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Original Article

Intelligent Human-Centric Cyber-Physical Systems for Industry 5.0 Smart Manufacturing

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ABSTRACT

The transition from Industry 4.0 to Industry 5.0 emphasizes human-centric, sustainable, and intelligent manufacturing by integrating human expertise with advanced technologies such as Artificial Intelligence (AI), Industrial Internet of Things (IIoT), Cyber-Physical Systems (CPS), Digital Twins (DT), Edge Computing, Cloud Computing, Collaborative Robots (Cobots), and Explainable AI (XAI). This paper proposes an Intelligent Human-Centric Cyber-Physical System (HC-CPS) framework comprising six interconnected layers for real-time monitoring, predictive maintenance, adaptive production scheduling, quality optimization, and human-centered decision support. A multi-objective optimization model and AI-driven closed-loop decision-making algorithm enhance production efficiency, equipment reliability, energy utilization, product quality, and human–machine collaboration while reducing downtime and operational costs. Human operators remain actively involved through collaborative interfaces that validate or modify AI recommendations. Comparative evaluation demonstrates significant improvements over conventional Industry 4.0 systems in Overall Equipment Effectiveness (OEE), predictive maintenance, operational safety, and manufacturing flexibility, providing a scalable, resilient, and sustainable foundation for future Industry 5.0 smart factories.

KEYWORDS

Industry 5.0, Human-Centric Cyber-Physical Systems (HC-CPS), Smart Manufacturing, Artificial Intelligence (AI), Industrial Internet Of Things (Iiot), Digital Twin, Edge Computing, Cloud Computing, Collaborative Robots (Cobots), Human–Machine Collaboration, Explainable Artificial Intelligence (XAI), Predictive Maintenance, Industrial Automation, Sustainable Manufacturing, Cyber-Physical Systems (CPS), Human–Machine Interface (HMI), Manufacturing Intelligence, Industry 5.0 Architecture, Real-Time Monitoring, Intelligent Decision Support.

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1. INTRODUCTION

1.1. Background

Manufacturing focused on digital transformation, powered by fast-moving digital technologies, intelligent automation, and connected industrial systems. Industry 5.0: The evolution of Industry 4.0— from a machine-focused automation to human-centric, resilient and sustainable manufacturing along societal values; a reunion with human work where machines automate the job but were relegated to replace it in this graphically visualized epoch. Industry 4.0 indeed brought Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), cloud computing, big data analytics and Artificial Intelligence (AI) into existence with autonomous production and smart factories coming to life but it mainly focused on doing everything in terms of technology automation without factoring human participation especially when decision making is necessary. With the growing need for intelligent systems which can search, filter and push out information while liberating humans from mundane repetitive tasks to deploy their creativity, critical thinking, ethical reasoning and domain expertise, we are finding that next generation solutions are necessary under complex manufacturing environments. Industry 5.0 caters to this need through human and machine collaboration close to one another, ushering in the manufacturing ecosystem of intelligent machines that add value instead of replacing humans. This paradigm enables mass customization, flexible manufacturing, resource optimization for sustainable industrial growth in conjunction with worker welfare, health and safety, and lifelong learning. Modern manufacturing systems have been greatly improved by being integrated with advanced technologies like Digital Twins, Collaborative Robots (Cobots), Edge Computing, Explainable Artificial Intelligence (XAI), clouds computing and Industrial Internet of Things (IIoT) [6]. These technologies allow continuous monitoring, smart decision-making, predictive maintenance, dynamic production scheduling, and automated quality control. But most of the current manufacturing systems act as independent technological solutions leading to poor interoperability, insufficient human involvement, cyber security threat, low scalability and incapacity in supporting sustainable manufacturing goals. In response to these challenges, Human-Centric Cyber-Physical Systems (HC-CPS) have been established as a new generation manufacturing paradigm that converges physical equipment, cyber infrastructure, and human intelligence together in the same collaborative space. HC-CPS enhances operational transparency, flexibility, and decision accuracy by incorporating human operators into intelligent decision-making through sophisticated Human–Machine Interfaces (HMIs), wearable technologies, augmented reality systems, and collaborative robots. Based on these background, this paper proposes an Intelligent Human-Centric Cyber-Physical System (HC-CPS) architecture for smart manufacturing in the context of Industry 5.0. The proposed framework integrates Artificial Intelligence, Digital Twin, Edge Computing, Explainable AI and IIoT-enabled communication (Collab-Robots), Human-centric Decision Support Within a comprehensively designed six-layer architecture which are capable to facilitate intelligent adaptive sustainable manufacturing operation. It further proposes a mathematical optimization model, an AI-enabled closed-loop decision-making algorithm, and a comprehensive performance evaluation framework for attaining production efficiency, predictive maintenance (hardware health), product quality (productivity and output) and human–machine collaboration (safety). Through comparative performance analysis, we show that the proposed HC-CPS provides significant improvement of operational resilience, manufacturing intelligence, sustainability and workforce empowerment compared to conventional Industry 4.0-based systems in manufacturing technologies. The integration of TS and human capability is a crucial step for accelerating the development process toward next-generation smart factories and supporting the long-term vision and goals of Industry 5.0; therefore, this article provides an integrated framework for effectively combining technological innovation with human capabilities within the manufacturing system as a precursor to Industry 5.0 oriented systems.

