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Human centered production systems for the new space economy

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Politecnico
di Bari

Department of Mechanics, Mathematics and Management

Aerospace Science and Engineering

Ph.D. Program

SSD: ING-IND/16 –

Manufacturing Technologies and Systems

Final Dissertation

Human Centered Production Systems for the New Space Economy

by

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Supervisors:

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Prof. Caterina Ciminelli

Course n°38, 01/11/2022 - 31/10/2023



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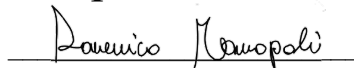
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ABSTRACT

As the New Space Economy drives aerospace manufacturing beyond traditional paradigms, this thesis explores a transition toward Industry 5.0 by embedding human-centric design principles into advanced production systems. The research proposes a methodological framework integrating enabling technologies—Digital Twins, Augmented Reality, and adaptive human–machine collaboration frameworks—to create intelligent, empathic, and collaborative production systems that support human operators rather than replace them. Conceptually, the framework envisions production as a symbiosis between human expertise and digital tools, ensuring that automation amplifies human capabilities. Experimentally, the framework is validated through a Wizard-of-Oz study in a real manufacturing context, where various human–machine interaction scenarios (ranging from human execution with machine supervision to shared control and negotiation) are simulated. Objective performance measures (task completion time, error rates) along with cognitive load (NASA-TLX) and user perception metrics demonstrate how different role allocations impact productivity and operator well-being. Results indicate that assistive automation significantly reduces cognitive effort and errors for less-experienced operators, while experienced operators prefer supervisory modes that maintain autonomy and transparency. An industrial case study in a satellite Assembly, Integration, and Testing environment further identifies process inefficiencies and shows that human-centered digital interventions (like context-aware guidance and transparent automation) can improve coordination and decision-making while preserving human responsibility. These findings validate the proposed human-centered Industry 5.0 approach, offering a practical pathway to enhance both operational performance and operator experience. The thesis concludes that aligning advanced manufacturing technologies with human-centric principles enables aerospace production systems to achieve greater efficiency, resilience, and sustainability without dehumanization, exemplifying a balanced paradigm where human skill is augmented—not replaced—by intelligent automation.

ACKNOWLEDGEMENTS

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CHAPTER 1

Introduction

1 INTRODUCTION

1.1 CONTEXT AND MOTIVATION

1.1.1 The aerospace context

The aerospace industry represents one of the most technologically advanced and strategically relevant sectors worldwide. It combines high-precision engineering, complex system integration, and long product lifecycles, requiring an exceptional degree of coordination among design, manufacturing, and testing functions. Historically, the evolution of this sector can be divided into three distinct phases: the government-driven era, the commercial space phase, and the emergence of the New Space Economy [1]. During the government-driven phase, space activities were largely motivated by national prestige and geopolitical competition, with programs funded and managed by public agencies such as NASA and ESA. This period, spanning from the 1950s to the 1980s, established the technological foundations for satellite communication, space exploration, and defense applications [2]. The commercial space phase began in the 1990s, when privatization and outsourcing strategies encouraged the entry of industrial actors in launch and satellite services. Large aerospace contractors adopted risk-sharing partnerships and internationalized their supply networks to optimize costs and leverage specialized competencies across regions [3]. The resulting global aerospace value network became characterized by complex multi-tier supply chains, long development cycles, and high certification requirements [4], [5]. More recently, the sector has entered a third stage — the New Space Economy — marked by the convergence of technological democratization, private investment, and digital transformation. This transition has shifted the sector from a government-centric to a multi-actor and competitive industrial ecosystem, where agility, efficiency, and manufacturability play an increasing role in competitiveness [2], [6].

1.1.2 The new space economy

The New Space Economy is redefining both the scale and the structure of global space activities. According to the World Economic Forum and McKinsey [7], the global space economy is projected to grow from \$630 billion in 2023 to \$1.8 trillion by 2035, expanding at roughly 9 % per year, nearly double the rate of global GDP growth. ESA in [2] estimates a parallel rise in Europe, where the total value reached €106 billion in 2023, with an annual increase of 11 %.

