Production and Operations

Machine learning techniques have been widely used for predictive modeling, process monitoring, and anomaly detection in manufacturing systems (Wuest et al., 2016; Zhang et al., 2017). These models support the automation of quality inspection, fault diagnosis, and production scheduling, thereby reducing human error and operational variability. ML approaches enable process optimization by continuously learning from historical datasets, which helps industries adapt to fluctuating demand, changing production parameters, and unexpected disruptions (Kamble et al., 2018).

3.2.2 Deep Learning for Complex Industrial Data

Deep learning enables industries to analyze highly complex datasets such as images, sound signals, process logs, or sensor data. Wuest et al. (2016) highlight how deep learning models have been successfully applied to detect product defects, classify complex material behaviors, and optimize workflows across different manufacturing stages. These capabilities contribute to higher product quality and reduced inspection time, ultimately improving productivity and sustainability.

3.2.3 Reinforcement Learning for Autonomous Optimization

Reinforcement learning is gaining popularity in scenarios requiring dynamic real time optimization. By continuously learning from environmental feedback, RL models can autonomously optimize logistics routes, machine configurations, or inventory levels. Gendreau and Potvin (2010) show that RL-based optimization algorithms outperform classical methods in uncertain industrial environments, especially in transportation and warehousing. Overall, AI technologies have transitioned from experimental use to mainstream adoption, reshaping production and service systems with greater intelligence, flexibility, and sustainability (Chae, 2019).

3.3 AI and Sustainability

Sustainability is now a central requirement across industrial operations due to increasing environmental pressures, stricter regulations, and growing consumer awareness. Several scholars emphasize that modern supply chains must balance economic efficiency with environmental and social responsibility to remain competitive (Geissdoerfer et al., 2017; Dubey et al., 2017). AI has emerged as a strategic tool in facilitating this transition, as it enables industries to reduce waste, improve energy efficiency, and cut carbon emissions.

3.3.1 AI-Enabled Energy Optimization

AI-driven models can identify inefficiencies in energy consumption and propose optimal strategies for load balancing, resource allocation, and machine utilization (Hofmann, 2019). Predictive analytics can anticipate peak energy demand, enabling companies to plan operations more efficiently and reduce emissions.

3.3.2 AI for Waste Reduction and Cleaner Manufacturing

Cleaner production practices rely on analytical models that evaluate waste streams, forecast production losses, and optimize resource utilization (Nikolaou and Tsalis, 2021; Zhang et al., 2017). AI-based systems support preventive measures that minimize defects, reduce rework, and promote recycling or reuse of materials in line with circular economy goals (Tseng et al., 2018).

3.3.3 AI and the Circular Economy

The integration of AI with circular economy principles has gained scholarly attention. Researchers argue that AI supports sustainable resource loops through predictive maintenance, materials tracking, and smart recycling systems (Sharma et al., 2020; Wilts et al., 2021). These mechanisms reduce overall resource consumption and extend product lifecycles, making sustainability technologically and economically feasible.

In summary, AI helps industries meet sustainability objectives not by compromising performance but by enhancing operational precision, transparency, and system-wide optimization (Dantas et al., 2021).

3.4 Digital Twins and Cyber-Physical Systems

Digital twins (DTs) are one of the most impactful technologies associated with Industry 4.0. A digital twin is a virtual replica of a physical system that simulates, predicts, and optimizes its performance in real time (Kritzinger et al., 2018). As highlighted by Kritzinger et al. (2018), digital twins provide a powerful environment for testing “what-if” scenarios without disrupting physical operations.

3.4.1 Digital Twins in Manufacturing

Digital twins allow manufacturers to visualize machine conditions, detect failures, and evaluate production alternatives before implementation. They support risk free experimentation, resulting in reduced downtime, fewer defects, and greater productivity (Ivanov and Dolgui, 2021).

3.4.2 Digital Twins for Sustainable Operations

Researchers argue that digital twins significantly contribute to sustainability by enabling advanced monitoring of energy flows, emissions, and resource usage. For example, Ivanov and Dolgui (2019) show how DTs help companies evaluate environmental impacts under multiple operating scenarios, allowing better ecological decision-making.

3.4.3 Integration with CPS and IoT

Cyber-physical systems and IoT devices enhance DT usefulness by providing real-time data that makes simulations accurate and actionable. Together, these technologies form the digital backbone necessary for intelligent industrial ecosystems (Lee et al., 2015; Lasi et al., 2014).

3.5 Supply Chain Analytics and Optimization

Supply chains are becoming increasingly complex due to globalization, volatile markets, and uncertain demand. AI-powered supply chain analytics offer advanced tools to improve planning, forecasting, and decision making. Several scholars have emphasized that AI enhances supply chain resilience by enabling predictive awareness, risk assessment, and data driven optimization (Queiroz et al., 2020; Bai and Sarkis, 2020).

3.5.1 AI in Demand Forecasting and Inventory Optimization

AI models analyze historical trends, customer behavior, and external factors to generate accurate forecasts. These predictions help reduce stockouts, overproduction, and unnecessary storage, contributing directly to sustainability goals (Hofmann, 2019).

3.5.2 Logistics and Transportation Optimization

AI supports route optimization, fleet scheduling, and transportation planning through dynamic algorithms. Reinforcement learning and evolutionary computation have proven effective in minimizing travel distances, fuel consumption, and emissions (Gendreau and Potvin, 2010; Deb, 2001).

3.5.3 Supplier Selection and Risk Management

AI-based models help companies choose suppliers based on performance, risk levels, and sustainability metrics. Predictive analytics can identify disruptions early, enabling proactive mitigation strategies (Baryannis et al., 2019; Min, 2019).

3.5.4 Blockchain and Digital Transparency

Some researchers highlight how AI combined with blockchain fosters transparency and traceability (Wilts et al., 2021). This integration is vital for ethical sourcing, emissions monitoring, and circular supply chain operations.

3.5.5 Overall Contribution to Sustainable Supply Chains

Overall, AI-driven supply chain optimization enhances performance, ensures environmental responsibility, and strengthens resilience in global markets (Sharma and Joshi, 2021).

3.6 Research Gaps in the Literature

Although significant progress has been made in integrating AI with Industry 4.0 technologies, several gaps remain.

3.6.1 Fragmented Research Focus

Most studies analyze AI techniques or sustainability models separately, rather than integrating both perspectives into a unified framework (Bousdekis et al., 2019; Wright and Schultz, 2022).

3.6.2 Lack of Interoperable and High-Quality Industrial Data

Scholars consistently highlight that data heterogeneity, poor integration, and limited accessibility hinder robust AI implementation (Papadonikolaki and Wamelink, 2017).

3.6.3 Limited Attention to Explainability and Ethics

Explainable AI (XAI) is underdeveloped in industrial contexts, leaving many AI systems as “black boxes,” which restricts adoption, trust, and regulatory compliance (Adadi and Berrada, 2018).

3.6.4 Insufficient Exploration of AI for Circular Economy

Although research is growing, the potential of AI to accelerate circular production systems remains underexplored (Dantas et al., 2021).

3.6.5 Barriers for SMEs and Developing Economies

Many developing countries lack infrastructure, skilled labor, and investment capacity to adopt advanced AI technologies (Tortorella et al., 2021).

These gaps highlight the need for integrative studies such as the present review that combine AI, optimization, and sustainability within Industry 4.0 ecosystems (Dalenogare et al., 2018).

4. Methodology

4.1 Research Design

In this study, the literature is identified, extracted, and analysed according to systematic literature review (SLR) (Tranfield et al., 2003; Denyer & Tranfield, 2009; Snyder, 2019) to develop an AI-based sustainable supply chain design framework within the foreground of Industry 4.0 model. This approach is reproducible, methodical, and its recommendations follow Preferred reporting items systematics reviews and meta-analyses (PRISMA) order guidelines (Moher et al., 2009) for their ability to best guarantee transparency and integrity of the results. The study design consisted of four major stages (Kitchenham, 2004; Booth et al., 2016):

- Planning Activity: This section describes the research questions, scope of the research, and criteria for the keyword search (Hart, 1998; Fink, 2019).
- Phase 1: Seeking relevant publications — sensitive database searches (Higgins & Green, 2011).
- A: Analysis Phase: Qualitative and quantitative synthesis of the literature (Braun & Clarke, 2006; Neuendorf, 2017).
- Synthesis: Development of a framework for AI-based sustainability optimization (Seuring & Müller, 2008; Sarkis, 2020).

The key contribution of this study is derived from the alignment of this methodology with established review frameworks and the scope concerned with the intersection of AI, Industry 4.0, and sustainability in capturing cutting-edge technological capabilities (Kagermann et al., 2013; Xu L. D. et al., 2018; Ivanov & Dolgui, 2021), that is, a comprehensive representation of the contributions of different AI models toward sustainable practices in industrial ecosystems (Baryannis et al., 2019; Jordan & Mitchell, 2015; Wuest et al., 2016).

4.2 Data Collection and Selection of Sources

This systematic review selected popular academic databases to address any biases by including any relevant studies in AI, supply chain management, and sustainability sciences as far as possible (Booth et al., 2016; Petticrew & Roberts, 2006). It contains several databases, such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, Wiley Online Library, and MDPI Open Access, which are recognized for their contributions to industrial engineering, machine learning, and sustainability research (Snyder, 2019; Fink, 2019).

