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Integrating Digital Twins, Smart Materials, and Human Machine Collaboration for Sustainable Smart Manufacturing: Smart CNC & Industry 4.0 Applications

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Abstract

The rapid evolution of Industry 4.0 and the emerging transition toward Industry 5.0 have been catalyzed by the convergence of intelligent digital technologies such as digital twins, cyber–physical systems (CPS), artificial intelligence (AI), the Internet of Things (IoT), and human-in-the-loop (HITL) frameworks. These technologies have transformed traditional manufacturing into adaptive, data-centric ecosystems capable of real-time optimization and predictive decision-making. In recent years, the fusion of computer numerical control (CNC) machines, nanocellulose-based smart materials, and cloud-enabled manufacturing analytics has expanded the operational intelligence of smart factories. Additionally, the advent of AI-generated content (AIGC) and ontology-driven architectures has introduced new paradigms for knowledge representation, semantic interoperability, and self-adaptive industrial systems Despite these advancements, a significant research gap persists in integrating multi-modal sensing, digital twin-assisted learning environments, and agentic workflow automation into a unified, interoperable framework. Addressing this gap is crucial for realizing holistic industrial intelligence, where data, algorithms, and human expertise co-evolve symbiotically. This paper proposes a multi-layered framework that harmonizes software–hardware co-design, adaptive material intelligence, and collaborative human–machine interactions to enhance manufacturing resilience and sustainability. The proposed framework bridges industrial-scale foundation models with adaptive sensing networks and real-time control architectures, creating a scalable infrastructure for intelligent decision-making, energy-efficient operations, and agile supply-chain management. Through this integration, the study outlines pathways for embedding contextual awareness, self-learning mechanisms, and cognitive adaptability within industrial ecosystems. Ultimately, this approach extends beyond the automation-driven logic of Industry 4.0, envisioning an Industry 5.0 paradigm where human creativity, sustainability, and ethical intelligence are central to manufacturing innovation. The findings and conceptual model presented herein aim to guide future research toward developing resilient, human-centric, and sustainable smart factories powered by continuous human–machine collaboration.

Keywords: Smart manufacturing; industry 4.0; digital twin; human-in-the-loop; cyber-physical systems; AIGC; nano cellulose packaging; multi-sensor fusion; intelligent decision-making; sustainable production; industry 5.0

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INTRODUCTION

Background and Context

The Fourth Industrial Revolution, or Industry 4.0, has revolutionized manufacturing by shifting from traditional automation to cyber-physical, data-driven ecosystems. The integration of Internet of

Things (IoT), digital twins (DTs), artificial intelligence (AI), and human-in-the-loop (HIL) frameworks has enabled interconnected and adaptive environments [1-5]. This convergence defines the foundation of smart manufacturing, where machines, humans, and materials collaborate to achieve efficiency, flexibility, and sustainability [6,7,8]. Smart manufacturing is not limited to incremental productivity improvements but represents a paradigm shift toward self-adaptive, context-aware, and resilient industrial ecosystems [9]. Digital twin technology plays a pivotal role by enabling real-time synchronization between physical assets and their virtual models, thereby supporting predictive maintenance, immersive learning environments, and advanced analytics [10-19]. The application of multi-sensor fusion, smart packaging, and ontology-based architectures underscores the multidimensional nature of this transition [20-22].

Nevertheless, several challenges persist in realizing fully intelligent factories, including data interoperability, scalability, sustainability, and human–machine collaboration [16,15]. With the advent of Industry 5.0, which emphasizes human-centricity, resilience, and sustainability, the need to harmonize technology with human creativity is becoming increasingly critical [4,21].

Evolution of Smart Manufacturing

The progression from Industry 1.0 to Industry 5.0 illustrates the transformative journey of manufacturing systems (Table 1):

- *Industry 1.0*: Mechanization through steam and water power.
- *Industry 2.0*: Mass production driven by electricity.
- *Industry 3.0*: Digitization via electronics and IT systems.
- *Industry 4.0:* Cyber-physical systems, IoT, and data analytics [19].
- *Industry 5.0 (emerging):* Human-centered and sustainable manufacturing integrating human creativity with machine intelligence [12].

Industry 4.0 has laid the foundation for connectivity and automation, while Industry 5.0 focuses on sustainability, resilience, and the integration of human values [14].

Figure 1 showed Evolution from Industry 1.0 to Industry 5.0.

KEY ENABLING TECHNOLOGIES

Digital Twin (DT) and Cyber-Physical Systems (CPS)

DTs create virtual replicas of physical assets that interact in real-time, supporting predictive maintenance and training [3,20]. Coupled with CPS, they form feedback loops where machines adapt autonomously.