This unprecedented expansion is fueled by four structural drivers: the sharp reduction of launch costs, the miniaturization of satellites, the diversification of private investment, and growing integration between space and terrestrial industries [7]. The proliferation of constellations in low-Earth orbit (e.g., Starlink, OneWeb, Kuiper) exemplifies how commercial logics of time-to-market and cost efficiency have entered what was once an institutional domain [8].

Consequently, the space sector is evolving from a bespoke, project-based paradigm to one that increasingly demands industrialization of production and assembly processes. Traditional Engineer-to-Order (ETO) practices, characterized by unique designs, long lead times, and manual integration, are progressively being complemented by modular architectures, digital twins, and flexible production systems [9], [10]. At the same time, new organizational and technological challenges arise from the need to balance flexibility, quality assurance, and human expertise in highly customized environments.

Deloitte in [11], emphasizes that the sustainability of this growth will depend on how efficiently aerospace manufacturers adopt digital and collaborative technologies to address persistent bottlenecks in supply-chain coordination, testing operations, and workforce capability. In this sense, the industrial transformation of the space sector is not only a technological challenge but also a human-centric one, requiring the redesign of production systems that integrate human intelligence, digital technologies, and organizational learning.

1.2 TRENDS AND INDUSTRIAL TRANSFORMATION

The aerospace industry is currently undergoing a profound transformation driven by the convergence of digitalization, automation and new industrial paradigms [12]. This evolution marks the transition from traditional Engineer-to-Order and job-shop production models, characterized by craftsmanship, sequential operations and rigid certification chains, towards digitally integrated, data-driven and human-centric manufacturing ecosystems[10].

According to Deloitte and the European Commission, aerospace and defense companies are accelerating their digital-transformation agendas to enhance resilience, productivity and sustainability [13], [14], [15]. Cloud-based product-lifecycle management, digital twins and model-based systems engineering (MBSE) enable new forms of integration between design, manufacturing and testing shortening development cycles while preserving the sector's stringent safety and quality standards [16]. This digital convergence represents the pathway from Industry 4.0 to Industry 5.0, in which technological progress is

complemented by human-machine collaboration, sustainability and resilience [17].

In this context, human-machine collaboration has become a central pillar of competitiveness. NASA in [18] stresses that future aerospace systems will rely on Human-Machine Teaming to guarantee adaptability, safety and decision-making under uncertainty. Rather than replacing human intelligence, emerging technologies such as augmented-reality interfaces, cognitive digital twins and collaborative robotics are designed to enhance operators' cognitive and perceptual capabilities[19], [20]. Similarly, Gupta et al. [12] and Ahlstrand and Gautié [21] argue that the successful deployment of Industry 4.0 principles in aerospace manufacturing depends not on automation-driven downsizing but on upskilling and the active involvement of personnel.

Digitalization is also reshaping how industrial knowledge is captured and reused. Semantic and ontology-based engineering frameworks now support end-to-end traceability and the integration of heterogeneous data sources, bridging engineering and production domains [22]. The introduction of Cognitive Digital Twins, digital representations enhanced with reasoning capabilities and semantic interoperability, marks a major step toward adaptive and continuously improving manufacturing systems [23]. These approaches promote the convergence of product, process and resource knowledge, improving digital continuity and reducing the cognitive load on engineers and operators.

At the same time, international initiatives such as the European Space Agency's "Accelerators" and the World Economic Forum's "Space Economy 2035" underline that the competitiveness of the aerospace sector increasingly depends on three intertwined principles: (1) resilience, achieved through the ability to manage disruptions and ensure supply-chain robustness; (2) sustainability, through resource optimization and waste reduction; and (3) human-centricity, ensuring that technology empowers rather than replaces workers [7], [17], [24], [25] .