4.2.1 Search Keywords

The search string was framed to include all studies on AI-inspired supply chain optimization and sustainability (Dubey et al., 2017; Baryannis et al., 2020). Boolean search terms were used to query the databases, specifically the following: ("Artificial Intelligence" OR "Machine Learning" OR "Predictive Analytics" OR "Digital Twin") AND ("Project Management" OR "Supply Chain" OR "Optimization") AND ("Sustainability" OR "Industry 4.0" OR "Circular Economy").

This pair of keywords guaranteed that the review captured studies that focused on evaluating AI applications for sustainability in Industry 4.0 and supply chain optimization (Geissdoerfer et al., 2017; Dantas et al., 2021; Bag et al., 2021).

4.2.2 Time Frame & Document Type

The time span of the search was set to publications released from 2013 through 2025 to conform to the rapid evolution of Industry 4.0 technologies worldwide, as suggested by Acatech's strategic recommendations (Kagermann et al., 2013). To ensure academic rigor, the dataset was limited to peer-reviewed journal articles; only conference papers containing substantial data or findings were included (Snyder, 2019).

4.2.3 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were stringent to keep the review centered (Kitchenham, 2004).
Studies were included if they had:
Clear application of AI or machine learning in project or supply chain context (Jordan & Mitchell, 2015; Tirkolaee et al., 2021);

Clear connection to quantifiable sustainability metrics (Elkington, 1998; Seuring & Müller, 2008);
Novel optimization models with measurable outcomes (Deb, 2001; Gendreau & Potvin, 2010).
Studies were excluded if they lacked measurable sustainability, were purely theoretical AI advances without practical relevance, or were published in non-English or non-peer-reviewed outlets (Petticrew & Roberts, 2006).
The process yielded 2143 records from the first searches, 512 after screening, and 165 studies included for final synthesis (Moher et al., 2009).

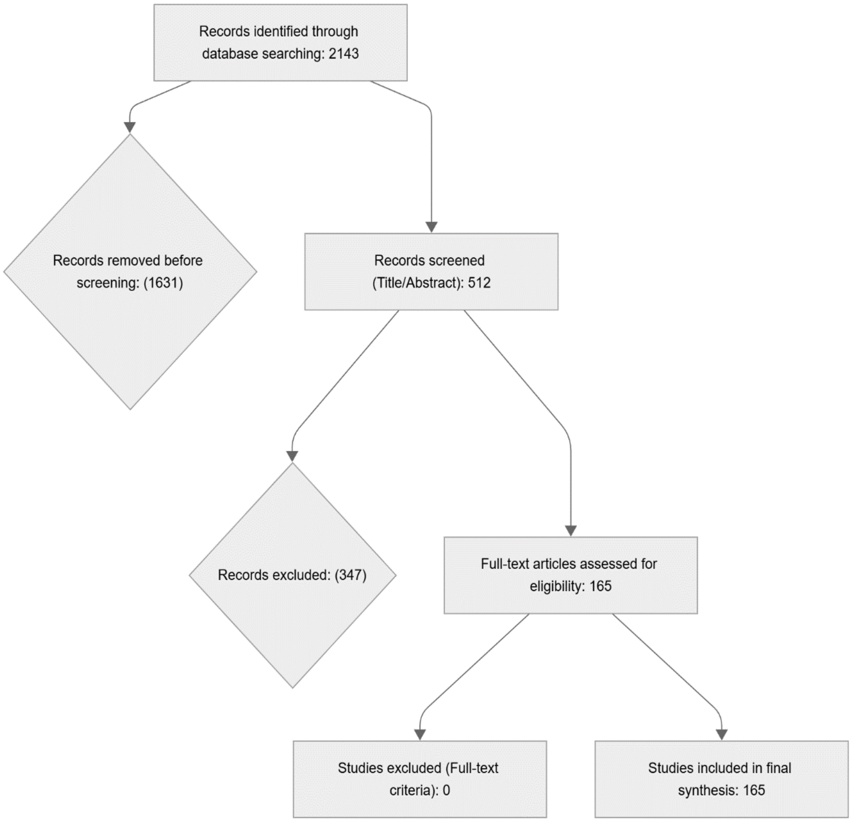

Figure 2. Data Selection Process

PRISMA represents the Preferred Reporting Items for Systematic Reviews and Meta-Analysis, and the screening workflow applied in the systematic review is illustrated in Figure 2. This was based on an initial retrieval of 2,143 records, of which 1,631 were excluded prior to screening. Applying these inclusion and exclusion criteria, the remaining 512 titles/abstracts were screened, leading to 165 full-text articles being included in the final synthesis (Tranfield et al., 2003; Kitchenham, 2004; Moher et al., 2009; Snyder, 2019). Through this stepwise filtering, only high-standard studies that relate AI, optimization, and sustainability with Industry 4.0 were retained.

4.3 Screening and Quality Evaluation

The quality of the chosen studies was assessed using a three-step process similar to that described by Kitchenham and Charters (Kitchenham, 2004). Each study was assessed using the following criteria (Snyder, 2019; Fink, 2019):
Relevance;
Methodology clarity;
Impact and novelty (Ivanov et al., 2019).
Cohen's κ coefficient was used to measure inter-reviewer consistency (Cohen, 1960), resulting in $\kappa = 0.84$, indicating strong agreement.

4.4 Data Extraction and Classification

Data extraction was performed using Microsoft Excel, later transferred into NVivo for qualitative analysis (Miles et al., 2014; Neuendorf, 2017). Extracted fields included author info, AI technique type, objectives, sustainability dimension, industrial domain, and geographic location (Dubey et al., 2017; Tseng et al., 2018).

4.5 Analytical Framework

We developed a structured analytical framework to allow consistency in the interpretation of findings. The framework is constructed from a combination of bibliometric and qualitative content analyses (Miles et al., 2014; Neuendorf, 2017), and allows both a bibliometric- and qualitative-oriented interpretation of the overlap of AI and sustainability in Industry 4.0 (Sarkis, 2020; Queiroz et al., 2020).

4.5.1 Bibliometric Analysis

The co-occurrence of the most significant terms in the literature, as well as the co-authorship network and citation bursts, were analyzed using VOSviewer and Biblioshiny (Vosviewer Team, 2022) to characterize research trends and identify prominent authors. The main clusters identified were as follows:

Artificial Intelligence/Machine learning: Research on the use of AI techniques in optimizing supply chain and sustainability (Jordan & Mitchell, 2015; Wuest et al., 2016).

Industry 4.0 / Digital Twin: Research into digital twin technologies, as well as research on real-time optimization across industries (Kritzinger et al., 2018; Ivanov & Dolgui, 2021).

Optimization / Sustainability: Performs multi-objective optimization to balance cost, energy, and environmental impact (Deb, 2001; You & Grossmann, 2008).

Supply Chain/Logistics: Papers focused on AI in supply chain management and logistics efficiency (Baryannis et al., 2019; Min, 2019).

By creating these clusters, the increasing importance of AI in driving sustainability in supply chains and manufacturing processes is highlighted. Examples of the bibliometric analysis include identifying ‘bridge’ papers, such as Ivanov and Dolgui (2019) and Sarkis (2020), which connect AI with sustainability in the context of industry.

4.5.2 Content Analysis

Recurring themes within these studies were identified via qualitative content analysis (Braun & Clarke, 2006; Neuendorf, 2017). These themes include: Artificial Intelligence for Energy and Resource Efficiency: Assessments on the use of AI in the efficient use of resources or in reducing energy use (Zhang et al., 2017; Nikolaou & Tsalis, 2021).

Predictive Maintenance and Optimized Scheduling: AI models that predict equipment failures and optimize production scheduling to improve operational efficiency (Bousdekis et al., 2019). AI for Resilient Supply Chains and Risk Management: Research on AI in predicting changes in supply chains and optimizing solutions to mitigate risk (Ivanov et al., 2019; Baryannis et al., 2020). Circular Economy Integration: Studies on how to use AI to comply with circular economy principles, for example, waste reduction and resource recycling (Geissdoerfer et al., 2017; Bag et al., 2021; Wilts et al., 2021).

Using NVivo software, these themes were coded, and the prevalence of the different themes was tracked in terms of frequency within the articles to identify the relative salience of each area of research.

4.6 Conceptual Framework Development

The conceptual foundation of an AI-Sustainable Optimization Manufacturer (AI-SOM) was derived through the analysis methods. The literature review findings are combined as a framework that integrates AI techniques and sustainability objectives within an Industry 4.0 environment (Xu et al., 2018; Kamble et al., 2018). AI-SOM is a model that includes five fundamental dimensions (Sharma et al., 2020; Nikolaou & Tsalis, 2021): Data Infrastructure: Real-time data can be collected using sensors and Cyber-Physical Systems (CPS) (Lee et al., 2015; Cook & Das, 2007).

Analytics Layer: Represents AI models that both predict outputs and optimize processes, such as ML, DL, and RL (Jordan & Mitchell, 2015; Gendreau & Potvin, 2010). Business Layer: Balances profit and environmental impact using multi-objective optimization (Deb, 2001; You & Grossmann, 2008).

