European Economic Letters
ISSN 2323-5233
Vol 15, Issue 2 (2025)
http://eelet.org.uk

Optimizing Sustainable Manufacturing with AI - Exploring the Potential of Multi-Objective Techniques in Industry 5.0

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Abstract

Background – Driven by the adoption of modern technologies like Internet of Things (IoT) and Artificial Intelligence (AI) and adoption, Industry 5.0 has emerged to bring a paradigm shift from industry 4.0. Though the manufacturing process is digitized by industry 4.0, interconnected smart devices and cyber-physical systems are leveraged to achieve productivity and efficiency in industry 5.0, which focuses on collaboration among machines and humans, with greater emphasis on customization, social well-being and sustainability. This new age balances intelligence and automation offered by AI with ethical and creative considerations of workers, building a humanized approach for manufacturing. As the international market keeps on demanding more sustainable and personalized products, optimization plays a vital role in industry 5.0.

In the context of Industry 5.0, optimization consists of solving various problems covering a lot of considerations, from efficiency in production and energy management to product customization and environmental sustainability. With the complex manufacturing systems, traditional approaches are not much sufficient. Modern AI-based approaches for optimization are needed for managing dynamic systems, where changing demands, real-time data, and complex processes in production should be responsible for. Along with automating decision-making, these techniques also help manufacturers to achieve conflicting, multiple goals at the same time, including reduced costs while also reducing environmental impact and retaining high product quality.

Objectives – This study is aimed to explore the application of multi-objective, AI-based optimization in industry 5.0. This study especially aims to investigate the use of modern optimization algorithms to achieve key objectives like enhanced energy efficiency, productivity, collaboration between humans and machines, and encouraging ecological sustainability in the setting of smart factories. By analyzing adaptive systems, this study explores how AI can promote manufacturing for optimal balance among conflicting goals while keeping human employees at the core of decision-making.

This study explored integration of AI with human insights with modern "multi-objective optimization techniques" to improve both customization and sustainability in manufacturing. This study investigates various optimization approaches like "reinforcement learning (RL), Particle Swarm Optimization (PSO), and genetic algorithms (GAs) personalized to manage efficiency, carbon footprint, and waste reduction. The proposed model enables creativity to work with AI processes, implanting human input into computational structure adapting well to operational goals. By combining optimization with the environment, including energy consumption, waste reduction, and carbon emissions, this study sets a path for sustainable production. This study fills the most important research gap by providing a practical, in-depth model to balance theoretical knowledge with real-life applications in the manufacturing industry. This way, it plays a vital role in ongoing industrial 5.0 development, focusing on how collaboration between human and AI can foster adaptable, smart, and sustainable systems for manufacturing.

Purpose of the study – Manufacturers constantly need to adapt to opportunities and challenges in industry 5.0. As manufacturing systems have been very complicated, there is a need for multi-objective solutions which can manage changing market demands, real-time data, and sustainable practices. Manufacturers are pressurized to reduce cost of production, while retaining customization and flexibility in the limitations of reducing ecological footprint. Integrating AI-based models into optimization systems act as a strong tool to address sustainability challenges, enabling real-time, dynamic decision-making which considers various competing goals. This study explains how to implement these systems in the context of smart factories, while focusing on multi-objective optimization plans aligning with Industry 5.0 principles.

Expected outcomes – The proposed framework of this study enables creativity to work with AI-based processes, combining human input into digital structure adapting to operational goals dynamically. By combining optimization with environmental impacts, including reduced waste, carbon emissions, and energy consumption, this study sets a path for sustainable production. This study offers an in-depth, practical model to balance theoretical insights with personalized manufacturing. This study will contribute to the existing development of industry 5.0, focusing on how collaboration between humans and machines can develop sustainable, adaptable, and smart manufacturing systems.

- **Contributions of the study** – This study is expected to make some contributions in optimizing manufacturing in industry 5.0.
- Integrating "Multi-Objective Optimization" into the context of "Smart Factory" – This study will propose an integrative framework for "multi-objective optimization" models in smart factory when it comes to address complex issues related to I5.0, including "real-time decision-making, collaboration between human and AI, and modern production practices."
- Implementing case study – This study will conduct a real-world case study analysis including international manufacturing scenario, focusing on application of AI-based optimization to improve energy use, operational efficiency, and tailored potential. This study acts as a foundation for other manufacturers seeking implementation of the same systems.
- AI-based Optimization - This study will cover an in-depth discussion on the application of AI-based optimization models like GA, RL, and MAS in smart factories. This study will compare and evaluate these techniques when it comes to managing several goals like energy consumption, productivity, and product customization.
- Power Consumption and Sustainability – This study highlights the importance of AI in efforts of sustainability, especially when it comes to optimising consumption of energy and adopting sustainable sources of energy into manufacturing. It focuses on reducing carbon footprint in factories while retaining high productivity levels.
- Human-friendly AI – This study also focuses on the human-oriented nature of industry 5.0, where AI programs can work apart from human operators instead of placing them. This study discovers how AI can improve the process of decision-making, well-being, and creativity in a collaborative setting.

Over the years, several studies have been focused on AI-based "multi-objective optimization" in the context of industry 4.0. To the best of our knowledge, this study will be first of its kind when it comes to industry 5.0. It will add to the growing body of literature with an increased value of improving several objectives like cost, efficiency, collaboration between humans and machines, and sustainability in digital transformation of manufacturing.

Keywords *– industry 5.0, multi-objective optimization, sustainable manufacturing, artificial intelligence, smart factory*

1. **Introduction**

Smart manufacturing and Artificial Intelligence (AI) have always been the center of attraction for researchers over the years in terms of multi-objective optimization (MOO) in the paradigms of industry 4.0 and industry 5.0. There is a need to optimize several competing objectives like cost sustainability, cost, efficiency, and human-machine collaboration in transforming manufacturing as per the rising body of literature. AI can boost sustainable manufacturing by optimizing processes and resources and there is a need to address challenges like cybersecurity and data quality for significant impact (Lodhi et al, 2024). AI and big data based strategies related to science and technology will redefine smart manufacturing and material discovery (Wang et al, 2024). Future engineers need to excel from producing materials to designing using materials by introducing the "Program for Material Evolution (ProME) platform.

