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SMART MANUFACTURING ON THE HORIZON: A Conceptual Shift from Industry 4.0 to Industry 5.0: Industrija

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The Future of Smart Manufacturing - Integration, Intelligence and Innovation

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Abstract: *Smart manufacturing represents the confluence of digital transformation and industrial evolution, redefining manufacturing paradigms through seamless integration, artificial intelligence (AI)-driven intelligence, and continuous innovation. This paper explores the future development of smart manufacturing, highlighting the synergistic interaction of Cyber-Physical Systems (CPS), Industrial Internet of Things (IIoT) and Advanced Analytics (BDA) to create adaptive, resilient and sustainable factories. Central to this vision is technology integration, which enables full visibility into supply chains, machines and business systems through standardized protocols and architectures from the edge to the cloud. Intelligence emerges through machine learning (ML), digital twins (DT) and generative artificial intelligence (GenAI), developing predictive maintenance (PrM), autonomous quality control (AQC) and real-time optimization. Innovation is manifested in revolutionary applications – additive manufacturing (AM), human-robot collaboration (cobot) and biologically inspired manufacturing models – that challenge conventional limitations of scalability and customization. Despite progress, significant challenges remain: interoperability gaps, cybersecurity vulnerabilities, workforce skills shortages, and ethical issues related to AI autonomy. The paper critically examines these obstacles while presenting practical ways forward, including modular architectures, federated learning and policy frameworks for responsible adoption. Looking ahead to 2035, the analysis predicts a shift towards Industry 5.0, dominated by human-centric systems, circular economy (CE) and quantum-enhanced systems. Synthesizing current research, industry case studies and emerging trends, this paper provides a strategic roadmap for stakeholders to navigate the next decade of intelligent manufacturing.*

Keywords: *Smart Manufacturing, Industry 4.0, AI Integration, Digital Twins, IIoT, Sustainability, Cyber-Physical Systems*

1. Introductory Notes

The evolution of manufacturing reflects humanity's progressive mastery of tools, energy and information, moving from manual craftsmanship to intelligent, interconnected ecosystems. Industry 1.0 (late 18th century) was created by the mechanization of textile production, driven by water and steam engines, enabling mass production through standardized processes [1]. Industry 2.0 (early 20th

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century) introduced electricity and assembly lines, epitomized by Ford's conveyor belt system, which dramatically increased throughput and reduced costs through the division of labor and interchangeable parts [2]. The emergence of Industry 3.0 (from the 1970s onwards) marked the era of automation, powered by programmable logic controllers (PLCs), robotics and early computing. This phase moved manufacturing from analog to digital control, enabling flexible manufacturing systems (FMS) and computer integrated manufacturing (CIM) [3]. However, the systems remained largely isolated (islands), with limited real-time data exchange. Industry 4.0, formalized in 2011 by the German government [4], represents a paradigm shift towards cyber-physical systems (CPS) – networks of embedded sensors, actuators and software that enable machines to perceive, decide and act autonomously. Key technologies Industrial Internet of Things (IIoT), cloud computing, big data analytics (BDA) and additive manufacturing (AM) have led to this development. Smart manufacturing, which in practice is often used interchangeably with Industry 4.0, is defined by the American National Institute of Standards and Technology (NIST) as "fully integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, supply network and customer needs" [5]. The new discourse on Industry 5.0 [6] revises the human role, emphasizing human-artificial intelligence (AI) collaboration, resilience and sustainability. In contrast to the technological focus of Industry 4.0, Industry 5.0 prioritizes social value, circular economies (CE) and personalized manufacturing. Smart manufacturing therefore evolves from connectivity (4.0) to cognitive, adaptive and value-driven systems (5.0), laying the foundations for the integrated, intelligent and innovative future explored in this paper.

Defining the problem: Despite the transformative potential of Industry 4.0 and the new vision of Industry 5.0, modern manufacturing systems are still hampered by systemic fragmentation, operational inefficiencies and scalability bottlenecks, which undermine competitiveness, resilience and sustainability. The main challenge is the existence of silos of data and functionality – disconnected islands of automation in design, manufacturing, logistics and enterprise resource planning (ERP) systems. According to Deloitte research [7], 68% of manufacturers still work with legacy systems that lack real-time interoperability, resulting in delayed decision-making, redundant data entry and error-prone manual interventions. Inefficiencies manifest in many forms: unplanned downtime (800 hours per year on average per facility, according to [8]), energy waste due to suboptimal process control, and quality deficiencies resulting from reactive rather than predictive monitoring. Supply chain volatility—exacerbated by geopolitical disruptions and post-pandemic recovery—further exposes the fragility of linear, "just-in-time" models that lack adaptive intelligence. Scalability issues arise when trying to deploy smart technologies after the pilot stages. High start-up costs (73% of firms

report a shortage of digital talent, [9]) and resistance to change. Furthermore, small and medium-sized enterprises (SMEs), which account for over 85% of the global manufacturing base,have difficulty integrating advanced solutions due to limited infrastructure and standardized frameworks. Without addressing barriers to integration, proactive intelligence scalable innovation, manufacturers risk obsolescence in an era that requires hyper-customization, net-zero operations, and real-time response to dynamic market and environmental pressures. This paper confronts these shortcomings in order to chart a strategic way forward.

Research Objectives and Research Questions: This paper provides a forward-looking, integrative analysis of smart manufacturing to guide industry transformation over the next decade (2025–2035.). It bridges theoretical frameworks with practical roadmaps, emphasizing the triad of integration, intelligence and innovation as the main drivers of the maturation of Industry - Industry 4.0 and the emergence of Industry 5.0.

The primary goal is to articulate a comprehensive vision of next-generation smart manufacturing by synthesizing current technology capabilities, identifying barriers to adoption, and anticipating evolutionary pathways toward resilient, human-centered, and sustainable manufacturing ecosystems. *The partial objectives* are: (a) examine the integration mechanisms that enable seamless connectivity between cyber-physical systems, supply networks, and enterprise layers, (b) assess the role of artificial intelligence in the transition from automation to autonomous, cognitive manufacturing, (c) explore advanced innovations, including additive manufacturing, bio-digital convergence, and circular manufacturing models—and their scalability potential, and (d) assess socioeconomic and environmental challenges (labour reskilling, energy efficiency, ethical artificial intelligence management) and suggest mitigation strategies. *The guiding research questions* are: *RQ1:* How can horizontal and vertical integration eliminate data silos and enable real-time, end-to-end visibility in complex manufacturing environments? *RQ2:* In what ways will AI-driven intelligence—via digital twins, generative design, and autonomous decision systems—transform operational efficiency and product personalization? *RQ3:* What new innovations will redefine manufacturing paradigms and how can they be scaled across different enterprise sizes and regions? *RQ4:* What are the key enablers and barriers to achieving sustainable, resilient and human-centered smart factories within Industry 5.0? RQ5: How will integration, intelligence, and innovation come together to shape manufacturing competitiveness, workforce dynamics, and environmental impact over the next decade?