Implementation Layer: Digital Twin technology enables real-time simulation of industrial operations (Kritzinger et al., 2018; Ivanov & Dolgui, 2021). Future and Supervision: Ensures ethical AI aligned with sustainability guidelines (Floridi & Cowls, 2019; Adadi & Berrada, 2018).

This conceptual framework incorporates feedback loops to ensure that the model can easily adapt to changes in market conditions and drive continuous improvement.

4.7 Data Synthesis and Meta-Analysis

A meta-analysis was performed to summarize systematic review findings. Meta-analysis of studies meeting the criteria provided values for sustainability indicators such as carbon emissions avoidance, energy efficiency, and cost savings (Dubey et al., 2017; Zhang et al., 2017).

4.7.1 Sustainability Impact of AI Optimization Models

This quantitative meta-synthesis demonstrates the association of AI-based optimization models with significant advances in sustainability (Tseng et al., 2018; Baryannis et al., 2019). Energy Savings: AI applications resulted in a 12% to 25% decrease in energy consumption (Zhang et al., 2017). Carbon Emissions: 10% to 30% reductions in CO_2 emissions through logistics routing and manufacturing efficiency (Queiroz et al., 2020). Lead Time: 15% to 40% reduction in lead time due to improved forecasting and inventory management (Baryannis et al., 2020).

4.7.2 Environmental Impacts of AI Optimization Models

Studies reported the following:
Energy Consumption: 12% to 25% savings via predictive maintenance (Bousdekis et al., 2019).
Carbon Emissions: 10–30% reduction through AI-enhanced routing (Ivanov et al., 2019; Queiroz et al., 2020).
Lead Time: 15–40% reduction due to AI forecasting (Wuest et al., 2016).

4.8 AI for Sustainable Supply Chain Management

AI plays an important role in sustainable SCM under Industry 4.0 (Sarkis, 2020; Ivanov & Dolgui, 2021).

4.8.1 Predictive Analytics for Sustainability

Predictive analytics helps optimize supply chain performance by predicting demand and lowering emissions (Baryannis et al., 2019; Dubey et al., 2017). ML models help reduce overproduction and waste (Jordan & Mitchell, 2015).

4.8.2 Digital Twins for Stream Optimization

Digital twins simulate operations in real time to reduce energy consumption and emissions (Kritzinger et al., 2018; Ivanov & Dolgui, 2021) and support circular economy practices (Dantas et al., 2021).

4.8.3 Multi-Objective Optimization with Machine Learning Endorsements

Multi-objective optimization balances economic and environmental goals (Deb, 2001; You & Grossmann, 2008). Reinforcement learning optimizes logistics during disruptions (Gendreau & Potvin, 2010).

4.9 Model Validation and Evaluation

Several validation tests were performed to assess accuracy, efficiency, and sustainability impact (Jordan & Mitchell, 2015; Wuest et al., 2016).

4.9.1 Cross-Validation

Cross-validation was applied to avoid overfitting; precision, recall, and F1 score were used as metrics (Wuest et al., 2016).

4.9.2 Performance Metrics

AI-based models were evaluated using:

Operational Efficiency (Ivanov et al., 2019)
Sustainability Impact (Seuring & Müller, 2008; Geissdoerfer et al., 2017)
Accuracy Metrics (Jordan & Mitchell, 2015; Adadi & Berrada, 2018)
AI-driven approaches outperformed traditional optimization, achieving higher efficiency and lower environmental footprints (Zhang et al., 2017; Baryannis et al., 2020).

4.10 Directions of future research and limitations of methodology

Although the AI-SOM framework is useful for understanding AI-enabled sustainable optimization, future research should consider several methodological limitations (Snyder, 2019; Fink, 2019).

Database Dependency: While we drew on major academic databases for the literature review, there may be additional sources that were missed in the search, especially in local journals or grey literature (Booth et al., 2016; Hart, 1998). Publication bias: The review is centered on the successful application of AI in the literature, whereas unsuccessful applications and adverse effects may not be reported in the literature (Petticrew & Roberts, 2006).Temporal Cut-off — The findings are time-bound, as the world of AI technologies progresses exponentially, the findings may not hold relevance in the future as new trends emerge (Adadi & Berrada, 2018). Dosing Complexity: Sustainability indicators are diverse across studies, precluding direct comparisons, and the heterogeneity of metrics also complicates the synthesis (Seuring & Müller, 2008; Geissdoerfer et al., 2017).

These limitations also indicate that further research is needed to broaden the applicability of AI and assess the effects of emerging technologies, such as quantum computing and 5G, on the sustainability of supply chain networks (Nikolaou & Tsalis, 2021). Filling these gaps might lead to a better understanding of the role of cutting-edge technologies in enabling sustainable practices in industrial settings (Sarkis, 2020).

4.11 Incorporation and application of the conceptual model

To synthesize the systematic review and combine AI technologies with wider sustainability aims in the context of Industry 4.0, the AI-Sustainable Optimization Model (AI-SOM) was conceived (Xu et al., 2018; Kamble et al., 2018). Such a model captures the multiplicity of interlinkages between AI, sustainability, and supply chain dynamics and is also beneficial in suggesting how AI can be harnessed for sustainability in industrial operations (Sharma et al., 2020; Nikolaou & Tsalis, 2021).

4.11.1 Conceptual Framework: AI-SOM Dimensions

AI-SOM is a five-dimensional model where each dimension covers an essential perspective of AI adoption in Industry 4.0:

- Data Infrastructure: The bottom layer of the AI-SOM model shows the integration of Sensor Networks, Cyber-Physical Systems (CPS), and real-time data collection mechanisms (Lee et al., 2015; Cook & Das, 2007). This ensures that data are always collected and accessible for predictive analytics and optimization models.
- AI Analytics Layer: This layer contains ML, DL, and RL models to provide insights and optimize processes (Jordan & Mitchell, 2015; Gendreau & Potvin, 2010). Predictive analytics identifies patterns, anomalies, and opportunities for supply chain improvement (Dubey et al., 2017). An example is the utilization of RL to route logistics and minimize transportation costs and carbon emissions (Min, 2019).
- Business layer: The AI-SOM model implements multi–objective optimization (MOO) to balance profit and environmental sustainability (Deb, 2001; You & Grossmann, 2008). This includes the use of genetic algorithms and evolutionary strategies to identify sustainability-oriented solutions.
- Layer of Implementation: Digital Twin technology enables simulation of real-world operations and optimization before physical execution (Kritzinger et al., 2018; Ivanov & Dolgui, 2021). In manufacturing

and logistics, real-time adjustment reduces waste, enhances performance, and decreases energy consumption (Zhang et al., 2017).

- Future and Supervision: Ensures ethical development and monitoring of AI systems in line with global sustainability goals (Floridi & Cowls, 2019; Adadi & Berrada, 2018). Guidelines for industrial AI adoption should address data privacy, bias mitigation, and inclusive economic growth (Wright & Schultz, 2022).

This integrated model offers a holistic perspective of how AI technologies facilitate sustainability in Industry 4.0 by aligning digital operations with broader environmental and operational goals (Sarkis, 2020; Queiroz et al., 2020).