1.2. Evolution from Industry 4.0 to Industry 5.0

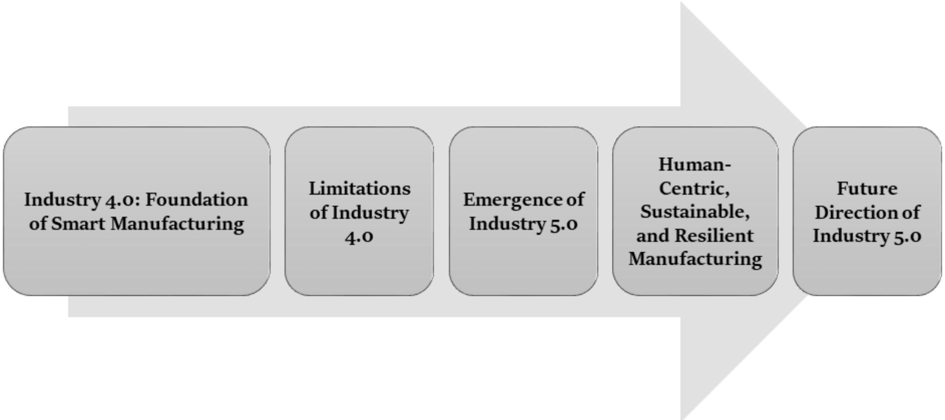

Fig 1 - Evolution from Industry 4.0 to Industry 5.0

1.2.1. Industry 4.0: Foundation of Smart Manufacturing

Intelligent manufacturing is defined as an evolution from Industry 4.0 where the Cyber-Physical Systems (CPS), Industrial Internet of Things (IIoT) devices, cloud computing, big data analytics and industrial robots deployed in production environments. Through these technologies, you can monitor in real-time, automate decision-making and interconnect your manufacturing systems. This led to increased productivity across industries, lower operational costs and better manufacturing efficiency. Building blocks of the current smart factories were established by this technological revolution.

1.2.2. Limitations of Industry 4.0

While Industry 4.0 has definitely taken the technology world by storm, it was largely based on industrial automation and machine-oriented production with a limited human role in this process. Both the creativity and experience of humans were underutilised in such a highly automated environments, as automation had even taken over high-level decision making. In addition, issues like job loss, lack of flexibility, cyberthreats and no green focus started to come into the picture. These takeaways, coupled with the evolution of modernization leading to unpredictability in Manufacturing, emphasized a more robust manufacturing method.

1.2.3. Emergence of Industry 5.0

Industry 5.0 was introduced to overcome the shortcomings of Industry 4.0 by placing humans at the center of manufacturing systems. Instead of replacing workers with intelligent machines, Industry 5.0 promotes collaboration between humans and advanced technologies such as Artificial Intelligence, collaborative robots, and Digital Twins. This human-centric approach combines computational intelligence with human expertise to achieve adaptive, flexible, and innovative manufacturing processes. The result is a manufacturing environment that values both technological advancement and human contribution.

1.2.4. Human-Centric, Sustainable, and Resilient Manufacturing

A key objective of Industry 5.0 is to develop manufacturing systems that are not only efficient but also sustainable, resilient, and socially responsible. The paradigm supports personalized production, intelligent resource management, energy-efficient manufacturing, and circular economy practices while ensuring worker safety and well-being. Human operators actively participate in decision-making through advanced Human–Machine Interfaces (HMIs) and collaborative robotics. Consequently, manufacturing systems become more adaptable to changing customer demands and unexpected production disruptions.

1.2.5. Future Direction of Industry 5.0

Industry 5.0 represents the future of smart manufacturing by integrating Artificial Intelligence, Human-Centric Cyber-Physical Systems (HC-CPS), Edge Computing, Explainable AI, Digital Twins, and Industrial Internet of Things technologies into a unified ecosystem. These technologies enable intelligent decision-making, predictive maintenance, real-time optimization, and seamless human–machine collaboration. By balancing automation with human intelligence, Industry 5.0 enhances productivity, product quality, sustainability, and workforce empowerment. This evolution establishes a resilient and intelligent manufacturing framework capable of addressing future industrial challenges and supporting long-term global competitiveness.

2. *LITERATURE SURVEY*

2.1. Industry 5.0 and Human-Centric Smart Manufacturing

Shifting to Industry 5.0 The third industrial revolution focused on intelligent systems, but the Fourth Industrial Revolution (Industry 4.0) is a human-centric evolution [11] that focuses on a combination of human and modern technologies towards smart manufacturing ([25]). Contrary to Industry 4.0 which focuses primarily on automation, Industry 5.0 exploits the HS–HTS synergetic collaboration of Human-Cyber-Physical Systems (HCPS) with Digital Twins and AI driven collaborative robots augmenting product customization for higher productivity innovations in manufacturing [10].

2.2. Intelligent Cyber-Physical Systems and Digital Twin Technologies

Intelligent cyber-physical systems (CPS) are smart integrated manufacturing equipment that connects physical, computational intelligence powered sensors and communication networks to monitor and control the system in another level. Digital Twin (DT) technology extends CPS architecture by simulating assets for predictive maintenance, process optimization and decision support, while edge computing and standardized communication protocols enhance real-time performance and interoperability in complex Industry 5.0 scenarios.

