Decision Intelligence in Collaborative Intelligent Manufacturing of smart and sustainable materials: A Comprehensive Review of Artificial Intelligence, Optimization, Digital Twins, and Human-Centered Decision-Making

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Abstract: The rapid transition from Industry 4.0 to Industry 5.0 has significantly increased the complexity of manufacturing systems while accelerating the development and deployment of smart and sustainable materials in advanced industrial applications. These emerging materials require intelligent decision-making approaches that integrate data, advanced analytics, optimization, digital twins, and human expertise throughout their design, production, monitoring, and lifecycle management. Although artificial intelligence, machine learning, digital twins, and mathematical optimization have independently advanced intelligent manufacturing, their isolated application often limits adaptability, explainability, and resilience. This study presents a systematic literature review of Decision Intelligence (DI) in collaborative intelligent manufacturing following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, synthesizing evidence from 140 peer-reviewed publications. The review comprehensively examines the evolution of Decision Intelligence, core enabling technologies, layered architectures, industrial applications, human-centered decision-making, implementation challenges, and emerging research trends. The findings indicate that effective Decision Intelligence requires the seamless integration of artificial intelligence, optimization, digital twins, knowledge graphs, explainable AI, and Human-in-the-Loop AI within a unified decision ecosystem that combines computational intelligence with human judgment. The proposed framework and research roadmap provide valuable theoretical insights and practical guidance for developing resilient, explainable, and human-centric Decision Intelligence systems that support the realization of Industry 5.0 manufacturing for smart and sustainable materials.

Keywords: Decision Intelligence, Collaborative Manufacturing, Industry 5.0, Artificial Intelligence, Optimization, Digital Twin, Human-Centered Manufacturing, Smart Manufacturing.

1. INTRODUCTION

Manufacturing has continuously evolved to address increasing market complexity, technological advancements, and changing societal expectations. From the mechanization of production during the First Industrial Revolution to the emergence of intelligent cyber-physical ecosystems in the era of Industry 5.0, each industrial transformation has fundamentally redefined manufacturing paradigms, production strategies, and decision-making processes (Esmaeilian *et al.*, 2016). Industry 5.0 also promotes the development and sustainable utilization of smart materials, environmentally friendly materials, recyclable materials, and circular manufacturing systems, requiring intelligent decision support across the entire material lifecycle. The current manufacturing landscape is characterized by unprecedented levels of data generation, interconnected systems, autonomous machines, and human-machine collaboration, creating opportunities as well as challenges for making timely, accurate, and sustainable decisions (Chirumalla *et al.*, 2025). Consequently, decision-making has become one of the most critical capabilities for modern manufacturing enterprises seeking competitiveness, resilience, and operational excellence.

1.1. Evolution of Manufacturing

The emergence of smart materials, multifunctional materials, advanced composites, bio-based materials, recyclable materials, and other sustainable materials has further increased manufacturing complexity. Their design,

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processing, quality assurance, lifecycle monitoring, and circular utilization require intelligent decision-making frameworks capable of integrating physical data, computational intelligence, and human expertise. The development of manufacturing can be viewed as a sequence of technological revolutions, each introducing new production philosophies and enabling technologies.

Industry 1.0 marked the transition from manual craftsmanship to mechanized production through the utilization of water and steam power (Szeszák *et al.*, 2025). This revolution significantly increased production capacity but relied heavily on human supervision and experience-based decision-making. This paper states that industrial evolution has been a key driver of global economic and technological development, while industrial mathematics provides essential tools for optimizing production, supply chain management, and decision-making, thereby enabling the development of smart industries capable of meeting customer demands in uncertain business environments (Akash Kadam *et al.*, 2025; Vinitha *et al.*, 2020).

The advent of Industry 2.0 introduced electricity, assembly lines, and mass production techniques (Al-Siah & Fioravanti, 2023; Lv, 2023). Standardization and division of labor dramatically improved productivity and reduced manufacturing costs. Decision-making during this era focused primarily on production planning, scheduling, and quality inspection using deterministic approaches. This relavent paper (Yin *et al.*, 2018) discusses the evolution of manufacturing during Industry 2.0, emphasizing the transition from steam-powered production to electrically driven mass manufacturing. It focuses on the introduction of assembly lines, standardized production methods, interchangeable parts, and scientific management principles that significantly enhanced productivity, efficiency, and product quality. The paper further examines how electrification enabled continuous production, reduced manufacturing costs, and supported large-scale industrialization, laying the technological and organizational foundation for modern manufacturing systems and subsequent industrial revolutions.

The emergence of Industry 3.0 transformed manufacturing through automation, programmable logic controllers (PLCs), industrial robotics, and computer-aided manufacturing (Adebayo *et al.*, 2025; Patel & Lim, 2025). Digital technologies enabled greater production flexibility and process control; however, most manufacturing systems remained isolated, with limited communication among machines and enterprise systems. The concept of Industry 4.0 represented a paradigm shift toward highly connected and intelligent manufacturing environments. Cyber-physical systems, Industrial Internet of Things (IIoT), cloud computing, artificial intelligence (AI), big data analytics, additive manufacturing, blockchain, and digital twins enabled real-time sensing, predictive analytics, autonomous control, and decentralized decision-making. Manufacturing systems evolved from automated production facilities into smart factories capable of continuously collecting and processing massive amounts of operational data (Khan *et al.*, 2025; Subrahmanyam, 2025; Zakoldaev *et al.*, 2019).

Although Industry 4.0 significantly enhanced manufacturing intelligence, its primary emphasis remained technology-driven. Growing concerns regarding workforce well-being, sustainability, resilience, ethical AI, and environmental responsibility motivated the transition toward Industry 5.0 (Luu *et al.*, 2025). Unlike its predecessor, Industry 5.0 advocates a human-centric manufacturing philosophy in which intelligent technologies complement rather than replace human expertise. Collaborative robots, explainable AI, digital twins, edge intelligence, and human-in-the-loop systems enable effective collaboration between humans and machines while simultaneously supporting sustainable production and resilient supply chains (Dehghan *et al.*, 2025).

As manufacturing systems become increasingly interconnected and autonomous, organizations face a new challenge that extends beyond data acquisition and automation: transforming vast amounts of heterogeneous information into actionable, reliable, and context-aware decisions. The complexity of modern manufacturing environments including dynamic production schedules, uncertain demand, supply chain disruptions, energy constraints, equipment failures, and sustainability objectives cannot be effectively managed through conventional optimization or standalone AI models alone. This study highlights the importance of resilient, human-centric, and adaptive manufacturing systems, aligning with the principles of Industry 5.0 by emphasizing supply chain agility, continuous learning, sustainability, and collaborative decision-making to effectively manage disruptions and uncertainty (Dey *et al.*, 2024; X. Li *et al.*, 2026).

This evolution has led to the emergence of the Decision Intelligence (DI) Era, representing the next stage in intelligent manufacturing. Decision Intelligence integrates artificial intelligence, machine learning, operations research, mathematical optimization, simulation, digital twins, knowledge graphs, causal reasoning, reinforcement learning, and human expertise into a unified decision-support framework. Rather than simply generating predictions or optimizing isolated objectives, Decision Intelligence aims to recommend, evaluate, explain, and continuously improve decisions across strategic, tactical, and operational levels of manufacturing.

Within collaborative intelligent manufacturing, Decision Intelligence enables seamless coordination among humans, robots, cyber-physical systems, and enterprise information systems (Dhanda *et al.*, 2025). Digital twins continuously mirror physical assets, AI models forecast future conditions, optimization algorithms determine optimal actions, and human experts provide contextual knowledge, ethical judgment, and strategic oversight. This synergistic integration creates adaptive manufacturing ecosystems capable of learning from experience, responding to uncertainty, and balancing multiple conflicting objectives such as productivity, quality, energy efficiency, sustainability, resilience, and worker well-being.

Despite the rapid growth of Decision Intelligence research, existing review articles predominantly focus on individual enabling technologies such as artificial intelligence, digital twins, collaborative robotics, optimization methods, or Industry 5.0 (Rahaman *et al.*, 2025). A comprehensive review that systematically integrates these technologies under the unified perspective of Decision Intelligence for collaborative intelligent manufacturing remains largely absent. Furthermore, limited attention has been given to understanding how AI, optimization, digital twins, human-centered decision-making, and explainable intelligence collectively contribute to intelligent manufacturing ecosystems.

To address this research gap, this review presents a comprehensive synthesis of Decision Intelligence in Collaborative Intelligent Manufacturing. The paper systematically examines the evolution of manufacturing intelligence, analyzes the integration of artificial intelligence, optimization techniques, digital twins, and human expertise, and reviews their applications across planning, scheduling, predictive maintenance, quality control, supply chain management, energy optimization, and autonomous manufacturing systems. In addition, the review discusses existing challenges, identifies emerging research trends, and proposes future research directions toward resilient, sustainable, explainable, and human-centric manufacturing systems. By providing an integrated conceptual framework and critical analysis of recent developments, this review aims to serve as a valuable reference for researchers, practitioners, and policymakers working toward the realization of next-generation intelligent manufacturing. The historical evolution of manufacturing, from Industry 1.0 to the emerging Decision Intelligence era, is illustrated in Figure **1**, highlighting the progressive integration of automation, digitalization, artificial intelligence, and human-centered decision-making.

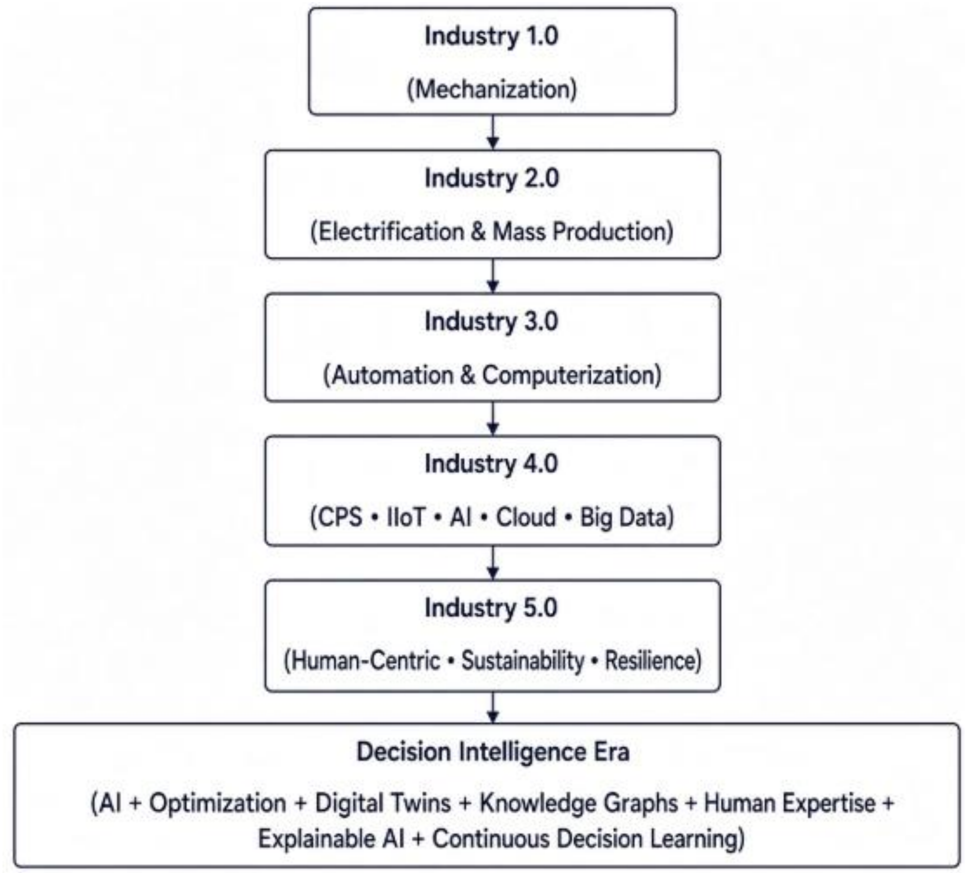

Figure 1: Evolution toward Decision Intelligence-driven Manufacturing.

1.2. From Automation to Intelligent Decision-Making

The transition from conventional automation to intelligent decision-making has transformed modern manufacturing by enabling data-driven, predictive, and adaptive operational strategies. In this context, Nadim Mahmud and Hrittik Mural (2025) proposed an integrated framework that combines ensemble machine learning with multi-criteria decision-making (MCDM) techniques to identify and prioritize the key drivers of inventory waste. Their study demonstrates how intelligent decision-support systems can optimize inventory management, minimize operational inefficiencies, and enhance manufacturing resilience through predictive analytics and automated decision-making (Mahmud & Mural, 2026). Smart manufacturing represents the evolution of conventional production systems into interconnected and data-driven environments, where cyber-physical systems, Industrial Internet of Things (IIoT), cloud computing, and digital twins enable real-time monitoring, autonomous control, and intelligent decision-making. It establishes the technological foundation for collaborative intelligent manufacturing by enhancing operational efficiency, flexibility, and responsiveness (Leng *et al.*, 2026). Artificial intelligence has transformed manufacturing from rule-based automation to cognitive and predictive systems capable of learning from data and optimizing complex processes. Through machine learning, deep learning, computer vision, and reinforcement learning, AI enables predictive maintenance, intelligent quality inspection, production scheduling, and autonomous process optimization, thereby supporting more informed and adaptive manufacturing decisions.

Human-centric manufacturing shifts the focus from fully automated factories to collaborative environments where human expertise complements intelligent technologies (Singh *et* *al.*, 2022). By integrating collaborative robots, explainable AI, ergonomic system design, and human-in-the-loop decision-making, manufacturing systems can improve productivity, safety, creativity, and worker well-being while maintaining flexibility in complex production scenarios (Talukder *et al.*, 2026; M. Wang *et al.*, 2025). Decision Intelligence represents the next stage in manufacturing evolution by integrating artificial intelligence, optimization techniques, digital twins, and human expertise into a unified decision-support framework. Rather than merely automating tasks, Decision Intelligence enables explainable, collaborative, and context-aware decision-making that improves strategic, tactical, and operational performance across intelligent manufacturing systems.

1.3. Why Decision Intelligence?

The rapid evolution of Industry 4.0 and the transition toward Industry 5.0 have significantly increased the complexity of manufacturing systems, creating decision environments characterized by high-dimensional data, dynamic operating conditions, uncertainty, and multiple conflicting objectives (L. Zhang *et al.*, 2024). As manufacturing enterprises adopt Industrial Internet of Things (IIoT), cyber–physical systems, cloud and edge computing, digital twins, autonomous robotics, and advanced analytics, traditional decision-support approaches have become increasingly inadequate for addressing real-time operational challenges (Bitencourt *et al.*, 2025). Although numerous intelligent technologies have been developed to improve manufacturing performance, each technology exhibits inherent limitations when applied independently. Consequently, recent research has emphasized the need for integrated Decision Intelligence (DI) frameworks capable of combining data-driven analytics, optimization, simulation, and human expertise into a unified decision-making paradigm.

Artificial intelligence (AI) and machine learning (ML) have demonstrated remarkable capabilities in pattern recognition, anomaly detection, predictive maintenance, quality inspection, and demand forecasting by learning complex relationships from large-scale manufacturing data (Alfaro-Viquez *et al.*, 2025). Nevertheless, these methods primarily generate predictive insights rather than prescriptive decisions and often suffer from challenges related to explainability, transparency, model generalization, data dependency, and robustness under changing production environments (Moosavi *et al.*, 2024). Mathematical optimization techniques, including linear programming, mixed-integer programming, evolutionary algorithms, and multi-objective optimization, provide systematic approaches for identifying optimal manufacturing decisions under predefined objectives and constraints. However, conventional optimization models frequently rely on deterministic assumptions, require accurate mathematical formulations, and have limited capability to adapt to uncertain, stochastic, and rapidly changing industrial environments (Saxena *et al.*, 2025). Similarly, digital twins enable real-time monitoring, virtual simulation, and predictive analysis of manufacturing systems but remain constrained by data synchronization, computational complexity, interoperability, and scalable deployment across heterogeneous production environments (Barata & Kayser, 2024; Grieves, 2023). Furthermore, while human expertise contributes contextual reasoning, ethical judgment, and experiential knowledge that cannot easily be replicated by intelligent algorithms, purely human-centered decision-making is often affected by cognitive bias, limited processing capacity, and inconsistent judgments under complex operational conditions. These complementary strengths and limitations have motivated the emergence of Decision Intelligence as a holistic framework that integrates artificial intelligence, optimization, digital twins, data analytics, and human-centered collaboration to deliver adaptive, explainable, trustworthy, and resilient decision-making across modern manufacturing systems.

Digital twins provide high-fidelity virtual representations of physical assets and manufacturing processes, enabling real-time monitoring, simulation, and scenario analysis (Javaid *et al.*, 2023). Nevertheless, digital twins primarily evaluate the consequences of different operational scenarios rather than autonomously selecting the most appropriate decision among competing alternatives. Human experts contribute tacit knowledge, contextual understanding, ethical judgment, and practical experience that are difficult to encode into computational models. Their ability to interpret ambiguous situations, consider organizational objectives, and adapt to unforeseen events remains indispensable. However, purely human decision-making is often constrained by cognitive biases, limited processing capacity, and the increasing complexity of industrial data(Yanytska, 2025). The overall ecosystem of Decision Intelligence in collaborative intelligent manufacturing is illustrated in Figure **2**, showing the interactions among data acquisition, intelligent analytics, optimization, human expertise, and manufacturing applications.