Table 1. Comparative evolution of industrial revolutions (industry 1.0 to industry 5.0).

Industrial era	Key drivers	Core features	Representative technologies	References
Industry 1.0	Steam power, mechanization	Shift from manual labor to machines	Steam engines, textile mechanization	[19], [21]
Industry 2.0	Electricity, assembly lines	Mass production, specialization	Electrification, conveyor systems	[16], [21]
Industry 3.0	Electronics, IT systems	Automation and digitization	PLCs, robotics, CNC	[12], [19], [21]
Industry 4.0	Cyber-Physical Systems, IoT, AI	Smart factories, connectivity, automation	IoT, DT, multi-sensor fusion, cloud computing	[1], [3], [5], [7], [15], [20]
Industry 5.0	Human–machine collaboration, sustainability	Human-centricity, resilience, creativity	HIL, AIGC, smart materials, circular economy	[4], [7], [8], [14], [17], [22]

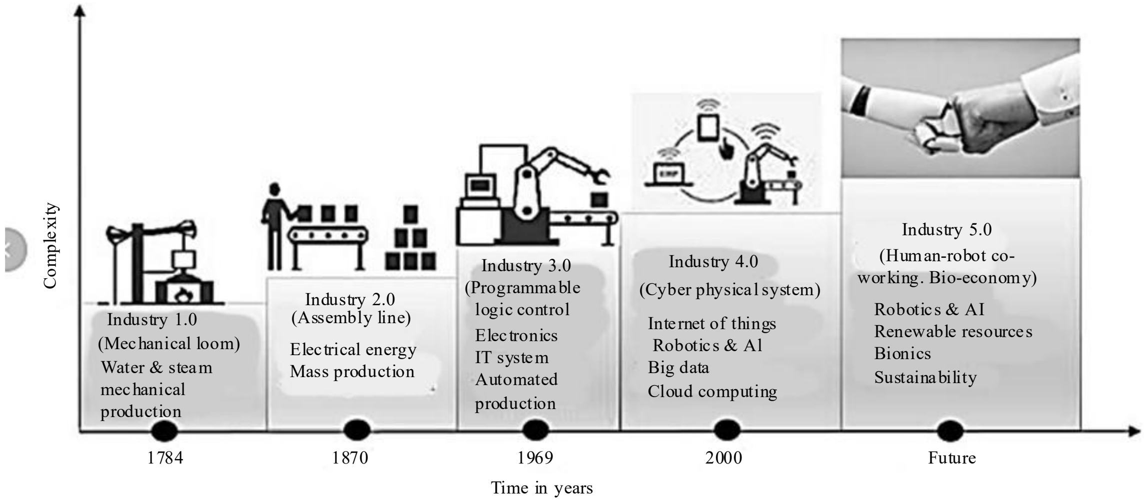

Figure 1. Evolution from industry 1.0 to industry 5.0.

Artificial Intelligence and AIGC

AI facilitates anomaly detection, optimization, and intelligent control, while AI-generated content (AIGC) extends its role to generative design and agentic workflows [8,22]. These innovations accelerate customization and improve decision-making in dynamic environments (Table 2).

Human-in-the-Loop (HIL)

Human collaboration remains essential. HIL systems integrate operator supervision with AI systems, supported by augmented and mixed reality platforms for interactive visualization [7,9].

Smart Materials and Packaging

Advances in smart packaging, such as nanocellulose hydrogels and Pickering emulsions, enable antibacterial, freshness-sensing, and biosensing functionalities [6,10,13,17,18]. These materials extend smart manufacturing concepts to food safety and sustainable packaging applications.

Multi-sensor Fusion and IoT

IoT-enabled systems and multi-sensor fusion enhance real-time monitoring of machine health and defect detection [1,15]. Acoustic emission, thermal imaging, and optical capture combined with cloud-based analytics ensure resilience and scalability [16].