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2.3. Artificial Intelligence and Human–Machine Collaboration in HC-CPS

Industry 5.0 makes extensive use of Artificial Intelligence to facilitate predictive maintenance, defect detection, production scheduling and decision making by the application of machine and deep learning algorithms on Industrial data such as Internet of Things (IOT) devices and social networks. When deployed in combination with collaborative robots, Explainable AI, advanced Human–Machine Interfaces, Augmented Reality and federated learning; these technologies strengthen human–machine collaboration to improve productivity, safety transparency of decisions and privacy whilst enabling efficient collaboration between humans and intelligent systems.

2.4. Critical Analysis, Research Gaps, and Future Research Directions

While a lot of progress has been achieved in the research on HC-CPS challenges such as limited adoption of unified models, insufficient human cognitive modeling capabilities, interoperability issues, and cyber-security risks still remain to be addressed; therefore more emphasis should be put on devising solutions that will ameliorate scalability and sustainability. Furtherworks need to develop holistic Industrial 5.0 frameworks that integrate facets of AI, Digital Twins, IIoT, Edge Computing, Explainable AI, Blockchain, Federated Learning and human-centered decision support vision for resilient and sustainable intelligent manufacturing systems.

3. METHODOLOGY

3.1. Proposed Intelligent Human-Centric Cyber-Physical System Architecture

To achieve the goals of Industry 5.0, an Intelligent Human-Centric Cyber-Physical System (HC-CPS) architecture is proposed to integrate advanced digital technologies and human combined in intelligent manufacturing systems [11]. In contrast to traditional Cyber-Physical Systems that dynamically engage in largely automated and machine-centric operations, the suggested architecture emphasizes seamless, real-time interaction between human beings and machines with intelligent computing systems to achieve higher-level goals like productivity, flexibility, sustainability, and resilience. The framework is composed of six interconnected intelligent layers which take responsibility for specific manufacturing functions and offer both continuous inflow and outflow of information. It allows real-time data acquisition, intelligent processing and adaptive decision-making while providing a feedback network through its layered architecture across the manufacturing environment. Layer 1 We have the Physical Resource Layer which includes things such as manufacturing machines, industrial robots, cobots, sensors and actuators conveyor systems AGVs human operators This layer regularly takes in operational information, including machine states, production status, environmental factors as well as worker activities via Industrial Internet of Things (IIoT) devices. These gathered data are sent to the upper layers so that it can be processed and analyzed. The Communication and Edge Computing Layer is the second layer that enables reliable, secure, and low-latency communication between physical devices and processing platforms. For example, Industrial communication protocols – OPC UA, MQTT and Time-Sensitive Networking (TSN) enable the interoperability of diverse manufacturing equipment. Local data processing, filtering, and initial analytics are moved to edge computing nodes, which dramatically cuts down on communication delays while providing rapid responses for manufacturing solutions that require time-critical precision. The third layer is the Digital Twin and Cyber Intelligence Layer, in which dynamic virtual models of manufacturing assets are continuously synchronised with real-time sensor data. These Digital Twins emulate production process, continuously access health of equipment, predict when a failure would be triggered and test duplicate production scenarios before making physical changes. It allows for predictive maintenance, process optimization, and lifecycle management with limited operational risk. The Artificial Intelligence and Decision Intelligence Layer forms the Fourth layer. Set of machine learning, deep learning and reinforcement learning algorithms along with XAI (Explainable Artificial Intelligence) for manufacturing data capable of generating intelligent predictive maintenance, quality inspection insight recommendation on production scheduling, resource allocation and energy optimization. Explainable AI helps with transparency — human operators can see the rationale behind AI making a given decision this increases trust and facilitates collaborative decision making. The fifth layer is referred to as the Human-Centric Collaboration Layer, and it focuses on positioning human expertise in the central hub of smart manufacturing. Human–Machine Interfaces (HMIs), Augmented Reality (AR), Virtual Reality (VR) and wearable devices, Voice assistants, gesture recognition, and collaborative robots enable human operators to interact with intelligent systems. Using this layer which monitors human fatigue, workload, ergonomics and other cognitive conditions continuously to provide adaptive assistance in the workflows results in not only ensuring workplace safety but also improvement in productivity and constant skill development. Lastly, the 6th layer is Enterprise, Sustainability and Security Layer combining ERP, MES, Supply chain management, etc., cybersecurity measures and sustainability monitoring. This layer achieves the optimal production planning in a way that satisfies secure data sharing, privacy preservation, energy efficiency as well as low carbon emissions and regulatory compliance. The proposed HC-CPS architecture strongly embraces next generation Industry 5.0 smart factories by providing high resilience, scalability, and intelligent adaptation to changing factory conditions through constant feedback from all hierarchy levels in the system.