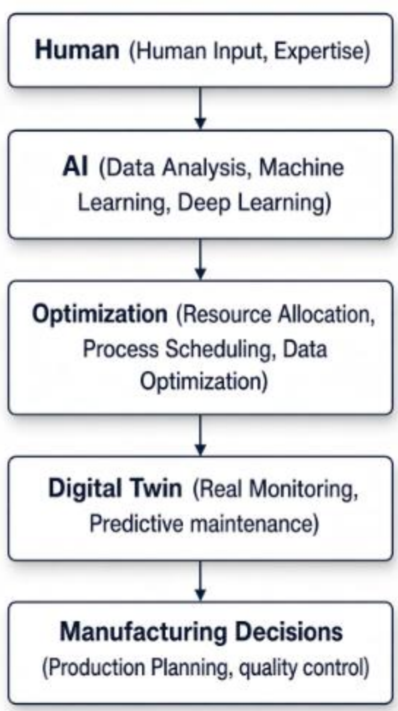

Figure 2: Decision Intelligence Ecosystem for Collaborative Intelligent Manufacturing of Smart and Sustainable Materials.

1.4. Smart and Sustainable Materials in the Era of Decision Intelligence

The transition from Industry 4.0 to Industry 5.0 has significantly accelerated the development and adoption of smart and sustainable materials, which are becoming fundamental components of next-generation manufacturing systems. Smart materials possess the capability to sense, respond, and adapt to changes in environmental conditions such as temperature, stress, pressure, electric fields, or magnetic fields, enabling self-monitoring, self-healing, and adaptive functionalities. Simultaneously, sustainable materials emphasize environmental responsibility through reduced resource consumption, lower carbon emissions, recyclability, circular material utilization, and improved lifecycle performance. Examples include advanced composites, shape memory alloys, piezoelectric materials, self-healing polymers, bio-based materials, recyclable composites, nanomaterials, and multifunctional materials.

The increasing complexity of these materials presents significant challenges throughout their design, characterization, processing, manufacturing, quality assurance, structural performance assessment, and end-of-life management. Conventional manufacturing approaches often lack the capability to efficiently integrate heterogeneous material data, predict material behavior under dynamic operating conditions, and optimize manufacturing processes while simultaneously satisfying mechanical performance, economic efficiency, and environmental sustainability objectives.

Decision Intelligence offers a promising solution by integrating artificial intelligence, machine learning, digital twins, optimization algorithms, simulation, and human expertise into a unified decision-support framework. Artificial intelligence enables intelligent material discovery, property prediction, defect identification, and process optimization, while Digital Twins continuously monitor material behavior throughout manufacturing and operational life. Optimization algorithms support intelligent material selection, process parameter optimization, resource allocation, and lifecycle management. Human expertise further contributes engineering judgment, safety evaluation, and sustainability assessment, ensuring that computational recommendations remain reliable and practically applicable.

Consequently, Decision Intelligence extends beyond intelligent manufacturing operations to support the complete lifecycle of smart and sustainable materials, including material design, processing, structural performance monitoring, lifecycle optimization, recycling, and circular manufacturing. This integration strongly aligns with the human-centric, resilient, and sustainable objectives of Industry 5.0.

1.5. Literature Gap

Explainable Artificial Intelligence (XAI) is crucial for the transition from the fourth to fifth industrial revolution, providing transparency and fostering user confidence in Artificial Intelligence (AI) powered systems. Since 2020, XAI applications demonstrate potential to transform manufacturing. Nikiforidis *et al.* (2025) provides an extensive overview of XAI-based applications in Industries 4.0 and 5.0 by highlighting the trends regarding methods used, connecting XAI methods with important parameters and presenting XAI visualization approaches. The survey provides valuable insights for researchers, practitioners and industry leaders as it underscores the potential of XAI in shaping the future of manufacturing by enhancing transparency and user acceptance of AI-powered applications (Nikiforidis *et al.*, 2025). Li *et al.* (2024) investigates the effects of artificial intelligence (AI) on manufacturing firms' energy intensity (EI) by examining the substitutive role of AI in factor inputs. We assess how AI advancements and the assimilation can improve productivity and enhance energy efficiency, potentially reducing EI. Using a dataset of Chinese listed manufacturing companies from 2006 to 2020, this study quantifies AI adoption through text analysis of firms' annual reports. The findings indicate that AI applications can significantly improve production efficiency and energy efficiency, thereby significantly diminishing firms' EI (H. Li *et al.*, 2025).

Protyai *et al.* (2026) presented Digital Twin (DT) technology as a key enabler of the industry 4.0 revolution, demonstrating how its integration with manufacturing and Project Lifecycle Management (PLM) enhances real-time monitoring, predictive maintenance, and operational efficiency. Their study further showed that DT-driven project evaluation supports data-driven decision-making, improves project execution, and promotes sustainable manufacturing through continuous digital synchronization (Protyai *et al.*, 2026). Karkaria *et al.* (2025) reviews optimization methods that enhance adaptability, efficiency and decision making in modern manufacturing, emphasizing the transformative role of artificial intelligence (AI) and digital twin technologies. By integrating AI and machine learning algorithms within digital twin frameworks, manufacturers can facilitate real-time monitoring, quality control and dynamic process adjustments (Karkaria *et al.*, 2025). Tudorache *et al.* (2025) stated in their paper that many studies present generic implementations for DTs that do not address the required level of detail to achieve an effective DT solution. Future work should focus on understanding the complex additive manufacturing process to build integrated and enhanced simulation capabilities of the DT and on employing standard engineering methodologies and tools for developing DTs in the context of AM (Tudorache *et al.*, 2025).

Debnath *et al.* demonstrates that optimization techniques are increasingly being adopted in modern manufacturing to improve aggregate production planning by minimizing total operational costs and enhancing production efficiency under uncertain industrial environments (Debnath *et al.*, 2025a). Shahriar *et al.* (2026) highlights the growing application of multi-criteria optimization and decision-making techniques in manufacturing and supply chain management to support sustainable supplier selection, enabling industries to balance economic, environmental, and social objectives through data-driven decision-making (Shahriar *et al.*, 2026a).

Although numerous review studies have investigated artificial intelligence, digital twins, optimization, and Industry 5.0 manufacturing, limited attention has been devoted to Decision Intelligence for the manufacturing of smart and sustainable materials. Existing reviews rarely examine how AI, optimization, digital twins, and human-centered decision-making can collectively support intelligent material design, sustainable material processing, quality assurance, lifecycle assessment, circular economy practices, and resource-efficient manufacturing. Sudden

Table 1: Comparison of Existing Review Papers

Authors	Year	AI	Optimization	Digital Twin	Human Factors	Decision Intelligence	Research Gap	Novelty
Nikiforidis *et al.* [11]	2025	✓	✗	✗	✓	✗	Focuses only on Explainable AI (XAI); lacks optimization, DT integration, and unified decision-making.	Comprehensive review of XAI applications for transparent and trustworthy manufacturing.
Li *et al.* [12]	2024	✓	✗	✗	✗	✗	Investigates AI for energy efficiency only; does not address manufacturing decision integration.	Demonstrates AI-driven improvements in production and energy efficiency.
Protyai *et al.* [13]	2026	✗	✗	✓	✗	Partial	DT framework is limited to monitoring and project lifecycle management without integrated optimization or human collaboration.	Presents DT integration with PLM for real-time project evaluation and sustainable manufacturing.
Karkaria *et al.* [14]	2025	✓	✓	✓	✗	Partial	Reviews AI, optimization, and DT but lacks human-centric and Decision Intelligence perspectives.	Reviews AI-enabled optimization within Digital Twin frameworks for smart manufacturing.
Tudorache *et al.* [15]	2025	✗	✗	✓	✗	✗	Focuses on Digital Twin implementation challenges in additive manufacturing only.	Identifies research challenges for high-fidelity Digital Twins in additive manufacturing.
Debnath *et al.* [16]	2026	✗	✓	✗	✗	✗	Concentrates on aggregate production planning without AI, DT, or collaborative intelligence.	Develops optimization-based production planning under uncertain manufacturing environments.
Shahriar *et al.* [17]	2026	✗	✓	✗	✓	Partial	Focuses on sustainable supplier selection without integrating AI or Digital Twins.	Integrates AHP-TOPSIS for sustainable manufacturing and supply chain decision-making.
Pant *et al.*(Pant *et al.*, 2025)	2025	✓	Partial	Partial	✓	✗	Reviews Industry 5.0 technologies but does not propose a unified Decision Intelligence framework.	Summarizes Industry 5.0 technologies emphasizing sustainability, agility, and human-machine collaboration.
This Review	2026	✓	✓	✓	✓	✓	Proposing Decision Intelligence as a unified framework integrating AI, optimization, Digital Twins, and human expertise for collaborative intelligent manufacturing.	Provides the first comprehensive review centered on Decision Intelligence in Collaborative Intelligent Manufacturing.

challenges have arisen in manufacturing from the last few years. These changes destroyed the traditional manufacturing system. High automation was introduced in the industry by connecting physical and virtual world, known as Industry 4.0. Since Industry 4.0 was unable to meet the emergent need for customization, the term Industry 5.0 was developed to address the customised manufacturing. This industry revaluation enhanced the customer satisfaction by creating their customised products. The primary goal of industrial transformation is to take into account the social and environmental advantages of the sector in order to become a true source of success. Pant *et al.* (2025) aims to categorise and summarise the research results from some papers on Industry 5.0 and key challenges of Industry 4.0 in order to provide guidance and insight to other researchers and professionals (Pant *et al.*, 2025).

Although recent studies have made significant advances in applying artificial intelligence, optimization techniques, digital twins, and human-centric manufacturing (Mural *et al.*, 2026) independently, the existing literature remains highly fragmented. Digital twin research has significantly improved real-time monitoring, simulation, and predictive maintenance; however, most frameworks remain simulation-oriented and lack integrated decision-support capabilities (Crespi *et al.*, 2023; Hananto *et al.*, 2024). Meanwhile, Industry 5.0 research highlights human-centricity, sustainability, and collaboration, yet human knowledge is rarely incorporated systematically into computational decision frameworks.

Therefore, a critical research gap exists in the absence of a comprehensive framework that simultaneously integrates Artificial Intelligence for predictive analytics, Optimization for prescriptive decision-making, Digital Twins for real-time simulation and system awareness, and Human Expertise for contextual reasoning and ethical judgment. More importantly, the concept of Decision Intelligence, which unifies these complementary technologies into a collaborative, explainable, adaptive, and human-centered decision-making ecosystem, has received limited attention in the context of collaborative intelligent manufacturing. Addressing this gap is essential for realizing the full vision of Industry 5.0, where intelligent technologies and human expertise work synergistically to support resilient, sustainable, and data-driven manufacturing systems. A comparison of representative review studies related to Decision Intelligence, intelligent manufacturing, Industry 5.0, and human–AI collaboration is presented in Table **1**, demonstrating the research gap addressed by this review.

1.5. Research Questions

Based on the identified research gaps, this review seeks to address the following research questions, which systematically explore the concepts, enabling technologies, integration strategies, and future challenges of Decision Intelligence in collaborative intelligent manufacturing.

RQ1: What is Decision Intelligence, and how does it transform collaborative intelligent manufacturing beyond Industry 4.0 and Industry 5.0?

RQ2: Which core technologies including Artificial Intelligence, optimization, Digital Twins, and human-centric systems enable Decision Intelligence in manufacturing?

RQ3: How are Artificial Intelligence and optimization techniques integrated to support predictive, prescriptive, and autonomous manufacturing decisions?

RQ4: What role do Digital Twins play in real-time monitoring, simulation, and decision support within collaborative manufacturing systems?

RQ5: How can human expertise be effectively integrated with intelligent systems to achieve explainable, trustworthy, and human-centered decision-making?

RQ6: What are the current research challenges, emerging trends, and future directions for implementing Decision Intelligence in collaborative intelligent manufacturing?

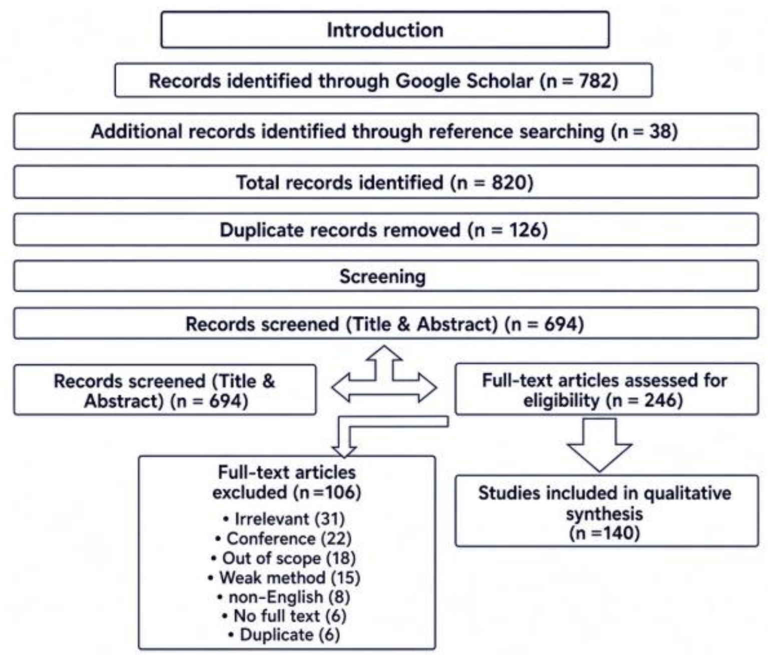

Figure 3: PRISMA Flow Diagram.

2. REVIEW METHODOLOGY

This review adopts a systematic literature review methodology based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, reproducibility, and methodological rigor. The objective of this review is to comprehensively examine the current state-of-the-art in Decision Intelligence for Collaborative Intelligent Manufacturing, with a particular focus on the integration of Artificial Intelligence (AI), optimization techniques, Digital Twins, and human-centered decision-making. The review process consisted of literature identification, screening, eligibility assessment, quality evaluation, and final inclusion of relevant studies.

2.1. PRISMA Framework

The literature selection process followed the four stages recommended by the PRISMA framework: identification, screening, eligibility, and inclusion (Nazir & Das, 2025). Initially, 820 records were identified through a comprehensive search, comprising 782 publications retrieved from Google Scholar and an additional 38 records obtained through manual reference searching. After removing 126 duplicate records, 694 unique publications remained for title and abstract screening. During this stage, 448 articles were excluded because they were outside the scope of this review. Consequently, 246 full-text articles were assessed for eligibility. Following detailed evaluation, 106 articles were excluded due to reasons including lack of relevance to collaborative intelligent manufacturing, insufficient methodological contribution, duplication, non-English publication, or unavailability of the full text. Finally, 140 peer-reviewed studies satisfied all eligibility and quality assessment criteria and were included in the qualitative synthesis. The complete study selection process is illustrated in the PRISMA flow diagram shown in Figure **3**.

2.2. Literature Databases

The primary literature search was conducted using Google Scholar, which provides broad coverage of multidisciplinary scientific publications. To ensure the quality and reliability of the reviewed literature, only peer-reviewed articles published by internationally recognized academic publishers were considered. Among the final 140 selected studies, 58 articles were published by Elsevier, 24 by Wiley, 21 by Taylor & Francis, 15 by IOP Publishing, 12 by Springer Nature, and 10 by IEEE. These publishers were selected because they consistently publish high-impact research in manufacturing systems, industrial engineering, artificial intelligence, optimization, digital manufacturing, and Industry 4.0/5.0.

2.3. Search Keywords

The search strategy was designed using combinations of keywords related to Decision Intelligence and collaborative intelligent manufacturing. Representative keywords included Decision Intelligence, Collaborative Intelligent Manufacturing, Artificial Intelligence, Machine Learning, Explainable Artificial Intelligence, Optimization, Digital Twin, Industry 4.0, Industry 5.0, Human-Centered Manufacturing, Human-in-the-Loop, Smart Manufacturing, Decision Support Systems, Predictive Analytics, and Multi-Criteria Decision Making. Boolean operators such as AND and OR were employed to combine these terms and maximize the retrieval of relevant publications.

The systematic literature selection process adopted in this review is summarized in Figure **3** following the PRISMA methodology.

2.4. Selection Criteria

Only peer-reviewed journal articles published in English and directly related to intelligent manufacturing, artificial intelligence, optimization, digital twins, Industry 4.0, Industry 5.0, and human-centered decision-making were included in this review. Studies presenting novel methodologies, conceptual frameworks, industrial applications, or comprehensive review articles were considered eligible. Publications such as editorials, book chapters, conference abstracts with insufficient technical information, duplicate studies, and articles unrelated to manufacturing decision-making were excluded. The inclusion and exclusion criteria used for selecting the relevant literature are summarized in Table **2**.