Technologies related to Industry 4.0 like blockchain, IoT, and AI can improve product quality, supply chain management, and production efficiency with automation and real-time data, while providing positive outlook on their transformative effect and real-time data (Motia et al, 2024). Deep learning and digital twin can be combined to boost smart manufacturing by predicting equipment failure, enhancing production processes, and analyzing real-time data, resulting in increased flexibility and efficiency (Ponnusamy et al, 2025). AI and digital twins are vital for Industry 4.0 to improve robotics and smart manufacturing. Huang et al (2021) conducted a review of more than 300 studies, highlighting AI-based advancements with digital twins, their sustainability benefits, and challenges to integrate digital twins and AI.

Danishvar et al (2021) proposed a deep learning-based "Multi-Objective Batch-based Flow shop Scheduling Optimization with Neural Networks (MOBS-NET)" framework to optimize batch processing in order to manage various objectives like cost, energy consumption and make span. It has been authenticated with simulations for effectiveness and robustness. Choi et al (7) proposed to extend "multi-objective reinforcement learning" to improve production quality and output in traditional manufacturing processes, achieving 7.25% productivity improvement and 87.02% accuracy in "fiber elongation predictions."

Upadhyay et al (2024) analyzed more than 30 studies on digital twin in industry 4.0, including advances in smart manufacturing, robotics, and sustainability. They focused on adopting AI in emerging and traditional approaches and investigated the challenges and development potential of AI-based digital twins (DTs). Lind et al (2024) proposed NSGA-II, PSO models, and digital human modeling (DHM) tools for integrating MOO for planning manufacturing layout, which enhance worker well-being, space efficiency, and productivity simultaneously. Xia et al (2024) proposed "cyber-physical production systems (AI-CPPS)" to address problems in retaining response and rising demands for intelligence and flexibility. They proposed hourglass approach for configuring and modeling computing, network, and manufacturing resources and quicksand approach to ensure reliable, secure, and efficient interaction of resources.

Rahmani et al (2023) conducted a study integrating 3D printing of composites or allows in context of Industry 5.0. They focused on sustainable and human-centric aspects of Industry 5.0 to investigate how "Additive Manufacturing (AM)" can improve the fabrication of assemblies and metallic parts while promoting interaction among human and technological aspects. They emphasize the role of 3D printing in achieving the goals of Industry 5.0 and highlighted important parameters for proper implementation.

Mourtzis (2023) explored the metaverse in Industry 5.0, aligning with the vision of Web 4.0 related to human-related digital ecosystem. The study focuses on how integration of AI, IoT, and VR with metaverse can improve productivity, innovation, and deliver valuable solutions in manufacturing. The study discusses the evolution, definition, challenges and benefits of metaverse, while presenting a theoretical framework for adopting this interconnected, virtual environment into manufacturing, highlighting how it addresses the goals of industry 5.0 related to well-being, efficiency, and personalization.

Turner and Oyekan (2023) categorized major types of manufacturing like holonic, agile, reconfigurable, and flexible in Industry 5.0 framework, determining how these methods are supported and affected by Industry 4.0 approaches and human-oriented focus of I5.0. The "Lifecycle Analysis (LCA)" is introduced as a holistic tool to assess emissions and align decisions related to manufacturing with sustainability goals. With the metrics of circular economy, LCA is proposed as an ideal framework for making decisions as per the scenario and visualizations in the digital twin. This study has integrated such tools as a critical gap in research and supported by manufacturing platforms as I5.0 is providing human-centric and sustainable research agenda.

Akundi et al (2022) identified and categorized its research trends and key themes using text-mining techniques and tools by proposing an in-depth analysis of Industry 5.0. Abstracts are analyzed from 196 papers published around several databases, adopting approaches like frequency analysis, key term extraction, and unsupervised ML for mining topics. They highlighted five key themes – enterprise digitization and innovation, supply chain optimization and evaluation, transformation with modern technologies, sustainable and smart manufacturing, and human-machine interaction. They focused on emerging role of Industry 5.0 in building coexistence of humans and machines and proposed such themes as guiding force in the field.

Agote-Garrido (2023) have proposed a theoretical framework for integrating sociotechnical systems with technologies used in industry 5.0 when it comes to address key aspects. The model is based on the concept of social metabolism and focuses on early adoption of sociotechnical systems for forming human-centric manufacturing environment which is resilient and sustainable. With complete analysis of current approaches, methods, and publications associated with sociotechnical systems, a framework is outlined which aligns production with social needs, fostering adaptable and conscious industry matching with the core of Industry 5.0.

1.1. Objectives of the study

- To investigate the application of AI-oriented "multi-objective optimization (MOO)" in Industry 5.0 framework
- To assess the use of modern optimization models to maximize productivity, enhance human-machine interaction, energy efficiency, and environmental sustainability
- To find out how AI can achieve optimal balance for manufacturers among conflicting goals so human workers are at the core of decision-making

1.2. Research Structure

To address "multi-objective optimization" in industry 5.0, this study consists of following sections –

- Section 2 conducts a review of recent literature related to evolution of Industry 4.0 and emergence of Industry 5.0 and AI playing vital role in "multi-objective optimization"
- Section 3 discusses research method adopted to fulfil the objectives of this study.
- Section 4 digs deeper into specific approaches of AI-based optimization in smart manufacturing, such as, their performance evaluation and implementation.
- Section 5 presents results and discussion of overall findings of the study related to application in real-world environments
- Section 6 concludes the study by summarizing overall findings and providing insights for future directions of research

2. Literature Review

2.1. Overview of Industry 5.0

The advancement of industry 5.0 has been important in the industrial and manufacturing practices, signaling a new age of technological innovation and sustainability (Valette et al, 2023; Battaglia et al, 2023; Contini et al, 2023). Even though this concept is emerging, it is gaining traction rapidly as it reconciles the contradictory goals of environmental stewardship and economic growth (Javaid et al, 2022; Ghobakhloo et al, 2023; Karmaker et al, 2023). Industry 5.0 has the essence of integrating craftsmanship and human creativity with the potential of automation and smart systems to improve environmental sustainability, efficiency, and productivity (Cronin & Doyle-Kent, 2022).

Industry 5.0 basically marks a drastic shift from Industry 4.0's focus on data exchange and automation in manufacturing to more inclusive method which uses sustainable practices and human intelligence (Strazzullo et al, 2023; Rahmani et al, 2023). This change requires sustainable development with global challenges like depletion of natural resources, climate change, and degradation of environment (Wang et al, 2023; Wen et al, 2023). Balanced approach is needed which uses technology to improve human potential while ensuring efficiency of resources and environmental protection. Industry 5.0 is convergent with sustainability goals, providing a way towards harmonizing industrial growth with environmental limits of the planet.