2. Defining the Context of Smart Production

The journey towards smart manufacturing can best be understood through four distinct industrial revolutions. Milestone 1 was Industry 1.0 – mechanization and steam power (late 18th century). The key change was the transition from manual production methods to production on machines powered by water and steam. This led to the creation of the "factory system", as production was centralized, leading to the mass production of goods such as textiles. It was a transition from craft work to mechanized work. Milestone 2 was Industry 2.0 – electrification, mass production and the assembly line (pioneer Henry Ford) [11] (late 19th - early 20th century), which enabled more flexible factory machine layouts and division of labor. Mass production became the gold standard, and the assembly line [12] drastically reduced production costs and made goods like cars affordable to the masses. This era also marked the introduction of concepts such as scientific management (Taylorism) to optimize human work. This model added "nervous system" (electricity) and "process" (assembly line) to the industrial muscle. Milestone 3 was Industry 3.0 – Automation, Computers and Robotics (1970s - 1990s), where the invention of the programmable logic controller (PLC) and the rise of electronics and computers were the main features of this era. A key change came from the integration of digital technology and automation into manufacturing processes [13], where the PLC replaced complex relay systems, facilitating the automation of individual machines and processes. Industrial robots have begun to perform dangerous, repetitive or precise tasks (automotive welding and painting). The development and implementation of IT systems for enterprise resource planning (ERP) and work order management systems (MES) began, which started the digitization of business operations and the management of production plants. Thus, these systems have become "islands of automation". A robot or CNC machine was automated, but could not communicate with other systems. This was "the brain" - the introduction of digital control and computation, but the brain could not easily communicate with other brains or the body. Thus we have reached the dawn of smart manufacturing: the Era of Industry 4.0 (2000s - today), where the concept of "smart" appears. Industry 4.0 is characterized by the fusion of the physical and digital world through cyber-physical systems (CPS) [14]. In this period, there was a convergence and maturation of several basic technologies that form the backbone of smart production, Figure 1 [15]: (a) Industrial Internet of Things (IIoT) - installation of sensors in machines, tools and products to collect data in real time.

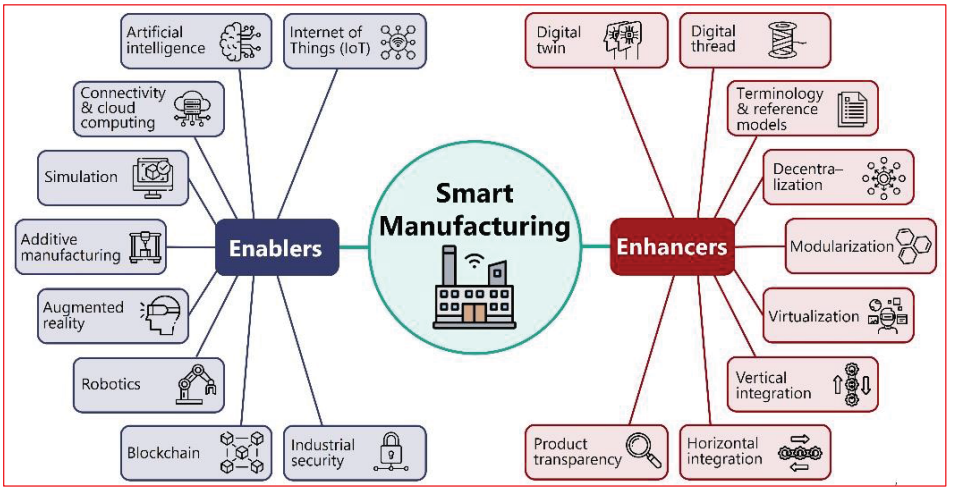

Figure 1. Smart manufacturing model structure [15]

This is the nervous system of the smart factory, (b) big data and advanced analytics (BDA) - the ability to store and process vast amounts of data generated by the IIoT to gain insights, predict failures and optimize processes, (c) cloud/edge computing - providing the scalable, affordable computing power needed to analyze data and connect global operations, in real time, (d) artificial intelligence (AI) and machine learning (ML) - moving from descriptive analytics to predictive and prescriptive actions. AI can optimize production schedules, perform quality control via computer vision and predict maintenance needs (predictive maintenance), (e) additive manufacturing (3D printing) - moving from mass production to mass customization and rapid prototyping, enabling complex geometries and on-demand production, (g) digital twin (DT) - creating a virtual, dynamic replica of a physical asset or process,

3. Defining The Framework of the Smart Production Concept (Integration, Intelligence, Innovation)

Integration (ERP, MES, vertical/horizontal). Integration in smart manufacturing is a strategic and technological practice of seamlessly connecting all systems, data and processes throughout the value chain to create a unified, transparent and fast operation [16]. The central nervous system makes the factory "smart". Without deep integration, technologies like the Internet of Things and artificial intelligence operate in isolation, failing to realize their full transformative potential. The essence of this integration lies in the vertical and horizontal connection of three critical systems: ERP (Enterprise Resource Planning), MES (Work Order Management) and Supply Chain Platform (SCM). The ERP system

is the business brain of the enterprise, managing operations at the business level - finance, human resources, procurement, order management and high-level planning [17]. It answers the question: "What should we produce, at what price and when? It uses low-frequency (cloud computing), high-context business data (customer orders, financial forecasts, raw material orders). MES is the nervous system of the production plant, which monitors, monitors and controls the production process in the production plant [18]. It is the bridge between planning (ERP) and physical operations (OT). It answers the question: "How do we make it, is it according to specification and how far have we come in production? It uses high-frequency (edge computing), operational data (machine status, material consumption, production in progress). And finally, supply chain management (product life cycle management), represents the external connective tissue in this model in warehouses, Product BOMs (BOMs) and engineering change orders. Integration is not just connecting cables, the smart manufacturing model is about creating a continuous, two-way flow of contextualized data. *Vertical integration* is a model that connects the production plant (MES and OT) and all levels up to the top of the enterprise (ERP) [19], Figure 2. The smart integration of production is realized according to the following model - ERP → MES, where a detailed production order is sent, including the specific version of the product, BOM and technological manufacturing process. MES → ERP, provides real-time feedback (edge computing) on order progress, material consumption, produced quantity and work tracking. The moment the planned quantity is produced, the quality check is completed, the work order (WO), the ERP system closes for this WO, with the following facts: (a) real-time costing with actual material and labor consumption, (b) finished goods inventory update is done in real-time, and (c) real-time delivery tracking. *Horizontal integration* is integration throughout the supply chain, from suppliers to customers. Smart manufacturing integration, at this level, starts with connecting to suppliers, so that the manufacturer's MES or ERP, via EDI (Electronic Data Interchange) or API, automatically initiates replenishment orders to suppliers based on real-time consumption data. Suppliers can see manufacturers' inventory levels and production schedules, enabling vendor-managed inventory (VMI) and just-in-time delivery. Connecting with customers is done in such a way that customers can access real-time order status portals or even influence production scheduling. This is the basis of mass customization. PLM integration is performed in such a way that when an engineer finalizes a change to a product design in the PLM system, that change is made automatically transfers to ERP (BOM Update) and MES (Work Order Update), ensuring the factory is always building the latest version. According to the concept presented, integration is the driver of key features of smart manufacturing: (a) end-to-end product visibility and digital thread, because integration creates a "digital thread" - a single, seamless flow of data that connects every aspect of a product's life cycle, from design to disposal.