2.5. Eligibility Assessment

The eligibility assessment involved a detailed full-text evaluation of the screened articles to

Table 2: Inclusion and Exclusion Criteria for Literature Selection

Criterion	Inclusion Criteria	Exclusion Criteria
Publication type	Peer-reviewed journal articles and review papers	Conference abstracts, editorials, book chapters, dissertations, reports, patents, and non-peer-reviewed publications
Language	Articles published in English	Articles published in languages other than English
Publication period	Studies published between 2020 and 2026	Studies published before 2020 unless considered seminal references
Research domain	Manufacturing, Industry 4.0, Industry 5.0, Artificial Intelligence, Optimization, Digital Twins, Human-Centered Manufacturing, Decision Intelligence, and Collaborative Manufacturing	Studies unrelated to manufacturing or industrial decision-making
Research scope	Studies presenting methodologies, frameworks, applications, industrial case studies, or comprehensive reviews	Studies with insufficient technical contribution or outside the scope of the review
Quality	Articles published in reputable international journals with clear methodology and validated results	Studies with poor methodological quality, incomplete validation, or insufficient technical details
Accessibility	Full-text articles available for review	Publications with unavailable or inaccessible full text
Duplicates	Most recent and complete version of a study	Duplicate publications or multiple versions of the same work

determine their relevance to the objectives of this review. Each study was assessed according to its contribution to Decision Intelligence, integration of enabling technologies, methodological rigor, industrial applicability, and significance to collaborative intelligent manufacturing. Only publications that demonstrated substantial technical contributions and clear relevance to the review scope were retained.

2.6. Quality Assessment

To ensure scientific quality and reliability, all eligible studies underwent a rigorous quality assessment based on methodological soundness, technical contribution, industrial relevance, validation of proposed approaches, and publication quality. Preference was given to studies published in reputable international journals with clearly defined objectives, validated methodologies, and significant contributions to intelligent manufacturing research. Following this assessment process, 140 high-quality publications, published predominantly between 2020 and 2026, formed the final dataset for this systematic review and served as the basis for identifying research trends, technological developments, existing research gaps, and future directions in Decision Intelligence for collaborative intelligent manufacturing.

3. CONCEPTUAL FOUNDATIONS OF DECISION INTELLIGENCE

3.1. Decision Intelligence

Decision Intelligence (DI) is an interdisciplinary approach that integrates artificial intelligence, data analytics, mathematical optimization, operations research, simulation, and human expertise to improve decision-making in complex systems. Unlike traditional decision support systems that primarily focus on data analysis or prediction, Decision Intelligence combines predictive, prescriptive, and explainable capabilities to support informed, transparent, and data-driven decisions across strategic, tactical, operational, and real-time levels. The evolution of Decision Intelligence has been driven by advances in digital manufacturing technologies (Parra-Martinez *et al.*, 2023; Ren *et al.*, 2023). Early manufacturing decisions relied mainly on human experience and mathematical models, while Industry 4.0 introduced cyber-physical systems, the Industrial Internet of Things (IIoT), cloud computing, big data analytics, and digital twins to enable real-time data collection and intelligent automation. As manufacturing systems became increasingly interconnected and complex, conventional decision-making approaches proved insufficient, leading to the emergence of Decision Intelligence as an integrated framework for managing uncertainty and supporting complex industrial decisions (Kalinaki *et al.*, 2024) (Zhao *et al.*, 2025).

Decision Intelligence combines multiple enabling technologies to generate actionable insights and optimize manufacturing performance (Kumar *et al.*, 2025). Artificial intelligence and machine learning provide predictive capabilities, mathematical optimization identifies optimal solutions under operational constraints, while simulation and digital twins enable virtual evaluation of manufacturing processes before implementation. In addition, explainable AI enhances transparency and trust by allowing decision-makers to understand the reasoning behind AI-generated recommendations, thereby facilitating effective human–AI collaboration(Saraswat *et al.*, 2022). Within the context of Industry 5.0, Decision Intelligence extends beyond automation by emphasizing human-centric, resilient, and sustainable manufacturing (Infant *et al.*, 2025; Suri *et al.*, 2025). Rather than replacing human expertise, it augments decision-making through collaboration between intelligent computational systems and human operators. Consequently, Decision Intelligence has become a key enabler of collaborative intelligent manufacturing, supporting production planning, scheduling, quality management, predictive maintenance, supply chain optimization, resource allocation, and sustainable manufacturing. By integrating advanced digital technologies into a unified decision-making framework, Decision

Intelligence enables manufacturing systems to become more adaptive, efficient, and resilient in increasingly dynamic industrial environments (S.-C. Chen *et al.*, 2024).

3.2. Collaborative Intelligent Manufacturing

Collaborative Intelligent Manufacturing (CIM) is an advanced manufacturing paradigm that integrates human expertise, intelligent machines, artificial intelligence, robotics, cyber-physical systems, and digital communication technologies to enable collaborative, adaptive, and data-driven production environments. The architecture of collaborative intelligent manufacturing consists of multiple interconnected layers, including the physical layer, data layer, intelligence layer, decision layer, and application layer. The physical layer comprises manufacturing resources such as machines, robots, sensors, and production equipment that continuously generate operational data (Xiang *et al.*, 2024). These data are collected and integrated through Industrial Internet of Things (IIoT) platforms, cloud computing, and edge computing infrastructures. The intelligence layer utilizes artificial intelligence, machine learning, optimization algorithms, simulation, and digital twin technologies to analyze manufacturing data and generate actionable insights (Samal, 2025; W. Zhang *et al.*, 2025). The decision layer transforms these insights into optimized production plans, scheduling decisions, quality control strategies, predictive maintenance actions, and resource allocation policies, while the application layer implements these decisions across manufacturing operations. Collaborative intelligent manufacturing is characterized by real-time data integration, autonomous decision support, human–AI collaboration, interoperability, adaptability, and continuous learning (Z. Wang *et al.*, 2025). The integration of digital twins, artificial intelligence, and optimization techniques enables manufacturing systems to respond dynamically to changing production conditions, equipment failures, and market demands. Furthermore, human operators remain actively involved in supervising, validating, and improving intelligent decisions, ensuring that manufacturing systems remain transparent, reliable, and aligned with organizational objectives. As manufacturing evolves toward Industry 5.0, collaborative intelligent manufacturing serves as a key enabler of human-centric, resilient, and sustainable production systems (Xu *et al.*, 2025). By combining advanced digital technologies with human knowledge and expertise, it enhances operational efficiency, resource utilization, product quality, and supply chain resilience while supporting intelligent decision-making across the entire manufacturing lifecycle.

3.3. Industry 5.0 Perspective

Industry 5.0 represents the next evolution of manufacturing by extending the technological advancements of Industry 4.0 toward a more human-centric, resilient, and sustainable production paradigm (Rijwani *et al.*, 2025; Z. Wang *et al.*, 2025). While Industry 4.0 primarily emphasizes automation, digitalization, and intelligent manufacturing through technologies such as artificial intelligence, the Industrial Internet of Things (IIoT), cloud computing, and digital twins, Industry 5.0 integrates these technologies with human creativity, expertise, and decision-making to achieve collaborative and value-driven manufacturing (Monferdini *et al.*, 2025; Sun & Song, 2025). Decision Intelligence plays a pivotal role in this transformation by combining artificial intelligence, optimization, simulation, and explainable analytics to support informed and transparent decision-making while maintaining human oversight. This collaborative approach enables manufacturing systems to respond adaptively to dynamic production environments, optimize resource utilization, improve operational resilience, and minimize environmental impacts. The conceptual Decision Intelligence framework for collaborative intelligent manufacturing in the industry 5.0 era is presented in **Figure 4**, illustrating the hierarchical integration of data acquisition, intelligent analytics, and decision support.

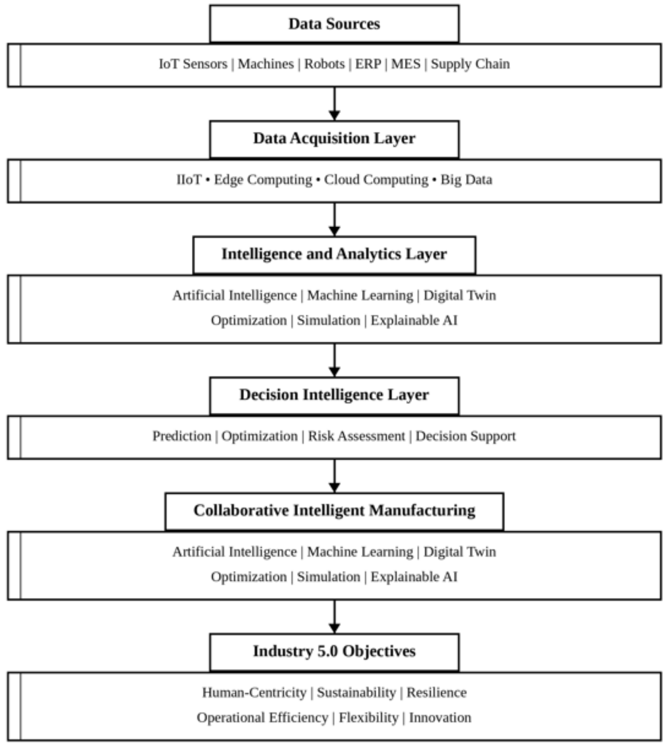

Figure 4: Decision Intelligence Framework for Collaborative Intelligent Manufacturing of Smart and Sustainable Materials in Industry 5.0.

Table 3: Core Technologies Enabling Decision Intelligence in Collaborative Intelligent Manufacturing

Technology	Primary Function	Manufacturing Applications	Industry 5.0 Contribution
Artificial Intelligence (Pan *et al.*, 2026)	Intelligent decision-making	Production planning, quality inspection	Human-assisted intelligent decisions
Machine Learning (Sarkar *et al.*, 2025)	Pattern recognition and prediction	Predictive maintenance, demand forecasting	Adaptive manufacturing
Digital Twin (Langås *et al.*, 2026)	Virtual representation of physical systems	Process simulation, performance monitoring	Real-time decision support
Industrial Internet of Things (IIoT) (P. Li *et al.*, 2026)	Real-time data acquisition	Equipment monitoring, smart factories	Connected manufacturing
Cloud Computing (Pradhan *et al.*, 2025)	Large-scale data storage and processing	Enterprise-wide collaboration	Scalable decision support
Edge Computing (Pradhan *et al.*, 2025)	Low-latency data processing	Real-time machine control	Faster operational decisions
Mathematical Optimization	Optimal resource allocation	Scheduling, production optimization	Efficient resource utilization
Simulation (Jiang *et al.*, 2026)	Performance evaluation	Process validation and system analysis	Risk reduction before implementation
Explainable AI (XAI) (D. H. Nguyen *et al.*, 2026)	Transparent AI recommendations	Human–AI collaborative decision-making	Improved trust and accountability
Robotics and Automation (Shabur *et al.*, 2025)	Automated manufacturing operations	Material handling, assembly, inspection	Human–robot collaboration

Figure **4**. Conceptual framework illustrating how Decision Intelligence integrates advanced digital technologies with collaborative intelligent manufacturing to support the human-centric, resilient, and sustainable objectives of Industry 5.0. The core digital technologies enabling Decision Intelligence in collaborative intelligent manufacturing and their respective industrial contributions are summarized in Table **3**.

4. CORE TECHNOLOGIES ENABLING DECISION INTELLIGENCE

Decision Intelligence is built upon the integration of several advanced digital technologies that collectively enable intelligent, adaptive, and data-driven decision-making in collaborative manufacturing systems. Rather than relying on a single technology, Decision Intelligence combines the predictive capabilities of Artificial Intelligence (AI) and Machine Learning (ML), the real-time virtual representation offered by Digital Twins, the optimal resource allocation achieved through Mathematical Optimization, and the contextual knowledge and expertise provided by Human-Centered Decision-Making (Chander *et al.*, 2022). Together, these technologies form a comprehensive decision-making ecosystem capable of improving production efficiency, operational flexibility, product quality, and system resilience. The following subsections discuss these four core technologies and their roles in enabling collaborative intelligent manufacturing within the context of Industry 5.0.

Human-centricity is the core value behind the evolution of manufacturing towards Industry 5.0. Nevertheless, there is a lack of architecture that considers safety, trustworthiness, and human-centricity at its core (Rožanec *et al.*, 2023). Artificial intelligence (AI) algorithms have proven to play a key role in Industry 4.0. Moving to Industry 5.0, with the human-centric orientation, AI was developed in combination with human intelligence (HI), leading to the new concept of Augmented Intelligence (AuI). AI and AuI algorithms are expected to bring significant benefits for enabling smart manufacturing in Industry 5.0. In this study, we provide a survey on AI-based methods, applications, and challenges for smart manufacturing in Industry 5.0 (H. D. Nguyen & Tran, 2023). Martini et al's paper concludes with the challenges HCAI poses to

Table 4: Comparison of Enabling Technologies

Technology	Key Advantages	Limitations	Contribution to Decision Intelligence	Typical Manufacturing Applications
Artificial Intelligence (AI)	High prediction accuracy, automation, adaptive learning	Requires large datasets, computational resources, and model interpretability	Enables predictive analytics, anomaly detection, and intelligent decision support	Quality inspection, fault diagnosis, predictive maintenance, process monitoring
Digital Twins (Mon *et al.*, 2025; T. Wang *et al.*, 2025)	Real-time visualization, virtual testing, performance optimization	High implementation cost and dependence on accurate data integration	Supports simulation-driven decision-making and continuous system optimization	Production planning, equipment monitoring, process optimization, lifecycle management
Mathematical Optimization	Improves efficiency, minimizes cost, and optimizes resource allocation	Computational complexity for large-scale problems and dependence on mathematical models	Provides prescriptive decision support for optimal manufacturing operations	Scheduling, resource allocation, production planning, supply chain optimization
Human-Centered Decision-Making (Rajyakalshmi *et al.*, 2026; J. Zhang, 2025)	Transparency, explainability, flexibility, and trust	Subject to human bias and limited scalability	Enhances collaboration between human experts and intelligent systems for reliable decision-making	Strategic planning, supervisory control, risk assessment, collaborative manufacturing

public policymakers, who face significant policy challenges in regulating artificial intelligence, and addressing the socioeconomic and technological impacts. Decision-makers are required to address these challenges by adopting some tentative policy recommendations (Martini *et al.*, 2024). A comparative analysis of the major enabling technologies, including their advantages, limitations, and manufacturing applications, is provided in Table **4**.

4.5. Artificial Intelligence and Digital Twins for Smart and Sustainable Materials

Artificial Intelligence (AI) and Digital Twin technologies have emerged as key enablers for the intelligent design, characterization, processing, and lifecycle management of smart and sustainable materials. Unlike conventional manufacturing systems that primarily optimize production processes, modern material systems require continuous analysis of complex physical, chemical, and mechanical interactions occurring throughout their lifecycle. AI algorithms facilitate material property prediction, microstructure analysis, defect detection, process optimization, and accelerated material discovery by learning complex relationships from large experimental and simulation datasets. Machine learning models are increasingly employed to predict mechanical strength, fatigue behavior, corrosion resistance, thermal conductivity, and durability of advanced materials, thereby reducing experimental costs and accelerating product development.

Digital Twins complement these capabilities by creating high-fidelity virtual representations of materials, components, and manufacturing processes that continuously synchronize with physical systems through real-time sensor data. During manufacturing, Digital Twins enable monitoring of material processing conditions, simulation of microstructural evolution, prediction of residual stresses, and optimization of manufacturing parameters. Throughout the operational lifecycle, Digital Twins support structural health monitoring, predictive maintenance, degradation assessment, and remaining useful life estimation for intelligent infrastructure and engineering systems.

The integration of AI and Digital Twins establishes a closed-loop Decision Intelligence framework capable of continuously learning from operational data while adapting manufacturing decisions in real time. This capability is particularly important for advanced composites, functional materials, smart sensors, additive manufacturing, aerospace components, biomedical materials, and energy systems where material performance directly influences system reliability and sustainability. Furthermore, combining AI-driven analytics with Digital Twin technology enables intelligent lifecycle management, circular material utilization, and environmentally responsible manufacturing practices that align with the sustainability objectives of Industry 5.0.

5. DECISION INTELLIGENCE ARCHITECTURE

Decision Intelligence in collaborative intelligent manufacturing is enabled through a layered architecture that integrates data acquisition, intelligent analytics, decision-making, and human expertise into a unified framework (Fanfani *et al.*, 2026). Each layer performs a distinct function while continuously exchanging information with the others to support real-time, adaptive, and explainable decision-making. The data layer collects and integrates information from diverse manufacturing resources, the intelligence layer transforms data into actionable knowledge using advanced computational techniques, the decision layer generates optimized operational strategies, and the human layer ensures that intelligent recommendations remain transparent, reliable, and aligned with organizational objectives (Rajyakalshmi *et al.*, 2026). Together, these interconnected layers establish the foundation for human-centric, resilient, and sustainable manufacturing systems envisioned in Industry 5.0.

5.1. Data Layer

The data layer forms the foundation of the Decision Intelligence architecture by continuously collecting, integrating, and managing information from multiple manufacturing sources. Industrial sensors provide real-time operational data on machine conditions and production processes, while Enterprise Resource Planning (ERP) systems manage organizational resources, inventory, and business operations (Varma Alluri, 2026). Manufacturing Execution Systems (MES) monitor and control shop-floor activities, whereas Supervisory Control and Data Acquisition (SCADA) systems enable real-time monitoring and control of industrial equipment. Product Lifecycle Management (PLM) systems maintain product information throughout its lifecycle, and Digital Twins create virtual representations of physical assets for continuous monitoring and simulation. Together, these technologies establish a comprehensive and reliable data infrastructure for intelligent manufacturing (Nemati *et al.*, 2002).