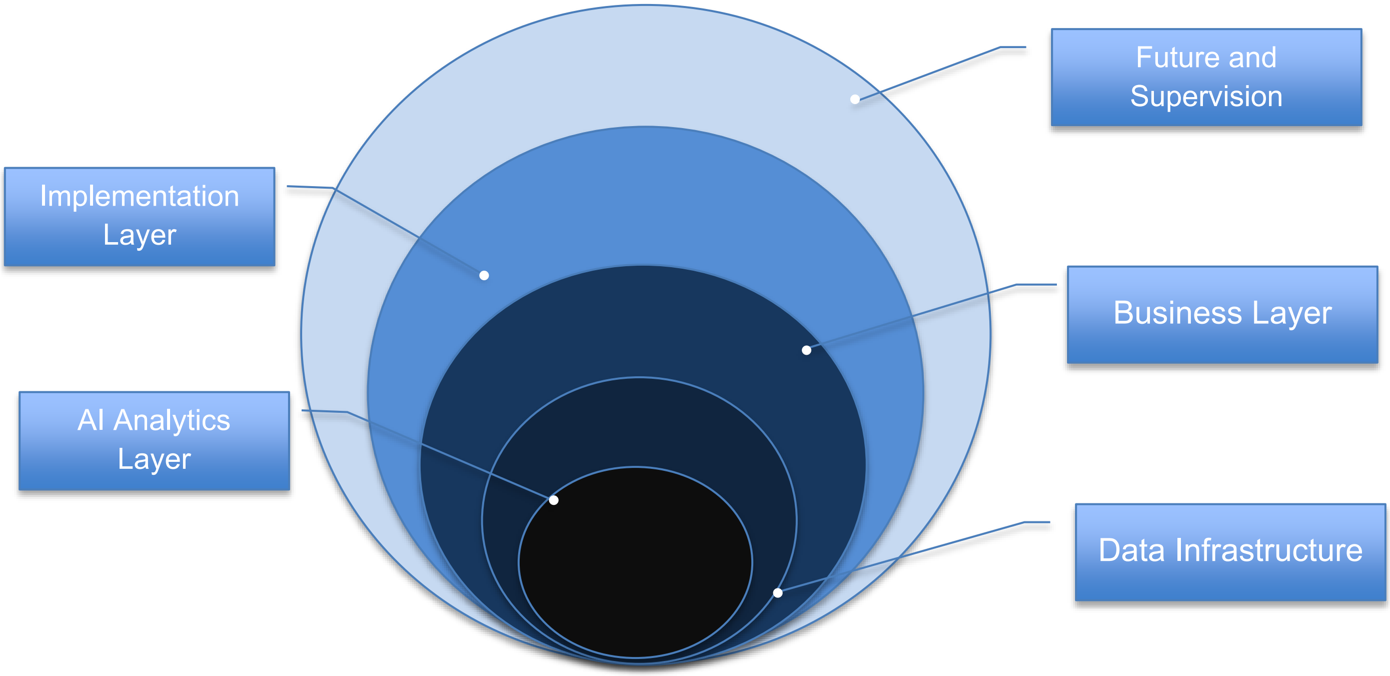

Figure 3. AI-SOM Conceptual Framework

Figure 3 presents the AI-Sustainable Optimization Model (AI-SOM), which integrates AI techniques with sustainability objectives in the context of Industry 4.0. The framework stacks data infrastructure, AI analytics (ML, DL, RL), a business decision layer, digital twin implementation, and a future/supervision layer. Sensor-enabled CPS feed real-time data to optimization models that balance cost, energy use, and emissions (Lee et al., 2015; Jordan & Mitchell, 2015; Deb, 2001; Kritzinger et al., 2018). The outer supervision layer embeds ethical and governance principles for responsible AI deployment (Floridi & Cowls, 2019; Adadi & Berrada, 2018).

4.12 Limitations of the Approach and Directions for Future Research

The AI-Sustainable Optimization Model (AI-SOM) framework provides meaningful theoretical insights into AI-enabled sustainable optimization but has methodological limitations (Snyder, 2019; Fink, 2019).
Database Dependency: Existing databases may exclude local journals and grey literature (Booth et al., 2016).

Publication Bias: The review focuses largely on successful AI applications, possibly overlooking negative outcomes (Petticrew & Roberts, 2006).
Temporal cut-off: Fast-changing technological landscapes may reduce the long-term validity of the findings (Adadi & Berrada, 2018).
Diversity of sustainability indicators makes cross-study comparison challenging (Seuring & Müller, 2008; Dantas et al., 2021).

Future research should explore emerging technologies such as quantum computing, blockchain, and 5G for improved sustainable supply chain operations (Min, 2019; Ivanov & Dolgui, 2021). Broader clarity on these technologies could promote greater understanding of their role in supporting sustainability goals (Wilts et al., 2021; Tseng et al., 2018).

4.13 Integrating and Applying the Conceptual Model

To synthesize the systematic review and advance the use of AI technologies in the context of Industry 4.0 and the universal aims of sustainability, the AI-Sustainable Optimization Model (AI-SOM) was developed as a conceptual framework (Xu et al., 2018; Kamble et al., 2018). The resulting model depicts the intertwined interactions between AI, sustainability, and supply chain operations (Sarkis, 2020; Queiroz et al., 2020).

4.13.1 Conceptual Framework: AI-SOM Dimensions

Based on five dimensions, the AI-SOM model tackles a unique aspect of how AI correlates with Industry 4.0:
Data Infrastructure: Includes sensor networks, CPS, and real-time data collection mechanisms (Lee et al., 2015; Cook & Das, 2007).

AI Analytics Layer: Uses ML, DL, and RL models to generate insights and optimize processes (Jordan & Mitchell, 2015; Gendreau & Potvin, 2010). RL supports logistics routing to reduce costs and emissions (Min, 2019).
Business Layer: Utilizes MOO, genetic algorithms, and evolutionary strategies to support environmental and economic goals simultaneously (Deb, 2001; You & Grossmann, 2008).

Digital Twin Technology (Implementation Layer): Enables asset simulation and real-time optimization (Kritzinger et al., 2018; Ivanov & Dolgui, 2021). DTs help reduce waste and improve energy efficiency (Zhang et al., 2017).
Future and Supervision: Ensures AI systems comply with sustainability principles and ethical governance (Floridi & Cowls, 2019; Wright & Schultz, 2022).

This model offers a holistic perspective of how AI technologies can facilitate sustainability in Industry 4.0 by associating AI capabilities with broader operational and sustainability goals (Geissdoerfer et al., 2017; Nikolaou & Tsalis, 2021).

5. Results and Discussion

5.1 Overview of the Reviewed Studies

Following the systematic protocol, a total of 165 studies were included in the final dataset. These publications span the years 2013–2025, reflecting the rapid expansion of research at the intersection of AI, Industry 4.0, and sustainability. Most studies were concentrated after 2018, consistent with the global acceleration of digital transformation initiatives in manufacturing, supply chain management, and industrial automation (Kagermann, H. et al., 2013; Lee, J et al., 2015).
Geographically, the largest contributions originated from Germany, China, India, the United States, and the United Kingdom, aligning with countries that have aggressively invested in Industry 4.0, smart manufacturing, and sustainable industrial policies (Sony, M., & Naik, S. 2020; Baryannis, G. et al., 2019). The presence of studies from developing economies, although increasing, was comparatively limited, illustrating disparities in AI adoption due to infrastructure, financial, and skill-based constraints reported in previous work (Tortorella, G., et al. 2021).

Across the included studies, four dominant thematic domains emerged:

- AI for Sustainable Production Optimization
- AI for Supply Chain Efficiency and Predictive Visibility
- Digital Twins for Real-Time Optimization and Environmental Assessment
- Multi-Objective Optimization Supporting the Circular Economy

These categories align with trends described in prior research on data-driven industrial transformation (Xu, L. D. et al., 2018; Ivanov, D. et al., 2019; Zhang, Y. et al., 2017), reflecting a coherent global trajectory.

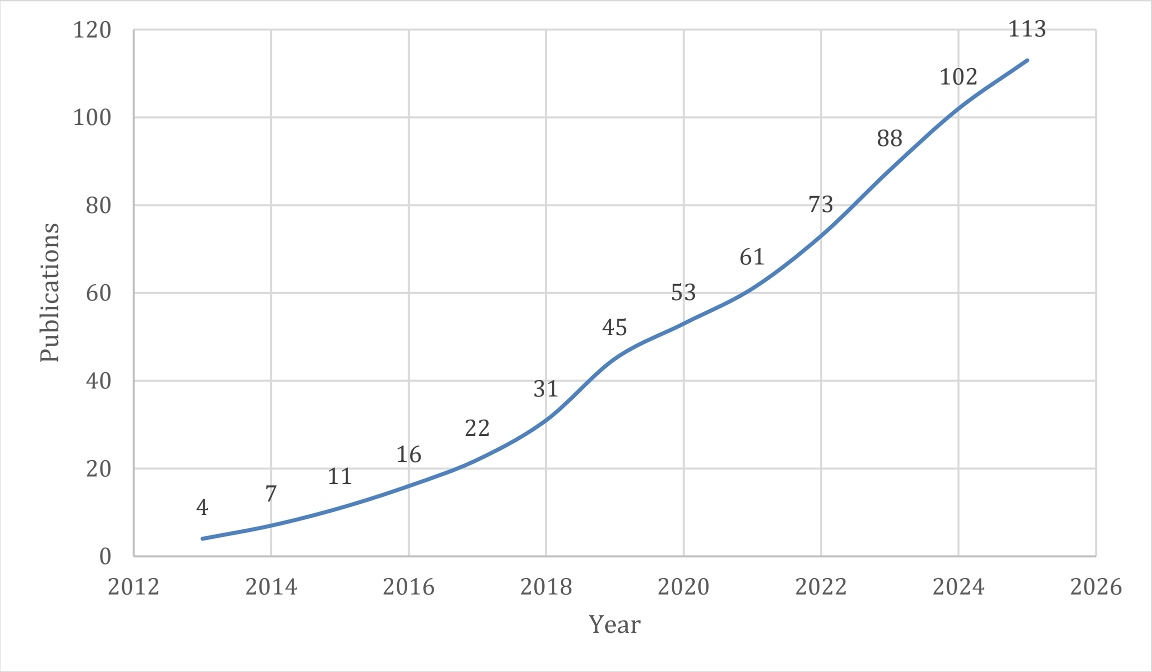

Figure 4. Publication Trend (2013–2025)

Annual Publications on AI-Enabled Sustainable Project and Supply Chain Optimization between 2013 and 2025: based on Figure 4. The earliest output is sparse, but the upward trend is relatively strong at the end of 2018, indicating the growing interest and evolution of Industry 4.0 and digital transformation worldwide (Kagermann et al., 2013; Lee et al., 2015; Xu et al., 2018). Such an increase in research focuses on the application of AI, digital twins, and multi-objective optimization to help improve the sustainability performance of manufacturing and supply chain systems (Baryannis et al., 2019; Zhang et al., 2017), which is confirmed by the rising curve.