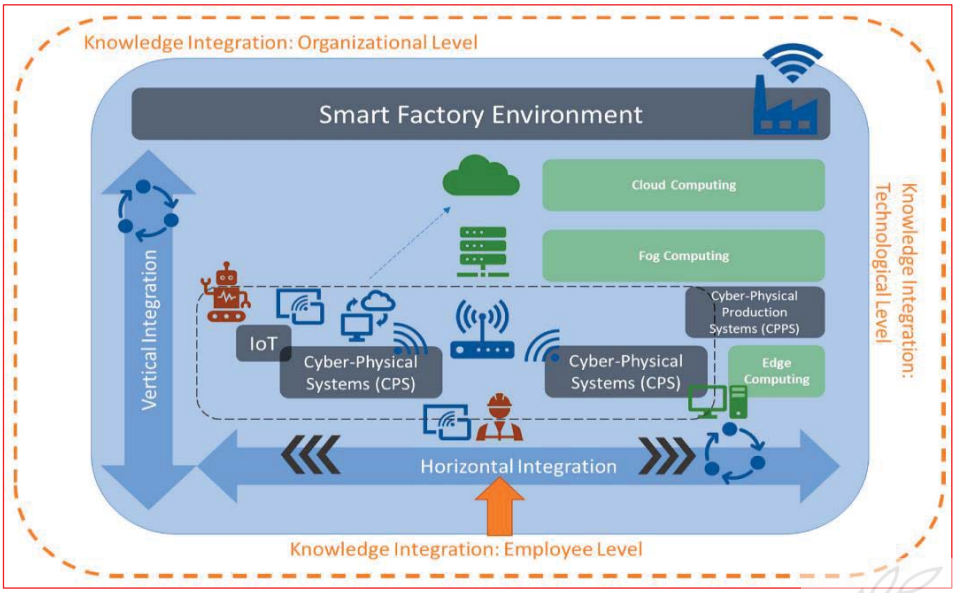

Figure 2. Model and integrations in smart manufacturing [19]

This provides an unprecedented possibility for traceability of all aspects of production, so if a quality problem arises, you can trace it to a specific batch of raw materials, the machine that produced it and the operator on the shift, (b) agile and fast production operations, with real-time data from the production plant (edge computing), the company can immediately react to disruptions. Machine failure automatically triggers order rescheduling in ERP and then informs suppliers of delays in material needs, (c) data-driven decision making, where integration breaks down data silos, creating a single database. This model is now the basis for advanced analytics and artificial intelligence (AI), where an AI algorithm can optimize the entire production plan, if it has access to data from ERP (orders, costs), MES (machine availability, setup time) and SCM (supplier constraints), (d) efficient resource management, where we have real-time material consumption data from the MES, thus preventing both overstocks and stock shortages. Real-time energy monitoring integrated with production scheduling allows optimization of energy consumption, and (e) mass customization, means that in order to profitably produce a " one-piece-sized batch", it also forms a system that must be synchronized. ERP receives a custom order, PLM provides a single BOM and instructions, and MES orchestrates the line to build that particular product non-stop. This is impossible without seamless integration. *The challenges of successful integration* can be defined as [20]: (a) outdated systems, because many factories have decades-old machines and software that were not designed to connect. Retrofitting or bridging these systems is complex and expensive, (b) data

silos and culture - departments may be resistant to sharing data, fearing a loss of control. The cultural shift towards collaboration is as important as the technological one, (c) interoperability - different systems speak different "languages" (protocols). ERP from SAP, MES from Siemens and legacy PLCs from the 1990s all need a common way of communicating, and (d) cyber security, where every new connection point is a potential vulnerability. A secure integration architecture is undeniable and essential. The key technologies that support this concept are: (a) standardized communication protocols - OPC UA (Open Platform Communications Unified Architecture), which provide a secure framework for data exchange, independent of the manufacturer, from the sensor level to the cloud/edge, (b) APIs (application programming interfaces) - modern cloud-based systems, which rely heavily on RESTful APIs, which are the standard method for communicating different software applications over the Internet, (c) midlever and integration platforms (iPaaS) - tools like MuleSoft or Azure Integration Services act as translators and routers, connecting different systems and transforming data formats between them, (d) cloud/edge - where platforms act as a central hub, facilitating the connection of systems that were previously locked behind corporate protective passwords. They provide scalable computation and storage for the vast amounts of data generated by the integration, and (e) a digital twin - the DT of the production process is both the consumer and the result of the integration. It needs direct transfer of integrated data from ERP, MES and PLC to accurately reflect the physical world. In conclusion, we can say that integration is not a side actor in smart production, it is the main protagonist. It transforms a collection of automated islands into a cohesive, intelligent and self-optimizing organism. While the challenges are significant, the result is a level of operational efficiency, agility and insight that was previously unimaginable. The journey to a truly smart factory does not begin with the purchase of a single advanced robot, but with the strategic and meticulous weaving of the digital thread that connects every asset, process and decision maker.

Intelligence (AI/ML, predictive maintenance, quality control, generative design). Intelligence in smart manufacturing represents a leap from automated to cognitive operations and systems. It is the ability of a production system to learn from data, reason about complex situations, predict future states and make (or recommend) optimal decisions with minimal human intervention. This was developed by bringing together artificial intelligence (AI), machine learning (ML) and predictive analytics (PA), transforming data from a historical record into a proactive, strategic asset. *Predictive analytics* uses historical data and statistical models to predict what is likely to happen. ("based on past vibration patterns, this bearing has an 85% chance of failing within the next 14 days."). *Machine learning* (ML) is a subset of AI, which uses algorithms to analyze data, learn from it, and make decisions or predictions without explicitly programming for that particular

task. The results of learning, and thus of decision-making, are automatically improved through experience. *Artificial intelligence* (AI) is a broad discipline, which as a broader concept of a machine, which has the ability to perform tasks in a way that we would consider "intelligent". ML is the primary way we currently use AI. In manufacturing, this culminates in systems that can perceive, reason and act. Intelligence is not a monolithic system but a set of capabilities applied to specific production domains. *Predictive maintenance (PdM)* is an intelligent approach, as machine learning models analyze sensor data in real time (vibration, temperature, acoustic emissions, wear, power consumption) to detect anomalies and predict failures before they happen, Figure 3 [21].