In summary, the aerospace industry is evolving toward an integrated socio-technical paradigm in which digital intelligence and human expertise coexist symbiotically [26], [27], [28]. This transformation requires not only technological innovation but also organizational adaptation—embedding collaboration, learning and ethics at the core of industrial systems to realize the vision of a sustainable, resilient and human-centered Industry 5.0 [29], [30].

1.3 CHALLENGES IN AEROSPACE INDUSTRY

Despite its rapid evolution and technological sophistication, the aerospace manufacturing sector continues to face significant challenges that hinder efficiency, flexibility, and industrial scalability [31], [32]. These challenges can be grouped into three interrelated domains — technical, organizational, and human — which together define the boundaries of transformation toward a sustainable and human-centered aerospace industry [33].

From a technical perspective, aerospace production remains constrained by the inherent complexity of its products and processes. Each spacecraft or satellite is an Engineer-to-Order system requiring the integration of thousands of bespoke components, assembled under stringent quality and traceability requirements [9]. Production cycles are long, often spanning several years, and rely on intricate testing and verification procedures. As highlighted by Strandhagen et al. [10] the low level of process repeatability typical of ETO environments limits the application of conventional lean and mass-production principles. Furthermore, the progressive miniaturization of spacecraft and the adoption of composite and additive-manufactured materials have introduced new constraints in design-for-assembly and precision alignment [33]. The convergence of these factors amplifies the need for robust digital infrastructures capable of managing complex interdependencies across design, production, and testing phases [34].

On the organizational level, aerospace companies face a growing tension between the rigidity of certified procedures and the demand for agility. Certification regimes such as ECSS ensure the reliability and safety of space systems, but they also make process modification slow and resource-intensive. Global supply chains — often fragmented across multiple countries and industrial partners — add further uncertainty in scheduling, material availability, and quality assurance [35]. The MIT Lean Aerospace Initiative identified decades ago that while lean principles can reduce waste and lead time, their full deployment in aerospace is limited by the hierarchical structure of projects and the long design-to-production handover[36].

Finally, the human dimension represents both the greatest asset and one of the most complex challenges for the sector. Aerospace assembly and integration activities depend heavily on the expertise of highly qualified operators whose cognitive load is significant and whose tasks often combine manual precision with procedural compliance [26]. Studies by Ahlstrand and Gautié in [21] show that when lean systems prioritize efficiency over participation, the resulting

technocratic models can reduce job quality and hinder innovation. Conversely, human-centered approaches that emphasize autonomy, learning, and ergonomic design foster engagement and long-term productivity. Graydon et al. in [18] further stresses that the future of aerospace manufacturing will rely on Human–Machine Teaming frameworks in which intelligent systems support, rather than replace, human decision-making. In this view, human-machine collaboration becomes a strategic lever to maintain reliability while coping with increasing process complexity [12], [27].

In summary, aerospace production stands at a crossroads. Technical intricacy, organizational rigidity, and human-factor challenges interact to create a high-reliability yet low-flexibility environment. Overcoming these limitations will require a balanced integration of digital technologies, adaptive organizational models, and human-centered design principles the pillars upon which the next phase of Industry 5.0 aerospace manufacturing must be built.

1.4 RESEARCH QUESTIONS

The progressive digitalization of aerospace manufacturing has opened new pathways to enhance productivity, flexibility, and knowledge management. However, as underlined by the European Commission and the European Space Agency, the transition from Industry 4.0 to Industry 5.0 requires a renewed focus on the human role within production systems, ensuring that technological evolution remains socially sustainable and aligned with human values.