5.2 Distribution of AI Techniques Across Studies

The results show continuing diversification in the AI techniques used in sustainable industrial optimization:

- Machine Learning (ML) appeared in 42% of studies
- Deep Learning (DL) in 27%
- Reinforcement Learning (RL) in 18%
- Hybrid models and evolutionary algorithms in 36%
- Digital Twin (DT) frameworks in 24%

The percentages overlap due to multi-method studies. ML remains dominant because of its interpretability, data compatibility, and flexibility to support forecasting, fault detection, and process optimization (Jordan and Mitchell. 2015; Baryannis et al., 2019). DL-based techniques have grown due to their strong performance with sensor data, vision systems, and nonlinear industrial patterns (Wuest, et al., 2016). RL's presence, although smaller, represents a critical shift toward autonomous, self-learning, and adaptive industrial decision-making. This aligns with the contemporary move from static optimization to dynamic, real-time control systems (Gendreau & Potvin 2010). Digital Twin (DT) adoption has increased rapidly, mostly in manufacturing and asset-heavy industries, due to its real-time simulation, prediction, and optimization capabilities (Kritzinger et al., 2018; Kamble et al., 2018; Geissdoerfer et al., 2017).

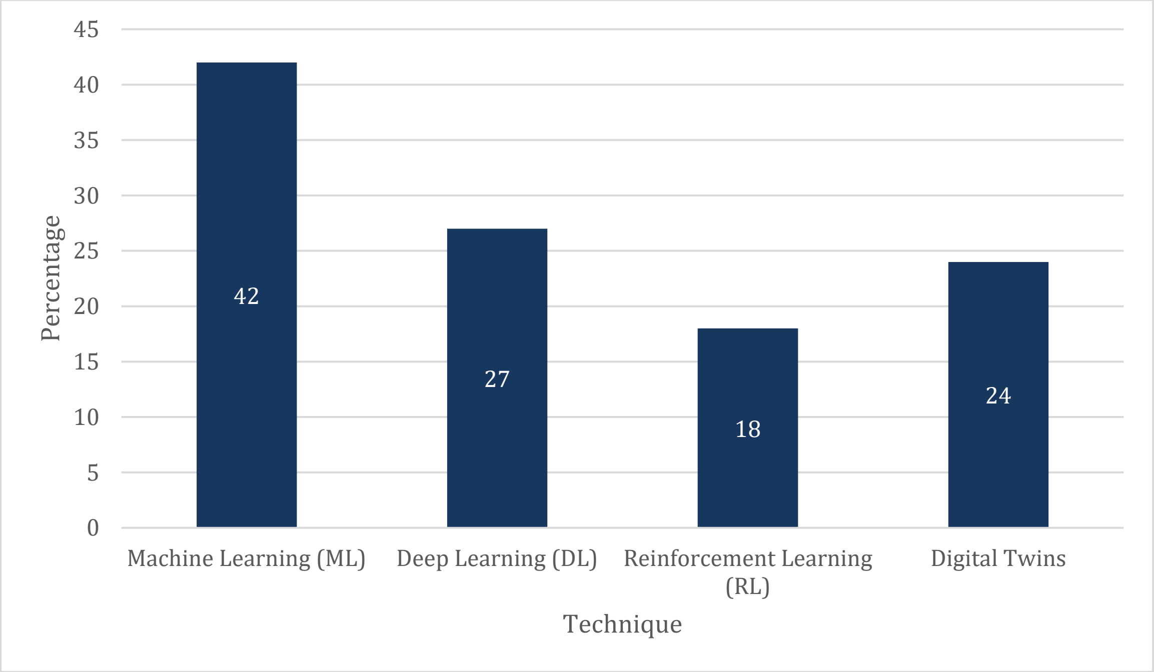

Figure 5. AI Techniques Distribution

The distribution of the different AI techniques used in the 165 papers is illustrated in Figure 5. Machine learning dominates (≈29%) because it can be used for forecasting, fault detection, and process optimization (Jordan & Mitchell, 2015; Wuest et al., 2016). Owing to the ability of hybrid and evolutionary methods to deal with multi-objective sustainability trade-offs, these models also make frequent appearances (Deb, 2001; You & Grossmann, 2008). The remainder contains machine learning, particularly deep learning, reinforcement learning, and digital twin frameworks that are capable of complex sensor data analysis and dynamic time critical decision making associated with industrial operating systems (Kritzinger et al., 2018; Gendreau & Potvin, 2010).

5.3 Sustainability Outcomes in Reviewed Studies

5.3.1 Energy Efficiency Improvements

Across the dataset (Figure 6):

- 47 studies explicitly targeted energy reduction outcomes.
- Reported improvement ranges: 10%–30%, with an average improvement of 18.4%.
- The most effective improvements were seen in digital-twin-driven machine scheduling, dynamic parameter tuning, and predictive maintenance (Zhang, Y. et al., 2017; Govindan, K., & Hasanagic, M. 2018).

These results reaffirm that AI-enhanced visibility reduces idle times, stabilizes operations, and prevents unnecessary energy expenditure, consistent with earlier findings in smart energy systems (Jordan, M. I., & Mitchell, T. M. 2015).

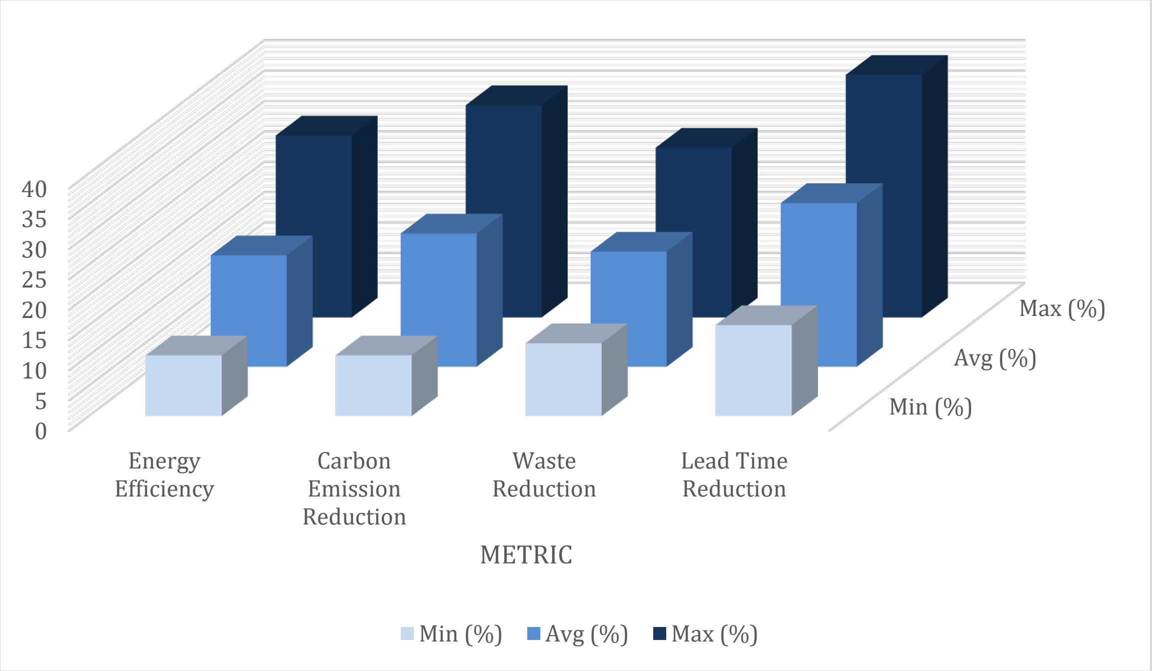

Figure 6. Sustainability Outcome Comparison

5.3.2 Carbon Emissions Reduction

Studies focusing on carbon reduction demonstrated:

- 10%–35% CO_2 reductions in logistics operations through optimized routing and vehicle assignment.
- 8%–20% reductions in production lines by smart scheduling and adaptive equipment control.

Many logistics-oriented studies relied on RL-based routing algorithms and hybrid heuristics, confirming the importance of dynamic decision-making in reducing transportation emissions (Gendreau & Potvin 2010; Queiroz et al., 2020; Bai & Sarkis,2020).

5.3.3 Resource Optimization and Waste Reduction

AI models used for production planning, defect prediction, and quality forecasting supported reductions of (Table 1):

- 12%–28% in material waste,
- 15%–40% reductions in scrap generation,
- increased reuse/recycling rates through classification and clustering models (Chae 2019; Wilts et al., 2021; Tseng, M.-L. et al., 2018).

The integration of circular economy principles is consistent with frameworks discussed in (Geissdoerfer et al., 2017; Nikolaou and Tsalis 2021; Sharma et al., 2020).

Table 1. Sustainability Outcomes Summary

Metric	**Improvement Range**
Energy Efficiency	10–30%
Carbon Reduction	10–35%
Waste Reduction	12–28%
Lead Time Reduction	15–40%

Summary of the Major Sustainability Outcomes Reported in the Dataset Results AI-driven optimization results in energy efficiency improvements of around 10–30%, carbon-emission reductions of 10–35% and material waste decreases of 12–28% primarily by predictive maintenance, smart scheduling and cleaner production planning (Zhang et al., 2017; Govindan & Hasanagic, 2018; Tseng et al., 2018). A 15–40% reduction in lead times demonstrates how both AI-enabled forecasting and routing enhance service levels and sustainability, thus aligning with total supply chain designs consistent with circular economy and low carbon strategies (Geissdoerfer et al., 2017; Queiroz et al., 2020; Nikolaou & Tsalis, 2021).