Earlier studies have discovered a lot of aspects of industry 5.0, such as, its economic implications, potential for innovation, and technological underpinnings (Hu et al, 2022; Madsen et al, 2023; Haddad et al, 2022; Wen et al, 2023; Wang et al, 2023). There is a significant research gap in the whole spectrum of sustainability. Previous studies have just touched Industry 5.0 at the surface level like Internet of Things (IoT), AI, and robotics (De Giovanni, 2023; Bajic et al, 2023; Guo et al, 2023; Espina-Romero et al, 2023; Rahmani et al, 2023; Kasinathan et al., 2022; Waltersmann et al, 2021). Hence, more nuanced exploration is needed on mitigating environmental impacts, realizing SDGs, and ensuring efficient utilization of resources.

There is a lack of in-depth exploration of interaction among sustainability and industry 5.0 which marks a missed opportunity. The existing research gap restricts our knowledge of Industry 5.0's potential to catalyze significant changes aligning the sustainability and industrial processes. Without complete understanding, the shift towards Industry 5.0 for economic resilience, conservation of environment, and social well-being may be ignored. This ignorance affects theoretical development and identification of innovative, practical solutions for challenges related to sustainable development. There are different sectors covered by Industry 5.0 from textile to farming, power supply and urban planning (Figure 1).

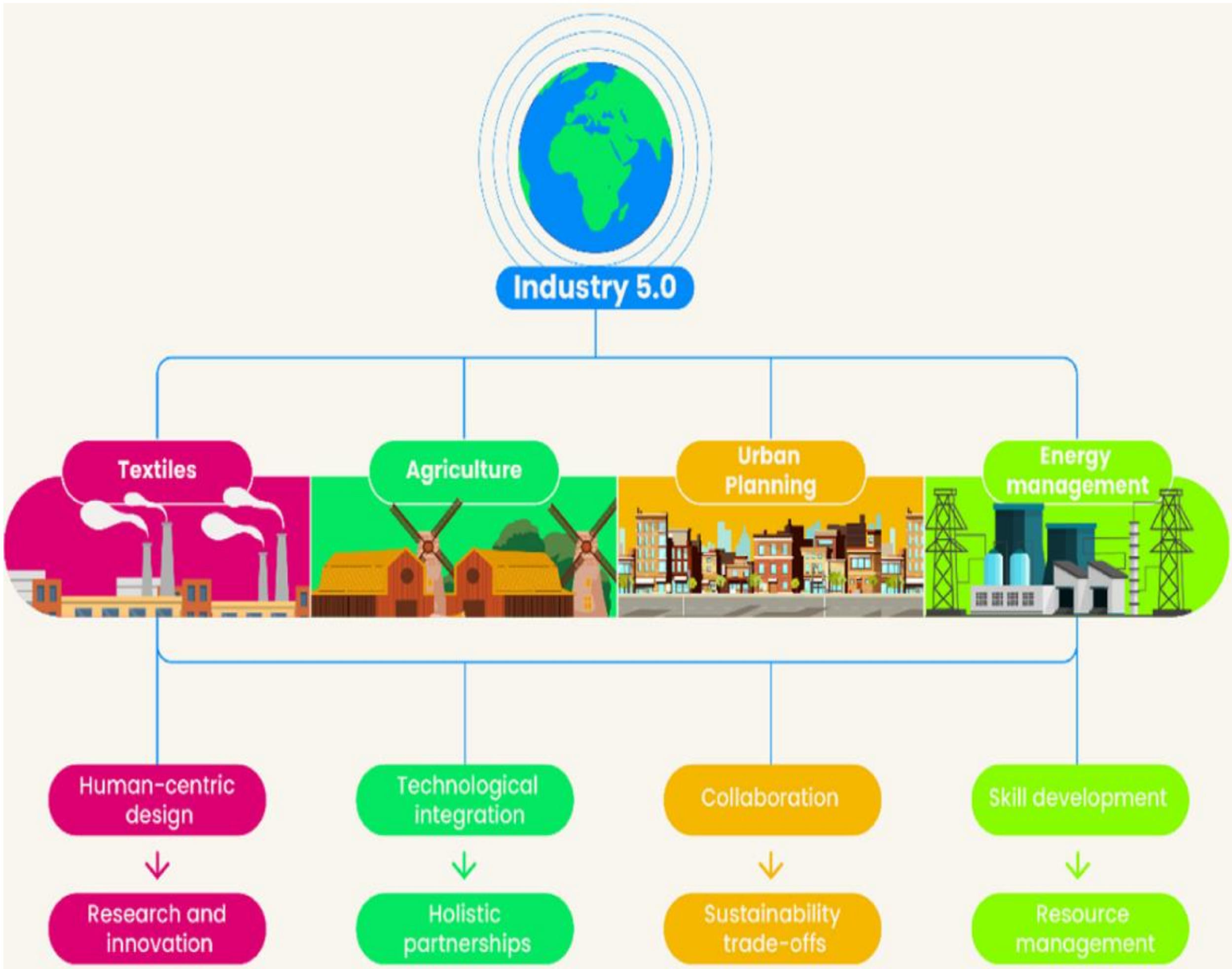

Figure 1 – Key areas and aspects of Industry 5.0
Source – Rame et al (2024)

There is a need to focus on the human-centric design and value of collaboration, technological integration, resource management, and skills development. There is a need to examine these elements through the lens of sustainability. Holistic partnerships play a vital role in research and innovation and there is a trade-off in sustainable transformation. Figure 1 highlights the interconnectivity of such domains as a guide towards multifaceted relation among sustainability programs and Industry 5.0. This inclusive approach is needed to know Industry 5.0's potential to create more sustainable and balanced future.

2.2. Evolution from Fourth to Fifth Industrial Revolution

Industry 5.0 is the concept of forming a manufacturing environment where human values, resilience, and sustainability are highly focused (Madsen and Berg, 2021; Lyngstadaas and Berg, 2024). Policies and academic research have propelled this paradigm shift to fulfill societal goals to transcend economic growth and employment (van Oudenhoven et al, 2022). Responsible use of resources using AI and preferring employee well-being in production are some of the key features of Industry 5.0 (Breque et al, 2021). Industry 5.0 has partly emerged by the perceived limitations of Industry 4.0 related to sustainability and humanization, adoption to improve production efficiency, and giving priority to technological advancement, while promoting elements of social fairness and sustainability (Leng et al, 2022; Grabowska et al, 2022).