This doctoral research builds upon that premise: it focuses on how digital and cognitive technologies can support the industrialization of aerospace processes while maintaining the human operator at the center. The work investigates the interplay between technological enablers—specifically Augmented Reality (AR) and Digital Twins (DT)—and the human dimension of manufacturing, exploring how human–machine collaboration can enhance both performance and well-being. Accordingly, the general objective of the thesis is to design and validate a human-centered framework that integrates digital tools and human capabilities to support the industrialization of satellite Assembly, Integration, and Testing (AIT) processes. The research aims to define not only how these technologies can improve efficiency and scalability, but also how they can do so in a socially sustainable way, empowering operators instead of marginalizing them. From this overarching objective, the following research questions (RQs) have been formulated:

RQ1. *How can digital technologies be designed to understand and support complex production processes?*

This question investigates how digital representations—through Digital Twins and data-driven models—can capture, interpret, and optimize the complexity of aerospace production systems.

RQ2. *How can human–machine collaboration evolve toward adaptive systems that respect and enhance human capabilities?*

This question focuses on the evolution of human–machine interaction toward adaptive collaboration models that preserve human autonomy while leveraging digital and cognitive assistance to improve task performance and decision-making.

RQ3. *How can the effectiveness and social sustainability of these human-centered systems be experimentally assessed in real industrial environments?*

This question addresses how the proposed framework can be validated through empirical studies, combining objective performance metrics with indicators of cognitive workload, acceptance, and overall well-being in real aerospace AIT settings. Together, these questions guide the research toward a dual contribution:

- Scientific, by advancing the theoretical understanding of human–machine collaboration and the role of human-centered digitalization in high-reliability manufacturing; and
- Industrial, by providing a validated framework and methodological guidelines for integrating digital technologies that enhance both process efficiency and human experience within the New Space Economy.

This research therefore bridges the gap between technological innovation and human sustainability, contributing to the development of a new generation of human-centered production systems for the emerging New Space Economy.

1.5 STRUCTURE

The thesis is structured into five chapters, each addressing one or more of the Research Questions introduced in Section 1.4. The overall structure follows a logical progression from theoretical foundations to experimental validation and industrial application.

Chapter 1 – Introduction

Defines the research context, motivation, and objectives, presenting the challenges of aerospace industrialization in the transition from Industry 4.0 to Industry 5.0. It formulates the research questions and outlines the human-centered perspective adopted throughout the work.

Chapter 2 – State of the Art

Reviews the evolution of production paradigms from automation to human-centric manufacturing, highlighting the enabling technologies that support this transition. Special attention is given to Digital Twins and Augmented Reality, which serve as the core enablers for the proposed framework. This chapter primarily contributes to RQ1 and RQ2 by establishing the theoretical and technological foundations of the research.

Chapter 3 – Experimental Methodology for Human–Machine Collaboration

Describes the experimental design adopted to study different forms of human–machine interaction, ranging from supervision to co-execution. It presents the evaluation metrics, the cognitive workload assessment, and the observed behavioral trends. This chapter mainly contributes to RQ2 and RQ3, providing methodological insights into how human-centered systems can be tested and validated.

Chapter 4 – Industrial Case Study: Satellite Assembly, Integration, and Testing

Applies the developed framework within an aerospace industrial environment to analyze and optimize real AIT processes. It investigates production data, operator workload, and critical bottlenecks to derive requirements for human-centered digital tools. This chapter contributes to RQ1 and RQ3, bridging theoretical concepts with industrial practice.

Chapter 5 – Conclusions and Future Work

Summarizes the main findings and highlights the scientific and industrial contributions of the thesis. It discusses the implications of the proposed framework for the aerospace sector and outlines directions for future research and technology development.

In summary, Chapters 2 and 3 provide the conceptual and methodological foundations of the work, while Chapters 4 and 5 demonstrate its applicability and impact in real-world industrial contexts. Together, they contribute to

answering the three Research Questions and advancing the development of human-centered production systems for the New Space Economy.