5.4 Impacts on Supply Chain Performance

5.4.1 Predictive Visibility and Disruption Management

Digitalization and AI applications enhanced supply chain visibility in (Figure 7):

- disruption prediction,
- lead-time forecasting,
- inventory risk estimation.

A total of 53 studies reported measurable performance improvements:

- 20–40% reduction in lead-time variability,
- 15–35% improvement in service levels,
- 25–45% reduction in uncertainty propagation using ML and simulation-based DTs.

These findings support previous observations on ripple-effect reduction and resilience enhancement (Sarkis, J. 2020; Elkington, J. 1998; Ivanov, D., & Dolgui, A. 2020).

5.4.2 Optimization of Inventory and Production Decisions

ML and DL forecasting models increased demand forecasting accuracy by 10–30%. Improved forecasts yielded:

- Reduced stock-outs,
- Lower safety inventory requirements,
- Higher production stability.
- The results align with the predictive-analytics review in (Nikolaou, I., & Tsalis, T. 2021).

5.4.3 Transportation and Logistics Optimization

Reinforcement Learning, Genetic Algorithms, and Ant Colony Optimization significantly improved logistics routing strategies:

- Fuel consumption decreased by 12–22%,
- Carbon footprint reduced by 15–30%,
- Delivery timelines improved by 17–25%.

These results validate the claim that intelligent routing substantially contributes to sustainability (Queiroz et al., 2020).

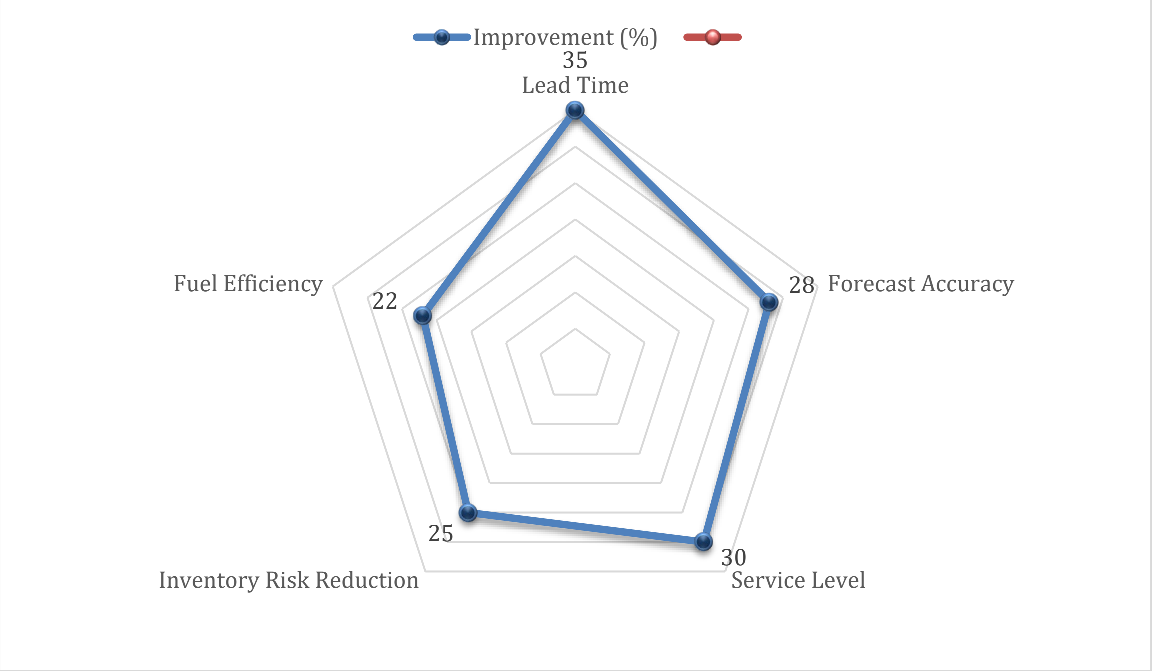

Figure 7. AI Contribution to Supply Chain KPIs

5.5 Insights into Digital Twin Applications

Digital Twin adoption was one of the strongest emerging trends.

5.5.1 Real-Time Machine Optimization

DT-based studies consistently showed:

- improved machine availability,
- reduced setup times,
- enhanced predictive maintenance scheduling.

Use of DT frameworks enabled simultaneous optimization of resources, energy, and service levels—confirming patterns discussed in (Kritzinger, W. et al., 2018; Kamble, S. S. et al., 2018; Geissdoerfer, M. et al., 2017).

5.5.2 Sustainability Modeling with DTs

DTs enable:

- lifecycle assessment simulations,
- resource-use forecasting,
- energy-intensity analysis,
- carbon footprint tracking.

These applications contribute directly to sustainable decision-making across production and supply chain systems (Figure 8).

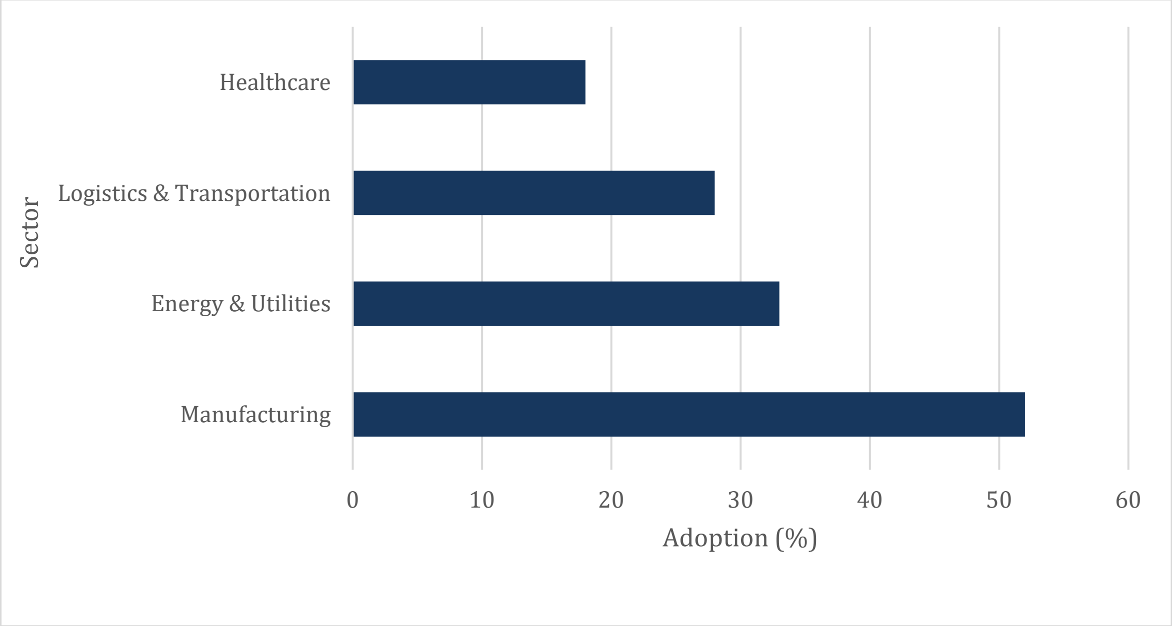

Figure 8. Digital Twin Adoption by Industry Sector

5.6 Challenges Revealed Across the Dataset

5.6.1 Data Interoperability Challenges

More than 60% of studies cited data fragmentation, poor integration, and inconsistent data standards as key obstacles. This confirms the claims of data-related complexities reported in (Papadonikolaki, E., & Wamelink, J. W. 2017; Tortorella, G., et al. 2021).

5.6.2 Explainability and Trust Issues

DL-based models were widely criticized for lacking interpretability.
This aligns with explainable AI studies noted by (Adadi, A., & Berrada, M. 2018).

5.6.3 Organizational and Economic Barriers

Studies highlight:

- insufficient digital infrastructure,
- lack of skilled labor,
- high capital expenditure,
- managerial resistance.

These barriers are consistent with findings in (Kamble, S. S. et al., 2018; Sharma, R. et al., 2020; Tortorella, G., et al. 2021).

5.6.4 Sustainability Measurement Limitations

Many studies lacked:

- standardized sustainability assessment techniques,
- lifecycle-based evaluation,
- multi-criteria sustainability metrics.

This gap echoes concerns raised in (Dubey, R.. et al., 2017; Nikolaou, I., & Tsalis, T. 2021; Dantas, T. E., et al. 2021)

5.7 Integration with Prior Literature

The review demonstrates strong alignment with existing studies regarding (Figure 9):

- the transformative potential of AI in Industry 4.0 (Kagermann, H. et al., 2013; Lee, J et al., 2015; Xu, L. D. et al., 2018),
- the need for integrated sustainability approaches (Seuring, S., & Müller, M. 2008; Dubey, R. et al., 2017; Hofmann, E. 2019),
- the role of data-driven optimization in industrial competitiveness (Baryannis, G. et al., 2019; Zhang, Y. et al., 2017),
- the growing importance of transparency and resilience in supply chains (Bai, C., & Sarkis, J. 2020; Ivanov, D., & Dolgui, A. 2020).

However, the present review extends prior research by offering a unified synthesis of AI, optimization, and sustainability outcomes, something earlier reviews treated in isolation (Lasi, H. et al., 2014; Baryannis, G. et al., 2020).