5.2. Intelligence Layer

The intelligence layer transforms raw manufacturing data into meaningful knowledge through advanced analytical and computational techniques. Artificial Intelligence (AI) and Machine Learning (ML) identify complex patterns, predict system behavior, and support intelligent decision-making (Lawniczak & Di Stefano, 2010). Mathematical optimization determines the best operational strategies while satisfying production constraints, and simulation models evaluate manufacturing scenarios before physical implementation (Spelt *et al.*, 1991). Knowledge graphs organize and represent relationships among manufacturing entities, enabling semantic reasoning and contextual understanding. The integration of these technologies provides the analytical capabilities required for adaptive and data-driven manufacturing systems.

5.3. Decision Layer

The decision layer converts analytical insights into actionable manufacturing decisions. Predictive models estimate future system conditions and identify potential operational risks, while planning algorithms optimize production strategies according to demand and resource availability (Callaghan *et al.*, 2001). Scheduling techniques allocate manufacturing tasks efficiently to improve productivity and reduce idle time. Resource allocation models optimize the utilization of machines, materials, labor, and energy, whereas risk assessment techniques evaluate operational uncertainties and support resilient manufacturing decisions. This layer ensures that manufacturing operations remain efficient, responsive, and aligned with organizational objectives (Ma *et al.*, 2018).

5.4. Human Layer

The human layer represents the collaborative component of Decision Intelligence by integrating human expertise with intelligent computational systems (Huang *et al.*, 2020). Manufacturing experts contribute domain knowledge for complex engineering decisions, operators supervise production processes and validate automated recommendations, and managers make strategic decisions based on analytical insights and organizational goals. Collaborative AI serves as an intelligent assistant that augments rather than replaces human decision-making by providing explainable recommendations, scenario analysis, and real-time decision support (Sanepalli, 2024; Trihandaru *et al.*, 2025). This human-centered approach enhances transparency, trust, adaptability, and ethical decision-making, making it a defining characteristic of Industry 5.0 manufacturing systems.

6. DECISION INTELLIGENCE APPLICATIONS

Decision Intelligence has transformed modern manufacturing by enabling intelligent, data-driven, and collaborative decision-making across various industrial functions (González Rodríguez *et al.*, 2020). By integrating artificial intelligence, machine learning, optimization, digital twins, simulation, and human expertise, Decision Intelligence supports both strategic and operational decisions throughout the manufacturing lifecycle. Its applications extend beyond traditional production management to encompass quality assurance, predictive maintenance, supply chain optimization, sustainable manufacturing, and autonomous production systems. The following subsections discuss the major applications of Decision Intelligence in collaborative intelligent manufacturing and their contributions to the realization of Industry 5.0 (Ahmad *et al.*, 2017; Haque & Rahman, 2025).

6.1. Production Planning

Decision Intelligence enhances production planning by integrating demand forecasting, resource availability, production capacity, and operational constraints into a unified decision-making framework (Chan & Ding, 2023). AI-driven predictive analytics and optimization algorithms enable manufacturers to generate adaptive production plans that respond to market fluctuations and resource uncertainties. By combining real-time shop-floor data with digital twins and simulation models, Decision Intelligence improves production efficiency, minimizes idle time, and supports flexible manufacturing operations (Ahmad *et al.*, 2017).

6.2. Scheduling

Production scheduling is one of the most important applications of Decision Intelligence, where AI, optimization algorithms, and real-time data analytics are employed to allocate manufacturing tasks efficiently. Intelligent scheduling systems dynamically adjust production sequences based on machine availability, workforce capacity, equipment failures, and changing customer demands (Aissani *et al.*, 2012). This adaptive scheduling capability improves machine utilization, reduces production delays, and enhances overall manufacturing productivity.

6.3. Quality Control

Decision Intelligence significantly improves quality management by combining machine vision, artificial intelligence, sensor technologies, and statistical process control to detect product defects in real time(Yu *et al.*, 2025). Machine learning models continuously analyze production data to identify abnormal process conditions and predict quality deviations before defective products are manufactured. This proactive quality assurance approach reduces waste, improves product consistency, and enhances customer satisfaction(Mahmud & Mural, 2026).

6.4. Predictive Maintenance

Predictive maintenance utilizes Decision Intelligence to continuously monitor equipment health and predict potential failures before they occur (J. Chen *et al.*, 2025; Rojas *et al.*, 2025). Data collected from industrial sensors are analyzed using artificial intelligence and machine learning algorithms to identify abnormal operating conditions and estimate the remaining useful life of critical machinery. This approach minimizes unexpected equipment failures, reduces maintenance costs, improves equipment availability, and increases manufacturing reliability.

6.5. Supply Chain

Decision Intelligence supports intelligent supply chain management by integrating demand forecasting, inventory optimization, logistics planning, supplier evaluation, and risk assessment into a unified decision-making process. AI-powered predictive models enable organizations to anticipate supply disruptions and optimize procurement strategies, while optimization algorithms improve transportation efficiency and warehouse operations. Consequently, Decision Intelligence enhances supply chain resilience, responsiveness, and operational efficiency (Hussain *et al.*, 2025).

6.6. Inventory

Effective inventory management is achieved through intelligent forecasting, demand prediction, and optimization techniques that balance inventory availability with operational costs. Decision Intelligence continuously analyzes sales patterns, production schedules, and supplier performance to determine optimal inventory levels and replenishment strategies. This data-driven approach minimizes stock shortages, reduces excessive inventory, and improves resource utilization across manufacturing operations.

Table 5: Decision Problems and Artificial Intelligence Methods in Collaborative Intelligent Manufacturing

Decision Problem	AI Method	Input Data	Expected Output	Manufacturing Benefit
Production planning	Machine Learning, Reinforcement Learning	Demand, capacity, inventory	Optimal production plan	Improved productivity and flexibility
Production scheduling	Genetic Algorithm, Deep Reinforcement Learning	Machine status, job priority	Optimized scheduling sequence	Reduced makespan and idle time
Quality control	Computer Vision, Convolutional Neural Networks (CNNs)	Product images, sensor data	Defect detection and classification	Improved product quality
Predictive maintenance	Machine Learning, Deep Learning	Vibration, temperature, acoustic signals	Failure prediction and Remaining Useful Life (RUL) estimation	Reduced maintenance cost and downtime
Supply chain optimization	Artificial Intelligence, Bayesian Networks	Supplier data, logistics, demand	Supply chain risk assessment	Enhanced resilience and responsiveness
Inventory management	Time-Series Forecasting, Machine Learning	Sales history, inventory records	Inventory optimization	Reduced stockouts and inventory costs
Energy management	Artificial Neural Networks (ANN), Reinforcement Learning	Energy consumption, production data	Energy optimization strategy	Improved energy efficiency
Human–robot collaboration	Computer Vision, Reinforcement Learning	Human motion, robot sensors	Safe collaborative operations	Enhanced workplace safety
Autonomous manufacturing	Multi-Agent Systems, Deep Learning	Production and sensor data	Autonomous operational decisions	Increased manufacturing autonomy
Sustainable manufacturing	AI-based Multi-objective Optimization	Environmental and operational data	Sustainable production strategies	Reduced environmental impact

Table 6: Optimization Models by Manufacturing Application

	Manufacturing Application	Optimization Model	Objective Function	Decision Variables	Performance Indicators
(Shapiro, 1993)	Production planning	Linear Programming (LP)	Maximize production efficiency	Production quantity, capacity	Throughput, utilization
(Bakirtzis *et al.*, 2012)	Production scheduling	Mixed Integer Linear Programming (MILP)	Minimize makespan	Job sequence, machine allocation	Makespan, machine utilization
(Oraei Zare *et al.*, 2012)	Quality control	Multi-objective Optimization	Minimize defect rate	Inspection parameters	Defect rate, process capability
(Teoh *et al.*, 2023)	Predictive maintenance	Genetic Algorithm (GA)	Minimize maintenance cost	Maintenance interval	Equipment availability
(Shahriar *et al.*, 2026b)	Supply chain	Network Optimization	Minimize logistics cost	Supplier allocation, transportation	Total supply chain cost
(Silver, 1981)	Inventory management	Inventory Optimization Models	Minimize inventory cost	Reorder point, order quantity	Inventory turnover
(Rathor & Saxena, 2020)	Energy management	Multi-objective Optimization	Minimize energy consumption	Machine operation schedule	Energy usage, carbon emissions
(Talukder *et al.*, 2026)	Human–robot collaboration	Task Allocation Optimization	Balance workload	Human–robot task assignment	Productivity, safety
(Ding *et al.*, 2019)	Autonomous manufacturing	Reinforcement Learning Optimization	Maximize operational efficiency	Machine actions	System adaptability
(Machado *et al.*, 2020)	Sustainable manufacturing	Multi-objective Evolutionary Algorithms (MOEA)	Balance cost, quality, and sustainability	Resource allocation	Sustainability index

6.7. Energy Management

Decision Intelligence contributes to sustainable manufacturing by optimizing energy consumption across production systems. AI-based energy forecasting models, combined with optimization algorithms and real-time monitoring, enable manufacturers to identify energy-intensive processes and recommend efficient operating strategies. Intelligent energy management reduces operational costs, lowers carbon emissions, and supports environmental sustainability while maintaining production performance (Lee & Cheng, 2016).

6.8. Human-Robot Collaboration

Human–robot collaboration represents a key application of Decision Intelligence in Industry 5.0, where intelligent systems assist rather than replace human workers. Decision Intelligence enables collaborative robots (cobots) to interact safely with operators by combining sensor information, AI-based perception, and real-time decision-making. This collaboration enhances productivity, improves workplace safety, reduces repetitive tasks, and allows human workers to focus on complex decision-making and creative problem-solving.

6.9. Autonomous Manufacturing

Decision Intelligence enables autonomous manufacturing by integrating artificial intelligence, digital twins, optimization, robotics, and Industrial Internet of Things (IIoT) technologies into self-adaptive production systems (H. Wang *et al.*, 2024). Autonomous manufacturing systems continuously monitor production processes, detect operational changes, and implement corrective actions with minimal human intervention. This capability improves operational flexibility, manufacturing efficiency, and system resilience in dynamic production environments.

6.10. Sustainable Manufacturing

Sustainability has become a central objective of Industry 5.0, and Decision Intelligence plays a crucial role in achieving environmentally responsible manufacturing (Sartal *et al.*, 2020). By integrating environmental data, life-cycle assessment, resource optimization, and energy management, Decision Intelligence supports decisions that minimize waste generation, reduce carbon emissions, and improve resource efficiency. Furthermore, intelligent decision-making facilitates circular economy practices, enabling manufacturers to balance economic performance with environmental and social sustainability (Carvalho *et al.*, 2018).

The application of artificial intelligence in collaborative intelligent manufacturing varies according to the nature of the decision problem. Different AI techniques, including machine learning, deep learning, reinforcement learning, computer vision, and Bayesian networks, have been developed to address specific manufacturing challenges such as production planning, scheduling, quality inspection, predictive maintenance, supply chain optimization, and energy management. The selection of an appropriate AI method depends on the availability of manufacturing data, the complexity of the decision problem, and the desired operational objectives. Table **5** summarizes the major manufacturing decision problems, corresponding AI methods, required input data, expected outputs, and their associated industrial benefits.

Optimization is a fundamental component of Decision Intelligence because it transforms analytical insights into actionable manufacturing decisions. Various optimization models have been developed to solve different industrial problems, including production planning, scheduling, inventory management, predictive maintenance, supply chain design, and energy optimization (Debnath *et al.*, 2025b). The choice of an optimization technique depends on the characteristics of the manufacturing problem, decision variables, and performance objectives. Table **6** presents a comparative overview of commonly used optimization models, their objective functions, decision variables, and key performance indicators across different manufacturing applications

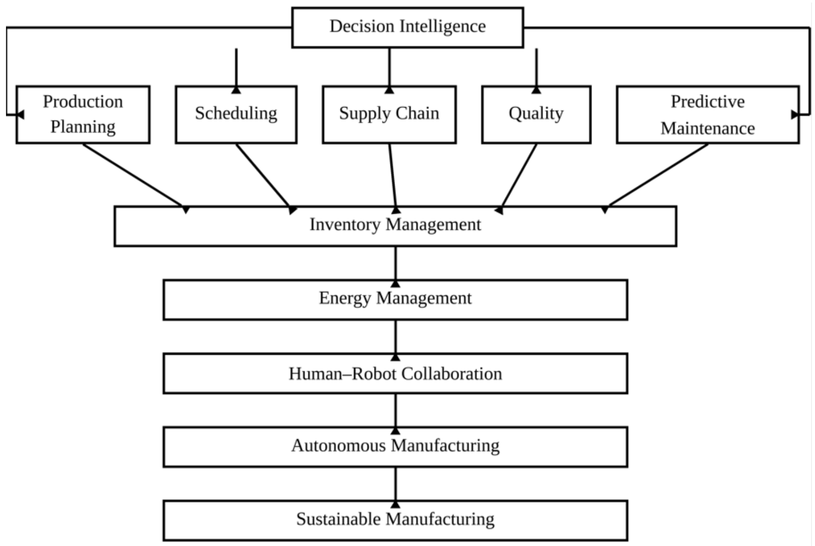

Figure 5: Application Landscape of Decision Intelligence in Collaborative Intelligent Manufacturing.

Table 7: Decision Intelligence Applications in Smart and Sustainable Materials

Material Domain	AI Applications	Digital Twin Applications	Decision Intelligence Contribution
Advanced Composites	Property prediction	Process simulation	Process optimization
Smart Materials	Material characterization	Real-time monitoring	Intelligent control
Sustainable Materials	Material selection	Lifecycle assessment	Sustainable manufacturing
Structural Systems	Damage detection	Structural Health Monitoring	Predictive maintenance
Intelligent Infrastructure	Anomaly detection	Asset management	Infrastructure resilience
Additive Manufacturing	Process optimization	Build monitoring	Quality improvement

Figure **5.** Application landscape of Decision Intelligence in collaborative intelligent manufacturing of smart materials, illustrating how artificial intelligence, optimization, and data-driven decision-making support major manufacturing functions, ranging from production planning and scheduling to sustainable and autonomous manufacturing within the industry 5.0 paradigm.

6.11. Smart and Sustainable Materials Manufacturing

Decision Intelligence plays an increasingly important role in the development and manufacturing of smart and sustainable materials by integrating artificial intelligence, optimization, digital twins, and lifecycle analytics. AI models support material discovery, property prediction, and process optimization, while digital twins enable real-time monitoring of material behavior during manufacturing. Optimization techniques improve resource utilization, minimize waste generation, and reduce energy consumption, thereby supporting sustainable production. Human-centered decision-making further enhances material selection, circular economy implementation, and environmentally responsible manufacturing practices aligned with the objectives of Industry 5.0.

7. HUMAN-CENTERED DECISION INTELLIGENCE

7.1. Human-in-the-Loop Artificial Intelligence

Kumar *et al.* proposed a comprehensive review of Human-in-the-Loop Artificial

Intelligence (HITL-AI), emphasizing the integration of human expertise with machine learning algorithms to improve decision-making accuracy, transparency, and accountability. Their study demonstrated that incorporating human knowledge through active learning, iterative machine learning, and reinforcement learning significantly enhances model performance while maintaining human oversight. (Panigutti *et al.*, 2023a). Kim *et al.* reviewed Human-in-the-Loop Smart Manufacturing (H-SM) from the perspectives of Industry 4.0, Industry 5.0, and Operator 5.0, identifying seven major technology clusters and twenty-one enabling technologies supporting human participation throughout manufacturing decision processes. Their review emphasized that HITL frameworks enhance production flexibility, decision quality, and operational resilience by enabling continuous collaboration between intelligent systems and manufacturing personnel (Kim *et al.*, 2025).

Denno proposed a human-centered AI framework for future manufacturing systems, arguing that AI should augment engineers in refining manufacturing models rather than replacing human expertise (Denno, 2024). Hartikainen *et al.* investigated Human–AI collaboration in smart manufacturing and proposed a design framework highlighting the complementary roles of AI-enabled agents and human operators (Hartikainen *et al.*, 2024). Collectively, these studies demonstrate that Human-in-the-Loop Artificial Intelligence is a fundamental pillar of Human-Centered Decision Intelligence. By combining computational intelligence with human expertise, HITL-AI enhances decision accuracy, transparency, adaptability, and accountability while ensuring that manufacturing decisions remain aligned with operational objectives and human values.

