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Industry 5.0 Engineering Frameworks for Human-Centric, Sustainable, and Autonomous Industrial Ecosystems

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ABSTRACT

The transition from the technology-driven hyper-automation of Industry 4.0 to the socio-technical paradigm of Industry 5.0 demands a fundamental restructuring of manufacturing architectures. While Industry 4.0 successfully optimized industrial throughput and cost efficiency through Cyber-Physical Systems (CPS) and the Industrial Internet of Things (IIoT), its rigid focus frequently marginalized worker well-being, system resilience, and ecological footprints. This paper outlines an advanced Industry 5.0 engineering framework designed to reconcile high-level autonomy with human-centricity, sustainability, and systemic resilience. At the core of this framework is the evolution of legacy industrial control into Human-Cyber-Physical Systems (HCPS), which seamlessly integrate the physical, cyber, and human spaces through Human-in-the-Loop (HITL), Human-on-the-Loop (HOTL), and Human-in-the-Society (HITS) operational paradigms. Central to the execution of this socio-technical alignment is the implementation of the Human Digital Twin (HDT). By leveraging multimodal, non-invasive sensing modalities including wearable inertial measurement units (IMUs), surface electromyography (sEMG), and infrared eye-tracking the HDT dynamically models operator ergonomics, cognitive workloads, and emotional stress levels. These mathematical state vectors are fed directly into industrial robotic loops to enable real-time, adaptive Human-Robot Collaboration (HRC) compliant with ISO/TS 15066

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safety standards. To ensure cross-vendor compatibility and secure lifecycle-wide data orchestration, the framework establishes semantic interoperability across the edge-to-enterprise continuum using standardized Asset Administration Shells (AAS), Digital Product Passports (DPP), and deterministic communication via OPC UA Field Exchange (FX) over Time-Sensitive Networking (TSN). Furthermore, to address the high energy footprints traditional to industrial AI, a low-power hybrid Edge/Mist computing architecture is integrated to process geometric edge data locally, drastically reducing computational overhead. Finally, the framework embeds a Zero-Trust Architecture (ZTA) to safeguard sensitive human biometric telemetry and operational assets. The paper validates these integrated dimensions through a flexible automotive sub-assembly use-case walkthrough while critically reviewing open implementation bottlenecks, including real-time compute latency, legacy brownfield integration, and worker data privacy governance.

Keywords: Industry 5.0, Human-Cyber-Physical Systems (HCPS), Human Digital Twin (HDT), Semantic Interoperability, Asset Administration Shell (AAS), Edge/Mist Computing, Zero-Trust Architecture (ZTA

1. Introduction:

The global manufacturing landscape is undergoing a systemic paradigm shift. While the Industry 4.0 initiative focused on hyper-connectivity, end-to-end digitalization, and automated process optimization through Cyber-Physical Systems (CPS) and the Industrial Internet of Things (IIoT), it was largely driven by technology and efficiency gains. This primary emphasis on throughput and cost minimization frequently marginalized human ergonomic considerations, worker well-being, and broader ecological footprints (Nahavandi, 2019). Early digital transformations often encountered operational barriers, including system rigidity during sudden supply chain shocks, skill mismatches between operators and fully automated equipment, high energy consumption footprints, and worker alienation (Breque et al., 2021).

Industry 5.0 addresses these systemic limitations by reframing industrial production through three core pillars: human-centricity, sustainability, and resilience. Rather than aiming to replace human operators with autonomous algorithms and machines, Industry 5.0 seeks to integrate human cognitive flexibility, physical ingenuity, and ethical judgment directly into the digital control loop. This paradigm evolves the classical Cyber-Physical System (CPS) into a Human-Cyber-Physical System (HCPS) or Cyber-Physical Human-centered System (CPHS) (Romero et al., 2022). Within this framework, advanced technologies are explicitly designed to augment human capabilities, protect operator health and safety, reduce operational energy overhead, and maintain process continuity under dynamic market demands (Xu et al., 2021).

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Figure 1: The Convergence Framework mapping the systemic interaction between Industry 5.0 (Resilience, Sustainability, Tools & Enablers) and Society 5.0 (Super Smart, Values & Goals, Lean Products/Services) anchored on human-centricity, sustainable production, and sustainable consumption.