Researchers and policymakers are more and more interested in targeting increasing focus of organizations on higher energy consumption with technology and dehumanizing manufacturing processes (Santhi and Muthuswamy, 2023). For instance, it is important to improve the performance of supply chain under the framework of Industry 4.0 related to sustainability (Birkel and Müller, 2021; Bai et al, 2020; Ghobakhloo, 2020; Ding et al, 2021), resilience (Razak et al, 2021; Ivanov and Dolgui, 2021), and human-centric approach (Mukhuty et al, 2022). Neither socially nor environmentally sustainable development has been the important design principle by researchers.

Studies have showed the potential for drastic transformation in the sector, surpassing the scope for I4.0 (Lyngstadaas and Berg, 2024; Ivanov, 2022; van Oudenhoven et al, 2022). Nevertheless, existing studies have focused majorly on discussing and exploring components in paired combinations. Some of the notable examples are environmental and economic sustainability, resilience, sustainability, human-centricity, etc. (Kamble et al, 2018; Bai et al, 2020; Kazancoglu et al, 2021). However, industry 5.0 must identify the role played by organizations to address challenges in societies in different dimensions like climate change, conservation of resources, and social stability, by establishing triangulating sustainability and comprehensive context, resilience, and human-centricity in supply chain management (Leng et al, 2022; Saniuk et al, 2022; Mourtzis et al, 2022a; 2022b).

In Industry 5.0, research is based completely on the growth of Industry 4.0. The substitution of human workforce with increasing energy consumption, automation, and carbon emissions are more acute with advancement of Industry 4.0. Industry 5.0 has refined and enhanced Industry 4.0 and addressed and reversed the disruptive effects in supply chains and wider sustainability in the society amid the constant growth of I4.0.

2.3. Impact of Industry 5.0 on Manufacturing Supply Chains

Supply chains act as the backbone for manufacturing organizations, supporting the transition of raw materials into finished goods and connecting consumers and suppliers (Yadav et al, 2020; Gawusu et al, 2022). The emergence of Industry 4.0 was observed in 2010s as a paradigm shift for technological evolution. Optimizing efficiency and productivity with latest technologies is its core objective. This transition has led to the digitalization of manufacturing, digitalization of whole value chain, and smart manufacturing (Xu et al, 2021). Industry 5.0 is the succeeding reiteration of Industry 4.0 with a transition from technological innovations to a systematic, holistic approach.

It advocates for sustainability in the industries by integrating human ingenuity with potential of accurate, efficient, and smart machinery (Maddikunta et al, 2022). In supply chains, adopting Industry 4.0 has been known as “digital supply chain” and “supply chain 4.0” (Garay-Rondero et al, 2020; Pandey et al, 2021; Büyüközkan and Göçer, 2018). It encapsulate the application and adoption of modern technologies to streamline the processes in supply chain, resulting in advancement of stakeholders in the processes of supply chain (Hahn, 2020; Frederico et al, 2020; Makris et al, 2019).

Industry 5.0 brings novel requirements and new perspectives challenging the current power dynamics and industrial structure between the actors of supply chain, resulting in reconfiguration of current supply chain (Sharma et al, 2022; Maddikunta et al., 2022). Supply chains in Industry 5.0 may use extant advancements of technology in Industry 4.0 and form a balanced collaboration between humans and robots for mass customization. Additionally, supply chains in Industry 5.0 can affect reduction of emissions and energy consumption while enhancing efficiency of the products and promoting employee interests (Humayun, 2021; Frederico, 2021; Sindhwani et al., 2022; Maddikunta et al., 2022).

Researchers are constantly focusing on the benefits of industry 5.0 on supply chain (Tran et al, 2022; Lyngstadaas and Berg, 2022; Yuan et al, 2022). Some have reviewed the evolution and identified supporting technologies and new applications (Maddikunta et al., 2022; Zizic et al, 2022). Mukherjee et al (2023) focused on the need to integrate sustainability, human-centricity, and technology when it comes to adoption of Industry 5.0. There is a research gap when transitioning to I5.0 in the domain of supply chain. Frederico (2021) proposed a model and focused on the constant need for industry plans to balance human and machine interactions to play a vital role in sustainable society, innovation and adoption of modern technologies. There is a need to review the influence of industry 5.0 on supply chain from the perspectives of management, organization, performance evaluation, and technology (Ivanov, 2022).

2.4. Multi-Objective Optimization (MOO)

MOO is an important tool to resolve several contradicting goals of complex systems. It identifies “Pareto optimal solutions” which promote balanced and informed decision-making (Caramia et al, 2020). There is a significance of MOO which is understood in the fields of supply chain management and industry 5.0, reaching beyond its traditional use in engineering and operations research (Lopes et al, 2020; Schütze et al, 2021). MOO outlines Pareto front in contrast to “single objective optimization”, presenting several solutions which balance the competing goals (Azzouz et al, 2016). The development of several models, including the ones based on swarm intelligence, evolutionary principles, and mathematical programming, which is vital for accurate articulation (Caramia et al, 2020; Deb et al, 2002).

In Industry 5.0, the complexity rises up with the new objectives, including operational efficiency and sustainability. While interaction between humans and machines is definitely an integral goal in this paradigm, this study recognizes its dimension as a significant factor for future research (Battini et al, 2022). In essence, Multi-Objective Optimization is an important tool for making informed decisions amongst complex demands to define I5.0.

3. Research Methodology

We have employed exploratory research design to present insights related to interrelationship between sustainable manufacturing and industry 5.0. This section clarifies research's methodology by adopting strategy of systematic literature review. While this approach has provided insights from available literature, they have been fine-tuned to provide intricate information related to industry 5.0 and its role in sustainability.

3.1. Search Strategy

Various esteemed databases have been used for conducting literature survey which are known for peer-reviewed articles and repositories, conference, and other scholarly materials. We have especially sourced papers from Scopus, ScienceDirect, MDPI, and Google Scholar. These databases were preferred because of their vast coverage of technological advancements related to industry 5.0 and detailed analysis of dimensions of sustainability. A targeted search strategy was employed to manage a huge volume of literature to balance vast coverage and content.