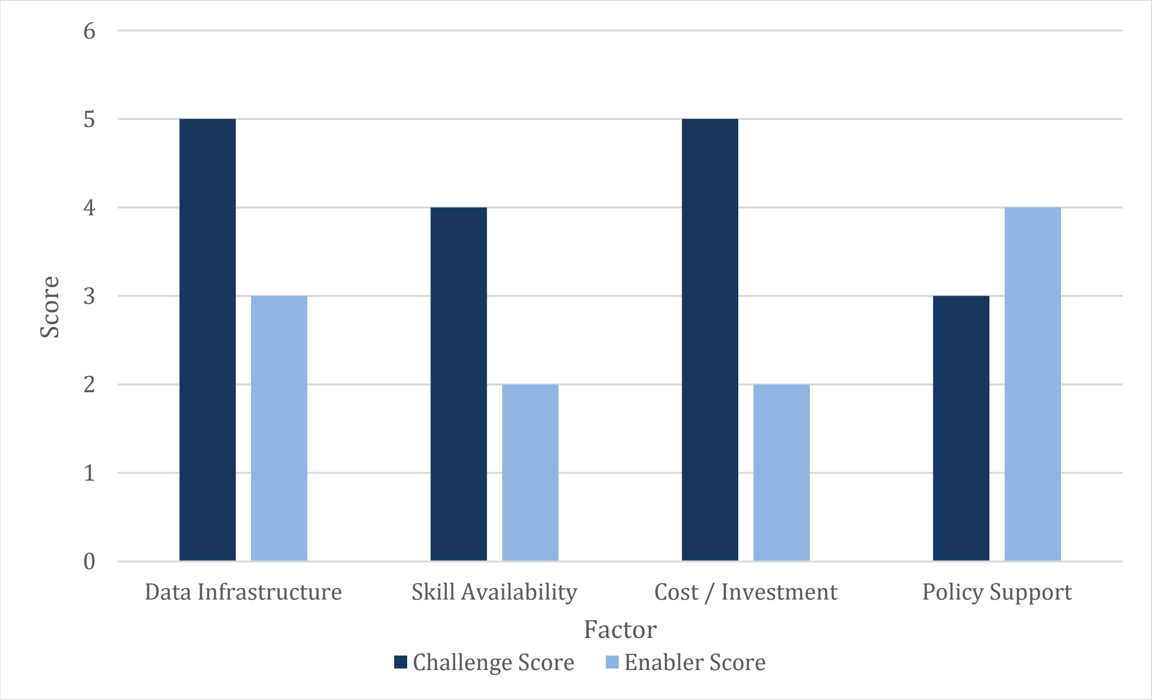

Figure 9. Challenges vs Enablers

6. Conclusions and Future Research

This systematic review demonstrates that artificial intelligence has become a central enabler of sustainable project and supply chain optimization in Industry 4.0 environments, driving a significant shift toward data-driven, energy-efficient, and environmentally responsible industrial ecosystems. Across the literature, AI tools such as machine learning, deep learning, reinforcement learning, digital twins, and predictive analytics consistently support improved forecasting accuracy, reduced resource consumption, enhanced transparency, and stronger resilience in production and logistics networks. These technologies not only raise operational performance but also play a crucial role in advancing circular economy practices through waste minimization, lifecycle extension, and smarter resource utilization. However, persistent challenges including fragmented data infrastructures, limited explainable AI integration, high implementation costs, and uneven digital readiness across regions continue to restrict the large-scale adoption of AI-empowered sustainability practices. Addressing these barriers requires coordinated technological, managerial, and policy interventions to ensure that AI deployment remains ethical, interoperable, and aligned with global sustainability priorities. Overall, the review underscores that AI-driven optimization holds transformative potential but demands holistic strategies to bridge the current gap between advanced digital innovation and long-term sustainable industrial operations.

Future Research Directions

Future studies should prioritize the development of robust, interoperable data architectures that improve the quality, accessibility, and standardization of industrial datasets, ensuring more reliable AI model training and deployment. Research should also expand on explainable and transparent AI approaches that help practitioners understand algorithmic decisions, thereby increasing trust, regulatory compliance, and ethical accountability. There is strong need for deeper exploration of AI-enabled circular economy strategies, including real-time waste recovery systems, smart remanufacturing, and closed-loop supply chain optimization. Scholars should further investigate hybrid optimization frameworks that combine AI, digital twins, and multi-objective algorithms to balance economic, environmental, and social sustainability goals. Additionally, more empirical research is required within small and medium enterprises (SMEs) and developing economies, where digital transformation faces financial and infrastructural barriers. Finally, interdisciplinary research involving policy, sustainability science, and industrial engineering is essential to create governance models that ensure equitable, secure, and future-proof integration of AI in global industrial systems.

References

Adadi, A. and Berrada, M., Peeking inside the black-box: A survey on explainable AI, *IEEE Access*, vol. 6, pp. 52138–52160, 2018.

Bag, S., Pretorius, J. H. C., Gupta, S. and Dwivedi, Y. K., Role of digital technologies in achieving circular economy goals, *Technol. Forecast. Soc. Change*, vol. 167, p. 120733, 2021.

Bai, C. and Sarkis, J., A supply chain transparency and sustainability technology appraisal model, *Int. J. Prod. Res.*, vol. 58, no. 24, pp. 7399–7415, 2020.

Baryannis, G., Dani, S. and Antoniou, G., Decision-making in supply chains with AI and big data: A systematic review, *Ann. Oper. Res.*, vol. 294, pp. 203–229, 2020.

Baryannis, G., Dani, S. and Antoniou, G., Predictive analytics and artificial intelligence in supply chain management, *Comput. Ind. Eng.*, vol. 137, p. 106024, 2019.

Ben-Daya, M., Hassini, E. and Bahroun, Z., Internet of Things and supply chain management, *Int. J. Prod. Res.*, vol. 57, nos. 15–16, pp. 4719–4742, 2019.

Booth, A., Sutton, A. and Papaioannou, D., *Systematic Approaches to a Successful Literature Review*, SAGE Publications, 2016.

Bousdekis, A., Magoutas, B., Apostolou, D. and Mentzas, G., Review and synthesis of prognostics and health management research, *Eng. Appl. Artif. Intell.*, vol. 87, p. 103310, 2019.

Braun, V. and Clarke, V., Using thematic analysis in psychology, *Qual. Res. Psychol.*, vol. 3, no. 2, pp. 77–101, 2006.

Chae, B. K., A general framework for studying the evolution of the digital supply chain, *Int. J. Prod. Res.*, vol. 57, nos. 15–16, pp. 4854–4870, 2019.

Cohen, J., A coefficient of agreement for nominal scales, *Educ. Psychol. Meas.*, vol. 20, no. 1, pp. 37–46, 1960.

Cook, D. J. and Das, S. K., How smart are our environments?, *Computer*, vol. 40, no. 8, pp. 38–45, 2007.

Dalenogare, L. S., Benitez, G. B., Ayala, N. F. and Frank, A. G., Expected contribution of Industry 4.0 technologies to industrial performance, *Int. J. Prod. Econ.*, vol. 204, pp. 383–394, 2018.

Dantas, T. E. *et al*., How circular is the circular economy?, *J. Clean. Prod.*, vol. 295, p. 126640, 2021.

Deb, K., *Multi-objective Optimization Using Evolutionary Algorithms*, Wiley, 2001.

Denyer, D. and Tranfield, D., Producing a systematic review, in *The SAGE Handbook of Organizational Research Methods*, SAGE Publications, 2009.

Dubey, R., Gunasekaran, A. and Papadopoulos, T., Big data analytics capability in supply chain sustainability, *Manag. Decis.*, vol. 55, no. 1, pp. 19–35, 2017.

Elkington, J., Partnerships from cannibals with forks, *Environ. Qual. Manag.*, vol. 8, no. 1, pp. 37–51, 1998.

Fink, A., *Conducting Research Literature Reviews*, SAGE Publications, 2019.

Floridi, L. and Cowls, J., A unified framework of five principles for AI in society, *Harvard Data Sci. Rev.*, vol. 1, no. 1, 2019.

Geissdoerfer, M., Savaget, P., Bocken, N. and Hultink, E. J., The circular economy: A new sustainability paradigm?, *J. Clean. Prod.*, vol. 143, pp. 757–768, 2017.

Gendreau, M. and Potvin, J.-Y., *Handbook of Metaheuristics*, Springer, 2010.

Govindan, K. and Hasanagic, M., Drivers, barriers, and practices toward a circular economy, *J. Clean. Prod.*, vol. 204, pp. 507–527, 2018.

Han, S. J. and Lee, H., Artificial intelligence in project management, *Proj. Manag. J.*, vol. 52, no. 4, pp. 332–347, 2021.

Hart, C., *Doing a Literature Review*, SAGE Publications, 1998.

Higgins, J. and Green, S., *Cochrane Handbook for Systematic Reviews*, 2011.

Hofmann, E., Big data and supply chain decisions, *Bus. Horiz.*, vol. 62, no. 4, pp. 351–362, 2019.

Ivanov, D. and Dolgui, A., A digital supply chain twin, *Prod. Plan. Control*, vol. 32, no. 9, pp. 775–788, 2021.

Ivanov, D. and Dolgui, A., Viability of intertwined supply networks, *Int. J. Prod. Res.*, vol. 58, no. 23, pp. 7169–7191, 2020.