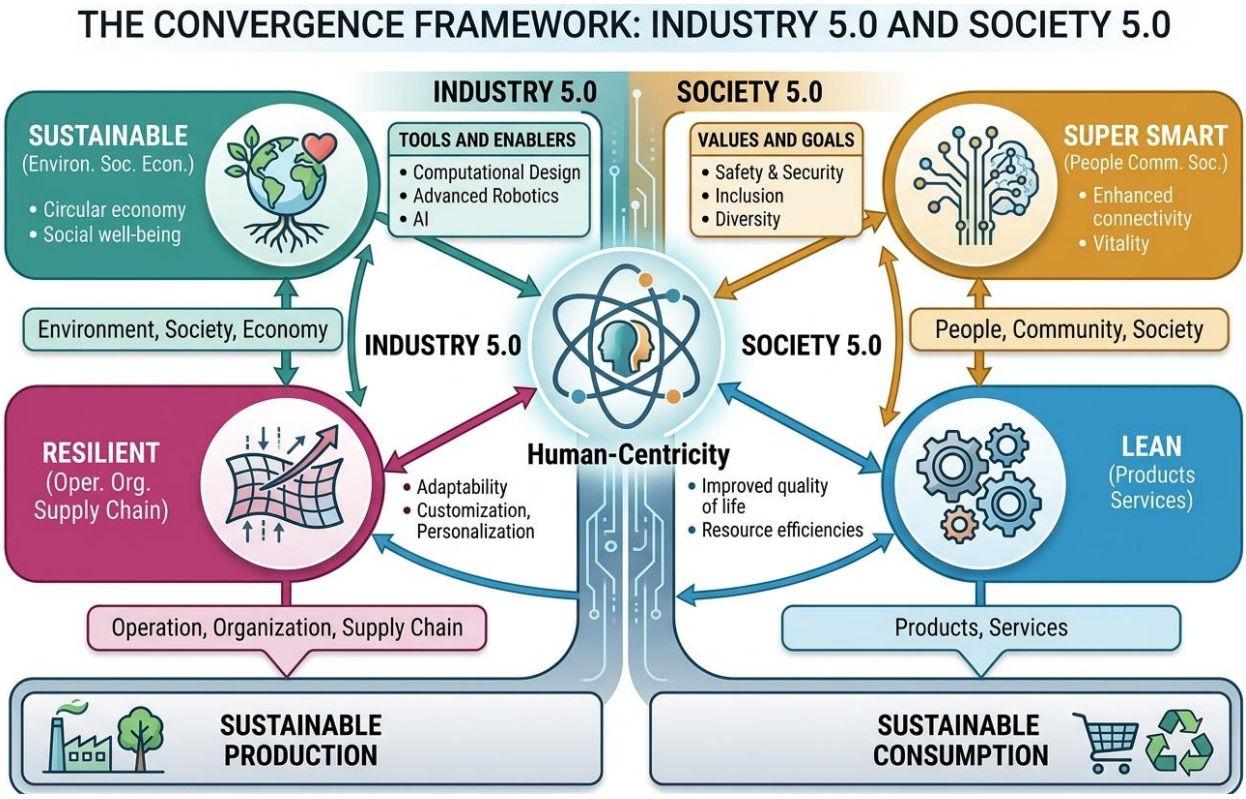

Table 1: Comparative Analysis of Industry 4.0 vs. Industry 5.0 Engineering Frameworks

Structural Dimension	Industry 4.0 Paradigm	Industry 5.0 Paradigm	Primary Enabling Technology / Protocol
System Focus	Technology-driven hyper-automation and cost minimization	Socio-technical alignment, human well-being, sustainability, and resilience	Human-Cyber-Physical Systems (HCPS)
Role of Human	Operator as a supervisor or cost component to be automated out	Central source of value creation, adaptability, dynamic reasoning, and creativity	Human Digital Twins (HDTs) & Operator 5.0 concept

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Control Topology	Closed-loop CPS, fully automated edge-to-cloud execution	Human-in-the-Loop (HITL), Human-on-the-Loop (HOTL), and Human-in-the-Society (HITS) control	Adaptive HMIs, Wearable Biometrics, & AI Co-Pilots
Environmental Objective	Secondary compliance; carbon footprint tied to overall unit volume	Primary systemic constraint; low-power edge nodes and circular lifecycle design	Low-power Mist/Edge nodes, AAS Digital Product Passports
Interoperability Standards	Proprietary fieldbuses, basic OPC UA Client/Server models	Deterministic OPC UA FX PubSub, standardized Asset Administration Shells (AAS)	OPC UA (IEC 62541), OPC UA FX, AAS (RAMI 4.0 / Manufacturing-X)
System Resilience	Rigid efficiency optimization; vulnerable to unexpected disruptions	Dynamic auto-reconfiguration, flexible human-robot reallocation	Self-learning adaptive algorithms, modular CPPS architectures