The bedrock of searches are formed by the keywords optimized with combinations to get into the core of matter. Some of the terms like "Industry 5.0, sustainable manufacturing, artificial intelligence, multi-objective techniques, sustainability", etc. These keywords are very versatile and harnessed well with unique search functions of each database. This adaptable and robust strategy has ensured that exploration has captured contemporary challenges, advancements, and debates around Industry 5.0 in terms of sustainability.

3.2. Inclusion and Exclusion Criteria

When it comes to conduct literature search, it was important to retain quality and relevance. Only those articles are selected which met specific criteria. Only peer-reviewed were selected over the past decades to ensure only reliable and recent insights. In addition, articles which explored industry 5.0 but didn't mention sustainability were excluded. In the same way, we have not considered generic discourses of sustainability without mentioning any relation to Industry 5.0. Hence, crux of this chapter has been firmly rooted towards the interrelation between both domains. Table 1 lists eligibility criteria for selecting the relevant studies.

Table 1 – Exclusion and Inclusion Criteria

Exclusion Criteria	**Inclusion Criteria**	
Articles not available in full text	Study investigates supply chains and industry 5.0 in manufacturing	
Articles without mentioning supply chain or industry 5.0	Impacts of Industry 5.0 are discussed on the entire part of supply chain.	
Supply chain/Industry 5.0 describes only research trends	Industry 5.0 and supply chain are the part of main research effort	
No focus on manufacturing sector		

3.3. Data Extraction

Once relevant materials are selected, we have adopted a systematic extraction of data, such as, gathering key insights, trends, findings, opportunities, and challenges related to literature. With vast amount of data, we adopted a thematic approach and findings are grouped under relevant themes like environmental implications, technological innovations, etc.

3.4. Quality Assurance

It is very important to ensure the credibility and reliability of information. We adopted a two-branched method. We emphasized articles published in peer-reviewed journals, which have been through a strict quality check. Second, we scrutinized any findings or data which were derived from the verified sources. Secondly, we conducted bibliometric study for mapping the landscape of research in sustainability and industry 5.0. With this approach, we have visualized the literature's growth, volume, and thematic concentration to depict research frontiers and emerging trends. With this well-crafted method, we provided an up-to-date, comprehensive, and holistic review of joining paths of sustainability and Industry 5.0.

4. AI-based Optimization in Smart Manufacturing

Multi-Objective Optimization (MOO) has become very critical to manage various inconsistent goals in terms of industry 5.0, such as, sustainability, efficiency, customization, and interaction between humans and technology. As manufacturing has been more interconnected and complex, traditional techniques of optimization have addressed challenges of smart factories. Advanced models have been developed with the rise of machine learning (ML) and artificial intelligence (AI) which can manage multi-objective, high-dimensional issues with real-time inputs and dynamic limitations. This section focuses on modern AI models for “multi-objective optimization”, focusing on their methodologies, applicability, and strengths in “Industry 5.0”. Various “state-of-the-art techniques” like “Particle Swarm Optimizations, Genetic Algorithms (GAs), Deep Learning (DL), and Reinforcement Learning (RL)” approaches to transform and solve optimization problems in smart cities.

4.1. Genetic Algorithms

GAs are among the most versatile and popular models for multi-objective optimization problems (Aljaidi et al, 2024; Zhou et al, 2024). As the name suggests, genetic algorithms are inspired by biological evolution using mechanisms like crossover, selection, and mutation to find optimal solutions iteratively in the specified space. The “Non-dominated Sorting Genetic Algorithm II (NSGA-II)” is efficient to manage trade-offs in terms of “multi-objective optimization”. NSGA-II is especially suitable for meeting Industry 5.0 standards, where it is important to balance production efficiency with human factors and sustainability (Deb et al, 2002). Figure 2 illustrates the overall mechanism of GAs.

- Selection – This model selects people as per Pareto ranking which detects solutions not used by others.
- Initialization – It randomly generates a population of possible solutions, each having potential configuration of system.
- Crossover and Mutation – Selected people go through mutation and crossover operations to for offspring to bring exploration and diversity to solution.
- Termination – It keeps up for specific generations or until it meets the convergence criterion.
- Elitism – Elitist strategy is used by NSGA-II where best solutions are maintained from the last generation to ensure that process of optimization improves over time steadily.

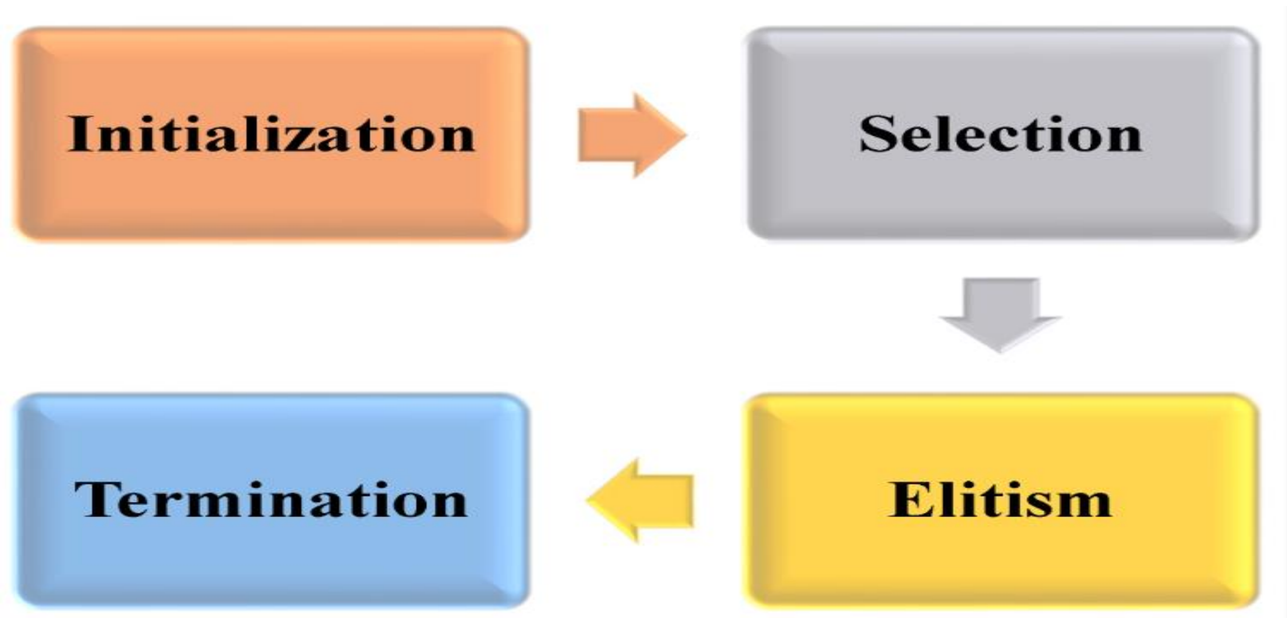

Figure 2 – Process of Genetic Algorithms

Source – Chen et al (2024)

NSGA-II can generate a range of "Pareto-optimal solutions" to provide a lot of trade-offs to decision-makers among objectives like increasing throughput of production, while saving energy. Figure 3 illustrates the key features of NSGA-II and its details and features are listed in Table 2.