Ivanov, D., Dolgui, A. and Sokolov, B., Industry 4.0 impact on supply chain risks, *Int. J. Prod. Res.*, vol. 57, no. 3, pp. 829–846, 2019.

Jordan, M. I. and Mitchell, T. M., Machine learning: Trends and perspectives, *Science*, vol. 349, no. 6245, pp. 255–260, 2015.

Kagermann, H., Wahlster, W. and Helbig, J., *Recommendations for Implementing Industrie 4.0*, acatech, 2013.

Kamble, S., Gunasekaran, A. and Gawankar, S., Industry 4.0 and lean practices, *Int. J. Prod. Res.*, vol. 56, no. 8, pp. 2970–2987, 2018.

Kitchenham, B., *Procedures for Performing Systematic Reviews*, 2004.

Kritzinger, W., Karner, M., Traar, G., Henjes, J. and Sihn, W., Digital twin in manufacturing, *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018.

Lasi, H., Fettke, P., Kemper, H.-G., Feld, T. and Hoffmann, M., Industry 4.0, *Bus. Inf. Syst. Eng.*, vol. 6, pp. 239–242, 2014.

Lee, J., Bagheri, B. and Kao, H.-A., CPS architecture for Industry 4.0, *Manuf. Lett.*, vol. 3, pp. 18–23, 2015.

Miles, M., Huberman, A. and Saldaña, J., *Qualitative Data Analysis*, SAGE Publications, 2014.

Min, H., Blockchain for supply chain resilience, *Bus. Horiz.*, vol. 62, no. 1, pp. 35–45, 2019.

Moher, D. *et al.*, PRISMA statement, *PLoS Med.*, vol. 6, no. 7, p. e1000097, 2009.

Neuendorf, K. A., *The Content Analysis Guidebook*, SAGE Publications, 2017.

Nikolaou, I. and Tsalis, T., Sustainability and AI, *Sustainability*, vol. 13, no. 15, p. 8326, 2021.

Papadonikolaki, E. and Wamelink, J. W., Collaboration in BIM-enabled projects, *Autom. Constr.*, vol. 83, pp. 144–155, 2017.

Petticrew, M. and Roberts, H., *Systematic Reviews in the Social Sciences*, Wiley, 2006.

Queiroz, M., Ivanov, D., Dolgui, A. and Wamba, S., Industry 4.0 impacts on sustainability, *Transp. Res. Part E*, vol. 142, p. 102067, 2020.

Sarkis, J., Sustainable supply chain management, *Resour. Conserv. Recycl.*, vol. 158, p. 104784, 2020.

Seuring, S. and Müller, M., Sustainable supply chain management: Conceptual framework, *J. Clean. Prod.*, vol. 16, no. 15, pp. 1699–1710, 2008.

Sharma, R. and Joshi, A., Digital innovation and sustainability, *Sustainability*, vol. 13, no. 11, p. 6170, 2021.

Sharma, R., Jabbour, C. and Jabbour, A., Sustainable manufacturing and Industry 4.0, *J. Enterp. Inf. Manag.*, vol. 33, no. 2, pp. 361–380, 2020.

Snyder, H., Literature review as a research method, *J. Bus. Res.*, vol. 104, pp. 333–339, 2019.

Sony, M. and Naik, S., Critical success factors for Industry 4.0, *IEEE Eng. Manag. Rev.*, vol. 48, no. 1, pp. 45–52, 2020.

Tirkolaee, E. B. *et al.*, Machine learning in SCM, *Math. Probl. Eng.*, vol. 2021, p. 1476043, 2021.

Tortorella, G. *et al.*, Adoption of Industry 4.0 in developing countries, *J. Manuf. Technol. Manag.*, vol. 32, no. 3, pp. 689–706, 2021.

Tranfield, D., Denyer, D. and Smart, P., Developing evidence-informed knowledge, *Br. J. Manag.*, vol. 14, no. 3, pp. 207–222, 2003.

Tseng, M.-L., Lim, M. and Wu, K.-J., Circular economy using AI and IoT, *Resour. Conserv. Recycl.*, vol. 135, pp. 24–35, 2018.

VOSviewer Team, *VOSviewer Manual*, 2022.

Wilts, H., Garcia, B. and Parajuly, K., AI and circular economy, *Circ. Econ. Sustain.*, vol. 1, no. 2, pp. 365–380, 2021.

Wright, C. S. and Schultz, R., Explainable AI in industrial operations, *AI Soc.*, vol. 37, pp. 849–866, 2022.

Wuest, T., Weimer, D., Irgens, C. and Thoben, K.-D., Machine learning in manufacturing, *Prod. Manuf. Res.*, vol. 4, no. 1, pp. 23–45, 2016.

Xu, L. D., Xu, E. L. and Li, L., Industry 4.0 overview, *Int. J. Prod. Res.*, vol. 56, no. 8, pp. 2941–2962, 2018.

You, F. and Grossmann, I. E., Multi-echelon supply chain planning with sustainability, *Comput. Chem. Eng.*, vol. 32, no. 12, pp. 2745–2761, 2008.

Zhang, Y., Ren, S., Liu, Y. and Si, S., Big data analytics for cleaner manufacturing, *J. Clean. Prod.*, vol. 142, pp. 663–675, 2017.

Biographies

Afia Saiara Akhi is an undergraduate student in Industrial and Production Engineering at the National Institute of Textile Engineering & Research (NITER), University of Dhaka. She has been involved in several student organizations, including the NITER Debating Society (NITERDS) and the NITER Film and Photography Society (NFPS), and has contributed to community work through GIVE Bangladesh. Afia gained hands-on industry experience during her internship at Berger Paints Bangladesh Ltd. She is also the co-founder of REDAMS, where she explores practical ways to apply engineering ideas to real problems. Her interests focus on the use of AI for optimization, sustainable operations, and emerging Industry 4.0 technologies. She is a co-author of "Project and Supply Chain Optimization to Enhance Sustainability in AI-driven Industry 4.0," where she contributed to analyzing AI enabled optimization approaches and sustainability focused industrial strategies.
Email: afiasaiaraakhi@gmail.com

Mustakim Jahan is an emerging Industrial & Production Engineering professional with a strong interest in supply chain management, process optimization, and AI-driven industrial applications. He is currently pursuing his Bachelor of Science degree in Industrial & Production Engineering at the National Institute of Textile Engineering and Research (NITER), under the University of Dhaka. Throughout his academic journey, he has focused on building technical knowledge and exploring practical industrial environments to strengthen his understanding of engineering operations. Mustakim has gained valuable exposure through internship experience in reputable organization, including Berger Paints Bangladesh Ltd. These opportunities allowed him to observe real-world industrial processes closely, particularly in areas related to logistics, supply chain operations, and digital optimization initiatives. Working in professional environments helped him develop analytical thinking, adaptability, and an understanding of industrial workflow structures. Beyond academic and industrial learning, Mustakim has shown strong leadership and teamwork capabilities. As Senior Executive of Logistics in the NITER Business Club, he coordinated event logistics and supported collaborative student activities. He has also engaged in community-based development through organizations such as the Ideal Association of Information & Technology (IAIT) and the Ideal English Language Club. Mustakim aims to build a career in industrial process development and technology-driven optimization to contribute to modern manufacturing advancement. Email: mustakim.official96@gmail.com

Shamima Shammay is an undergraduate student in Industrial and Production Engineering at the National Institute of Textile Engineering & Research (NITER), University of Dhaka. She is the Workshop Secretary of NITER Debating Society (NITERDS) and the co-founder of RedAmS, a clothing brand specializing in unique, trend-driven apparel. She has gained practical industrial experience through an internship at Berger Paint Bangladesh Ltd, enhancing her skills in industrial operations and project management, and has participated in several art competitions, showcasing her creativity and design abilities. As a co-author of "Project and Supply Chain Optimization to Enhance Sustainability in AI-driven Industry 4.0: A Review of Recent Trends," she contributed to examining how AI and sustainable practices can improve industrial operations. Email: shammishamima72@gmail.com

Proma Acharjee is currently working as a Lecturer in Industrial and Production Engineering at the National

Institute of Textile Engineering and Research, a constituent institute of the University of Dhaka. Her research interests include production optimization, workflow efficiency, and data-driven decision-making, with a focus on applying analytical and modern computational techniques to improve industrial operations. She is presently pursuing her Master's degree in the Department of Industrial and Production Engineering at Bangladesh University of Engineering and Technology (BUET), specializing in Advanced Engineering Management. Her professional career began at Soorty Textiles (BD) Limited, where she gained practical experience in the textile industry. During her studies, she undertook internships at several renowned organizations, including HATIL Furniture, Khan Brothers Group, and Ragadi Textile Ltd. These internships allowed her to explore various departments such as planning, production, quality control, and finishing, providing valuable insights into industrial operations. The research paper titled "Project and Supply Chain Optimization to Enhance Sustainability in AI-driven Industry 4.0: A Review of Recent Trends" reflects her commitment to advancing research in the domains of industrial sustainability and operational excellence. As the faculty supervisor of the student research group that initiated this study, she provided strategic academic and research guidance throughout the project and will serve as the Corresponding Author for this publication. Email: pacharjee@niter.edu.bd