2. Human-Cyber-Physical System (HCPS) Architectural Frameworks

At the structural foundation of Industry 5.0 lies the Human-Cyber-Physical System (HCPS), a composite socio-technical architecture that unifies the biological, cognitive, and social dimensions of human operators with digital computing networks and physical production assets. Whereas classical CPS models physical equipment through differential equations and sensor telemetry, HCPS expands this space into three interconnected domains: Physical Space, Cyberspace, and Human Space (Longo et al., 2020). Physical Space encompasses machines, collaborative robots, and material flows. Cyberspace manages digital representations, edge/cloud analytics, self-learning algorithms, and deterministic communication networks. Human Space accounts for biometric states, cognitive workloads, psychological stress, physical ergonomics, and creative problem-solving capacities (Lasi et al., 2014).

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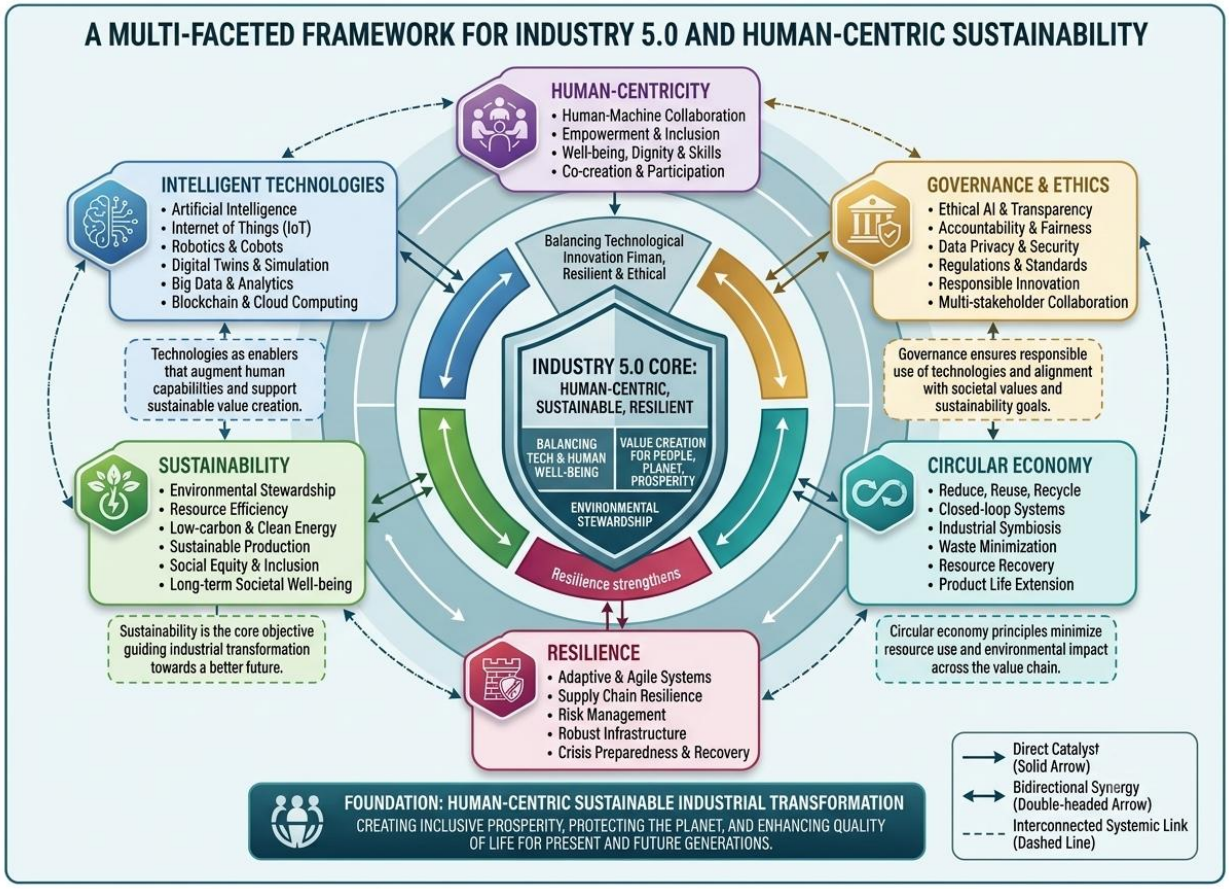
Figure 2: Systemic Multi-Faceted Framework detailing the dynamic interactions between the core Industry 5.0 tenets (Human-Centricity, Resilience, Sustainability, Circular Economy, Governance & Ethics, and Intelligent Technologies) and their direct, bidirectional, and interconnected systemic dependencies.