CHAPTER 2

State of the Art

This chapter is extensively based on the following publications:

Monopoli, D., Miciaccia, P., Semeraro, C., Dassisti, M. (2025). *Guidelines for Conceptualization and Design of Human - Centered Empathetic Intelligent Machines in Production Systems Within the Industry 5.0 Paradigm. Decarbonizing Value Chains.*

Monopoli, D., Semeraro, C., Abdelkareem, M. A., Alami, A. H., Olabi, A. G., & Dassisti, M. (2024). *How to build a Digital Twin for operating PEM-Electrolyser system—A reference approach. Annual Reviews in Control, 57, 100943.*

2 STATE OF THE ART

2.1 HUMAN CENTERED PRODUCTION SYSTEMS

In production systems, the introduction of advanced technologies has historically relieved human workers from repetitive tasks, improved safety, and reduced physical fatigue through better workstation ergonomics. Technological development has therefore brought undeniable benefits to industry and society. However, the scientific community has increasingly recognized that, if not properly conceived, these technologies may also generate forms of unsustainable development. Dieste et al. [37] identify several unintended consequences associated with Industry 4.0 technologies, such as negative impacts on employment, loss of worker privacy and autonomy, difficulties in maintaining a healthy work–life balance due to constant connectivity, and safety issues stemming from the coexistence of autonomous machines and humans in shared workspaces. Alongside these organizational and social risks, further effects have been reported, including lack of transparency, trust issues, user frustration, and stress in interacting with complex digital systems, all of which can hinder the actual adoption and effectiveness of innovative solutions.

In response to these challenges, the European Union revised its industrial vision and introduced the concept of Industry 5.0, whose goal is to ensure the sustainable, human-centric, and resilient development of European industry [17]. In this perspective, machines are not conceived as substitutes for human labour but as partners that work alongside operators, supporting production efficiency and flexibility while at the same time safeguarding worker well-being. The emphasis therefore shifts from technology-centred productivity to the creation of human-centered socio-technical systems, in which digital technologies are deliberately designed to amplify human capabilities instead of marginalizing them.

This view is consistent with the definition proposed by Caggiano et al. [38], who describe Industry 5.0 as a framework in which enabling technologies – Internet of Things (IoT), Artificial Intelligence (AI), robotics, automation – are leveraged not only to improve process performance, but also to promote social sustainability, create better jobs, and foster more comfortable and safe working environments, all while respecting environmental constraints. Nevertheless, in many industrial applications the primary goals of these innovations have remained the improvement of efficiency and quality, often overlooking the well-being of operators [39]. As a result, recent literature has tried to formalize the

emerging challenges associated with human–machine collaboration in highly digitalized workplaces. These challenges can be grouped into two broad classes.

- Social challenges concern the operator's ability to accept and trust technology, to adapt to newly emerging roles within human–machine teams, and to engage in continuous and lifelong learning to keep pace with evolving systems [37], [40], [41], [42].
- Technical challenges concern the adaptability and customization of technological solutions to user needs, the transparency and explainability of automated decisions, the development of novel interaction modalities, and the definition of performance evaluation metrics that explicitly include human factors[37], [41], [43].

Within this paradigm shift, Romero et al. [44] introduced the concept of the Operator 4.0, envisioned as a smart and skilled human agent who performs work aided by machines when needed. This vision led to the notion of Human Cyber-Physical Systems (H-CPS), i.e. systems designed to enhance human capabilities through intelligent interfaces and adaptive automation. H-CPS aim to improve human interaction with machines in both the physical and the cyber domains by exploiting intelligent Human–Machine Interfaces (HMI) and human-in-the-loop control models. A distinctive feature of these systems is the dynamic allocation of control and decision-making between humans and automation, enabling a genuine human–automation symbiosis in which both act as collaborative agents pursuing shared production goals [30], [45]. Romero et al.[44] identify three main augmentation dimensions for the Operator 4.0: (i) physical augmentation, enabled by wearable or exoskeletal devices that enhance strength, endurance, and ergonomics; (ii) sensorial augmentation, enabled by advanced sensing and data-fusion technologies that expand the operator's perceptual field; and (iii) cognitive augmentation, enabled by AI, Augmented Reality (AR), and intelligent HMI to support diagnosis, situational awareness, and decision-making. These dimensions clearly illustrate the evolution from “automation of tasks” toward augmentation of human capabilities. Yet, for these solutions to be effectively adopted, they must be designed to optimize productivity, reduce operator workload, and ensure well-being – not to overwhelm the user with information or impose opaque automation [46]. In other words, adopting a human-centered approach is essential to minimize the negative impacts of technology adoption and to balance efficiency with social sustainability [47].