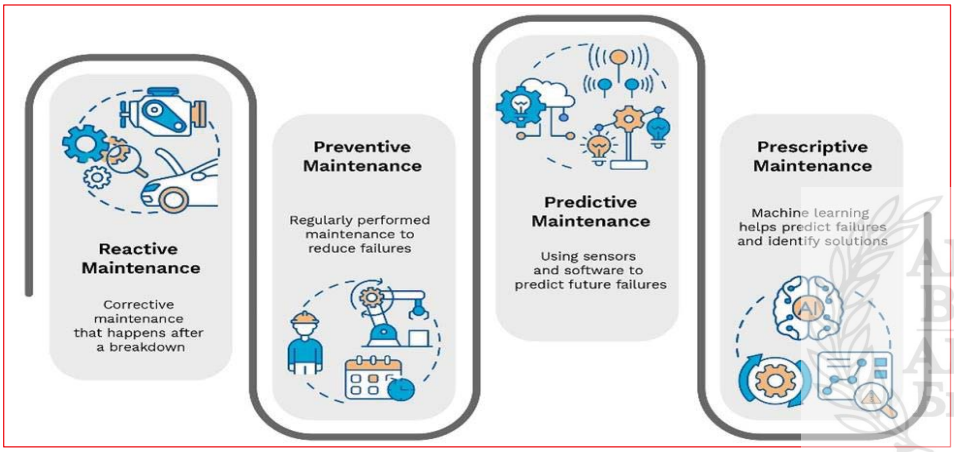

Figure 3. Development of the maintenance model

Using deep data analysis models, such as recurrent neural networks (RNNs), which are extremely good at learning from time series data. They don't just see a high temperature; they learn the complex sequence of events—a slight increase in vibration, followed by a subtle thermal shift, and then a specific increase in energy consumption—that precedes a particular type of failure. In other words, they perform a multifactorial analysis of causes and consequences. This model (PrM) [22], drastically reduces unplanned downtime, extends asset life, optimizes spare parts inventory and shifts maintenance from a cost center to a reliability function. AI-based *quality control* is an intelligent approach that uses computer vision and convolutional neural networks (CNNs) to analyze high-resolution camera images to detect defects that are often invisible to the human eye. The system is trained on thousands of images of "good" and "bad" products. It learns to identify complex, non-linear patterns of defects – microcracks, subtle color changes or misalignments. Unlike a human, it works with 100% consistency, 24/7, without fatigue. Thus, we get "zero scrap" and the ability to trace defects to their root cause

in the process ("95% of defects occur when machine 3 is operating outside parameter set B"), Figure 4 [23].

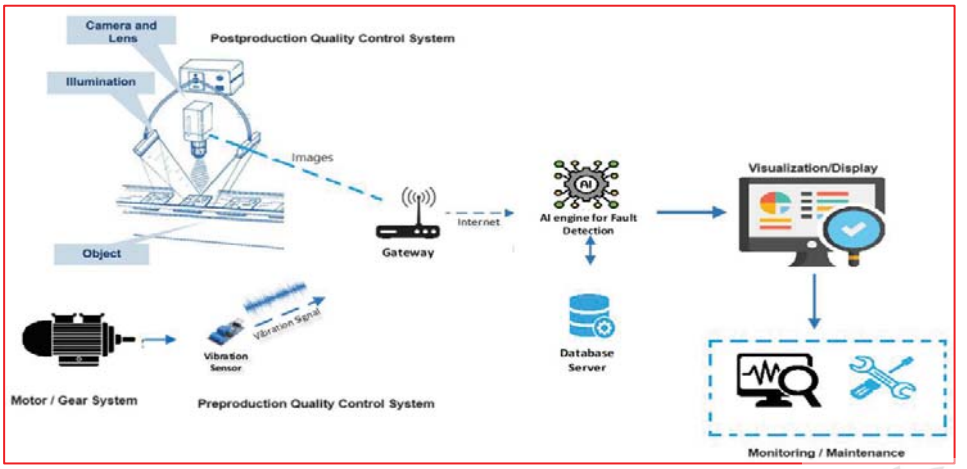

Figure 4. Intelligent Framework for Quality Control in Industry 4.0

Generative design and process optimization guided by artificial intelligence, is based on the application of concepts, where engineers define design goals (weight, strength, material, cost limits), and AI algorithms generate thousands of valid alternative solutions, often giving original, highly efficient forms that a human cannot imagine. Process optimization, uses "reinforcement" learning algorithms, where optimal solutions for the production process are "learned" by generating virtual experiments using digital twins (DT). They continuously adjust the parameters (temperature, pressure, speed) in order to achieve the best result (highest number of produced pieces (productivity), lowest energy consumption), and this knowledge is then applied to the real production line. Radical innovations in product design ensure significant material savings and continuous, autonomous optimization of complex, multivariable production processes. *Self-optimizing supply chains,* based on an intelligent approach, use machine learning models, which analyze a wide range of internal and external data - real- time order flow, weather patterns, geopolitical events, traffic data, supplier risk - to predict disruptions and dynamically reroute logistics, adjust production schedules and reallocate inventory. This creates a resilient, demand-driven supply chain that can anticipate and absorb shocks, minimizing inventory and excess inventory. The basic *prerequisites for the development and application of an intelligent model* in this area are, Figure 4: (a) a reliable and large enough database, because AI/ML models are big consumers of high-quality, contextualized data, (b) they are reached through integration (previous chapter), because data must flow

seamlessly from machines (IoT sensors), MES, ERP and SCM systems to form a complete picture of the model, (c) data management means that clean, labeled and reliable data is indisputable, inconsistent data must be discarded, (d) cloud/edge computing support is essential, as training complex ML models, especially deep learning networks, requires massive computing resources, which are easily provided by cloud platforms and edge computing devices, and (e) domain expertise is essential, as IT experts must collaborate with production engineers, operators and maintenance technicians who understand the process physics and data context. This partnership is necessary for feature selection and interpretation of results. That is why *the development and application of an intelligent model has several stages* (5 in total) [24], from descriptive analytics to autonomous operation, which at the same time represent the maturity curve of this model. Level 1: Descriptive analytics - "what happened?" (Reporting, dashboards). Level 2: Diagnostic analytics - "why did it happen?" (Analysis of causes). Level 3: Predictive analytics - "what will happen?" (Focus of this analysis). Level 4: Prescriptive analytics - "what should I do about it?" (Automatic intelligence recommends actions). Level 5: Autonomous operations - "the system operates by itself." (Automatic intelligence automatically executes the optimal action, such as a self-adjusting production line - CPS). Smart manufacturing refers to the last two levels.