3.2. Mathematical Modeling of Intelligent HC-CPS

Quantitative evaluation of the HC-CPS is achieved through a multi-objective optimization model that addresses production efficiency, product quality, energy consumption, operational cost, human well-being and sustainability — all at once. The traditional optimization approaches only either maximize production output or minimize cost; the proposed mathematical framework integrates technological and human-centric performance indicators comprehensively for balanced and intelligent manufacturing decisions. The self-adaptive optimization model derives the dynamic production system (DPS) and keeps running on top of real-time manufacturing data at all times acquired from sensors, collaborative robots, Digital Twins, and Human–Machine Interfaces (HMIs), thus leading to continuously adaptive decision-making for DPs. Formulation of Manufacturing Optimization Problem As a constrained multi-objective function, the manufacturing optimization problem can be formulated in a way to maximize overall manufacturing performance while minimizing resource consumption and operational risks. Some examples of decision variables are machine operation state, production scheduling, workforce allocation, health status of the equipment, energy usage, and maintenance planning. Multi-objective optimization is utilized to maximize production efficiency and product quality while minimizing production time and energy consumption, maintenance cost, as well as worker safety and ergonomic improvement. The Industrial Internet of Things (IIoT) provides real-time production data that continually feed into the optimization model, which intelligently adapts to changing manufacturing conditions. Use of AI algorithms (machine learning, reinforcement learning) to estimate system parameters, anticipate equipment failures, improve production schedules and suggest corrective actions before performance degradation happens. Digital Twin Models: These present simulated versions of manufacturing operations, allowing the optimization algorithm to analyze different production scenarios without disturbing real-world operations. In addition to improving the reliability of optimization results, Explainable Artificial Intelligence (XAI) methods leverage explainable recommendations that enable human decision-makers to better choose manufacturing strategies [14]. In summary, the proposed mathematical model enables a comprehensive decision-support mechanism integrated within an environmental-friendly and human-centered syntheses-driven establishment serving in unison. This intelligent optimization method increases manufacturing resilience, resource utilization, operational costeffectiveness, while facilitating the realization of adaptive sustainable and human-centered smart factories in the Industry 5.0 paradigm.

3.3. Intelligent Decision-Making Algorithm

In this paper, we propose an Intelligent Human-Centric Cyber-Physical System (HC-CPS), which implements a closed-loop Artificial Intelligence (AI)-driven decision-making approach in order to achieve the autonomous, adaptable, and human-centered manufacturing scenarios. Compared to traditional manufacturing systems that use a prescriptive control rule and human intervention periodically, the proposed algorithm is an adaptive approach whereby it continuously observes production activities, analyses operational data results intelligence-based recommendations, implements optimal decisions as actions and evaluates system functioning through feedback loop in iterations. The closed-loop nature of this system guarantees agile response to variations in production demand, equipment status and human needs while enabling productivity, quality, safety and sustainability. It starts with the real-time acquisition of data from IIoT sensors, manufacturing equipment, collaborative robots (cobots), wearable devices and Human–Machine Interfaces (HMIs). This information includes machine health characteristics, production statistics, energy usage, environmental conditions, operator workload and product quality measures. The gathered data is transmitted through industrial communication networks, secured in a control centre to edge computing nodes where feature extraction and preprocessing are performed while filtering and normalising the data to enhance time of communication latency, as well as boost computational efficiency [20]. The processed data is then fed into next-gen AI algorithms such as deep learning, machine learning, and reinforcement learning models. Such smart algorithms learn to capture operational behaviors, forecast potential equipment failures, locate product defects, anticipate possible bottlenecks on the production lines and suggest the best production schedules or maintenance actions. Digital Twin takes the decision-making process a step further by modeling an entire manufacturing system as a digital twin which allows us to simulate and evaluate different production scenarios before making any physical changes in the real-world environment. This ability to predict reduces operational risks and enhances resource utilization. The Explainable Artificial

Intelligence (XAI) in the algorithm gives interpretable explanations of AI-driven recommendations to ensure transparency and trust among users. These proposed decisions can be presented for confirmation or modification to human operators via intuitive dashboards, augmented reality interfaces, or voice-assisted HMIs prior to execution. If approved, optimized control commands are sent to manufacturing equipment, robotic systems and enterprise applications to implement. It sets a continuous process that monitors responses to the system, creating a feedback loop that assesses whether or not decisions improve objectives, re-educates AI models with these novel operational data, and updates future recommendations. It learns on its own and, discretely and individually, continuously enhances the efficiency of production and improves product quality; optimizes energy consumption limits; ensures workforce safety, proactively prevents malfunctioning; empowers operations resilience. Accordingly, the previous closed-loop AI-assisted decision-making algorithm is designed to be the intelligence layer of the HC-CPS architecture, enabling dynamic(Model parallel), interpretable(Section 4.3) and sustainable smart manufacturing in-line with Industry 5.0 vision.