2.1 Tri-Space Integration and Operational Paradigms

The orchestrational dynamics within an industrial HCPS operate across three primary control paradigms that define how human intent, computational intelligence, and physical execution interact (Lu, 2017):

In the Human-in-the-Loop (HITL) paradigm, the human operator functions as an active decision-maker directly embedded within the real-time feedback control loop. Physical micro-gestures, physiological signals, and cognitive inputs dynamically adjust machine actions. For example, during complex sub-assembly operations, force-torque limits and movement trajectories of a collaborative robot arm are continuously modulated based on real-time feedback measuring the operator's muscle fatigue and limb positioning (Chen et al., 2025).

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In the Human-on-the-Loop (HOTL) paradigm, autonomous systems execute routine operations independently under human supervision. The underlying AI software manages path planning, quality inspections, and parameter adjustments, while the human operator retains high-level oversight. When operational anomalies or novel defect types occur, the human supervisor steps in to provide contextual reasoning, reconfigure process limits, or override autonomous decisions via intuitive Human-Machine Interfaces (HMIs) (Lantu et al., 2026).

In the Human-in-the-Society (HITS) paradigm, system boundaries expand beyond the factory floor to integrate societal, ecological, and ethical constraints into manufacturing decision-making. HITS aligns factory master schedules with renewable energy availability on the electrical grid, evaluates long-term workplace ergonomics to prevent chronic occupational injuries, and adheres to regulatory standards governing ethical technology deployment (Muhammad, 2021).

2.2 Lifecycle-Wide HCPS Orchestration

The integration of HCPS spans every phase of the industrial value chain, altering product design, production execution, and post-deployment maintenance services:

During the product and process co-design phase, cross-functional teams use immersive Virtual Reality (VR), Augmented Reality (AR), and digital twin simulation tools to evaluate assembly ergonomics, spatial layouts, and cognitive task loads prior to physical tooling setup. Virtual human models interact with simulated equipment to refine workstation design, ensuring that physical strain is minimized before commissioning (Chowdhury & Nuruzzaman, 2023).

During production execution, factory scheduling algorithms dynamically assign tasks based on real-time capabilities. Standardized, high-precision, or heavy-lifting tasks are assigned to automated units or collaborative robots, while complex custom assembly, quality verification, and adaptive troubleshooting are routed to human operators. This distribution reduces physical fatigue while utilizing human expertise (Boy, 2026).

During maintenance and field service operations, technicians utilize head-mounted AR devices linked to cloud-based asset management systems. Edge devices deliver contextual diagnostic overlays, component histories, and step-by-step repair guides directly into the operator's field of view. This setup supports rapid troubleshooting, lowers operational downtime, and keeps field workers safely connected to enterprise knowledge platforms (Enose Kamalabai, 2025).

3. Human Digital Twins (HDTs) and the Operator 5.0 Ecosystem

Where conventional Digital Twins (DTs) create virtual replicas of physical equipment to predict mechanical failures or model thermal profiles, Industry 5.0 introduces the Human Digital Twin (HDT) also referred to as the Operator Digital Twin (ODT) to model human state variables. The HDT provides a dynamic computational representation of an operator’s physical, cognitive, and emotional status, enabling industrial automation systems to recognize and adapt to worker needs in real time (Bucci et al., 2024).

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http://amresearchreview.com/index.php/Journal/about

3.1 Multimodal Sensing and Mathematical Modeling

Constructing an accurate, real-time HDT requires continuous data collection across physical, physiological, and psychological dimensions. Non-invasive smart wearables, thermal imaging cameras, eye-tracking systems, and natural language processing (NLP) models collect operator telemetry, which is processed at the edge to update state models (Hashimoto, 2026).