The challenges and ethical dimensions of this field are: (a) the "black box" problem, where some complex machine learning models (such as deep neural networks) can be incomprehensible, making it difficult to understand why a certain decision was made. This is a major obstacle in safety-critical industries (pharmaceutical, process, military), (b) data quality and availability is the single biggest obstacle, especially for older machines, (d) skills and knowledge shortages, as there is a severe shortage of experts with both data science skills and manufacturing knowledge, (e) change management, as workers may fear that AI will make their jobs obsolete, requiring a thoughtful strategy to retrain and demonstrate how AI augments human capabilities, rather than it replaces them, and (f) security and ethics of AI, because as systems become more autonomous, ensuring their safe operation and making ethical decisions (when allocating resources during a crisis, etc.) becomes paramount. Ultimately, intelligence is the fundamental pillar of smart manufacturing that ensures its full potential. It's moving the industry beyond just doing things faster and cheaper, to doing things significantly better and in entirely new ways. By embedding AI/ML into the very fabric of production, manufacturers gain not only efficiency, but also agility, resilience and a strong new capacity for innovation. The ultimate goal is a symbiotic relationship, where human creativity and strategic oversight are enhanced by tireless, data-driven cognitive systems, creating a future of manufacturing that is not just smart but wise.

Innovations (additive manufacturing, cobots). While the other pillars of smart manufacturing, integration and intelligence, focus on optimizing existing production paradigms, *innovation* is the pillar that fundamentally transforms it. It's about adopting and adapting revolutionary technologies that redefine what's possible in design, manufacturing and the very nature of the factory floor. Innovation in this context goes beyond simply increasing efficiency. It enables new business models, creates unprecedented product capabilities, and reshapes the relationship between workers and machines. Two of the most powerful expressions of this innovative spirit are additive manufacturing (AM) and advanced human-robot collaboration (HRC), Figure 5 [25].

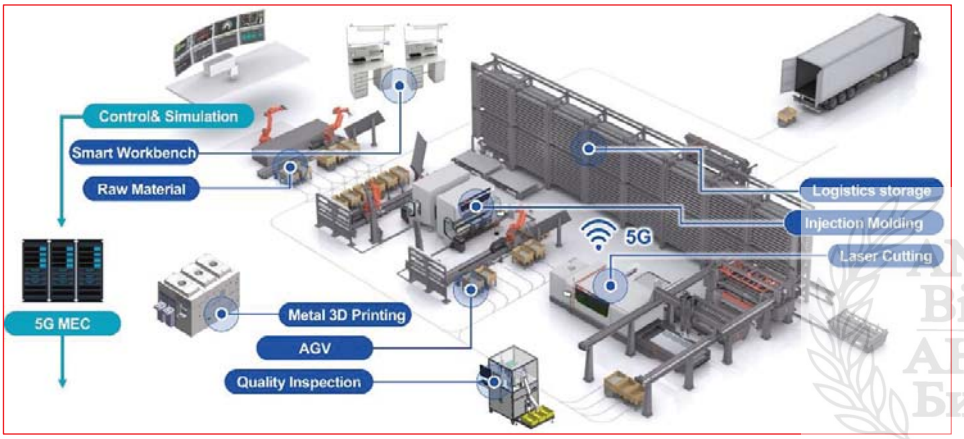

Figure 5. Innovation smart manufacturing [25]

Additive manufacturing is not just a new way of making parts, it is a philosophical shift from subtractive and formative manufacturing (cutting, milling, shaping) to an additive process, building parts layer by layer from digital models. The innovative shift is reflected in the following facts [26]: (a) from design for manufacturing (DFM) to manufacturing for design (MFD). Traditional manufacturing imposes design limitations (inclination angles for molds, tool access paths). AM removes many of these limitations, allowing engineers to design for pure function, (b) from mass production to mass customization, where the economics of AM are decoupled from the scale of production. The production of one unique part is as economically viable as the production of ten identical ones, breaking the centuries-old dominance of the assembly line for certain applications. This concept (AM) has had a profound impact on the manufacturing value chain, product innovation and weight reduction, from the following angles: (a) generative design synergy, where AM physically enabled generative design. AI can create complex, organic and topologically optimized structures that are

traditionally impossible to produce, and AM concept manufacturing can produce them. This is revolutionary in aerospace, automotive and medical implants, where weight reduction leads directly to part performance and efficiency in use, (b) parts consolidation, means that a complex assembly of dozens of parts can be redesigned and printed as a single, integrated component. This reduces assembly time, eliminates potential failure points (fasteners, gaskets) and improves overall operational reliability, (c) digital inventory and make-to-order, where instead of storing physical spare parts in warehouses around the world, companies only need to store digital CAD files and print parts locally and to order. This drastically reduces inventory costs, CO_2 emissions from logistics and delivery time, while mitigating disruptions in the supply chain, and (d) distributed manufacturing, where the concept of a centralized mega-factory is challenged. AM enables a network of smaller, localized "micro-factories" that can quickly respond to regional demand. A particularly important aspect of AM is reflected in tooling and prototyping, from two angles: (a) rapid tooling, where accessories and their components can be printed overnight, speeding up changes and adaptation of production lines, in the morning, at the beginning of the work shift, and (b) functional prototyping, where we have that prototypes are no longer just visual models, they can be full-power functional parts made from final production material, drastically shortening product development cycles. *Human-Robot Collaboration (HRC)* refers to the development and application of cobots [27]. Traditional industrial robots are powerful, precise and dangerous, requiring isolation in safety cages. HRC, primarily through collaborative robots (cobots), breaks this paradigm by creating a shared workspace where humans and robots work together, using their strengths. The innovative shift is reflected in the development of the paradigm - from automation to augmentation. The goal is not to replace the worker, but to increase his opportunities. The system uses human cognition, dexterity and problem-solving skills, along with robotic strength, precision and endurance. Cobots have made a profound impact on factory operations, through three aspects: (a) ergonomics and safety, where cobots are designed with force-limiting sensors and have rounded edges to stop accidental contact, making them inherently safer. Also, they take on "3D" tasks - boring, dirty and dangerous - such as heavy lifting, repetitive work overhead or handling hazardous materials, reducing worker fatigue and injury, (b) improved flexibility and skill enhancement, where we have that unlike fixed automation, cobots are mobile and easily reprogrammed. One cobot can perform multiple tasks during the day – screwing in the morning, packaging in the afternoon and quality control in the evening. Also, they act as a force multiplier for skilled workers, where an experienced technician can guide the cobot through a complex assembly process by demonstration (programming through guidance) and the cobot can then replicate it with perfect consistency, enhancing the technician's expertise, (c) hybrid work cell, which is the physical manifestation of HRC. In a hybrid