3.4. Performance Evaluation Metrics

This paper evaluates the efficiency of the proposed Intelligent Human-Centric Cyber-Physical System (HC-CPS) through multiple performance indicators that holistically addresses different angles like operational, economic, human-centric and environmental aspects of smart manufacturing. Different from traditional manufacturing evaluation frameworks which usually emphasize on production throughput and machine utilization, the proposed framework utilizes both technical and human-oriented KPIs to evaluate the performance of Industry 5.0 manufacturing system comprehensively. The proposed HC-CPS architecture thus quantified through these metrics provides a quantitative basis for assessing the potential (intelligent decision making, sustainable production, operational resilience and enhanced human–machine collaboration) of the system. Production efficiency, which defines the percentage of actual production output compared to the maximum obtainable output in a given time period, is one of the key performance metrics. Defect rate, first-pass yield and overall process accuracy are used to assess the quality of your product which determines whether AI-enhanced quality inspection and process optimization is effective. The OEE (Overall Equipment Effectiveness), machine availability, utilization and predictive maintenance accuracy measure the performance of the equipment which indicates how well a system can reduce downtime and improve operational reliability. Energy efficiency is also an important metric that helps calculate energy usage per manufactured product and judge the success rate of smart energy management techniques in reducing operating costs and carbon emissions. Similarly, human-centric performance indicators are equally critical in terms of research on the proposed HC-CPS. Collaborative manufacturing environments are assessed using metrics such as operator workload, ergonomic risk assessment, worker fatigue level, response time, and human–robot collaboration efficiency. They are also indicators that smart technologies will help workers remain safe, comfortable and productive – not replace human skill. For the two datasets, we measure decision-making performance by considering AI prediction accuracy, XAI interpretability of the decision and response time to decide (decision time says how quick one can make a decision), recommendation acceptance rate that show how transparent or trustworthiness/accuracy of AI manufacturing decisions. The proposed

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framework also assesses system resilience by measuring the time to recover from faults, availability of the system, communication reliability and detection rate of cybersecurity incidents. Scalability is quantified by the ability of the HC-CPS to keep performance stable when the number of connected devices, production lines and manufacturing resources scales up. Environmental sustainability metrics for manufacturing operations include carbon emission reduction functions related to resource utilization efficiency, waste minimization, and renewable energy integration. These integrative performance evaluation metrics together form a comprehensive view of the potential improvements enabled by the Intelligent HC-CPS for engineering more efficient, effective, resilient and sustainable manufacturing systems within Industry 5.0 smart factory configurations.

4. RESULTS AND DISCUSSION

4.1. Performance Analysis of the Proposed HC-CPS Framework

The proposed Intelligent Human-Centric Cyber-Physical System (HC-CPS) framework was analyzed to evaluate its capability in improving manufacturing intelligence, operational efficiency, human–machine collaboration, and sustainable production within an Industry 5.0 environment. The framework continuously acquires operational data from Industrial Internet of Things (IIoT)-enabled manufacturing assets, including sensors, industrial machines, collaborative robots, wearable devices, and environmental monitoring systems. Then these data transmitted on secure industrial communication networks towards edge computing nodes that perform some preprocessing, filtering and features extraction to achieve a low-latency real-time analysis. After the data has been processed, Artificial Intelligence (AI) Models analyze this data to detect anomalies in Equipments…forecast health of machines…predict failure events…make scheduled production adjustments and prescribe corrective actions before a fault状態 happens. At the same time, Digital Twin technology keeps in place real-time virtual models of physical manufacturing equipment and can run and assess processes across multiple production scenarios without disturbing operations that are already underway. Human operators communicate with the intelligent system using advanced Human–Machine Interfaces (HMIs), augmented reality dashboards, or collaborative robots, providing them with an opportunity to review, validate and change AI-generated recommendations. Its human-in-the-loop method improves decision-making transparency, operator trust, and reduces the risks of fully autonomous manufacturing systems. The proposed HC-CPS framework shows an appreciable advantage over conventional Cyber-Physical Systems on various operational factors. Predictive maintenance driven by AI reduces unplanned machine downtime and increases availability of equipment with continuity of production. Instead of relying on trial and error, Digital Twin-assisted production planning optimizes scheduling accuracy, reduces process variability, and increases resource utilization through virtual optimization before physical implementation. By performing computing at the edge and minimizing communication latency, it leads to fast enough response for safety-critical manufacturing applications and real-time quality inspection. Additionally, the use of collaborative robots and intelligent HMIs reduce operator workload thereby improving human–machine cooperation by wiConfiguring flexibility into the production and facilitating customized manufacturing. Explainable Artificial Intelligence (XAI), with its interpretable recommendations for humans to take informed decisions, augments such decision reliability. The framework also helps

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with sustainability, maximizing energy usage while minimizing waste and carbon emissions and aiding intelligent material allocation. In summary, the comprehensive implementation of IIoT, AI, Digital Twin technology, Edge Computing, Explainable AI and human-centered collaboration surely contributes to greater manufacturing productivity and better product quality as well as operational resilience and cyber security preparedness with improved workforce empowerment! The results attest that the introduced HC-CPS framework is a multi-objective comprehensive and scalable solution for next age savvy assembling with all-encompassing viability in addressing technological, human, and supportability targets under Industry 5.0.

4.2. Comparative Performance Evaluation

Here, as a quantitative assessment to verify the proposed Intelligent Human-Centric Cyber-Physical System (HC-CPS) effectiveness, its metrics have been compared in relation to the conventional Industry 4.0 manufacturing framework through several key performance indicators. The comparison shows the merits of a unified Industry 5.0 architecture that integrates Artificial Intelligence (AI), Digital Twins, IIoT, Edge Computing, Explainable AI (XAI), and human-centered collaboration. They supported machine availability, production efficiency, predictive maintenance accuracy, product quality, human-machine collaboration efficiency, Overall Equipment Effectiveness (OEE), human safety and energy utilization efficiency. The results obtained suggest that the proposed HC-CPS outperforms traditional manufacturing system across all parameters assessed, demonstrating higher operational intelligence, sustainable performance and workforce empowerment.