The dynamic state of an operator, denoted as $S_{operator}(t)$, can be modeled at time t through a multi-vector functional mapping:

$$S_{operator}(t) = f\big(\mathbf{P}(t), \mathbf{C}(t), \mathbf{E}(t)\big)$$

where:

- $\mathbf{P}(t) \in \mathbb{R}^n$ represents the physical ergonomic vector, incorporating posture joint angles, surface electromyography (sEMG) muscle activity, heart rate variability (HRV), and physical fatigue indices.
- $\mathbf{C}(t) \in \mathbb{R}^m$ represents the cognitive workload vector, derived from gaze duration, eye saccade frequency, task completion latency, and reaction time variations (Salem et al., 2022).
- $\mathbf{E}(t) \in \mathbb{R}^k$ represents the psychological stress vector, synthesized from micro-expression tracking via thermal cameras, vocal pitch frequency shifts, and NLP analysis during worker-system communications.

Table 2 highlights the sensing modalities, derived physiological and psychological parameters, and dynamic system adaptations across Human Digital Twin implementations (Cui et al., 2025).

Table 2: Multimodal Human Digital Twin Sensing Taxonomy and Operational Applications

Sensing Dimension	Sensor Modality & Hardware	Derived Parameter / Trait	Real-Time System Adaptation
Physical Ergonomics	Wearable IMU suits, sEMG bands, Smart Garments	Rapid Upper Limb Assessment (RULA) scores, localized muscle fatigue	Automatic workstation height adjustment, component feed repositioning
Cardiovascular Strain	Photoplethysmography (PPG), ECG chest straps	Heart Rate Variability (HRV), physical over-exertion indicators	Workload redistribution, automated insertion of physical rest/relief cycles
Cognitive Load	Infrared Eye-Tracking, Head-mounted AR glasses	Pupil dilation, gaze fixation frequency, cognitive saturation	Contextual HMI simplification, suppression of non-critical system alerts

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http://amresearchreview.com/index.php/Journal/about

Emotional/Stress State	Thermal infrared cameras, NLP Chatbots, Voice analysis	Stress indices, micro-expression markers, acute anxiety/burnout risk	Cobot speed reduction, automated line routing to lower-intensity tasks

3.2 Human-Robot Collaboration (HRC) and Safety Standards

In Industry 5.0, Human-Robot Collaboration (HRC) moves past rigid physical segregation such as light curtains and safety fences toward shared workspaces where collaborative robots (cobots) and operators perform tasks concurrently. The integration of real-time HDT telemetry into robotic controllers ensures compliance with international safety frameworks, specifically ISO/TS 15066, which defines four distinct technical collaborative modes (Villani et al., 2018):

1. **Safety-Rated Monitored Stop:** The cobot halts all automatic motion when an operator enters the designated collaborative zone, maintaining full power to servos and resuming operation automatically once the workspace is clear.
2. **Hand Guiding:** The operator controls cobot motion directly through force-torque sensing interfaces mounted on the end-effector, enabling intuitive positioning during heavy positioning tasks (Rosenstrauch & Krüger, 2017).
3. **Speed and Separation Monitoring (SSM):** The system tracks the dynamic distance between the operator and the cobot. As the human moves closer, the cobot automatically scales down its operational speed to maintain safe stopping margins.
4. **Power and Force Limiting (PFL):** Physical contact between cobot and operator is permissible, but mechanical forces and energy transfer are strictly constrained to non-injurious levels mapped via biomechanical safety thresholds.

By feeding real-time HDT metrics such as sudden operator distraction or physical fatigue directly into SSM and PFL control loops, cobots can adjust their speed profiles and spatial envelopes before physical safety thresholds are violated (Tao et al., 2019).

4. Semantic Interoperability, Communication Protocols, and Dataspaces

A key engineering requirement for Industry 5.0 ecosystems is establishing semantic interoperability across fragmented field devices, controllers, edge nodes, enterprise databases, and supply chain platforms. Achieving real-time closed-loop control alongside secure data exchange requires standardizing communication layers, structural data models, and enterprise dataspace architectures (Lasota et al., 2017).