7.2. Explainable Artificial Intelligence

Panigutti *et al.* investigated the role of Explainable Artificial Intelligence (XAI) in supporting human decision-makers through transparent and interpretable AI systems. Their study focused on the development of an explainable clinical decision support system and demonstrated that the design of effective explanation interfaces is equally important as the underlying explanation algorithms. Through iterative prototype development and user evaluation, the authors found that interpretable explanations significantly increased users' trust in AI-generated recommendations while improving their understanding of system behavior (Panigutti *et al.*, 2023b). Ali *et al.* (2024**)** reviewed the current state of Explainable Artificial Intelligence (XAI) and emphasized that explainability is fundamental for achieving trustworthy AI in safety-critical applications. The authors discussed the strengths and limitations of existing post-hoc and intrinsic explanation methods and highlighted that future XAI systems should improve transparency, fairness, robustness, and user trust while maintaining predictive performance (Ali *et al.*, 2023). Hassija *et al.* (2024) presented a comprehensive review of explainable AI techniques for interpreting black-box machine learning models. Their study classified existing explanation approaches into model-specific, model-agnostic, local, and global methods, concluding that interpretable AI improves transparency, accountability, and user confidence, particularly in high-risk decision-making environments (Hassija *et al.*, 2024). Yang *et al.* (2023) conducted a systematic survey on Explainable Artificial Intelligence, reviewing explanation methodologies, applications, and existing challenges. Their study highlighted that effective XAI should balance model accuracy with interpretability while addressing fairness, robustness, and human-centered interaction to improve trust in AI-assisted decision-making (Yang *et al.*, 2023).

7.3. TRUST IN HUMAN-CENTERED ARTIFICIAL INTELLIGENCE

Almpani *et al.* presented a comprehensive survey on Human-Centered Artificial Intelligence, emphasizing the importance of trust, communication, and collaborative reasoning in intelligent decision-making. The authors argued that trustworthy AI systems should not only generate accurate predictions but also support meaningful interactions between humans and intelligent agents through transparent reasoning and argumentation. To achieve this objective, they introduced the Argumentation-based Proof-Event Calculus (APEC), a framework designed to strengthen collaboration in multi-agent decision environments by incorporating temporal reasoning and iterative refinement of decisions. (Almpani & Stefaneas, 2026). Zhai proposed the Human-Centered AI (HCAI) framework, emphasizing that trustworthy AI should augment rather than replace human capabilities (Zhai *et al.*, 2020) .Zeng *et al.* investigated trust calibration in human–AI collaboration and demonstrated that appropriately calibrated trust significantly improves decision quality, task performance, and human acceptance of AI-generated recommendations (Zeng *et al.*, 2024). Shneiderman proposed the Human-Centered Artificial Intelligence (HCAI) framework, emphasizing that AI systems should augment rather than replace human capabilities (Shneiderman, 2020). Glikson and Woolley conducted a comprehensive review of empirical studies on trust in artificial intelligence and found that users' trust is influenced by system transparency, explainability, perceived reliability, task characteristics, and human factors (Glikson & Woolley, 2020). Carter *et al.* investigated trust calibration in human–automation interaction and demonstrated that meaningful communication and contextually relevant explanations significantly improve users' confidence and trust in intelligent systems, whereas superficial anthropomorphic features alone do not enhance trust. Their Human–Automation Trust Expectation Model (HATEM) highlights the importance of informative interactions for establishing appropriate trust in AI-assisted decision-making (Carter *et al.*, 2024).

7.4. Ethical Decision Making

Handoko introdu.ced the Adaptive Cognitive and Ethical Learning Decision System (ACELDS), a human-centered framework that integrates artificial intelligence, data analytics, ethical governance, and collaborative decision-making. The proposed framework consists of five interconnected modules that support data integration, learning analytics, ethical AI governance, personalized decision support, and human–AI collaboration. Experimental evaluation involving educators demonstrated improvements in transparency, ethical awareness, inclusiveness, and collaborative decision-making compared with existing intelligent learning frameworks. The study highlighted the significance of embedded ethical auditing, participatory decision mechanisms, and responsible AI governance in ensuring fairness and accountability. These findings emphasize that ethical considerations should be integrated throughout the Decision Intelligence lifecycle to develop responsible and human-centric intelligent systems (Handoko *et al.*, 2025).

7.5. Human–AI Collaboration

Li conducted a systematic literature review and bibliometric analysis to investigate the evolving relationship between humans and artificial intelligence in collaborative decision-making. The authors demonstrated that decision outcomes depend on both the degree of AI involvement and the level of human participation throughout the decision process. Their framework illustrates that effective Decision Intelligence should balance computational efficiency with human judgment, contextual understanding, and ethical reasoning. Consequently, Human–AI collaboration is identified as a key enabler of Industry 5.0, where intelligent technologies augment rather than replace human expertise, leading to more adaptive, transparent, and resilient manufacturing systems (H. Li & Tian, 2026).

As illustrated in Figure **6**, the Human-Centered Decision Loop places human expertise at the core of intelligent decision-making while leveraging artificial intelligence to provide analytical support and predictive insights. Human experts define decision objectives, validate AI-generated recommendations, and ensure ethical compliance before operational implementation. The continuous feedback mechanism enables both AI models and human decision-makers to learn from system performance, thereby improving prediction accuracy, transparency, trust, and overall decision quality. This iterative

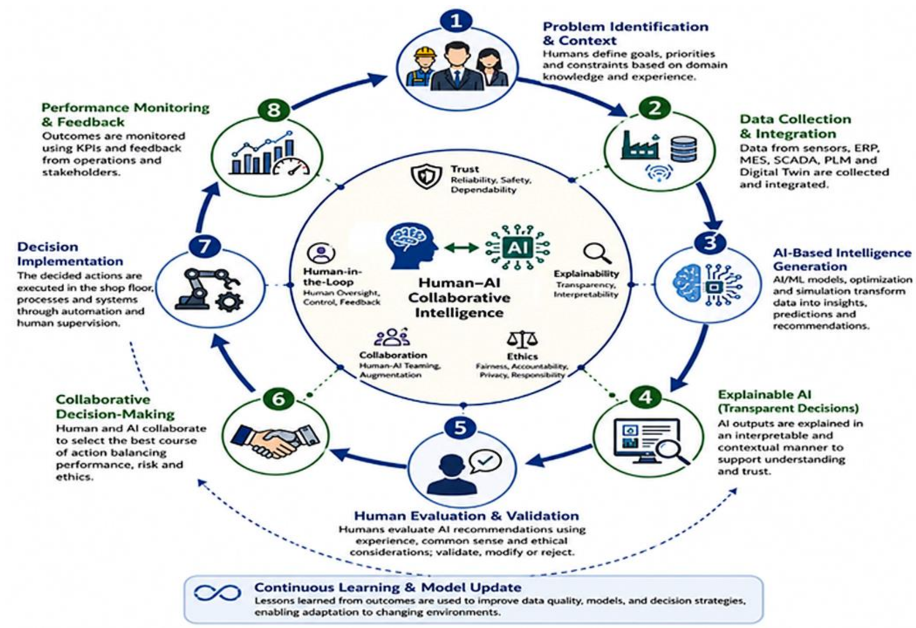

Figure 6: Human-Centered Decision Loop.

collaboration between humans and AI aligns with the principles of Industry 5.0 by promoting human-centric, resilient, and sustainable manufacturing systems through explainable, trustworthy, and adaptive Decision Intelligence.

8. CHALLENGES

Recent advances in Decision Intelligence have demonstrated significant potential for improving manufacturing performance through the integration of artificial intelligence, machine learning, digital twins, optimization, and human-centered decision-making. However, despite these technological developments, several challenges continue to limit the large-scale adoption of Decision Intelligence in collaborative intelligent manufacturing. The literature identifies multiple barriers spanning technical integration, organizational readiness, economic feasibility, cybersecurity, data privacy, interoperability, computational scalability, model generalization, and human trust. In addition, ensuring ethical, transparent, and explainable AI has become increasingly important as manufacturing systems transition toward the human-centric principles of Industry 5.0. Addressing these challenges requires not only technological innovations but also standardized architectures, robust data governance, explainable AI frameworks, secure communication protocols, workforce upskilling, and collaborative human–AI decision-making strategies. Table **8** summarizes the major challenges reported in recent studies together with their corresponding mitigation strategies, providing a comprehensive overview of current research directions for developing trustworthy, resilient, and sustainable Decision Intelligence systems in collaborative intelligent manufacturing.

9. FUTURE RESEARCH DIRECTIONS

This review comprehensively addressed the research questions by examining the evolution of Decision Intelligence, identifying its core enabling technologies, analyzing its architectural framework, reviewing major manufacturing applications, exploring the role of human-centered decision-making, and synthesizing the technical, organizational, ethical, and operational challenges associated with its implementation in collaborative intelligent manufacturing. The findings demonstrate that Decision Intelligence has evolved into a multidisciplinary paradigm that integrates artificial intelligence, machine learning, optimization, digital twins, simulation, and human expertise to support intelligent, adaptive, and

Table 7: Challenges and Possible Solutions

Author	Challenge	Description	Possible Solutions
Abhilash *et al.* (2024); (Abhilash *et al.*, 2024)	Technical Complexity	Integration of AI, Digital Twins, IIoT, and cyber-physical systems increases implementation complexity.	Modular system architectures, edge–cloud computing, standardized AI deployment frameworks.
Gallego *et al.* (2025) (Gálvez Del Postigo Gallego *et al.*, 2025)	Organizational Readiness	Resistance to digital transformation, lack of AI expertise, and insufficient workforce training hinder adoption.	Continuous workforce training, cross-functional collaboration, change management strategies, human-centered AI.
El Kalach *et al.* (2024) (El Kalach *et al.*, 2025)	Economic Cost	High investment requirements for infrastructure, sensors, computing resources, and AI implementation.	Scalable cloud platforms, phased implementation, return-on-investment (ROI) assessment, digital transformation roadmaps.
Abhilash *et al.* (2025) (Puthanveettil Madathil *et al.*, 2025)	Ethical Decision-Making	AI bias, fairness, accountability, and transparency remain significant concerns.	Explainable AI (XAI), ethical AI governance, bias auditing, responsible AI frameworks.
Decision Analytics Journal Review (2025) (Balaha *et al.*, 2025)	Cybersecurity	Connected manufacturing systems are increasingly vulnerable to cyberattacks and malicious manipulation.	Zero-trust architecture, AI-driven intrusion detection, secure communication protocols, blockchain-based security.
Buggineni *et al.* (2024) (Buggineni *et al.*, 2024a)	Data Privacy	Industrial data sharing raises concerns regarding confidentiality, ownership, and regulatory compliance.	Privacy-preserving AI, federated learning, encryption, secure data governance policies.
Buggineni *et al.* (2024) (Buggineni *et al.*, 2024b)	Data Quality	Missing, noisy, inconsistent, and imbalanced datasets reduce AI model reliability and prediction accuracy.	Data preprocessing, synthetic data generation, data validation, automated cleaning pipelines.
Nilsson *et al.* (2024); (Nilsson *et al.*, 2024)	Interoperability	Heterogeneous manufacturing systems often lack standardized communication and semantic compatibility.	OPC UA, standardized ontologies, semantic interoperability frameworks, knowledge graphs.
Data–Model Fusion Review (2025) (Tao *et al.*, 2025)	Model Generalization	AI models trained in one manufacturing environment often perform poorly in different production settings.	Transfer learning, foundation models, domain adaptation, continual learning.
Kerrouchi *et al.* (2024); (Kerrouchi *et al.*, 2024)	Computational Cost	Large AI models, simulations, and Digital Twins require substantial computational resources and low-latency processing.	Edge computing, model compression, distributed computing, hybrid cloud architectures.
Abhilash *et al.* (2025) (Abhilash *et al.*, 2024)	Human Trust	Limited transparency and explainability reduce user confidence in AI-generated decisions.	Explainable AI, Human-in-the-Loop AI, interactive decision support, transparent interfaces.

explainable manufacturing decisions. Furthermore, the review highlights that successful implementation depends not only on technological advancement but also on human trust, ethical governance, interoperability, and organizational readiness, thereby addressing the primary objectives and research questions of this study.

Despite these advances, several important research opportunities remain. First, future studies should investigate unified Decision Intelligence architectures that seamlessly integrate artificial intelligence, digital twins, Industrial Internet of Things (IIoT), knowledge graphs, optimization algorithms, and edge–cloud computing into interoperable manufacturing platforms. Current implementations often focus on individual technologies, while comprehensive end-to-end Decision Intelligence frameworks remain limited.

Second, explainable and trustworthy artificial intelligence requires further investigation. Although Explainable AI (XAI) has improved transparency, additional research is needed to develop adaptive explanation mechanisms, uncertainty-aware decision models, and human-centered interfaces that increase user confidence while maintaining high predictive performance in complex manufacturing environments.

Third, future research should focus on developing robust and transferable AI models capable of generalizing across different manufacturing processes, products, and industrial sectors (C. Chen *et al.*, 2025). Domain adaptation, continual learning, transfer learning, and foundation models offer promising directions for improving the scalability and robustness of Decision Intelligence systems.

Another important research direction involves strengthening cybersecurity, privacy preservation, and ethical governance. As manufacturing systems become increasingly interconnected, future Decision Intelligence platforms should integrate privacy-preserving machine learning, federated learning, blockchain-enabled data sharing, secure communication protocols, and continuous ethical auditing to ensure trustworthy and responsible industrial decision-making (Leng *et al.*, 2024). The integration of advanced optimization techniques with real-time decision support also presents significant opportunities. Future studies should investigate hybrid optimization frameworks combining mathematical programming, metaheuristic algorithms, reinforcement learning, and digital twins to enable adaptive, multi-objective, and real-time manufacturing optimization under uncertainty.

Human-centered manufacturing will remain a defining characteristic of Industry 5.0 (Rejeb *et al.*, 2025). Consequently, future research should explore more effective Human-in-the-Loop AI frameworks, collaborative decision-support systems, cognitive digital twins, and human–AI co-learning mechanisms that preserve human expertise while leveraging intelligent automation. These systems should emphasize explainability, transparency, fairness, and collaborative intelligence rather than fully autonomous decision-making. Another promising direction is the development of sustainability-aware Decision Intelligence models capable of simultaneously optimizing economic performance, environmental impact, energy efficiency, circular manufacturing, and social responsibility. Multi-objective decision frameworks integrating sustainability indicators with intelligent manufacturing technologies will play a critical role in supporting net-zero manufacturing and circular economy initiatives.

Finally, although the reviewed studies demonstrate considerable progress in computational methods and intelligent decision support, relatively few have reported large-scale industrial validation. Future research should prioritize experimental implementation, industrial case studies, benchmark datasets, and standardized performance evaluation frameworks to validate Decision Intelligence solutions under realistic manufacturing conditions. Such efforts will facilitate technology transfer from academic research to industrial practice and accelerate the adoption of collaborative intelligent manufacturing systems aligned with the principles of Industry 5.0. Future research should investigate Decision Intelligence frameworks that support intelligent material discovery, sustainable material selection, circular material flows, lifecycle assessment, recyclable materials, and AI-assisted design of next-generation smart materials.

9.1. Future Research Directions for Smart Materials and Structural Systems

Future research should move beyond technology-specific applications toward integrated, scalable, trustworthy, and autonomous Decision Intelligence ecosystems for Industry 5.0. Several emerging research opportunities are particularly important.

First, Generative AI and Foundation Models offer opportunities for intelligent material discovery, process design, knowledge extraction, and adaptive decision support. Future studies should investigate domain-specific foundation models that combine manufacturing data, material properties, simulation results, and engineering knowledge to support design and decision-making across different manufacturing environments. Second, Edge AI and distributed intelligence should be investigated for real-time Decision Intelligence. Deploying AI models closer to machines, sensors, and production equipment can reduce latency, communication requirements, and dependence on centralized cloud infrastructure, enabling faster responses to process deviations and equipment failures. Third, Federated Learning and privacy-preserving intelligence represent promising directions for collaborative manufacturing environments where sensitive industrial data cannot be directly shared. Future research should develop federated Decision Intelligence frameworks that enable organizations or manufacturing sites to collaboratively train models while maintaining data privacy and security. Fourth, Trustworthy and explainable AI requires greater attention, particularly for safety-critical manufacturing and structural applications. Future Decision Intelligence systems should incorporate uncertainty estimation, explainability, fairness, robustness, and human oversight so that AI-generated recommendations can be understood and validated by engineers and operators.

Fifth, the cybersecurity of Digital Twins and interconnected manufacturing systems requires systematic investigation. Future work should address secure data exchange, cyberattack detection, authentication, privacy preservation, and resilient Digital Twin architectures to prevent manipulation of real-time industrial data and intelligent decisions.

Finally, future research should explore autonomous and human–AI collaborative decision-making in Industry 5.0. Rather than pursuing complete automation, research should investigate adaptive human-in-the-loop and agent-based Decision Intelligence systems capable of learning from operational feedback, evaluating alternatives, and autonomously recommending or executing decisions while maintaining appropriate human supervision.

Collectively, these directions can transform the proposed conceptual framework from a technology-integration architecture into a scalable, secure, trustworthy, and increasingly autonomous Decision Intelligence ecosystem for sustainable Industry 5.0 manufacturing.

10. PROPOSED RESEARCH FRAMEWORK

Based on the comprehensive analysis of existing literature, this review proposes an integrated Decision Intelligence framework for collaborative intelligent manufacturing that unifies data acquisition, intelligent analytics, optimization, human-centered decision-making, and continuous learning within a single architecture. Unlike existing studies that primarily investigate individual technologies such as artificial intelligence, digital twins, machine learning, optimization, or explainable AI independently, the proposed framework integrates these complementary technologies into a closed-loop decision ecosystem that supports adaptive, explainable, and sustainable manufacturing in the context of Industry 5.0.