workcell, a human can perform complex, variable tasks (final assembly, inspection), while a cobot performs precise, repetitive subtasks (applying glue, holding parts, presenting components). This creates a symbiotic relationship that is more productive and adaptive than if a human or robot were working alone. *The synergistic power of combined innovations* is reflected in the fact that real transformative power is realized when these innovative pillars are connected to each other and to the wider ecosystem of smart production. Here are some examples: (a) AM + HRC, where a cobot is used to post-process a 3D printed part (polishing, cutting) or to load and unload multiple AM assemblies, creating a flexible, seamless cell for the digital production of parts, (b) AM + intelligence, where we have AI algorithms able to monitor the AM process in real time (using computer vision and thermal sensors) to detect anomalies such as voids or bends and correct process parameters in gait, ensuring the quality of the first part, and (c) HRC + Intelligence, where we have that computer vision and AI enable the cobot to perform complex picking from containers (identifying and grabbing disordered parts from containers) and adaptive assembly, where it can adjust its actions based on small variations in the parts that a human presents. *The application of these innovative technologies is not without significant obstacles* : (a) the economy and the required knowledge for application are reflected in the fact that new business models need to be developed, because companies must change their value proposition, from the sale of physical products to the potential sale of "part as a service" or digital files, (b) the workforce needs retraining, engineers need training in AM design, and operators must become programmers and supervisors of cobots, not just physical workers. Technical obstacles relate to: (a) AM limitations, reflected in the fact that speed, material properties, surface finish and multi-material printing are still areas of active development of AM technology in application, (b) HRC complexity, as truly seamless collaboration requires advanced perception and AI, for the robot to understand human intent and operate safely in dynamic, unstructured environments. Finally, there are cultural and organizational changes, as trust must be built between workers and collaborative robots. Management must foster a culture of experimentation and accept that the return on investment for innovation can be in strategic agility and new markets, not just in outright replacement of the workforce. Finally, in conclusion we can say that the pillar of innovation moves smart production from the theory of optimization to the practice of transformation. AM defines new rules of design and supply chains, while human-robot collaboration redefines the factory floor as a dynamic, hybrid space of human and machine intelligence in an advanced form of collaboration. Together, they enable a future of manufacturing that is not only more efficient but also more agile, sustainable and human-centered. These are key technologies that enable companies to respond to hyper-customization demand, build resilient supply chains and create higher-value jobs, ultimately providing a competitive advantage in an evolving global environment.

Factories that master this concept will not only be smarter, they will be fundamentally different.

4. Interoperable Smart Production Models

Interoperable models provide horizontal and vertical data integration in smart manufacturing. *RAMI 4.0* is a three-dimensional model developed in Germany for the standardization and structuring of the application of Industry 4.0 [28]. It provides a reference architecture for the integration of technologies, processes and systems in smart manufacturing. The model is designed to ensure interoperability, scalability and uniform application across industries. It has three axes: hierarchy levels (vertical axis), life cycle and value stream (horizontal axis), and layers (depth axis). *The NIST (National Institute of Standards and Technology)* smart manufacturing ecosystem is a framework developed in the United States of America for the advancement of smart manufacturing through interoperable, secure and scalable systems [29]. Emphasizes standards, reference architectures, and test platforms to enable data-driven manufacturing. It has the following components: product life cycle, cross-cutting issues, supporting technologies and reference architecture. NIST develops standards (NIST SP 800-82 for Cybersecurity) and reference models to ensure interoperability. The focus is on open standards to avoid vendor lock-in. *Cyber-physical production systems (CPPS)* are the backbone of Industry 4.0, which integrate physical production processes with digital systems through cyber-physical systems (CPS) [30]. CPPS refers to networked, smart systems that connect sensors, actuators, control systems and computing systems to enable real-time adaptive manufacturing. CPPS is not a single framework, but a conceptual model with the following components: physical layer, cyber layer, communication layer, human-machine interaction, and control and optimization. A comparison of the basic characteristics of these three models is given in Table 1 [28-30].

The relevance and trends of these models are reflected in the following facts: (a) framework convergence, which is reflected in the fact that there is a growing trend of harmonizing the concepts of RAMI 4.0, NIST and CPPS to create globally accepted standards. For example, efforts by organizations like the Industrial Internet Consortium (IIC) aim to harmonize these models for interoperability. Also, web searches and recent discussions on platforms like X highlight increased collaboration between US and European initiatives to bridge the RAMI 4.0 framework and NIST, (b) DT and AI integration, reflected in CPPS and RAMI 4.0 strongly emphasizing DT, now powered by generative AI and real-time analytics. This enables predictive maintenance (PrM) and process optimization on a large scale. NIST's focus on data analytics aligns with this trend, with test platforms exploring AI-driven manufacturing, (c) the imperative of cyber security,

stemming from the fact that cyber attacks on industrial systems (ransomware targeting IoT devices) are increasing, NIST's focus on cyber security is gaining in importance. RAMI 4.0 and CPPS include stronger security protocols to address vulnerabilities, (d) sustainability and circular economy (CE), where we have all three frameworks adapting to prioritize sustainability.

Table 1. Overview of interoperable models for smart manufacturing

Aspect	RAM 4.0	NIST Smart Manufacturing	CPPS
Origin	Germany (Industry 4.0 Platform)	NIST (USA)	Global, conceptual model
Scope	Comprehensive, life cycle focused	Focused on technology and standards	Integration of technology and processes
Structure	3D model (Hierarchy, Lifecycle, Layers)	An ecosystem with cross-cutting aspects	Layers (Physical, Cybernetic, Communication)
Basic concept	Administrative shell, Interoperability	Data Driven Manufacturing, Cyber Security	Digital twins, Decentralized intelligence
Cyber security	Moderate focus	Strong focus	Limited, depends on application
Suitable for SMEs	Complex, less suitable for SMEs	Moderately, with custom tools	Complex, requires a lot of resources
Standardization	Strong (IEC, ISO compliant)	Strong (open standards)	Weak, lack of universal standards
Applications	Smart factories, supply chains	Optimization, additive manufacturing	Flexible production, predictive maintenance
Maturity	Mature, widely accepted	Development, practical test environments	Conceptually, the implementation varies