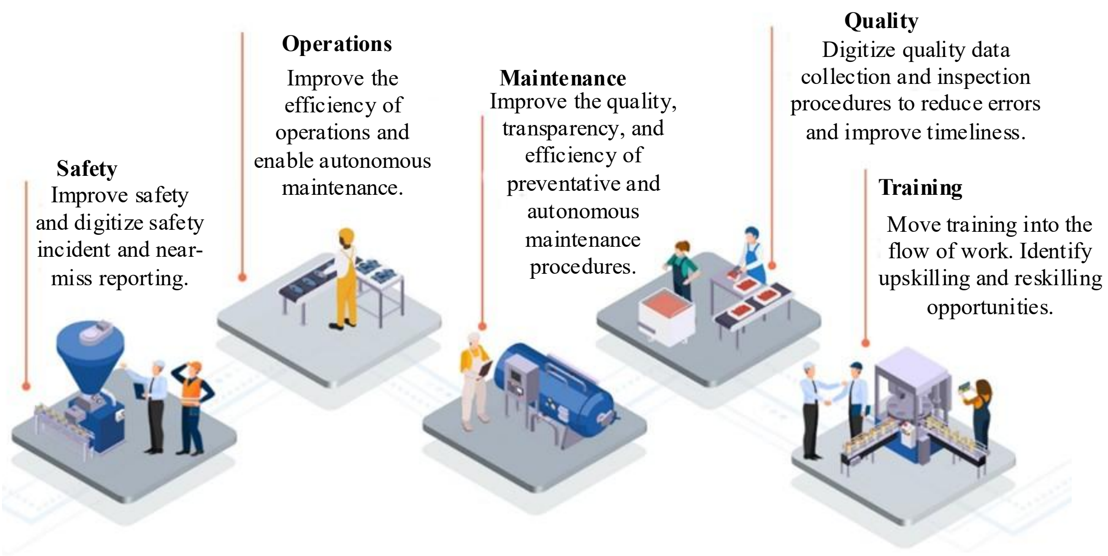

Figure 2. Core technologies enabling smart manufacturing.

Table 2. Key Enabling technologies in smart manufacturing.

Technology	Description	Applications	Limitations	References
Digital Twin (DT)	Real-time virtual representation of assets	Predictive maintenance, training, process optimization	High cost of deployment, data integration challenges	[2], [3], [20], [22]
AI & AIGC	Intelligent algorithms and generative design	Defect detection, adaptive design, intelligent decision-making	Data bias, explainability issues	[5], [8], [22]
Human-in-the-Loop (HIL)	Human oversight with AI collaboration	Mixed reality training, operator decision-support	Operator fatigue, interface complexity	[7], [9]
IoT & Multi-Sensor Fusion	Networked devices and combined sensing	Machine condition monitoring, real-time analytics	Cybersecurity risks, scalability	[1], [15], [16], [20]
Smart Materials	Nanocellulose, hydrogels, Pickering emulsions	Smart packaging, biosensing, freshness monitoring	Processing costs, stability concerns	[6], [10], [13], [14], [17], [18]

Table 3. Sustainability-oriented innovations in smart manufacturing.

Innovation	Contribution to sustainability	Industry application	References
Nanocellulose Hydrogels	Biodegradable and renewable packaging	Food packaging, sensors	[6], [17]
Pickering Emulsions	Reduced chemical stabilizers, eco-friendly films	Smart packaging, antibacterial coatings	[10], [13], [18]
Smart Hydrogels	Waste reduction, responsive sensing	Biosensing, wearable tech	[14], [17]
Circular Economy Models	Resource efficiency, waste minimization	Manufacturing ecosystems	[4], [16]
AIGC-driven Design	Lower prototyping waste, adaptive manufacturing	Automotive, electronics	[8], [22]

Figure 2 showed the Core technologies enabling smart manufacturing. Table 3 showed the Sustainability-Oriented Innovations in Smart Manufacturing.

RESEARCH GAPS AND CHALLENGES

Despite these advancements, critical gaps remain:

1. *Interoperability*: Lack of standardized protocols across industrial domains [12].
2. *Scalability*: Difficulty in extending pilot systems across global supply chains [5].
3. *Sustainability*: Limited integration of eco-friendly materials and circular economy models [6,14].
4. *Human–machine collaboration*: Underdeveloped frameworks for balancing automation with human creativity [7].
5. *Cybersecurity and ethics*: Growing vulnerability of interconnected systems to cyber threats [21].

These challenges underscore the importance of a multi-layered framework combining digital systems, materials innovation, and human-centric methods.

NOVELTY AND CONTRIBUTION OF THIS STUDY

This study provides a novel integrative perspective by synthesizing developments across digital twins, smart packaging, industrial software, and HIL systems. Its contributions include:

- Proposing a multi-layered smart manufacturing framework bridging industrial large models with adaptive sensing [22,8].
- Integrating materials research (e.g., nanocellulose packaging, hydrogels) with digital innovation [6,17].
- Advancing the discourse from Industry 4.0 toward Industry 5.0, emphasizing sustainability and human-machine synergy [4].
- Outlining pathways for resilient supply chains powered by intelligent decision-making [20,15].