The proposed framework consists of six interconnected layers. The first layer is the **Data Foundation Layer**, where heterogeneous manufacturing data are continuously collected from Industrial Internet of Things (IIoT) sensors, Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), Supervisory Control and Data Acquisition (SCADA), Product Lifecycle Management (PLM) systems, and Digital Twins. These data provide real-time visibility into manufacturing operations and establish the foundation for intelligent decision-making.

The second layer is the **Intelligence Layer**, where artificial intelligence, machine learning, knowledge graphs, simulation, digital twins, and data analytics transform raw manufacturing data into actionable knowledge. This layer continuously predicts equipment conditions, product quality, production performance, and operational risks while generating contextual intelligence for downstream decision processes.

The third layer is the **Optimization Layer**, where mathematical optimization, multi-objective optimization, reinforcement learning, and simulation-based optimization determine optimal production plans, scheduling policies, inventory levels, energy utilization, maintenance strategies, and supply chain decisions under multiple operational constraints and uncertainties.

The fourth layer is the **Human-Centered Decision Layer**, which represents the core novelty of the proposed framework. Rather than allowing fully autonomous AI decision-making, this layer integrates Human-in-the-Loop Artificial Intelligence, Explainable AI, ethical governance, collaborative intelligence, and trust-aware decision support. Human experts validate AI-generated recommendations, provide contextual knowledge, evaluate ethical implications, and participate in final decision-making, ensuring transparency, accountability, and organizational acceptance.

The fifth layer is the **Application Layer**, where optimized decisions are implemented across production planning, intelligent scheduling, quality control, predictive maintenance, inventory management, supply chain optimization, energy management, autonomous manufacturing, human–robot collaboration, and sustainable manufacturing. Continuous monitoring enables adaptive responses to changing operational conditions and evolving customer requirements.

Finally, the **Continuous Learning Layer** establishes a feedback mechanism that captures operational outcomes and manufacturing performance indicators to continuously retrain AI models, update optimization strategies, refine digital twins, and improve future decision quality. This self-improving capability enables resilient, adaptive, and sustainable manufacturing systems that evolve over time.

The proposed framework contributes to the literature in four major ways. First, it integrates multiple Decision Intelligence technologies into a unified architecture rather than treating them as isolated research domains. Second, it explicitly incorporates human-centered decision-making through explainability, trust, ethics, and Human-in-the-Loop AI as fundamental components of intelligent manufacturing. Third, it establishes a continuous learning mechanism that enables adaptive improvement through operational feedback and digital twin synchronization. Finally, the framework aligns technological innovation with the principles of Industry 5.0 by simultaneously supporting operational efficiency, human-centricity, resilience, and sustainability. Consequently, the proposed framework provides both a conceptual foundation for future academic research and a practical roadmap for industrial implementation of Decision Intelligence in collaborative intelligent manufacturing.

Figure **7** illustrates the proposed conceptual framework developed in this review, integrating the core technologies, human-centered intelligence, and continuous learning mechanisms required for Industry 5.0 manufacturing.

11. CONCLUSIONS

This review comprehensively examined the emerging role of **Decision Intelligence (DI)** in

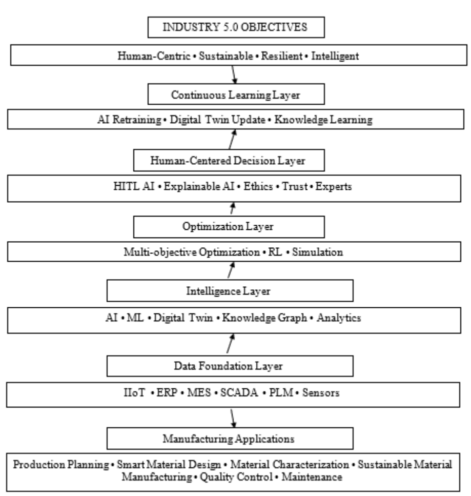

Figure 7: Integrated Decision Intelligence Framework for Smart and Sustainable Materials Manufacturing.

collaborative intelligent manufacturing **of smart and sustainable materials**, by synthesizing recent advances in artificial intelligence, machine learning, optimization, digital twins, knowledge graphs, and human-centered decision-making within the context of **Industry 5.0**. The study demonstrated that Decision Intelligence extends beyond conventional data-driven analytics by integrating intelligent technologies with human expertise to support adaptive, explainable, trustworthy, and sustainable manufacturing decisions across applications such as production planning, scheduling, quality control, predictive maintenance, supply chain management, energy optimization, human–robot collaboration, autonomous manufacturing, and sustainable production. Beyond summarizing the existing literature, this review contributes by identifying current research trends, implementation challenges, future research opportunities, and proposing a novel integrated Decision Intelligence framework that unifies data acquisition, intelligent analytics, optimization, human-centered collaboration, and continuous learning into a single conceptual architecture. The review further highlights the industrial significance of Decision Intelligence in improving operational efficiency, resilience, flexibility, transparency, and sustainability while acknowledging existing limitations related to interoperability, data quality, cybersecurity, computational scalability, explainability, and limited industrial-scale validation. Overall, the findings indicate that future research should focus on developing interoperable, trustworthy, and human-centric Decision Intelligence ecosystems that integrate emerging technologies such as foundation AI models, large language models, cognitive digital twins, federated learning, and explainable AI, thereby accelerating the realization of resilient, sustainable, and intelligent manufacturing systems envisioned under the industry 5.0 paradigm.

12. DISCUSSIONS

Although Decision Intelligence provides a strong conceptual basis for smart and sustainable materials manufacturing, its practical effectiveness depends on validation under realistic industrial conditions. The reviewed literature demonstrates that individual enabling technologies—particularly Artificial Intelligence (AI), Digital Twins (DTs), optimization, and IoT—have already been applied to manufacturing-related tasks such as process monitoring, defect detection, predictive maintenance, material property prediction, process optimization, and lifecycle management. AI can support prediction of material properties, identification of manufacturing defects, and process optimization, while Digital Twins enable continuous monitoring, virtual testing, degradation assessment, and predictive maintenance.

From an industrial perspective, these applications demonstrate the potential of Decision Intelligence to move from prediction toward actionable decision support. For example, AI-based monitoring can identify abnormal process or quality conditions, after which Digital Twins can evaluate the expected consequences of alternative operating conditions and optimization methods can identify appropriate process adjustments. In structural and advanced-material applications, the same architecture can support damage detection, structural health monitoring, predictive maintenance, and lifecycle assessment. The manuscript's application landscape therefore extends Decision Intelligence beyond conventional production planning to include advanced composites, structural systems, intelligent infrastructure, and additive manufacturing.

However, the literature also reveals an important limitation: most reported implementations concentrate on individual technologies or specific application stages rather than fully integrated, end-to-end Decision Intelligence systems. Integration of heterogeneous data sources, interoperability between AI and Digital Twin platforms, computational scalability, cybersecurity, explainability, and the availability of reliable real-time data remain major barriers to industrial deployment. Consequently, high predictive accuracy in laboratory or pilot environments does not necessarily guarantee reliable performance in complex industrial environments.

The quality assessment conducted in this review considered industrial applicability and validation as important criteria, and 140 studies were retained for the systematic review. Nevertheless, the synthesis indicates that large-scale industrial validation remains relatively limited. Future studies should therefore move toward longitudinal industrial case studies, pilot-scale demonstrations, benchmark datasets, standardized performance indicators, and quantitative comparisons with conventional decision-making approaches. Validation should assess not only prediction accuracy but also decision quality, computational cost, implementation complexity, sustainability impact, reliability, scalability, and human acceptance.

Accordingly, the proposed Decision Intelligence framework should be viewed as an integrative architecture that provides a pathway for connecting currently demonstrated AI, Digital Twin, optimization, and human-centered technologies into a closed-loop industrial decision ecosystem. Its practical validation should be conducted through real manufacturing environments involving smart materials, advanced composites, additive manufacturing, structural systems, and sustainable production processes. This would help establish the transition from technology-specific demonstrations to scalable, trustworthy, and industry-ready Decision Intelligence solutions.

ACKNOWLEDGEMENTS

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process: During the preparation of this work, the authors used Gemini (Google) and ChatGPT (OpenAI) for language refinement, structural optimisation and the conceptual generation of high-fidelity figures.

FUNDING

The author has nothing to report.

ETHICS STATEMENT

The author has nothing to report.

CONSENT

The author has nothing to report

CONFLICTS OF INTEREST

The author declares no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study. The manuscript is based on a systematic review of previously published literature.

PERMISSION TO REPRODUCE MATERIALS FROM OTHER SOURCES

The author has nothing to report

REFERENCES

Abhilash, P. M., Luo, X., Liu, Q., Madarkar, R., & Walker, C. (2024). Towards next-gen smart manufacturing systems: The explainability revolution. *Npj Advanced Manufacturing*, *1*(1), 8. https://doi.org/10.1038/s44334-024-00006-9

Adebayo, Y., Udoh, P., Kamudyariwa, X. B., & Osobajo, O. A. (2025). Artificial Intelligence in Construction Project Management: A Structured Literature Review of Its Evolution in Application and Future Trends. *Digital*, *5*(3), 26. https://doi.org/10.3390/digital5030026

Ahmad, R., Tichadou, S., & Hascoet, J.-Y. (2017). A knowledge-based intelligent decision system for production planning. *The International Journal of Advanced Manufacturing Technology*, *89*(5–8), 1717–1729. https://doi.org/10.1007/s00170-016-9214-z

Aissani, N., Bekrar, A., Trentesaux, D., & Beldjilali, B. (2012). Dynamic scheduling for multi-site companies: A decisional approach based on reinforcement multi-agent learning. *Journal of Intelligent Manufacturing*, *23*(6), 2513–2529. https://doi.org/10.1007/s10845-011-0580-y

Akash Kadam, Diwakar Reddy Peddinti, & Aditya Gupta. (2025). The Evolution of Smart Factories: Integrating IOT and Machine Learning in Supply Chain and Manufacturing. *Journal of Computer Science and Technology Studies*, *7*(5), 251–261. https://doi.org/10.32996/jcsts.2025.7.5.32

Alfaro-Viquez, D., Zamora-Hernandez, M., Fernandez-Vega, M., Garcia-Rodriguez, J., & Azorin-Lopez, J. (2025). A Comprehensive Review of AI-Based Digital Twin Applications in Manufacturing: Integration Across Operator, Product, and Process Dimensions. *Electronics*, *14*(4), 646. https://doi.org/10.3390/electronics14040646

Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., Guidotti, R., Del Ser, J., Díaz-Rodríguez, N., & Herrera, F. (2023). Explainable

Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence. *Information Fusion*, *99*, 101805. https://doi.org/10.1016/j.inffus.2023.101805

Almpani, S., & Stefaneas, P. (2026). Exploring the Role of Argumentation in Human–Centered Artificial Intelligence: Communication, Collaboration, and Trust. *International Journal on Artificial Intelligence Tools*, 2650014. https://doi.org/10.1142/S0218213026500144

Al-Siah, H., & Fioravanti, A. (2023). BIM and BPMN 2.0 Integration for Interoperability Challenge in Construction Industry. In E. Arbizzani, E. Cangelli, C. Clemente, F. Cumo, F. Giofrè, A. M. Giovenale, M. Palme, & S. Paris (Eds.), *Technological Imagination in the Green and Digital Transition* (pp. 227–235). Springer International Publishing. https://doi.org/10.1007/978-3-031-29515-7_21

Bakirtzis, G. A., Biskas, P. N., & Chatziathanasiou, V. (2012). Generation Expansion Planning by MILP considering mid-term scheduling decisions. *Electric Power Systems Research*, *86*, 98–112. https://doi.org/10.1016/j.epsr.2011.12.008

Balaha, F., Albinali, H., Alrabiah, H., Ali, M., & Bahroun, Z. (2025). An analytical review of data integration for decision support in smart manufacturing. *Decision Analytics Journal*, *17*, 100647. https://doi.org/10.1016/j.dajour.2025.100647

Barata, J., & Kayser, I. (2024). How will the digital twin shape the future of industry 5.0? *Technovation*, *134*, 103025. https://doi.org/10.1016/j.technovation.2024.103025

Bitencourt, J., Wooley, A., & Harris, G. (2025). Verification and validation of digital twins: A systematic literature review for manufacturing applications. *International Journal of Production Research*, *63*(1), 342–370. https://doi.org/10.1080/00207543.2024.2357741

Buggineni, V., Chen, C., & Camelio, J. (2024a). Enhancing manufacturing operations with synthetic data: A systematic framework for data generation, accuracy, and utility. *Frontiers in Manufacturing Technology*, *4*, 1320166. https://doi.org/10.3389/fmtec.2024.1320166

Buggineni, V., Chen, C., & Camelio, J. (2024b). Enhancing manufacturing operations with synthetic data: A systematic framework for data generation, accuracy, and utility. *Frontiers in Manufacturing Technology*, *4*, 1320166. https://doi.org/10.3389/fmtec.2024.1320166

Callaghan, V., Clarke, G., Colley, M., & Hagras, H. (2001). A Soft-Computing Distributed Artificial Intelligence Architecture for Intelligent Buildings. In V. Loia & S. Sessa (Eds.), *Soft Computing Agents* (Vol. 75, pp. 117–145). Physica-Verlag HD. https://doi.org/10.1007/978-3-7908-1815-4_5

Carter, O. B. J., Loft, S., & Visser, T. A. W. (2024). Meaningful Communication but not Superficial Anthropomorphism Facilitates Human-Automation Trust Calibration: The Human-Automation Trust Expectation Model (HATEM). *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *66*(11), 2485–2502. https://doi.org/10.1177/00187208231218156

Carvalho, N., Chaim, O., Cazarini, E., & Gerolamo, M. (2018). Manufacturing in the fourth industrial revolution: A positive prospect in Sustainable Manufacturing. *Procedia Manufacturing*, *21*, 671–678. https://doi.org/10.1016/j.promfg.2018.02.170

Chan, F. T. S., & Ding, K. (2023). Industrial intelligence-driven production and operations management. *International Journal of Production Research*, *61*(13), 4215–4219. https://doi.org/10.1080/00207543.2023.2207956

Chander, B., Pal, S., De, D., & Buyya, R. (2022). Artificial Intelligence-based Internet of Things for Industry 5.0. In S. Pal, D. De, & R. Buyya (Eds.), *Artificial Intelligence-based Internet of Things Systems* (pp. 3–45). Springer International Publishing. https://doi.org/10.1007/978-3-030-87059-1_1

Chen, C., Zhao, K., Leng, J., Liu, C., Fan, J., & Zheng, P. (2025). Integrating large language model and digital twins in the context of industry 5.0: Framework, challenges and opportunities. *Robotics and Computer-Integrated Manufacturing*, *94*, 102982. https://doi.org/10.1016/j.rcim.2025.102982

Chen, J., Lim, C. P., Tan, K. H., Govindan, K., & Kumar, A. (2025). Artificial intelligence-based human-centric decision support framework: An application to predictive maintenance in asset management under pandemic environments. *Annals of Operations Research*, *350*(2), 493–516. https://doi.org/10.1007/s10479-021-04373-w

Chen, S.-C., Chen, H.-M., Chen, H.-K., & Li, C.-L. (2024). Multi-Objective Optimization in Industry 5.0: Human-Centric AI Integration for Sustainable and Intelligent Manufacturing. *Processes*, *12*(12), 2723. https://doi.org/10.3390/pr12122723

Chirumalla, K., Oghazi, P., Nnewuku, R. E., Tuncay, H., & Yahyapour, N. (2025). Critical factors affecting digital transformation in manufacturing companies. *International Entrepreneurship and Management Journal*, *21*(1), 54. https://doi.org/10.1007/s11365-024-01056-3

Crespi, N., Drobot, A. T., & Minerva, R. (2023). The Digital Twin: What and Why? In N. Crespi, A. T. Drobot, & R. Minerva (Eds.), *The Digital Twin* (pp. 3–20). Springer International Publishing. https://doi.org/10.1007/978-3-031-21343-4_1

Debnath, A., Faisal, S. M. F., Mural, H., Hossain, Md. M., & Hasan, M. (2025a). Aggregate Production Planning Optimization: Comparing the Efficiency of Particle Swarm Optimization and Simulated Annealing Algorithms. *2025 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, 1–6. https://doi.org/10.1109/ECCE64574.2025.11013082

Debnath, A., Faisal, S. M. F., Mural, H., Hossain, Md. M., & Hasan, M. (2025b). Aggregate Production Planning Optimization: Comparing the Efficiency of Particle Swarm Optimization and Simulated Annealing Algorithms. *2025 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, 1–6. https://doi.org/10.1109/ECCE64574.2025.11013082

Dehghan, S., Sattarpanah Karganroudi, S., Echchakoui, S., & Barka, N. (2025). The Integration of Additive Manufacturing into Industry 4.0 and Industry 5.0: A Bibliometric Analysis (Trends, Opportunities, and Challenges). *Machines*, *13*(1), 62. https://doi.org/10.3390/machines13010062

Denno, P. (2024). Cognitive work in future manufacturing systems: Human-centered AI for joint work with models. *Journal of Integrated Design and Process*