This interoperable communications hierarchy is structured across three functional operational tiers:

- The Enterprise Dataspace Layer relies on frameworks like Catena-X, Manufacturing-X, and Factory-X to facilitate secure, cross-company data sharing and support Digital Product Passports (DPP) throughout the product lifecycle (Longo et al., 2020).
- The Industrial Communication Layer utilizes standardized protocols including OPC UA (IEC 62541), OPC UA Field Exchange (FX) with Publisher/Subscriber mechanisms over Time-Sensitive Networking (TSN), and private 5G-OT wireless infrastructure (3GPP SEAL) to maintain low latency and high reliability.

Annual Methodological Archive Research Review

http://amresearchreview.com/index.php/Journal/about

Volume 4, Issue 3 (2026)

Online ISSN 3007-3197

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- The Physical and Human Asset Layer connects field instrumentation, programmable logic controllers (PLCs), CNC machinery, cobots, and wearable human telemetry devices, converting raw signals into structured, standardized formats (Haddadin & Croft, 2016).

4.1 OPC UA and OPC UA Field Exchange (FX)

The Open Platform Communications Unified Architecture (OPC UA), codified under IEC 62541, serves as the primary industrial communication protocol for Industry 5.0 networks. OPC UA provides platform-independent, object-oriented information modeling alongside built-in security features, including AES-128/256 transport encryption, RSA asymmetric key exchanges, and X.509 certificate authentication (Haddadin & Croft, 2016).

To satisfy deterministic real-time control requirements at the field layer, the OPC Foundation introduced OPC UA Field Exchange (FX) via its Field Level Communications (FLC) initiative. OPC UA FX leverages a Publisher/Subscriber (PubSub) model deployed over Time-Sensitive Networking (TSN / IEEE 802.1Qbv), enabling cross-vendor, real-time controller-to-controller (C2C) and controller-to-device (C2D) communications. This setup bypasses legacy fieldbus constraints and allows automated work cells to adjust network configurations on the fly during live product changes (Leng et al., 2021).

Table 3: Standardized Communication Frameworks and Semantic Interoperability Enablers

Protocol / Standard	Governing Body / Standard ID	Core Architecture & Function	Role in Industry 5.0 Ecosystem
OPC UA	OPC Foundation / IEC 62541	Client/Server & PubSub secure object-oriented data modeling	Provides secure data transport from field assets to edge and enterprise cloud applications
OPC UA FX	OPC Foundation FLC Initiative	Deterministic C2C/C2D real-time communication over TSN	Replaces proprietary fieldbuses to support dynamic, multi-vendor work cell reconfiguration
Asset Administration Shell (AAS)	IDTA / Plattform Industrie 4.0 / VDMA	Virtual asset representation using standardized submodel templates	Serves as the digital twin data structure for equipment, products, and operators
5G-OT Systems (SEAL)	3GPP Rel 16/17	Private URLLC wireless networking integrated with TSN	Offers wireless, low-latency connectivity for mobile cobots, AMRs, and wearable operator devices
VDI/VDE 2193-2	VDI / VDE	Interaction protocol for dynamic bidding among autonomous components	Enables dynamic job allocation and automated task bidding across manufacturing cells

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http://amresearchreview.com/index.php/Journal/about

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Print ISSN 3007-3189

5. Sustainable, Resource-Efficient Edge Architectures

A central challenge of early digital twin and industrial AI deployments was their substantial computational energy footprint, often requiring power-hungry GPU clusters that run counter to sustainability mandates. Industry 5.0 addresses this issue by deploying energy-conscious mist computing, lightweight edge models, and low-power hardware configurations (Vlachos et al., 2016).

5.1 Hybrid Edge/Mist Architecture and Low-Power Visual Sensing

To satisfy both latency requirements (<10 ms response times) and energy efficiency goals, modern CPHS architectures deploy hierarchical edge/mist models. Low-power microcontroller units (MCUs), such as 32-bit ARM Cortex-M nodes, and compact single-board computers process localized sensor data directly at the machine layer (Majumder et al., 2023).

For example, research demonstrates a CPHS human-presence detection framework deployed in a collaborative work cell. Instead of streaming high-definition optical video to cloud servers running large deep learning models, the system processes low-resolution thermal camera arrays on localized mist computing nodes. Using non-machine-learning, threshold-based geometric algorithms, the edge node identifies human presence within hazardous regions in less than 10 milliseconds with 97.04% detection accuracy on low-power devices (Bhaskaran & Muthuraman, 2025).