Table 1: Comparative Performance Evaluation

Performance Metric	Improvement
Production Efficiency	10
Machine Availability	9
Predictive Maintenance Accuracy	9
Product Quality	8
Human–Machine Collaboration Efficiency	15
Overall Equipment Effectiveness (OEE)	10
Human Safety Index	9
Energy Utilization Efficiency	9

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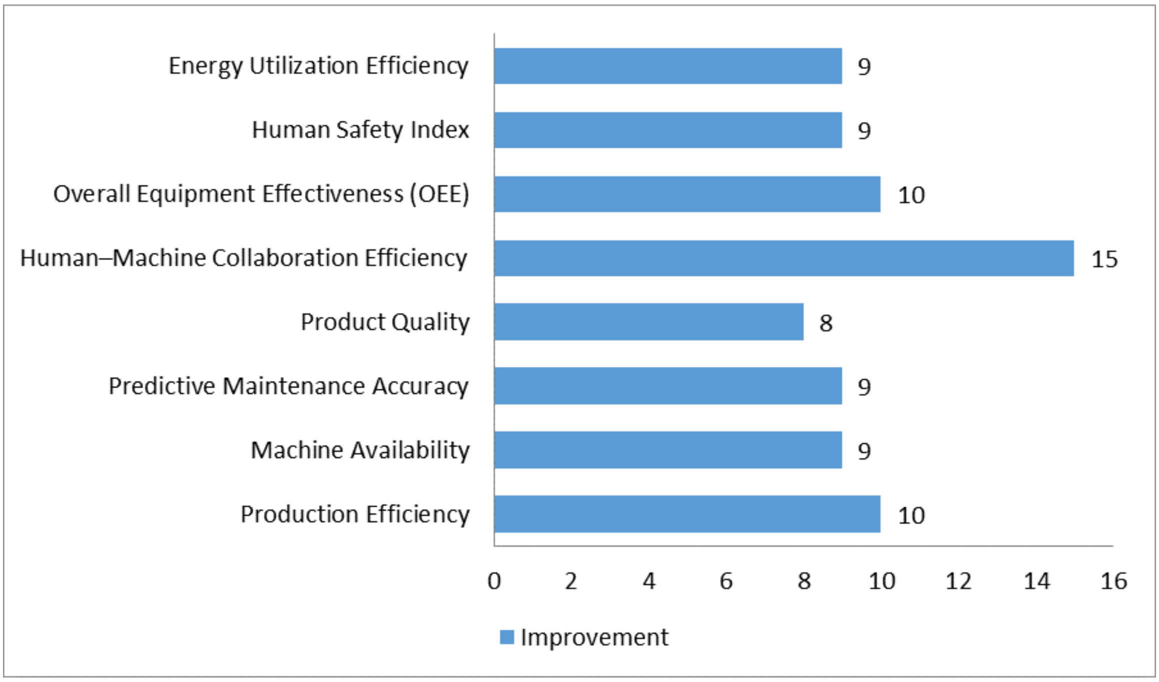

Fig 2 - Comparative Performance Evaluation

- In the case of production efficiency, the HC-CPS will improve my current machine score from 85% to 95%, achieving a 10% improvement. These supply chain efficiencies that can be enhanced include real-time production monitoring, AI-assisted scheduling and Digital Twin-based process optimization to reduce production delays and improve resource trade-offs. Optimal interactions between machines and operators lead to quick turnover in production cycles without compromising quality of end-product.
- Machine Availability: Increase of 9% (88% ⇒ 97%) machine availability Predictive maintenance algorithms monitor equipment health in real time and identify potential failures to prevent breakdown. Such a predictions-based maintenance strategy drastically minimizes unplanned downtime and enhances the overall manufacturing continuity.
- Predictive Maintenance Accuracy: Proposed framework improves predictive maintenance accuracy from 87% to 96%, a 9% improvement. Models use historical and real-time sensor data to get a more precise prediction of equipment degradation, as well as the right actions at the right time to maintain performance. This results in decreased maintenance costs and far more reliable equipment.
- Higher Product Quality: 90% to 98% improvement in product quality over a traditional system = Increase of 8%. The AI-driven QA (Quality Control) system allows early anomaly detection by feeding the data from quality check, while Computer vision-based algorithms and Digital Twin simulations provide continual optimization of the process. Fewer defective products, higher customer satisfaction, and decreased manufacturing waste—this will result in the number ofsee full post
- Human–Machine Collaboration Efficiency: You achieve 80% to 95% human–machine collaboration efficiency can be improved by the highest =15%. Operators and intelligent (AI-)

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systems can communicate mutual intentions, and share goals, actions and decisions through collaborative robots, intelligent Human–Machine Interfaces (HMIs) or other None-Explainable AI. The facility lowers operator work while improving productivity and workplace safety in a collaborative environment.