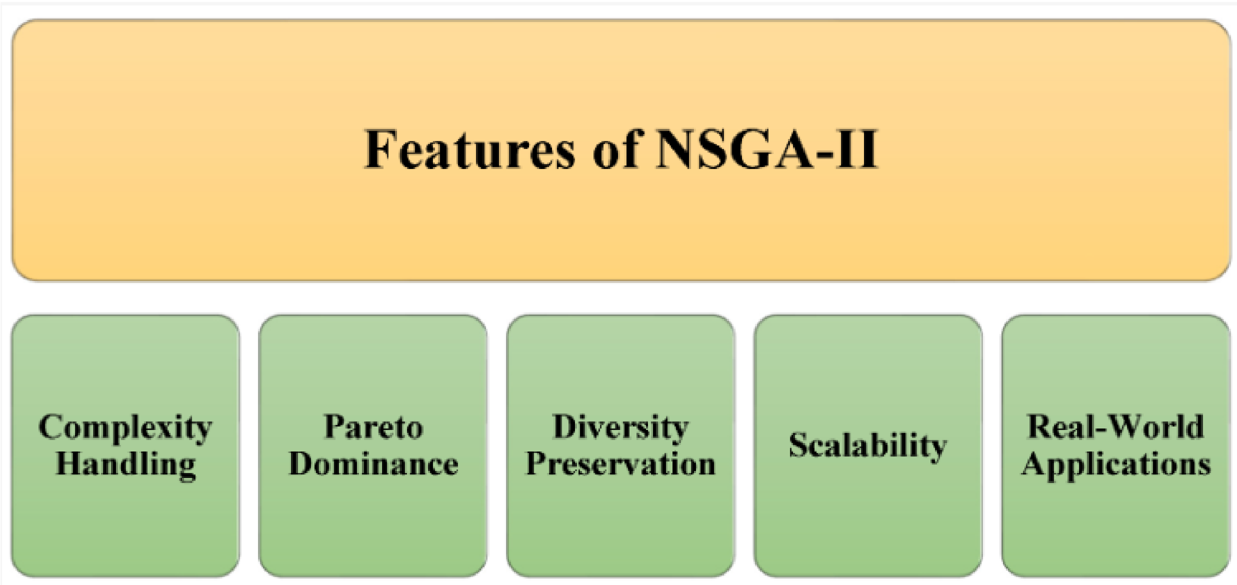

Figure 3 – Key Features of NSGA-II

Source – Chen et al (2024)

Table 2 – Features of NSGA-II and their specifications

Features	Characteristics
Pareto Dominance	Delivers a range of "Pareto-optimal, non-dominated" solutions
Managing complexity	Possible to solve multi-objective, complex issues smoothly
Scalability	Applicable to both large- and small-scale manufacturing roles related to optimization
Preserving Diversity	It maintains diversity in a set of solutions to avoid premature convergence
Real-world solutions	Scheduling, energy management, and resource allocation are some of the key tasks in factories

Source – Chen et al (2024)

4.2. Particle Swarm Optimization

PSO is another most popular AI model inspired by social activities like schooling of fish and birds flocking (Zhang et al, 2018; Shariati et al, 2019). In an MOO environment, the "Multi-Objective Particle Swarm Optimization (MOPSO)" is especially effective to manage various conflicting problems like increasing product quality and saving production time (Abualigah et al, 2024). PSO relies on swarm or population of candidate or particles which find the solution with two influences – well-known position and best-known position in the neighborhood. Particles meet the best-known solutions over time. PSO is efficient for global optima in large spaces. PSO is adopted by MOPSO for adopting "Pareto dominance-based selection" for multi-objective problems guiding particles for Pareto-optimal solution. This way, MOPSO is best suited for applications related to Industry 5.0, including enhancing production with various limitations like quality, cost, and sustainability. Table 3 lists features and their characteristics.

Table 3 – Features and Characteristics of MOPSO

Features	Characteristics
Efficiency	Pareto-optimal, non-dominated solutions
Swarm Intelligence	Particles working together and sharing data to find right solutions
Pareto Front	Identifies a range of "Pareto-optimal solutions" for decision-making
Dynamic Adaptation	Manages real-time, large-scale optimization roles and converges instantly

Use Cases	Supply Chain Optimization (SCO), logistics, and flexible manufacturing

Source - Chen et al (2024)

4.3. Reinforcement Learning (RL)

Reinforcement Learning (RL) has a lot of potential in scenarios of optimization where decisions have to be made in real-time in constantly-changing environment (Hu et al, 2018; Guo et al, 2020). Reinforcement Learning works on the code of agent interacting with the environment and learning from feedback through penalties and rewards (Razzaghi et al, 2024). The agent acts over time to increase combined rewards to optimize process. RL can be used to optimize complicated processes in industry 5.0, such as, allocation of resources, scheduling, and energy management. Reinforcement Learning can adapt to and learn from the smart factory environment where conditions may change constantly which needs quick changes.

Reinforcement Learning is extended by "Deep Reinforcement Learning (DRL)" with "deep neural networks" enabling the model to manage complex problems and "high-dimensional spaces" of input. For instance, DRL can optimize the processes of robotic assembly in smart factory by adjusting robotic movements constantly as per sensor data. With multiple objectives, cycle times can be reduced while ensuring quality of the product. DRL provides very strong and flexible approach to "multi-objective optimization". Table 4 lists the features and their characteristics.