The life cycle focus of RAMI 4.0 supports CE principles, while CPPS enables energy efficient manufacturing. NIST is developing standards for sustainable manufacturing metrics, and (e) 5G and edge computing, where we have CPPS making significant use of 5G and edge computing, enabling ultra-low latency communication in smart factories. RAMI 4.0 and NIST are updating their communication layers to include these technologies. *Challenges and future directions* are characterized by the following facts: (a) interoperability shortcomings are reflected in the fact that despite progress, differences in standards (OPC UA vs. MTConnect) create challenges for global adoption. Future efforts will focus on universal protocols, (b) adoption by SMEs, where we have them struggling with the complexity and cost of these frameworks. Simplified, modular implementations and government subsidies could bridge this gap, (c) workforce skills, where we know that implementing these models requires expertise in the Internet of Things (IoT), AI and cyber security. Training programs

and educational partnerships are key, and (d) Ethical and regulatory issues relate to As CPPS enables autonomous systems, ethical issues of human oversight and data privacy arise. Regulatory frameworks are being developed to address these issues. *In conclusion,*we can state the following: (a) RAMI 4.0 is ideal for organizations looking for a comprehensive, standardized approach to Industry 4.0, especially in Europe. Its product lifecycle focus and administrative shell make it a robust framework for large-scale deployment, (b) NIST's smart manufacturing ecosystem excels in practical, data-driven applications with a strong cybersecurity foundation, making it suitable for US-based industries and SMEs, and (e) CPPS offers flexibility and innovation, driving the future of autonomous, smart manufacturing, but requires significant investment and standardization. For companies adopting these models, the choice depends on their industry, scale and priorities (interoperability, cyber security or flexibility). Combining elements from all three - the structure of RAMI 4.0, the practicality of NIST, and the adaptability of CPPS - can result in a hybrid model for the next generation of smart manufacturing.

Research shortcomings and inconsistencies of the analyzed models. In the changing environment of smart manufacturing, theoretical models like RAMI 4.0, NIST's Smart Manufacturing Ecosystem, and Cyber-Physical Manufacturing Systems (CPPS) provide fundamental frameworks for integrating digital technologies into industrial processes. These models emphasize interoperability, data-driven decision making, and system resilience. However, as Industry 4.0 transitions to Industry 5.0, prioritizing human-centeredness, sustainability and ethical considerations, *significant research gaps remain.* These under-researched areas hinder the practical translation of these models into robust, equitable and future-proof systems. This analysis identifies key gaps, drawing on recent literature, including review papers, empirical studies and new papers. It focuses on *the ethical integration of AI, resilience in volatile markets, and additional underexplored domains such as human-AI collaboration,*cybersecurity in decentralized systems, and adoption by SMEs. For each, I discuss the nature of the deficiency, its implications for theoretical models, and opportunities for future research. The aim is to highlight how addressing these shortcomings could bridge theory and practice, achieving more adaptive and inclusive smart manufacturing ecosystems.

Ethical integration of AI in CPPS and RAMI 4.0 [31]. *Nature of Deficiencies:* While the administrative shell of RAMI 4.0 and the decentralized intelligence of CPPS enable AI-driven automation, research largely neglects ethical dimensions such as mitigating bias, transparency, and human oversight of AI decision-making. Existing studies focus on technical interoperability (OPC UA protocols), but rarely address how AI algorithms in CPPS might maintain biases in predictive

maintenance or resource allocation, leading to inequitable outcomes across different workforces. For example, the NIST ecosystem emphasizes cybersecurity, but provides limited guidance on the ethical governance of AI, with only initial exploration of truth metrics in industrial applications. Recent reviews highlight a "significant lack" of studies on the ethical implications of AI in smart factory education and training, extending to operational ethics such as prioritizing safety in human-robot interactions. *Implications for theoretical models:* In the layered structure of RAMI 4.0, the "business" layer could include ethical property shells, but without research, this risks non-compliance with ever-changing regulations (EU AI Law). Self-organizing CPPS systems amplify the risks, as autonomous decisions can be unaccountable, which undermines trust in volatile multi-stakeholder environments. *Opportunities for future research:* Development of hybrid ethics frameworks that integrate explainable AI (XAI) into CPPS, tested through simulations in NIST test environments. Longitudinal studies could assess bias reduction in real applications, addressing the gap between practitioner concerns (fairness in SMEs) and academic focus on efficiency. New discussions about XAI emphasize the need for ethical revisions in recursive production loops, where AI projects AI, to prevent unintended social harm.

Resilience in volatile markets and supply chains [32]. *Nature of Gaps:* Theoretical models like NIST's Ecosystem and CPPS emphasize real-time adaptability, while empirical research on resilience amid economic policy uncertainty (EPU), geopolitical disruptions, or pandemics remains fragmented. Post-COVID-19 studies call for predictions about Industry 4.0 technologies in supply chain resilience management (SCRM), but comprehensive models linking the RAMI 4.0 life cycle axis to dynamic market volatility are lacking. For example, while green AI and circular economy (CE) ESG show promise within the EPU, the interconnections with traditional energy markets are underexplored, and data from 2017–2023 reveals AI as a net transferor of spillovers, but not a proven stabilizer. This highlights "production resistance" due to bottlenecks in upstream materials, which are not addressed in current CPPS architectures. *Implications for theoretical models:* RAMI 4.0 hierarchy levels support end-to-end visibility, but without resilience metrics for volatile inputs (raw materials), models fail to mitigate "systemic bottlenecks" in global chains. NIST's cross-sector data management is resilient in theory, but lacks blockchain integration for traceable, adaptive logistics in uncertain markets. *Opportunities for future research:* Empirical studies based on the Delphi method could prioritize technologies (IoT-blockchain hybrids) for post-disruption SCRM, expanding the CPPS to include "survival" angles like Ivanov's sustainability models. Explore the role of AI in a predictive supply model, as in Toyota's IoT-blockchain tracking, to quantify resilience gains (34% delay reduction). This could develop NIST into a "first order of resilience" ecosystem for volatile sectors like semiconductors.

Cooperation between man and machine and training of the workforce in the transition to Industry 5.0 [33]. *Nature of Gaps:* As Industry 5.0 emphasizes human-centricity versus Industry 4.0's focus on automation, there are gaps in how RAMI 4.0 and CPPS accommodate collaborative robotics, emotional AI, and human-digital twins (HDT). The literature calls for in-depth research into the policies and ethical principles of human-AI symbiosis, but the longitudinal impacts on workforce sustainability and resilience are rare. NIST's technologies neglect training for SMEs, where 77% of factory data remains unused due to lack of skills. Discussions of "dark" factories reveal underexplored tensions between autonomy and human oversight in recursive systems. *Implications for theoretical models:* CPPS's cyber layer assumes seamless integration, but without the human factor there is a risk of workers losing qualifications, which reinforces inequalities in volatile labor markets. The RAMI 4.0 functional layer could incorporate empathy models, but current implementations prioritize efficiency over inclusivity. *Future Research Opportunities:* Live lab pilot projects for HDTs in NIST test environments to assess ethical human-machine interactions, with a focus on the role of quantum computing in bioengineering-enhanced collaboration. Case studies on retraining (via AR/VR in CPPS) could address gaps in the routinization stages of adoption.