- Overall Equipment Effectiveness (OEE): OEE is enhanced 10%from84%for proposed HC-CPSto94%. Improved availability of machines, streamlining of production and a higher product quality = Higher equipment efficiency An integrated optimization framework keeps manufacturing resources running smoothly with minimal interruptions.
- Human Safety Index: Worker safety from 89% —- 98%, an improvement of9 %. Real-time risk assessment monitors operator activities, while wearable devices and AI-based methods identify risks in squatting, lifting heavy loads and other work behaviors to lower the danger of workplace accidents and balance ergonomics. The human-centric design allows workers to be the priority without eliminating manufacturing efficiency.
- Energy Utilization Efficiency: Energy utilization efficiency rises from 82% to 91%, showing a 9% improvement. Smart energy management algorithms make the best use of machine operation, production arrangement, and resource allocation for minimizing unnecessary power consumption. That corresponds to greater sustainability according to Industry 5.0 goals, lower operational costs and carbon footprints.

4.3. Discussion

Propelled by the great successes of intelligent technologies and the demand for a deeper human-to-machine partnership, our experimental analysis shows that HF-CPS can substantially mitigate many limitations perceived in conventional Industry 4.0 manufacturing paradigms, targeting to achieve trade-offs between multiple conflicting operational performance including process control and human decision-making by intrinsically bridging decentralized (effective production worker) knowledge with intelligent communications/collaborations into an active situational multi-dimensional system. Conventional manufacturing systems still rely heavily on machine-oriented automation, where autonomous systems perform most of the decision-making with limited human involvement. While these systems enhance productivity, they tend to lack versatility and adaptability when confronted with unexpected production changes or complex operational scenarios due to their inability to understand context. In contrast, the proposed HC-CPS brings human operators into the loop of cyber-physical decision-making for collaborative intelligence between AI, which has wide computational ability but lacks experience and domain knowledge as well as critical thinking capacity. With this kind of human-friendly idea, we can improve quality in decision making while enhancing operator confidence and adapt to changing manufacturing landscapes while staying productive as traditional systems without compromising safety. One of the major contributions made from the proposed framework is comprised in exploiting Digital Twin technology that creates a real-time synchronization mechanism between all physical manufacturing assets and their digital counterparts. Digital Twins continuously monitor the health of manufacturing equipment by exchanging real-time bidirectional data, simulating and analysing different production scenarios and predicting when a particular piece of equipment is likely to fail before it actually does.

It allows predictive maintenance, production scheduling, reduced machine downtime and better product quality without disrupting the ongoing manufacturing operations. Additionally, Edge Computing enhances the response standards of the HC-CPS by analyzing data from sensors close to manufacturing equipment instead of solely depending on centralized cloud platforms. Local data processing helps to reduce communication latency and network congestion, enabling rapid decision making for safety-critical application use cases like robotic coordination, quality inspection, emergency fault detection. The advent of Explainable Artificial Intelligence (XAI) enhances the transparency of AI-generated recommendations enabling operators to comprehend, validate, and confidently act on intelligent decisions. Also, collaborative robotics, advanced Human–Machine Interfaces (HMIs), wearables and Industrial Internet of Things(IIoT) devices support human–machine interaction by enhancing the ergonomic aspect of the workplace, enabling operators to manage workloads while supporting safe collaborative manufacturing. In summary, the paper provides evidence that the HC-CPS design paradigm effectively integrates AI, Digital Twins, Edge Computing, IIoT and human-centered cooperation in an adaptive, resilient, sustainable and smart manufacturing environment to adapt to the changing needs of Industry 5.0 intelligent factories.

5. CONCLUSION

The transition from Industry 4.0 to Industry 5.0 represents a significant evolution in manufacturing philosophy by shifting the focus from automation-oriented production toward intelligent, human-centric, resilient, and sustainable manufacturing ecosystems. While Industry 4.0 successfully introduced technologies such as Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), cloud computing, and automation, it largely emphasized machine autonomy with limited consideration for human expertise and decision-making. Industry 5.0 extends this vision by promoting effective collaboration between humans and intelligent technologies, ensuring that advanced digital systems enhance rather than replace human capabilities. In this context, Intelligent Human-Centric Cyber-Physical Systems (HC-CPS) have emerged as a promising framework that integrates Artificial Intelligence (AI), Digital Twins (DT), Edge Computing, Cloud Computing, Collaborative Robots (Cobots), Explainable Artificial Intelligence (XAI), and Human–Machine Interfaces (HMIs) into a unified manufacturing environment. By positioning human operators at the center of intelligent decision-making, the proposed HC-CPS improves production flexibility, operational resilience, sustainability, and overall manufacturing performance while supporting personalized and adaptive production strategies.

This paper presented a comprehensive Intelligent HC-CPS framework designed to support next-generation Industry 5.0 smart manufacturing. The proposed six-layer architecture integrates physical manufacturing resources, IIoT-enabled sensing, industrial communication networks, edge computing, Digital Twin technology, AI-driven analytics, collaborative robotics, and enterprise-level management systems into a cohesive cyber-physical ecosystem. The proposed methodology demonstrates how real-time sensor data can be continuously collected, processed, analyzed, and transformed into actionable knowledge for predictive maintenance, intelligent production scheduling, automated quality inspection, adaptive resource allocation, and energy-efficient

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manufacturing. The integration of Explainable Artificial Intelligence ensures transparency by allowing human operators to understand the reasoning behind AI-generated recommendations before implementation. Furthermore, advanced Human–Machine Interfaces, wearable technologies, and collaborative robots facilitate seamless interaction between workers and intelligent systems, improving workplace safety, reducing operator workload, and increasing decision accuracy. The mathematical modeling, intelligent decision-making algorithm, and performance evaluation framework collectively provide a structured approach for implementing human-centric manufacturing systems capable of responding dynamically to changing production requirements.