Science: Transactions of the SDPS, Official Journal of the Society for Design and Process Science, *27*(2), 71–82. https://doi.org/10.3233/JID-230035

Dey, P., Mural, H., Dash, A., Kabir, Md. F., Nuva, T. J., & Islam Seyam, M. J. (2024, December 21). Evaluation of Strategies for Eradicating Supply Chain Disruption in Steel and Rolling Industries in Bangladesh by MCDM Approaches. *Proceedings of the International Conference on Industrial Engineering and Operations Management*. 7th Bangladesh International Conference on Industrial Engineering and Operations Management, AIUB, Dhaka, Bangladesh. https://doi.org/10.46254/BA07.20240058

Dhanda, M., Rogers, B. A., Hall, S., Dekoninck, E., & Dhokia, V. (2025). Reviewing human-robot collaboration in manufacturing: Opportunities and challenges in the context of industry 5.0. *Robotics and Computer-Integrated Manufacturing*, *93*, 102937. https://doi.org/10.1016/j.rcim.2024.102937

Ding, K., Chan, F. T. S., Zhang, X., Zhou, G., & Zhang, F. (2019). Defining a Digital Twin-based Cyber-Physical Production System for autonomous manufacturing in smart shop floors. *International Journal of Production Research*, *57*(20), 6315–6334. https://doi.org/10.1080/00207543.2019.1566661

El Kalach, F., Yousif, I., Wuest, T., Sheth, A., & Harik, R. (2025). Cognitive manufacturing: Definition and current trends. *Journal of Intelligent Manufacturing*, *36*(6), 3695–3715. https://doi.org/10.1007/s10845-024-02429-9

Esmaeilian, B., Behdad, S., & Wang, B. (2016). The evolution and future of manufacturing: A review. *Journal of Manufacturing Systems*, *39*, 79–100. https://doi.org/10.1016/j.jmsy.2016.03.001

Fanfani, M., Palesi, L. A. I., & Nesi, P. (2026). Human-Centered AI for Decision Support Systems: A Systematic Review of Application Domains, Architecture Designs, Current Trends and Future Directions. *Big Data and Cognitive Computing*, *10*(6), 186. https://doi.org/10.3390/bdcc10060186

Gálvez Del Postigo Gallego, L., Lazarova-Molnar, S., Del Real Torres, A., & Acevedo Galicia, L. E. (2025). Decision Support Within Digital Twins in Manufacturing Ecosystems: A Review. *IET Collaborative Intelligent Manufacturing*, *7*(1), e70041. https://doi.org/10.1049/cim2.70041

Glikson, E., & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

González Rodríguez, G., Gonzalez-Cava, J. M., & Méndez Pérez, J. A. (2020). An intelligent decision support system for production planning based on machine learning. *Journal of Intelligent Manufacturing*, *31*(5), 1257–1273. https://doi.org/10.1007/s10845-019-01510-y

Grieves, M. W. (2023). Digital Twins: Past, Present, and Future. In N. Crespi, A. T. Drobot, & R. Minerva (Eds.), *The Digital Twin* (pp. 97–121). Springer International Publishing. https://doi.org/10.1007/978-3-031-21343-4_4

Hananto, A. L., Tirta, A., Herawan, S. G., Idris, M., Soudagar, M. E. M., Djamari, D. W., & Veza, I. (2024). Digital Twin and 3D Digital Twin: Concepts, Applications, and Challenges in Industry 4.0 for Digital Twin. *Computers*, *13*(4), 100. https://doi.org/10.3390/computers13040100

Handoko, H., Indrajit, R. E., Mantoro, T., & Santoso, H. (2025). Transforming Educational Decision-Making through Human-Centered Information Systems. *2025 IEEE 11th International Conference on Computing, Engineering and Design (ICCED)*, 1–5. https://doi.org/10.1109/ICCED68324.2025.11324833

Haque, B. M. T., & Rahman, Md. A. (2025). Enterprise-Scale Risk Decision Intelligence Systems Using Large Language Models (LLMs) For Automated Governance, Compliance, and Policy Enforcement. *American Journal of Interdisciplinary Studies*, *06*(03), 254–305. https://doi.org/10.63125/te050f20

Hartikainen, M., Spurava, G., & Väänänen, K. (2024). Human-AI Collaboration in Smart Manufacturing: Key Concepts and Framework for Design. In F. Lorig, J. Tucker, A. Dahlgren Lindström, F. Dignum, P. Murukannaiah, A. Theodorou, & P. Yolum (Eds.), *Frontiers in Artificial Intelligence and Applications*. IOS Press. https://doi.org/10.3233/FAIA240192

Hassija, V., Chamola, V., Mahapatra, A., Singal, A., Goel, D., Huang, K., Scardapane, S., Spinelli, I., Mahmud, M., & Hussain, A. (2024). Interpreting Black-Box Models: A Review on Explainable Artificial Intelligence. *Cognitive Computation*, *16*(1), 45–74. https://doi.org/10.1007/s12559-023-10179-8

Huang, H., Zheng, X., Yang, Y., Liu, J., Liu, W., & Wang, J. (2020). An integrated architecture for intelligence evaluation of automated vehicles. *Accident Analysis & Prevention*, *145*, 105681. https://doi.org/10.1016/j.aap.2020.105681

Hussain, J., Lee, C.-C., & Lev, B. (2025). Optimizing AI-based emission reduction efficiency and subsidies in supply chain management: A sensitivity-based approach with duopoly game dynamics. *Journal of Cleaner Production*, *494*, 144991. https://doi.org/10.1016/j.jclepro.2025.144991

Infant, S. S., Vickram, S., Saravanan, A., Mathan Muthu, C. M., & Yuarajan, D. (2025). Explainable artificial intelligence for sustainable urban water systems engineering. *Results in Engineering*, *25*, 104349. https://doi.org/10.1016/j.rineng.2025.104349

Javaid, M., Haleem, A., & Suman, R. (2023). Digital Twin applications toward Industry 4.0: A Review. *Cognitive Robotics*, *3*, 71–92. https://doi.org/10.1016/j.cogr.2023.04.003

Jiang, Z., Ma, N., Yao, X., Zhou, J., Wang, K., Xie, T., & Meng, J. (2026). From smart manufacturing in Industry 4.0 to industrial metaverse for Industry 5.0. *International Journal of Computer Integrated Manufacturing*, *39*(4–5), 610–641. https://doi.org/10.1080/0951192X.2025.2556440

Kalinaki, K., Yahya, U., Malik, O. A., & Lai, D. T. C. (2024). A Review of Big Data Analytics and Artificial Intelligence in Industry 5.0 for Smart Decision-Making: In A. Hassan, P. K. Dutta, S. Gupta, E. Mattar, & S. Singh (Eds.), *Advances in Business Information Systems and Analytics* (pp. 24–47). IGI Global. https://doi.org/10.4018/979-8-3693-2647-3.ch002

Karkaria, V., Tsai, Y.-K., Chen, Y.-P., & Chen, W. (2025). An optimization-centric review on integrating artificial intelligence and digital twin technologies in manufacturing. *Engineering Optimization*, *57*(1), 161–207. https://doi.org/10.1080/0305215X.2024.2434201

Kerrouchi, S., Aghezzaf, E.-H., & Cottyn, J. (2024). Production digital twin: A systematic literature review of challenges. *International Journal of Computer Integrated Manufacturing*, *37*(10–11), 1168–1193. https://doi.org/10.1080/0951192X.2024.2314792

Khan, M. I., Yasmeen, T., Khan, M., Hadi, N. U., Asif, M., Farooq, M., & Al-Ghamdi, S. G. (2025). Integrating industry 4.0 for enhanced sustainability: Pathways and prospects. *Sustainable Production and Consumption*, *54*, 149–189. https://doi.org/10.1016/j.spc.2024.12.012

Kim, D. B., Bajestani, M. S., Lee, J. Y., Shin, S.-J., Kim, G.-Y., Sajadieh, S. M. M., & Noh, S. (2025). Human-in-the-loop in smart manufacturing (H-SM): A review and perspective. *Journal of Manufacturing Systems*, *82*, 178–199. https://doi.org/10.1016/j.jmsy.2025.05.020

Kumar, V., Prakash, R. R., & Pratihar, D. K. (2025). Intelligent ankle-foot prosthetics: From engineering fundamentals to integrated artificial intelligence systems. In *Advancing Healthcare through Decision Intelligence* (pp. 127–147). Elsevier. https://doi.org/10.1016/B978-0-443-26480-1.00008-4

Langås, E. F., Zafar, M. H., & Sanfilippo, F. (2026). Exploring the synergy of human-robot teaming, digital twins, and machine learning in Industry 5.0: A step towards sustainable manufacturing. *Journal of Intelligent Manufacturing*, *37*(3), 999–1022. https://doi.org/10.1007/s10845-025-02580-x

Lawniczak, A. T., & Di Stefano, B. N. (2010). Computational intelligence-based architecture for cognitive agents. *Procedia Computer Science*, *1*(1), 2227–2235. https://doi.org/10.1016/j.procs.2010.04.249

Lee, D., & Cheng, C.-C. (2016). Energy savings by energy management systems: A review. *Renewable and Sustainable Energy Reviews*, *56*, 760–777. https://doi.org/10.1016/j.rser.2015.11.067

Leng, J., Zheng, K., Li, R., Chen, C., Wang, B., Liu, Q., Chen, X., & Shen, W. (2026). AIGC-empowered smart manufacturing: Prospects and challenges. *Robotics and Computer-Integrated Manufacturing*, *97*, 103076. https://doi.org/10.1016/j.rcim.2025.103076

Leng, J., Zhu, X., Huang, Z., Li, X., Zheng, P., Zhou, X., Mourtzis, D., Wang, B., Qi, Q., Shao, H., Wan, J., Chen, X., Wang, L., & Liu, Q. (2024). Unlocking the power of industrial artificial intelligence towards Industry 5.0: Insights, pathways, and challenges. *Journal of Manufacturing Systems*, *73*, 349–363. https://doi.org/10.1016/j.jmsy.2024.02.010

Li, H., Lu, Z., Zhang, Z., & Tanasescu, C. (2025). How does artificial intelligence affect manufacturing firms' energy intensity? *Energy Economics*, *141*, 108109. https://doi.org/10.1016/j.eneco.2024.108109

Li, H., & Tian, F. (2026). Advancing Decision-Making through AI-Human Collaboration: A Systematic Review and Conceptual Framework. *Group Decision and Negotiation*, *35*(2), 26. https://doi.org/10.1007/s10726-026-09980-1

Li, P., Zhang, Y., Yin, L., Yang, M., & Jiang, P. (2026). Smart manufacturing service towards industry 5.0: Framework, characteristics and industrial case studies. *The International Journal of Advanced Manufacturing Technology*, *143*(9–10), 4595–4621. https://doi.org/10.1007/s00170-026-17743-0

Li, X., Gu, X., Huang, S., Wang, B., Leng, J., & Wang, L. (2026). Smart reconfigurable manufacturing towards Industry 5.0. *Journal of Manufacturing Systems*, *86*, 178–202. https://doi.org/10.1016/j.jmsy.2026.02.023

Luu, N. T. M., Pham, T. H., Siriwardana, A., Nguyen, L. C., & Tran, D. L. A. (2025). A Bibliometric Review of Digitalization in Tourism Supply Chains in the Context of Industry 4.0. *Strategic Change*, *34*(4), 577–595. https://doi.org/10.1002/jsc.2639

Lv, Z. (2023). Digital Twins in Industry 5.0. *Research*, *6*, 0071. https://doi.org/10.34133/research.0071

Ma, M., Lin, W., Pan, D., Lin, Y., Wang, P., Zhou, Y., & Liang, X. (2018). Data and Decision Intelligence for Human-in-the-Loop Cyber-Physical Systems: Reference Model, Recent Progresses and Challenges. *Journal of Signal Processing Systems*, *90*(8–9), 1167–1178. https://doi.org/10.1007/s11265-017-1304-0

Machado, C. G., Winroth, M. P., & Ribeiro Da Silva, E. H. D. (2020). Sustainable manufacturing in Industry 4.0: An emerging research agenda. *International Journal of Production Research*, *58*(5), 1462–1484. https://doi.org/10.1080/00207543.2019.1652777

Mahmud, N., & Mural, H. (2026). Integrating ensemble machine learning with TOPSIS and VIKOR for inventory waste index prediction and driver prioritization: Evidence from Bangladesh. *Waste Management Bulletin*, *4*(2), 100311. https://doi.org/10.1016/j.wmb.2026.100311

Martini, B., Bellisario, D., & Coletti, P. (2024). Human-Centered and Sustainable Artificial Intelligence in Industry 5.0: Challenges and Perspectives. *Sustainability*, *16*(13), 5448. https://doi.org/10.3390/su16135448

Mon, B. F., Hayajneh, M., Ali, N. A., Ullah, F., Ullah, H., & Alkobaisi, S. (2025). Digital Twins in the IIoT: Current Practices and Future Directions Toward Industry 5.0. *Computers, Materials & Continua*, *83*(3), 3675–3712. https://doi.org/10.32604/cmc.2025.061411

Monferdini, L., Tebaldi, L., & Bottani, E. (2025). From Industry 4.0 to Industry 5.0: Opportunities, Challenges, and Future Perspectives in Logistics. *Procedia Computer Science*, *253*, 2941–2950. https://doi.org/10.1016/j.procs.2025.02.018

Moosavi, S., Farajzadeh-Zanjani, M., Razavi-Far, R., Palade, V., & Saif, M. (2024). Explainable AI in Manufacturing and Industrial Cyber–Physical Systems: A Survey. *Electronics*, *13*(17), 3497. https://doi.org/10.3390/electronics13173497

Mural, H., Choudhury, I. A., Abid, Md. R., & Banik, S. C. (2026). Recent Advancements, Trends and Future Prospects of Upper Limb Prosthesis through 3D printing- A Systematic Review. *Journal of Sustainable Smart Materials and Structural Systems*, *2*, 1–23. https://doi.org/10.65904/3083-3604.2026.02.01

Nazir, J., & Das, P. K. (2025). A systematic literature review on factors of perception impacting entrepreneurial success based on PRISMA framework. *Journal of Innovation and Entrepreneurship*, *14*(1), 49. https://doi.org/10.1186/s13731-025-00491-y

Nemati, H. R., Steiger, D. M., Iyer, L. S., & Herschel, R. T. (2002). Knowledge warehouse: An architectural integration of knowledge management, decision support, artificial intelligence and data warehousing. *Decision Support Systems*, *33*(2), 143–161. https://doi.org/10.1016/S0167-9236(01)00141-5

Nguyen, D. H., Nguyen, D. P. T., Ta, Q. C., Tran, K. D., & Tran, K. P. (2026). Human-Centered Explainable Anomaly Detection in Smart Manufacturing: Bridging AI and Human Decision-Making in Industry 5.0. In K. P. Tran (Ed.), *Human-Centered Explainable Anomaly*

Detection for Smart Manufacturing in Industry 5.0 (pp. 93–108). Springer Nature Switzerland. https://doi.org/10.1007/978-3-032-13657-2_5

Nguyen, H. D., & Tran, K. P. (2023). Artificial Intelligence for Smart Manufacturing in Industry 5.0: Methods, Applications, and Challenges. In K. P. Tran (Ed.), *Artificial Intelligence for Smart Manufacturing* (pp. 5–33). Springer International Publishing. https://doi.org/10.1007/978-3-031-30510-8_2

Nikiforidis, K., Kyrtsoglou, A., Vafeiadis, T., Kotsiopoulos, T., Nizamis, A., Ioannidis, D., Votis, K., Tzovaras, D., & Sarigiannidis, P. (2025). Enhancing transparency and trust in AI-powered manufacturing: A survey of explainable AI (XAI) applications in smart manufacturing in the era of industry 4.0/5.0. *ICT Express*, *11*(1), 135–148. https://doi.org/10.1016/j.icte.2024.12.001

Nilsson, J., Javed, S., Albertsson, K., Delsing, J., Liwicki, M., & Sandin, F. (2024). AI Concepts for System of Systems Dynamic Interoperability. *Sensors*, *24*(9), 2921. https://doi.org/10.3390/s24092921

Oraei Zare, S., Saghafian, B., & Shamsai, A. (2012). Multi-objective optimization for combined quality–quantity urban runoff control. *Hydrology and Earth System Sciences*, *16*(12), 4531–4542. https://doi.org/10.5194/hess-16-4531-2012

Pan, Y., Huang, Z., Lev, B., Xu, L., & Olson, D. (2026). A literature review on the artificial intelligence in manufacturing systems under industry 5.0. *International Journal of Production Research*, *64*(12), 5120–5161. https://doi.org/10.1080/00207543.2026.2623537

Panigutti, C., Beretta, A., Fadda, D., Giannotti, F., Pedreschi, D., Perotti, A., & Rinzivillo, S. (2023a). Co-design of Human-centered, Explainable AI for Clinical Decision Support. *ACM Transactions on Interactive Intelligent Systems*, *13*(4), 1–35. https://doi.org/10.1145/3587271