This processing design yields energy savings across three main areas: First, avoiding continuous deep learning inference on dedicated GPU hardware significantly reduces processing power requirements. Second, analyzing thermal array data locally at the mist layer limits outbound network traffic to lightweight state updates, reducing network power consumption across 5G and Ethernet channels. Third, running light embedded OPC UA servers compiled via C-based SDKs (such as open62541) directly on low-power microcontrollers maintains small memory footprints, using under 100 kB of RAM/ROM for baseline operations (Vaithianathan, 2025).

5.2 Dynamic Reconfigurability and Systemic Resilience

Systemic resilience refers to an industrial ecosystem's ability to maintain production continuity during unexpected disruptions, such as supply chain delays, equipment breakdowns, or sudden labor shortages. Adaptive Cyber-Physical Production System (CPPS) frameworks achieve this resilience through autonomous dynamic reconfigurability (Feng et al., 2025).

When a disruption occurs such as an upstream part delay self-learning CPPS algorithms evaluate alternative production routes. Using standardized bidding mechanisms (such as VDI/VDE 2193-2) exposed via AAS submodel interfaces, autonomous machines bid on open work orders based on energy availability, current tool wear, and operator availability. Operators evaluate proposed routing changes via visual HMIs, combining human judgment with automated task reallocation to preserve overall throughput (Li et al., 2025).

6. Multi-Dimensional Cybersecurity and Ethical Governance

As autonomous industrial ecosystems become more interconnected through open communication protocols, cloud edge nodes, and shared dataspaces, the attack surface expands. Protecting operational safety, physical equipment, and sensitive human data requires a security framework grounded in technical resilience and ethical governance (Ahmad et al., 2024).

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http://amresearchreview.com/index.php/Journal/about

6.1 Zero-Trust Architecture (ZTA) and Cybersecurity-by-Design

Modern operational technology networks can no longer rely on perimeter-based firewall defenses. Industry 5.0 mandates a Zero-Trust Architecture (ZTA) built on the principle of continuous verification (Olakojo, 2025).

Implementing ZTA within autonomous industrial environments relies on three core security mechanisms:

- *Network Micro-segmentation:* Splitting the factory network into isolated operational zones (per cell, machine tool, or AAS node) prevents lateral malware movement if an edge device is compromised.
- *Mutual Cryptographic Identity:* Every sensor, edge node, cobot controller, and wearable device must authenticate using public key infrastructure (PKI) X.509 digital certificates enforced at the OPC UA layer.
- *AI-Driven Threat Detection:* Edge-level intrusion detection systems continuously monitor IIoT network traffic. Machine learning models establish baseline operational profiles and flag anomalous packet structures, unauthorized parameter changes, or unexpected control commands (Bondhala, 2025).

7. Lifecycle Implementation Framework and Operational Scenarios

To demonstrate how these integrated frameworks operate in practice, the following narrative traces an execution walkthrough within a flexible automotive sub-assembly cell. An operator begins their shift by approaching an adaptive work cell. An optical reader authenticates the worker's cryptographic credentials, retrieving their skill profile and ergonomic preferences from an encrypted Asset Administration Shell (AAS) container. The assembly bench automatically adjusts its physical height and lighting profile based on the retrieved profile (Song, 2026).

As assembly begins, non-invasive wrist wearables and localized thermal sensors track physiological telemetry. A mist computing node processes these signals, updating the dynamic Operator Digital Twin (ODT). The ODT publishes updated state metrics over OPC UA FX (PubSub over TSN). A collaborative robot working alongside the operator receives these updates via a private 5G-OT connection (Runola, 2024).

During the shift, the mist node detects signs of physical fatigue and elevated cognitive strain. The cell safety controller updates its Speed and Separation Monitoring (SSM) parameters, reducing cobot movement speed by 20% and adjusting component feed positions to reduce operator reach distance. Simultaneously, the AR display simplifies its graphical overlays to reduce visual clutter (Enose Kamalabai, 2025).

When an upstream component defect is identified, an AI assistant alerts the operator via the HMI. The operator inspects the part, confirms the defect, and approves a part re-route. The work cell issues an automated material request using VDI/VDE 2193-2 bidding protocols over the enterprise Manufacturing-X network (Boy, 2026).