Cyber security and standardization in decentralized CPPS [34]. *Nature of the Defects:* While NIST excels in cybersecurity standards, research into quantum intelligence-proof protocols for CPPS under RAMI 4.0 is in its infancy, especially amid growing threats in interconnected ecosystems. Gaps include interoperability between RAMI 4.0 and NIST in multi-agent CPPS architectures, with limited empirical validation of standards like IEC 62264 in volatile, decentralized settings. Only RAMI 4.0 and IIRA had CPPS use in development, leaving the others underexplored. *Implications for Theoretical Models:* Decentralized intelligence in CPPS increases vulnerabilities, undermining NIST's secure data exchange in EPU-prone global chains. *Future research opportunities:* Mapping multi-agent patterns to RAMI 4.0 for secure, X-only CPPS (self-healing networks), including post-quantum cryptography as in NVIDIA's cuPQC. Comparative studies of architectures could standardize resilience.

Application in SMEs and sustainability in green supply chains [33]. *Nature of the deficiency:* SMEs, key to global manufacturing, face under-researched barriers to adopting RAMI 4.0 or the NIST model, including financial constraints and the integration of ethical sustainability. Reviews point to a lack of links between Industry 4.0 technologies and Green Supply Chain Management (GSCM), with ethical business in SMEs requiring more case studies. China's 31,000 smart factories highlight efficiency gains, but the global gap between SMEs in reducing

carbon emissions remains. *Implications for theoretical models:* Models assume large-scale resources, marginalizing SMEs and limiting sustainable scalability. *Opportunities for future research:* Development of modular, low-cost variants of CPPS for SMEs, assessing the impacts of GSCM through bibliometric analyses. Explore the alchemy of data for the $900 billion opportunity in untapped factory data.

A comparative overview of the differences between the models is given in Table 2.

Table 2. Model analysis

Area of deficiencies	**RAM 4.0**	**NIST ecosystem**	**CPPS**	**A key research opportunity**
Ethical AI	Limited in the business tier	Emerging Equity Metrics	Bias in autonomous decisions	XAI integration pilot projects
Market resilience	Life cycle of EPU insufficiently researched	Strong data focus, low volatility	Gaps in self-organization after COVID	Blockchain and IoT hybrids
Human cooperation	Deficit of empathy in the functional layer	Technology enablement ignores skill enhancement	Immature H-CPPS models	Living laboratories for HDTs
Cyber security	Interoperability standards are evolving	Advanced, but without quantum intelligence	Decentralized vulnerabilities	Multi-Agent PQC Mapping
SMEs/Sustainability	Complex for SMEs	Tools for emerging SMEs	A resource-intensive adoption	Case studies of modular GSCM

Broader implications. These shortcomings reveal a technocentric bias in current models, with Industry 5.0's ambitious shift towards ethical, resilient paradigms revealing the need for interdisciplinary research. Implications include stalling adoption (93% of professionals prioritize resilience and face data silos) and risks like ethical lapses in dark factories. *Future directions:* Harmonize models through global consortia, fund grants targeted at SMEs, and use AI for gap-filling simulations. By prioritizing these, research can develop theoretical models in the development of smart, sustainable manufacturing due to uncertainty by 2028.

5. Conclusions and Future Research

The factory of tomorrow is not a place - it is a living system, as integration has dissolved silos, weaving every machine, material and mind into a single, real-time digital thread. Intelligence awakened within that thread, turning data into prediction, and prediction into flawless execution. Innovation now emerges not from isolated breakthroughs, but from the continuous pulse of this connected, cognitive core—giving birth to products that evolve, processes that heal themselves, and business models that scale with human needs. This convergence is irreversible. The lines between design and production, man and machine, factory and customer have disappeared. What remains is a resilient, adaptive, value-creating organism—sustainable by design, personalized by default, and profitable by outcome. The future does not come, it starts in the production plant. Integration built the foundation, intelligence gave it vision, and innovation set it free. With this, smart production has been achieved, and it is not the end of industry but the beginning of industry as intelligence.

For the academic community, the contributions of this theme are: New interdisciplinary fields in manufacturing systems science - combining control theory, AI, materials science and human factors. Open datasets and digital twin benchmarks, as standardized, anonymized lakes of factory data for training next-generation AI models. Real-world simulation frameworks, through validated DT methodologies that bridge physics-based and data-driven modeling. Implications relate to: (a) curriculum revision, where isolated engineering degrees will be replaced by Integrated Manufacturing Engineering (IME) programs, (b) commitment to lifelong learning, as Faculty and students will have to master real-time systems, edge AI and ethical data management, (c) transition to research funding, from component-level grants to convergence grants focused on system-level resilience and sustainability.

For the industrial community, the contributions of this topic are: (a) platform ecosystem, where we have neutral integration layers (industrial data spaces) that allow SMEs to engage in smart value chains, (b) AI as a useful service, where we have pre-trained, sector models (predictive quality for plastic injection molding) implemented via MaaS, (c) standards for CE, where we have industry-driven protocols for modular design, digital product passports and closed-loop recycling. On the other hand, we have implications, related to: (a) the transition from capital to operational costs, which means we have a transition from owning assets to subscription to results ("working time as a service"), (b) retraining of the workforce on a large scale: 70% of operators become process co-pilots - trained in augmented reality (AR) and adaptive decision-making, and (c) a redefinition of competition, because the market leaders will not be the biggest, they will be the most integrated, the most intelligent and the most innovative.

For policy makers and decision makers, the main contributions to the development and application of smart manufacturing should be: (a) global interoperability standards, as harmonized data schemas, cyber security core values and AI ethics for global manufacturing, (b) innovation hubs, as regulatory safe zones for testing autonomous manufacturing and AI-driven supply chains, and (c) sustainability metrics, as KPI parameters of ESG/CE models. The implications of this concept can be defined as: (a) Industrial policy 2.0, means the transition from tax breaks to incentives for integration - financing 5G factory networks, open APIs and shared DT, (d) immigration based on skills, where we have accelerated visas for convergence engineers (AI + manufacturing experts), and () geopolitical resilience, through a model of mandatory dual supply through DT, to reduce the risk in supply chains without protectionism.

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