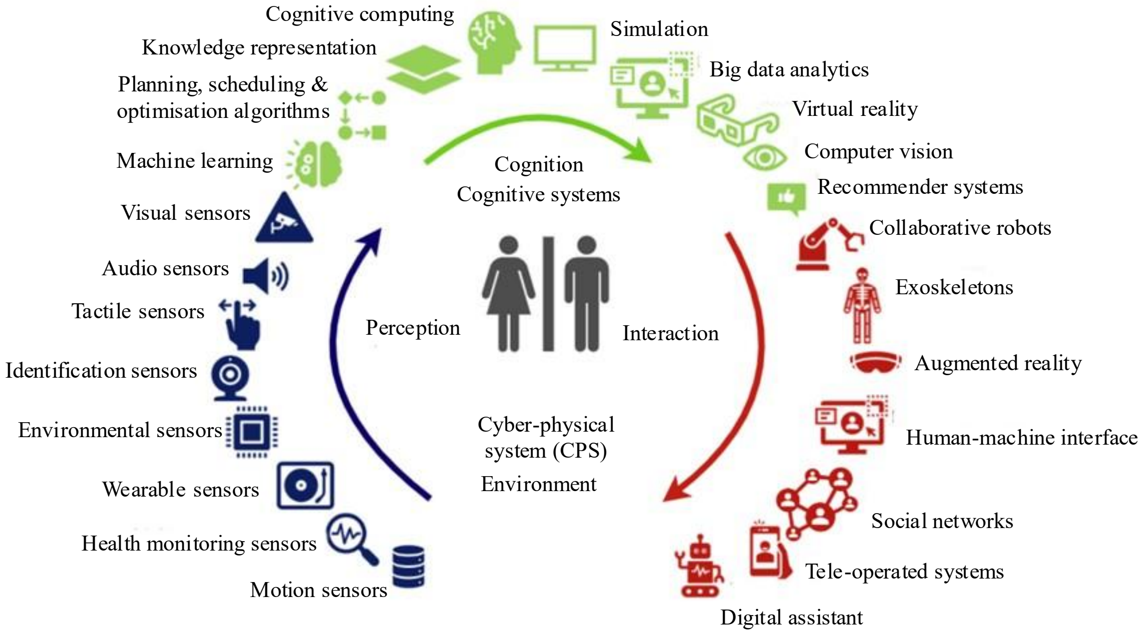

Figure 3. Human-in-the-loop collaboration in smart factories.

Figure 3 showed the Human-in-the-loop collaboration in smart factories.

LITERATURE REVIEW

Evolution of Smart Manufacturing Concepts in the foundation of smart manufacturing rests on the principles of connectivity, automation, and adaptability. The early stages of Industry 4.0 emphasized the convergence of cyber-physical systems (CPS) and the Internet of Things (IoT), enabling real-time data collection and analysis to improve efficiency [1]. As the concept evolved, integration with digital twins (DTs) introduced advanced synchronization between physical and virtual assets, promoting predictive maintenance and optimized production processes [2,3]. Research has demonstrated that DTs not only enhance operational efficiency but also foster immersive environments for training and knowledge transfer [4].\n\n Furthermore, the transition toward Industry 5.0 has shifted the focus to resilience, sustainability, and human-centricity, where humans and intelligent machines collaborate to create more sustainable and value-driven ecosystems [5,6].

This emerging paradigm emphasizes the importance of embedding human creativity into digital ecosystems to foster innovation. Digital Twin and Cyber-Physical Systems in Digital twins have been widely explored in manufacturing research for their potential to create real-time digital replicas of machinery and processes [3,7]. Studies indicate that DTs serve as the backbone for predictive analytics, simulation, and fault detection, making them indispensable for smart factories [2]. In parallel, CPS provide the infrastructure required for seamless feedback loops between digital and physical systems [8]. By integrating DTs with CPS, manufacturing operations can adapt autonomously, reducing downtime and increasing responsiveness. In Despite their promise, researchers have highlighted challenges in interoperability and scalability when deploying DT-based solutions across industries [9]. Addressing these challenges requires standardized protocols and adaptive frameworks that can operate in heterogeneous environments.

Artificial Intelligence and AI-Generated Content (AIGC), The incorporation of artificial intelligence (AI) in manufacturing has enabled breakthroughs in anomaly detection, optimization, and intelligent control [10]. AI has been particularly effective in improving defect detection using multi-modal sensing techniques such as acoustic emission, high-speed imaging, and thermal monitoring [1,11]. Recently, the concept of AI-generated content (AIGC) has emerged as an innovative approach to agentic workflows and generative design, providing adaptive solutions for dynamic production needs [12]. However, researchers point out that the deployment of AI and AIGC in manufacturing is often constrained by data privacy, cybersecurity, and trustworthiness of models [13]. These limitations must be addressed to ensure safe and ethical implementation in industrial environments.