Table 4 – Features and Specifications of RL/DRL

Features	Characteristics
Adaptability	Perfect in smart factories for real-time, dynamic optimization
Learning-based	Reinforcement Learning learns ideal policies with environment interactions.
Deep Learning	Neural networks are used by DRL to manage high-dimensional, complex challenges
Multi-Objective potential	To optimize various complex objectives at the same time
Applications	Automated systems, real-time scheduling, and robotics

Source - Chen et al (2024)

4.4. "Evolutionary Multi-Objective Optimization (EMO)"

EMO consists of a lot of models providing a population of solutions over generations with natural selection-based mechanisms (Liang et al, 2024). EMO models are especially effective to manage high-dimensional, complex problems with "multi-conflicting objectives". Production, resource allocation, and logistics are some of the complex tasks handled by models like Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D)" and "Strength Pareto Evolutionary Algorithm (SPEA2)" (Kim et al, 2004; Zhu et al, 2023). A multi-objective problem is split into various sub-problems and each one is optimized to provide a different range of "Pareto-optimal solutions" (Table 5).

Table 5 – Characteristics of EMO

Features	Characteristics
Diversity Maintenance	Diversity in set of solutions to reduce the odds of "premature convergence"
Multi-Objective Control	Efficiently solves multi-objective, complex problems
Modularity	Breaks down multi-objective problems into sub-portions to optimize efficiently
Applications	Resource allocation, supply chain management, and optimizing processes

Source - Chen et al (2024)

4.5. Comparing Multiple AI-Based MOO Techniques

For gaining better knowledge of weaknesses and strengths of various MOO techniques based on AI, Table 6 lists various AI-based MOO techniques and compares their strengths and weaknesses.

Table 6 – Comparative Analysis of AI-Based MOO Techniques

Models	Strengths	Weaknesses	Source
MOPSO	Best suited for dynamic settings to ensure rapid convergence	Risk of converging to local optima and subject to parameter settings	Tang and Jiang (2016)

NSGA-II	Diverse set of solutions for effective Pareto optimization	Needs to tune parameters for large-scale processing	Ahmadi et al (2020)
RL/DRL	Uses real-time data for learning and highly adaptable	Needs plenty of information to train and can be computationally costly	Chang et al (2022)
Metaheuristics (SA,GA)	Capable to solve different problems	May have trouble with high-dimensional spaces and real-time adaptation	Trojovský and Dehghani (2022)
EMO (like SPEA2)	Manages high-dimensional, complex issues	More powerful resources are needed and may be slower than heuristic approaches	Hussain et al (2023)

Source - Chen et al (2024)

5. **Sustainable Manufacturing in Industry 5.0**

In this age of Industry 5.0, sustainability has been an important aspect. A lot of well-recognized organizations have released their sustainability reports, including the companies adopting international supply chains. Additionally, a significant emphasis has been given by various universities on sustainability and they have integrated the principles of social responsibility in key functions (Larrán Jorge and Andrades Peña, 2017). As societies and organizations have gained more awareness of impacts of manufacturing on environment, increased attention is given on building efficient and sustainable production processes. Circular economy is the core component of the movement of sustainability, which redefines the way resources are reused and used until they end. Resources are used, gathered, and disposed of in a typical linear economy. On the other hand, circular economy makes the most of materials by designing recyclable, reusable products and reduces waste.

Consumer demand, regulatory pressures, resource depletion, and need to reduce the effects of climate change are some of the factors driving the shift for sustainability. The role of optimization is very significant in these challenges, which are widely being used to reduce waste, streamline processes, and reduce carbon footprint of operations. There is an emphasis of industry 5.0 on human-oriented production, combined with modern approaches. It has made the ways to ensure environmentally responsible and viable manufacturing systems and integrate optimization models and sustainability goals.

Sustainable manufacturing is the significant aspect of Industry 5.0 (Leng et al, 2022). The key here is to have a balance among environmental protection and efficient production to ensure that all the processes are planned to reduce waste, carbon emission, and environmental pollution. Businesses need to achieve more holistic approach in their operations to achieve sustainable manufacturing, given the long-term effects of production and full lifecycle of products. AI-based MOO models are very vital for businesses in industry 5.0 to achieve the goals related to sustainability. With the analysis of big data in supply chain, AI programs can recommend improvements, detect inefficiencies, and optimize the use of resources.

For instance, manufacturers can adjust levels of production with predictive analytics and demand forecasting to match the needs to reduce waste and overproduction. In the same way, ML models can optimize the use of energy by adjusting settings as per availability of energy and production demands. For instance, manufacturers can make changes to their production process with predictive analysis by predicting demand to match needs of consumers and reduce waste and overproduction. In the same way, ML models can adjust settings in the machines to optimize energy consumption in real-time as per energy availability and existing demands for production.

For sustainable manufacturing, adopting smart systems for energy management is a very common application. These systems use AI models and real-time data for optimization of energy utilization. This way, processes and machines run at high efficiency and reduce waste of energy. It can work in energy-consuming industries like chemical manufacturing and metal fabrication where one can significantly reduce costs and emissions with small changes in energy use.

5.1. Circular Economy

Circular economy can be considered as a new paradigm to manage resources. As per this concept, materials and products must be used constantly for longer period. It requires organizations to shift from "take-make-dispose" method to a system which prefers recycling, reusing, and remanufacturing. Resources are cycled constantly in a circular economy to reduce the demand for virgin materials and waste. For this shift, new production models are introduced in industry 5.0 which are naturally circular. AI-based models are important for implementation and design of circular processes so that organizations can reduce waste by finding opportunities, recover valuable goods at the end of lifecycle, and extend products' life.

For instance, AI can boost reverse logistics where products are disassembled, collected, and either recycled or remanufactured at the end of their lifecycle. AI can analyze data about location, condition, and use of products to find the best routes for recovery of products while reducing transport cost and ensuring cost-effective way to reclaim valuable products. Design phase is another significant area where AI is suitable. Manufacturers can use "generative design models" to manufacture products optimized for recycling and disassembly so that materials can be recovered and reused easily. With this approach, products can be more repairable and durable to further extend their life and reduce the effect of production on the environment.

5.2. MOO Process for Sustainable Manufacturing

There is a need to manage various processes to integrate manufacturing and sustainability. Businesses have to optimize production efficiency, meet customer demands, and reduce costs to integrate sustainability in manufacturing processes. Meanwhile, businesses have to optimize efficiency of production, meet customer demands, and reduce costs to stay competitive. They also have to address concerns related to environment, such as, conserving energy and water, reduce waste, and greenhouse gas emissions. These competing goals can make it challenging to find the right solution to promote sustainable manufacturing. Table 7 lists challenges, objectives, and results of multi-objective optimization for sustainable manufacturing.