Panigutti, C., Beretta, A., Fadda, D., Giannotti, F., Pedreschi, D., Perotti, A., & Rinzivillo, S. (2023b). Co-design of Human-centered, Explainable AI for Clinical Decision Support. *ACM Transactions on Interactive Intelligent Systems*, *13*(4), 1–35. https://doi.org/10.1145/3587271

Pant, R., Singh, R., Gehlot, A., & Thakur, A. K. (2025). A Systematic Review of Emerging Industry 5.0 Technologies: Enhancing Agile Manufacturing for Sustainability. *Operations Research Forum*, *6*(1), 29. https://doi.org/10.1007/s43069-025-00427-y

Parra-Martinez, F. A., Desmet, O. A., & Wai, J. (2023). The Evolution of Intelligence: Analysis of the Journal of Intelligence and Intelligence. *Journal of Intelligence*, *11*(2), 35. https://doi.org/10.3390/jintelligence11020035

Patel, N. S., & Lim, J. T. (2025). Critical design futures thinking and GenerativeAI: A Foresight 3.0 approach in higher education to design preferred futures for the industry. *Foresight*, *27*(2), 380–402. https://doi.org/10.1108/FS-11-2023-0228

Pradhan, A. K., Kumar, D., Mishra, M. K., & Singh, M. K. (2025). Edge, Fog, and Cloud Computing in Industry 5.0. In I. Sarkar, A. Hazra, & P. Maurya (Eds.), *Industry 5.0* (pp. 1–27). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-87837-4_1

Protyai, Md. I. H., Shariar, R., & Mural, H. (2026). Digital Twin Integration in Project Life Cycle Management—A Review. *Engineering Reports*, *8*(3), e70668. https://doi.org/10.1002/eng2.70668

Puthanveettil Madathil, A., Luo, X., Liu, Q., Walker, C., Madarkar, R., & Qin, Y. (2025). A review of explainable artificial intelligence in smart manufacturing. *International Journal of Production Research*, *63*(23), 8654–8697. https://doi.org/10.1080/00207543.2025.2513574

Rahaman, Md. T., Pranta, A. D., & Ahmed, S. (2025). Transitioning from Industry 4.0 to Industry 5.0 for Sustainable and Additive Manufacturing of Clothing: Framework, Case Studies, Recent Advances, and Future Prospects. *Materials Circular Economy*, *7*(1), 20. https://doi.org/10.1007/s42824-025-00176-7

Rajyakalshmi, G., Jishnu Prian, G., Srihari Reddy, P., Indumati, S., & Sreenivasulu, M. (2026). Industry 5.0: A New Era of Sustainable and Human-Centered Production. In Y. Kumar Singla, A. Kumar, & M. R. Maughan (Eds.), *Digital Manufacturing in Industry 5.0* (pp. 453–467). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-91500-0_19

Rathor, S. K., & Saxena, D. (2020). Energy management system for smart grid: An overview and key issues. *International Journal of Energy Research*, *44*(6), 4067–4109. https://doi.org/10.1002/er.4883

Rejeb, A., Rejeb, K., Zrelli, I., & Süle, E. (2025). Industry 5.0 as seen through its academic literature: An investigation using co-word analysis. *Discover Sustainability*, *6*(1), 307. https://doi.org/10.1007/s43621-025-01166-0

Ren, M., Chen, N., & Qiu, H. (2023). Human-machine Collaborative Decision-making: An Evolutionary Roadmap Based on Cognitive Intelligence. *International Journal of Social Robotics*, *15*(7), 1101–1114. https://doi.org/10.1007/s12369-023-01020-1

Rijwani, T., Kumari, S., Srinivas, R., Abhishek, K., Iyer, G., Vara, H., Dubey, S., Revathi, V., & Gupta, M. (2025). Industry 5.0: A review of emerging trends and transformative technologies in the next industrial revolution. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *19*(2), 667–679. https://doi.org/10.1007/s12008-024-01943-7

Rojas, L., Peña, Á., & Garcia, J. (2025). AI-Driven Predictive Maintenance in Mining: A Systematic Literature Review on Fault Detection, Digital Twins, and Intelligent Asset Management. *Applied Sciences*, *15*(6), 3337. https://doi.org/10.3390/app15063337

Rožanec, J. M., Novalija, I., Zajec, P., Kenda, K., Tavakoli Ghinani, H., Suh, S., Bian, S., Veliou, E., Papamartzivanos, D., Giannetsos, T., Menesidou, S. A., Alonso, R., Cauli, N., Meloni, A., Recupero, D. R., Kyriazis, D., Sofianidis, G., Theodoropoulos, S., Fortuna, B., … Soldatos, J. (2023). Human-centric artificial intelligence architecture for industry 5.0 applications. *International Journal of Production Research*, *61*(20), 6847–6872. https://doi.org/10.1080/00207543.2022.2138611

Samal, U. (2025). Evolution of machine learning and deep learning in intelligent manufacturing: A bibliometric study. *International Journal of System Assurance Engineering and Management*, *16*(9), 3134–3150. https://doi.org/10.1007/s13198-025-02846-w

Sanepalli, U. R. (2024). Enterprise Lakehouse Architecture for Customer Analytics: AI and Machine Learning - Synchronized Ingestion and Compute Optimization. *World Journal of Advanced Research and Reviews*, *23*(2), 2949–2959. https://doi.org/10.30574/wjarr.2024.23.2.2418

Saraswat, D., Bhattacharya, P., Verma, A., Prasad, V. K., Tanwar, S., Sharma, G., Bokoro, P. N., & Sharma, R. (2022). Explainable AI for Healthcare 5.0: Opportunities and Challenges. *IEEE Access*, *10*, 84486–84517. https://doi.org/10.1109/ACCESS.2022.3197671

Sarkar, I., Kakarla, J. H. H., Hazra, A., Gupta, K., Kumari, P., & Munusamy, A. (2025). Machine Learning for Industry 5.0: A Survey. *IEEE Internet of Things Journal*, 1–1. https://doi.org/10.1109/JIOT.2025.3604413

Sartal, A., Bellas, R., Mejías, A. M., & García-Collado, A. (2020). The sustainable manufacturing concept, evolution and opportunities within Industry 4.0: A literature review. *Advances in Mechanical Engineering*, *12*(5), 1687814020925232. https://doi.org/10.1177/1687814020925232

Saxena, V., Kumar, N., Manna, S., Rajput, S. K., Agarwal, K. L., Diwania, S., & Gupta, V. (2025). Modelling, solution and application of optimization techniques in HRES: From conventional to artificial intelligence. *Applied Energy*, *380*, 125047. https://doi.org/10.1016/j.apenergy.2024.125047

Shabur, Md. A., Shahriar, A., & Ara, Mst. A. (2025). From automation to collaboration: Exploring the impact of industry 5.0 on sustainable manufacturing. *Discover Sustainability*, *6*(1), 341. https://doi.org/10.1007/s43621-025-01201-0

Shahriar, K. A., Mural, H., & Hridoy, M. W. (2026a). Sustainable Supplier Selection of E-Commerce Industry in Bangladesh: An Integrated TOPSIS-AHP Approach. *Engineering Reports*, *8*(2), e70636. https://doi.org/10.1002/eng2.70636

Shahriar, K. A., Mural, H., & Hridoy, M. W. (2026b). Sustainable Supplier Selection of E-Commerce Industry in Bangladesh: An Integrated TOPSIS-AHP Approach. *Engineering Reports*, *8*(2), e70636. https://doi.org/10.1002/eng2.70636

Shapiro, J. F. (1993). Chapter 8 Mathematical programming models and methods for production planning and scheduling. In *Handbooks in Operations Research and Management Science* (Vol. 4, pp. 371–443). Elsevier. https://doi.org/10.1016/S0927-0507(05)80188-4

Shneiderman, B. (2020). Human-Centered Artificial Intelligence: Reliable, Safe & Trustworthy. *International Journal of Human–Computer Interaction*, *36*(6), 495–504. https://doi.org/10.1080/10447318.2020.1741118

Silver, E. A. (1981). Operations Research in Inventory Management: A Review and Critique. *Operations Research*, *29*(4), 628–645. https://doi.org/10.1287/opre.29.4.628

Singh, S., Mehla, S., Bhargava, S. K., & Ramakrishna, S. (2022). History and Evolution of Additive Manufacturing. In S. K. Bhargava, S. Ramakrishna, M. Brandt, & Pr. Selvakannan (Eds.), *Additive Manufacturing for Chemical Sciences and Engineering* (pp. 19–51). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-2293-0_2

Spelt, P. F., Knee, H. E., & Glover, C. W. (1991). Hybrid artificial intelligence architecture for diagnosis and decision-making in manufacturing. *Journal of Intelligent Manufacturing*, *2*(5), 261–268. https://doi.org/10.1007/BF01471174

Subrahmanyam, S. (2025). Leveraging AI and ML for Enhanced Efficiency and Innovation in Manufacturing: In V. Vyas, X. Bi, D. Pandey, Z. Xu, & B. K. Pandey (Eds.), *Advances in Computational Intelligence and Robotics* (pp. 319–344). IGI Global. https://doi.org/10.4018/979-8-3373-0442-7.ch021

Sun, X., & Song, Y. (2025). Unlocking the Synergy: Increasing productivity through Human-AI collaboration in the industry 5.0 Era. *Computers & Industrial Engineering*, *200*, 110657. https://doi.org/10.1016/j.cie.2024.110657

Suri, S., Mokashi, S. P., Guntupalli, B. K. R., Kiran, K. R., Linkalapalli, K., & Chaudhary, V. (2025). Intelligent Computing Framework for Real-Time Decision-Making in Industry 5.0 Applications. *2025 3rd International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT)*, 1–7. https://doi.org/10.1109/ICAICCIT68829.2025.11434024

Szeszák, B. M., Kerékjártó, I. G., Soltész, L., & Galambos, P. (2025). Industrial Revolutions and Automation: Tracing Economic and Social Transformations of Manufacturing. *Societies*, *15*(4), 88. https://doi.org/10.3390/soc15040088

Talukder, I. H. R., Mural, H., Faisal, S. M. F., Talukdar, A., Das, S. C., & Hassan, M. (2026). Autonomous Planetary Rover Navigation and Crater-Based Map Augmentation for Path Planning and Rock Localization Using Space ROS. *Engineering Reports*, *8*(3), e70681. https://doi.org/10.1002/eng2.70681

Tao, F., Li, Y., Wei, Y., Zhang, C., & Zuo, Y. (2025). Data–Model Fusion Methods and Applications Toward Smart Manufacturing and Digital Engineering. *Engineering*, *55*, 36–50. https://doi.org/10.1016/j.eng.2024.12.034

Teoh, Y. K., Gill, S. S., & Parlikad, A. K. (2023). IoT and Fog-Computing-Based Predictive Maintenance Model for Effective Asset Management in Industry 4.0 Using Machine Learning. *IEEE Internet of Things Journal*, *10*(3), 2087–2094. https://doi.org/10.1109/JIOT.2021.3050441

Trihandaru, S., Susetyo, Y. A., Parhusip, H. A., & Susanto, B. (2025). Human Capital Decision Intelligence (HCDI) architecture in microbiology laboratory based on machine learning and operations research models. *International Journal of Advances in Intelligent Informatics*, *11*(4), 602. https://doi.org/10.26555/ijain.v11i4.1676

Tudorache, L., Babur, Ö., Lucas, S. S., & Van Den Brand, M. (2025). Current approaches to digital twins in additive manufacturing: A systematic literature review. *Progress in Additive Manufacturing*, *10*(12), 10819–10853. https://doi.org/10.1007/s40964-025-01262-7

Varma Alluri, A. K. K. (2026). Governed Agentic AI for Salesforce CRM Platforms: A Reference Architecture for Data Grounding, Decision Intelligence, Trust Controls, and Lifecycle Reliability. *International Journal of Emerging Trends in Computer Science and Information Technology*, *7*, 374–382. https://doi.org/10.63282/3050-9246.IJETCSIT-V7I1P153

Vinitha, K., Ambrose Prabhu, R., Bhaskar, R., & Hariharan, R. (2020). Review on industrial mathematics and materials at Industry 1.0 to Industry 4.0. *Materials*

Today: Proceedings, *33*, 3956–3960. https://doi.org/10.1016/j.matpr.2020.06.331

Wang, H., Wang, C., Liu, Q., Zhang, X., Liu, M., Ma, Y., Yan, F., & Shen, W. (2024). A data and knowledge driven autonomous intelligent manufacturing system for intelligent factories. *Journal of Manufacturing Systems*, *74*, 512–526. https://doi.org/10.1016/j.jmsy.2024.04.011

Wang, M., Tong, Y., Zhuang, C., & Du, X. (2025). Towards industry 5.0: A framework of reconfigurable matrix-structured manufacturing system. *Journal of Manufacturing Systems*, *82*, 114–136. https://doi.org/10.1016/j.jmsy.2025.06.002

Wang, T., Liu, Z., Wang, L., Li, M., & Wang, X. V. (2025). A design framework for high-fidelity human-centric digital twin of collaborative work cell in Industry 5.0. *Journal of Manufacturing Systems*, *80*, 140–156. https://doi.org/10.1016/j.jmsy.2025.02.018

Wang, Z., Yan, J., Yan, G., & Yu, B. (2025). Multi-scale control and action recognition based human-robot collaboration framework facing new generation intelligent manufacturing. *Robotics and Computer-Integrated Manufacturing*, *91*, 102847. https://doi.org/10.1016/j.rcim.2024.102847

Xiang, W., Yu, K., Han, F., Fang, L., He, D., & Han, Q.-L. (2024). Advanced Manufacturing in Industry 5.0: A Survey of Key Enabling Technologies and Future Trends. *IEEE Transactions on Industrial Informatics*, *20*(2), 1055–1068. https://doi.org/10.1109/TII.2023.3274224

Xu, J., Sun, Q., Han, Q.-L., & Tang, Y. (2025). When Embodied AI Meets Industry 5.0: Human-Centered Smart Manufacturing. *IEEE/CAA Journal of Automatica Sinica*, *12*(3), 485–501. https://doi.org/10.1109/JAS.2025.125327

Yang, W., Wei, Y., Wei, H., Chen, Y., Huang, G., Li, X., Li, R., Yao, N., Wang, X., Gu, X., Amin, M. B., & Kang, B. (2023). Survey on Explainable AI: From Approaches, Limitations and Applications Aspects. *Human-Centric Intelligent Systems*, *3*(3), 161–188. https://doi.org/10.1007/s44230-023-00038-y

Yanytska, L. (2025). The rise of human-centric manufacturing in the industry 5.0 era. *The International Journal of Advanced Manufacturing Technology*, *139*(9–10), 5067–5077. https://doi.org/10.1007/s00170-025-16192-5

Yin, Y., Stecke, K. E., & Li, D. (2018). The evolution of production systems from Industry 2.0 through Industry 4.0. *International Journal of Production Research*, *56*(1–2), 848–861. https://doi.org/10.1080/00207543.2017.1403664

Yu, W., Ouyang, Z., Zhang, Y., Lu, Y., Wei, C., Tu, Y., & He, B. (2025). Research progress on the artificial intelligence applications in food safety and quality management. *Trends in Food Science & Technology*, *156*, 104855. https://doi.org/10.1016/j.tifs.2024.104855

Zakoldaev, D. A., Shukalov, A. V., & Zharinov, I. O. (2019). From Industry 3.0 to Industry 4.0: Production modernization and creation of innovative digital companies. *IOP Conference Series: Materials Science and Engineering*, *560*(1), 012206. https://doi.org/10.1088/1757-899X/560/1/012206

Zeng, H., Wang, J., Das, A., He, J., Han, K., Hu, H., & Sun, M. (2024). Effective Generation of Feasible Solutions for Integer Programming via Guided Diffusion. *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, 4107–4118. https://doi.org/10.1145/3637528.3671783

Zhai, B., Perez-Pozuelo, I., Clifton, E. A. D., Palotti, J., & Guan, Y. (2020). Making Sense of Sleep: Multimodal Sleep Stage Classification in a Large, Diverse Population Using Movement and Cardiac Sensing. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *4*(2), 1–33. https://doi.org/10.1145/3397325

Zhang, J. (2025). The Application of Artificial Intelligence Technology in Human Centered Manufacturing in Industry 5.0. *Scalable Computing: Practice and Experience*, *26*(3), 1242–1256. https://doi.org/10.12694/scpe.v26i3.4130

Zhang, L., Liu, J., & Zhuang, C. (2024). Digital Twin Modeling Enabled Machine Tool Intelligence: A Review. *Chinese Journal of Mechanical Engineering*, *37*(1), 47. https://doi.org/10.1186/s10033-024-01036-2

Zhang, W., Li, H., Qian, L., & Wang, X. (2025). How intelligent manufacturing improves corporate ESG performance: A three-dimensional analysis based on "Environment," "Society," and "Governance." *Journal of Environmental Management*, *380*, 125171. https://doi.org/10.1016/j.jenvman.2025.125171

Zhao, J., Ren, R., Nie, Y., & Wang, D. (2025). Decision Intelligence Empowering Resource Management for 6G-V2X Communications. *IEEE Internet of Things Magazine*, *8*(6), 88–96. https://doi.org/10.1109/MIOT.2025.3575883

Received on 02-07-2026 Accepted on 25-07-2026 Published on 18-08-2026

https://doi.org/10.65904/3083-3604.2026.02.09

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