Once assembly is complete, the unit's Digital Product Passport (DPP) submodel is updated with production telemetry, energy consumption data, quality checks, and material tracking metrics. The completed record is logged to the enterprise dataspace, maintaining traceability across the product lifecycle (Lasota et al., 2017).

Annual Methodological Archive Research Review

http://amresearchreview.com/index.php/Journal/about

Volume 4, Issue 3 (2026)

Online ISSN 3007-3197

Print ISSN 3007-3189

8. Critical Implementation Bottlenecks and Future Research Directions

While Industry 5.0 engineering frameworks offer clear operational benefits, widespread industrial adoption faces several technical, organizational, and economic hurdles (Muhammad, 2021):

8.1 Technical Bottlenecks

Processing multimodal biometric feeds, 3D spatial vision, and high-frequency force telemetry into real-time HDT models introduces compute latency constraints. Maintaining deterministic control loops below 10 milliseconds requires low-latency edge architectures (Cui et al., 2025).

Integrating legacy brownfield machinery which often relies on proprietary fieldbuses and unencrypted communications presents another operational barrier. Upgrading brownfield equipment to support OPC UA FX and AAS interfaces requires protocol translation gateways, which can introduce latency and security vulnerabilities (Lasota et al., 2017).

Additionally, standardized biometric AAS schema definitions remain incomplete. While equipment AAS submodels are well defined, establishing internationally recognized submodel standards for human cognitive and physiological states remains an ongoing effort (Rosenstrauch & Krüger, 2017).

8.2 Organizational and Socio-Economic Bottlenecks

Building operator trust in biometric monitoring systems requires transparent governance, strict privacy controls, and clear worker protections. Without clear policy boundaries, workers may reject monitoring technologies (Chowdhury & Nuruzzaman, 2023).

Transitioning to human-centric automated systems also requires workforce upskilling. Operators must be trained to work alongside AI co-pilots, AR diagnostics, and collaborative robotic systems.

Finally, justifying the initial capital expenditure (CAPEX) for private 5G networks, low-power edge arrays, software twins, and cobot infrastructure remains difficult for small and medium-sized enterprises (SMEs) without clear short-term ROI models (Nahavandi, 2019).

Conclusion

The evolution from Industry 4.0 to Industry 5.0 represents a necessary socio-technical course correction, moving industrial manufacturing away from technology-driven hyper-automation and toward a balanced triad of human-centricity, sustainability, and resilience. As demonstrated by the engineering frameworks presented in this paper, this shift does not reject automation but rather elevates it. By transitioning from traditional closed-loop Cyber-Physical Systems to highly integrated Human-Cyber-Physical Systems (HCPS), modern industrial ecosystems can seamlessly weave human cognitive ingenuity and physical adaptability into the digital control loop. The practical realization of this paradigm relies heavily on the convergence of several emerging technologies. The deployment of Human Digital Twins (HDTs)—driven by non-invasive multimodal sensing vectors allows collaborative automation to dynamically adapt to real-time human ergonomic and cognitive states, ensuring compliance with ISO/TS 15066 safety standards without sacrificing operational throughput. Furthermore, establishing semantic interoperability across the edge-to-enterprise continuum through standardizations like the Asset Administration Shell (AAS) and OPC UA Field Exchange (FX) over Time-Sensitive Networking (TSN) guarantees secure, real-time data orchestration and end-to-end product traceability via Digital

Annual Methodological Archive Research Review

http://amresearchreview.com/index.php/Journal/about

Volume 4, Issue 3 (2026)

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Product Passports. Critically, by routing these processes through low-power Edge/Mist computing architectures and protective Zero-Trust security topologies, the framework effectively addresses the modern imperatives of ecological sustainability and data privacy. While significant engineering bottlenecks remain—particularly regarding real-time compute latency for high-frequency biometric data, the cost-effective retrofitting of brownfield manufacturing cells, and the governance of worker data privacy—the operational benefits are unambiguous. Overcoming these technical and organizational hurdles will require concerted, cross-disciplinary collaboration between engineers, computer scientists, behavioral psychologists, and policymakers. Ultimately, the successful deployment of these Industry 5.0 frameworks will define the next generation of global manufacturing, unlocking industrial ecosystems that are not only highly autonomous and productive but also inherently sustainable and deeply respectful of the human workforce at their core.

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