Table 7 – Objectives, Limitations and Results of MOO for Sustainable Manufacturing

Objectives	**Limitations**	**Output**
Saving energy	Energy cost should be considered	Further research is needed to reduce consumption
Reducing carbon emissions	Should meet sustainability goals	Possible to ensure regulatory compliance to reduce emissions

MOO models come up with optimum solution with organizations to consider various criteria at the same time. These models can enable organizations to choose the ideal trade-offs among environmental sustainability and economic performance in terms of sustainable manufacturing. For example, one can use optimization model to balance the requirement for saving energy while maintaining high production output. By making changes to variables like energy input, machine speed, and material use, it is possible to identify the right settings which can save energy and fulfil production goals. With the use of MOO techniques, organizations can make best decisions to balance objectives to ensure both environmental and economic goals.

5.3. Digital Twins

Digital twin is the concept of latest industry 5.0 technology which can further boost sustainable manufacturing. Digital twin refers to a virtual model of physical process, product, or system which is updated regularly with real-time information. It is possible to use digital twins in manufacturing to optimize and simulate production processes, so that organizations can test various ways to improve sustainability and efficiency before they are adopted in real-world.

For instance, in a factory, digital twin can simulate the effect of various measures for saving energy, like upgrading to have solar panels for renewable energy or adding more energy-saving equipment. In the virtual environment, manufacturers can find out the best options for best economic and environmental benefits without having to disrupt operations. It enables more risk control and informed decision-making to avoid ineffective of expensive sustainability programs.

Digital twins are highly compatible to circular economy as it enables tracking of products in their lifecycle for manufacturing, i.e., from design to production for recycling, using, and disposal. Manufacturers can analyze data from digital twins and gain insights into use of products and how to reduce carbon footprint to improve them. For example, digital twin can provide feedback on overall performance of the product, enabling producers to identify inefficiencies or design flaws to be addressed in future changes.

1. **Discussion and Conclusion**

This study has provided a lot of insights related to application of AI-based MOO techniques in smart factories. These insights focus on how to address modern optimization techniques to address trade-offs and complexities related to advanced manufacturing while promoting a move towards the principles of Industry 5.0. Here are some of the key findings –

- **Pareto-front and trade-offs** – Using MOO techniques like genetic models enable evaluating and detecting the trade-offs between conflicting goals for smart factories. A Pareto front is used as a range of solutions where it is not possible to fulfill any single objective without affecting other, as in traditional approaches with single objective. On the Pareto front, each point has a unique balance among energy efficiencies, production speed, and waste management to provide a range of choices to decision-makers. For example, faster production cycles may be preferred by one solution at the cost of enhanced energy consumption, while other might reduce waste, although it needs longer time for production. With this flexibility, smart factories can align its operational plans with dynamic needs of organizations, including sustainability-based programs or high demand. The factory could be able to make informed decisions by visualizing such trade-offs that managed short-term performance with sustainability goals in the long-term.
- **Collaboration between humans and machines** – Smooth collaboration among machine intelligence and human expertise is the foundation of Industry 5.0. This study underscores the value of collaboration between humans and machines to achieve best outcomes for production. Human operators are very vital by offering operational insights and context-based knowledge, such as, setting schedules for maintenance, identifying nuanced issues for production, and showing improvements for processes. These inputs were used in "AI-based Optimization Engine" to refine its recommendations and predictions.
- **Reinforcement Learning** – This study has showed excellent flexibility of RL in unexpected and dynamic environments related to production. RL models are best in dealing with real-time changes, such as, constantly changing consumer demands, unexpected downtime of machines, or changes in availability of raw materials. When there is downtime in critical piece of equipment, the reinforcement learning model has adjusted schedules for production dynamically, modified machine settings, and reallocated resources to reduce the effect of output. In case of heavy demand, the model optimizes throughput in production by preferring speed while reducing waste or defects.

All in all, this study discusses transformative impact of AI-based MOO techniques for smart factories. This study has provided insights which suggest that it is possible to apply similar frameworks in different sectors, so that factors can balance adaptability, efficiency, and sustainability. The ability to adapt to changes in real-time, explore trade-offs, and integrate expertise ensures relevance of those systems in rapidly-changing landscapes. With modern approaches, manufacturing units can achieve competitive strength while resulting in efficiency and sustainability goals to make way for large-scale adoption of principles of industry 5.0.

This study has provided deeper insights to theoretical and practical impact of AI-based MOO techniques in smart factories. Along with optimizing the processes of production, machine learning and AI techniques are being used widely to measure and monitor the sustainability of manufacturing. AI-based metrics related to sustainability provides real-time data on "key performance indicators (KPIs)" like waste generation, energy consumption, and carbon emissions. AI programs can find areas where there is a need for improvements and recommend actions to reduce carbon footprint by tracking these KPIs constantly.

For instance, AI programs can track and analyze data provided by smart sensors which are installed across the factory to detect loopholes and track use of energy. If more energy is consumed by a machine than expected, AI system can suggest right actions and alert operators, such as, scheduled maintenance and changing machine settings. With constant feedback on performance related to sustainability, those programs help makers to achieve sustainability goals and make more informed decisions effectively.

Hence, industry 5.0 provides robust framework to integrate manufacturing and sustainability with the use of AI-based techniques for optimization, digital twins, and circular economy. By harmonizing environmental and economic goals, organizations can come up with more resilient and sustainable systems for manufacturing which can play a vital role in long-term health of the environment while staying competitive. Along with environmental challenges, sustainable manufacturing also acts as an opportunity for organizations to differentiate and innovate in a highly eco-conscious world.

The study has proposed an MOO framework which is designed to meet operational demands to match real-world applicability in industry 5.0. When traditional practices are based completely on automation in industry 4.0, the proposed framework adopts PSO, GAs, and RL for collaboration between humans and machines, complex optimization requirements, and sustainability in modern settings. Factories can manage conflicting goals like sustainability and productivity. Future studies can simplify data needs to enhance this framework and improve accessibility to meet several industry demands. Future studies are needed to determine the integration of blockchain and digital twins in industry 5.0 to improve transparency, data sharing, and traceability in real-time for sustainability.

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