Human-in-the-Loop (HIL) Systems while automation dominates Industry 4.0 narratives, human-in-the-loop (HIL) approaches remain essential for balancing automation with human oversight [4,14]. HIL systems enable humans to monitor, guide, and adjust automated systems, especially in scenarios requiring contextual judgment or ethical considerations. Research shows that integrating HIL with augmented and virtual reality platforms enhances operator situational awareness and decision-making [15]. Nevertheless, effective HIL deployment requires careful design of intuitive interfaces, training programs, and decision-support systems that empower operators without causing cognitive overload [14]. This is particularly relevant in Industry 5.0, where human-machine collaboration is a defining characteristic [6].

Smart Materials and Packaging In The extension of smart manufacturing concepts to materials science has introduced nanocellulose hydrogels, biosensors, and smart packaging technologies. Recent studies demonstrate the use of nanocellulose-based hydrogels for antibacterial and freshness-sensing applications [16]. Similarly, Pickering emulsions and nanocomposite hydrogels provide enhanced functionality in packaging and biomedical applications [17,18]. Research has also highlighted biosensing platforms for food safety and sustainability in packaging [19,20]. These advancements exemplify how smart materials contribute to manufacturing by linking material innovation with digital monitoring systems, thereby supporting sustainable production and the circular economy [21]. Yet, scalability and cost-efficiency remain barriers for widespread adoption.

Multi-Sensor Fusion and IoT in Multi-sensor fusion plays a central role in modern smart factories by integrating data from diverse sources, including thermal imaging, acoustic sensors, and optical systems [11]. Studies confirm that the fusion of heterogeneous data streams enhances defect detection accuracy and machine health monitoring [1,10]. IoT-enabled platforms further extend these capabilities by connecting machines to cloud-based analytics and industrial large models, enabling scalable and resilient solutions [22]. Despite the advantages, research has identified limitations in data interoperability, latency, and cybersecurity that hinder IoT deployment at scale [13]. Addressing these concerns is essential for achieving real-time, trustworthy, and secure industrial ecosystems.

Identified Research Gaps

The literature highlights significant progress but also reveals gaps:

- *Interoperability*: Need for standardized frameworks to integrate heterogeneous systems [9]. *Scalability*: Difficulty in extending pilot systems to global supply chains [22].
- *Sustainability*: Insufficient integration of eco-friendly materials and circular economy approaches [16,21].
- *Human–machine collaboration*: Limited frameworks balancing automation with creativity [14].
- *Cybersecurity*: Growing vulnerabilities due to interconnected industrial systems [13]. These gaps provide a clear motivation for developing integrated, multi-layered frameworks that align digital technologies, material innovations, and human-centric approaches (Table 4).

Summary of Literature Review

The literature demonstrates that digital twins, AI, smart packaging, IoT, and HIL frameworks form the backbone of smart manufacturing. However, their full potential can only be realized through integrative approaches that address interoperability, sustainability, and human-machine collaboration. Building on these insights, the present study proposes a novel framework that advances the transition from Industry 4.0 to Industry 5.0, emphasizing sustainability, adaptability, and resilience.

Table 4. Research gaps in smart manufacturing literature.

Area	Identified gap	Impact	References
Interoperability	Lack of standardized protocols across industrial platforms	Limits scalability of smart systems	[5], [12]
Scalability	Pilot projects rarely scale globally	Reduces adoption in multinational firms	[5], [15], [20]
Sustainability	Limited eco-material adoption	Hinders green manufacturing transitions	[6], [13], [14]
Human–Machine Collaboration	Inadequate balance between automation and creativity	Reduces workforce adaptability	[7], [9]
Cybersecurity	IoT and CPS vulnerable to attacks	Risk of data breaches and production downtime	[16], [21]
Education & Training	Limited use of DT in immersive education	Skill gaps in future workforce	[2], [9]

CONCLUSIONS

Smart manufacturing represents a transformative leap toward creating intelligent, adaptive, and sustainable industrial ecosystems. While existing research spans digital technologies, advanced materials, and human-centered methods, the challenge lies in harmonizing these diverse domains into a unified vision. This paper addresses this need by proposing a multi-layered framework that emphasizes interoperability, sustainability, and human–machine collaboration, thereby paving the way for the realization of Industry 5.0 paradigms.

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