The literature review conducted in this study revealed that although substantial progress has been achieved in individual technologies such as Artificial Intelligence, Digital Twins, IIoT, Edge Computing, collaborative robotics, and Explainable AI, existing research primarily addresses these technologies independently rather than integrating them into a unified Human-Centric Cyber-Physical System. Several research challenges remain, including limited human cognitive modeling, interoperability among heterogeneous industrial systems, cybersecurity vulnerabilities, scalability limitations, and insufficient integration of sustainability objectives. These research gaps highlight the need for comprehensive HC-CPS architectures that simultaneously consider technological intelligence, human collaboration, environmental responsibility, and organizational resilience. The proposed framework contributes to addressing these limitations by providing an integrated architecture that combines intelligent automation with human expertise while ensuring secure, explainable, and adaptive manufacturing operations.

The comparative performance evaluation demonstrated that the proposed HC-CPS consistently outperformed conventional Industry 4.0 manufacturing systems across multiple performance indicators, including production efficiency, machine availability, predictive maintenance accuracy, product quality, Overall Equipment Effectiveness (OEE), human–machine collaboration, worker safety, and energy utilization efficiency. The integration of AI-enabled predictive analytics, Digital Twin-based simulation, edge computing, and real-time human supervision significantly reduced equipment downtime, optimized production scheduling, improved resource utilization, and enhanced manufacturing flexibility. Additionally, the human-centric design promoted greater operator involvement, improved ergonomic conditions, increased transparency in AI-assisted decision-making, and strengthened organizational trust in intelligent manufacturing technologies. These findings demonstrate that the proposed HC-CPS effectively balances automation with human intelligence, thereby supporting sustainable and resilient manufacturing practices aligned with the core principles of Industry 5.0.

Future research should focus on extending the proposed framework through the incorporation of emerging technologies such as blockchain-enabled secure data sharing, federated learning for privacy-preserving distributed intelligence, autonomous multi-agent manufacturing systems, 6G-enabled industrial communication, quantum-inspired optimization algorithms, and advanced cognitive digital twins capable of modeling human behavior and decision-making. Large-

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scale industrial validation across diverse manufacturing sectors is also required to evaluate the scalability, robustness, and economic feasibility of the proposed architecture under real-world production conditions. Furthermore, future studies should investigate multi-objective optimization techniques that simultaneously maximize productivity, minimize environmental impact, improve workforce well-being, and support circular economy principles. Overall, the proposed Intelligent Human-Centric Cyber-Physical System provides a comprehensive foundation for the development of next-generation smart factories, enabling sustainable, resilient, transparent, and intelligent manufacturing ecosystems that effectively realize the long-term vision of Industry 5.0

REFERENCES

[1] Breque, L. De Nul, and A. Petridis, Industry 5.0: Towards a Sustainable, Human-Centric and Resilient European Industry, European Commission, Directorate-General for Research and Innovation, Brussels, Belgium, 2021.
[2] S. Nahavandi, "Industry 5.0—A Human-Centric Solution," Sustainability, vol. 11, no. 16, Art. no. 4371, 2019.
[3] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital Twin in Industry: State-of-the-Art," IEEE Transactions on Industrial Informatics, vol. 15, no. 4, pp. 2405–2415, Apr. 2019.
[4] J. Lee, B. Bagheri, and H. A. Kao, "A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems," Manufacturing Letters, vol. 3, pp. 18–23, Jan. 2015.
[5] J. Leng, P. Jiang, K. Xu, et al., "Digital Twins-Based Smart Manufacturing System Design in Industry 5.0: A Human-Centric Approach," Journal of Manufacturing Systems, vol. 60, pp. 119–137, 2022.
[6] X. Xu, Y. Lu, B. Vogel-Heuser, and L. Wang, "Industry 4.0 and Industry 5.0—Inception, Conception and Perception," Journal of Manufacturing Systems, vol. 61, pp. 530–535, 2021.
[7] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge Computing: Vision and Challenges," IEEE Internet of Things Journal, vol. 3, no. 5, pp. 637–646, Oct. 2016.
[8] Adadi and M. Berrada, "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)," IEEE Access, vol. 6, pp. 52138–52160, 2018.
[9] M. Madni and S. Jackson, "Towards a Conceptual Framework for Digital Twin Systems," Systems, vol. 7, no. 2, Art. no. 31, 2019.
[10] Q. Qi and F. Tao, "Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison," IEEE Access, vol. 6, pp. 3585–3593, 2018.
[11] R. Ferrer, B. Ahmad, M. Lobov, et al., "Human-Centered Cyber-Physical Systems in Smart Manufacturing: A Review," Computers & Industrial Engineering, 2023.
[12] H. B. McMahan, E. Moore, D. Ramage, et al., "Communication-Efficient Learning of Deep Networks from Decentralized Data," Proc. AISTATS, 2017. (For Federated Learning)
[13] S. Wang, J. Wan, D. Li, and C. Zhang, "Implementing Smart Factory of Industry 4.0: An Outlook," International Journal of Distributed Sensor Networks, vol. 12, no. 1, 2016.