In conclusion, Human-Centered Technologies emerge as the concrete technological enablers of the Industry 5.0 vision: by integrating cognitive, sensorial, and physical enhancement tools within structured human–machine collaboration frameworks, they make it possible to develop production systems that are at once efficient, resilient, and socially sustainable. Among these enabling technologies, Digital Twin, AI-based decision support systems, Augmented and Virtual Reality, and collaborative robotics play a crucial role in connecting data, processes, and people, supporting informed decisions while maintaining human oversight and responsibility.

2.2 HUMAN CENTERED TECHNOLOGIES

2.2.1 Augmented and Virtual Reality

Augmented and Virtual Reality (AR/VR) technologies are key enablers for human-centered production systems, allowing operators to visualize, interact with, and control complex information within immersive and context-aware environments. Their integration into industrial settings supports all stages of the product and process lifecycle—from design and validation to operation, assembly, and training—enhancing perception, decision-making, and collaboration between humans and machines.

Within the Industry 5.0 vision, these technologies embody the principles of human-in-the-loop systems, where digital tools empower rather than replace human capabilities.

2.2.1.1 Virtual Reality for Design and Process Validation

Virtual Reality (VR) has long been used to support system design, validation, and process planning, enabling human participation at the earliest development stages. Dammacco et al. [48] proposed a VR-based virtual commissioning framework for complex manufacturing systems, showing that immersive environments can improve ergonomic analysis, team communication, and early detection of design flaws before physical implementation. Rueckert et al. [49], [50] extended this approach by integrating VR into the assembly planning process through structured virtual workshops involving both engineers and shop-floor workers. Their study demonstrated that VR workshops enable ergonomic optimization, co-design of tools, and higher user acceptance, as workers actively contribute to the solution development process rather than passively receiving design outcomes. These works highlight how VR transforms design and planning from static and sequential processes into collaborative,

iterative, and human-centered activities, anticipating the human factor already at the early development stage.

2.2.1.2 Extended and Mixed Reality for Collaboration and Monitoring

Beyond design validation, Extended Reality (XR) and Mixed Reality (MR) technologies bridge the virtual and real worlds, allowing humans to interact with digital information directly within physical contexts. Eredia et al. [50] demonstrated the integration of XR tools within concurrent design facilities, enabling engineers and operators to collaboratively explore 3D system models, identify potential integration issues, and plan maintenance tasks in real-time virtual spaces. Tu et al. [51] further developed a Mixed Reality interface for a digital-twin-based overhead crane, where operators could monitor and control the crane using interactive holograms displayed through a Microsoft HoloLens device. The MR application featured bi-directional data exchange with the digital twin, enabling real-time monitoring, control, and feedback. Quantitative evaluations showed that MR interfaces significantly improved situational awareness, mobility, and interaction efficiency, paving the way for industrial applications where humans and machines share the same spatial and digital workspace. Together, these studies reveal how XR and MR technologies enable intuitive, human-centered interaction with digital twins, transforming monitoring and control tasks into cognitively assisted experiences rather than manual supervision activities.

2.2.1.3 Augmented Reality for Human-in-the-Loop Assembly and Training

Augmented Reality (AR) plays a critical role in manual assembly, maintenance, and operator training, where human expertise remains irreplaceable but can be enhanced through digital assistance. Leins et al. [52] compared head-mounted and handheld AR systems for guided assembly operations, showing that both configurations improve task accuracy and reduce error rates compared to traditional paper or 2D-based instructions, though user experience depends on the level of immersion and cognitive load. Marino et al. [53] introduced an AR Assembly Guidance Tool (ARAGT) designed according to user-centered design principles, which overlays digital 3D instructions and annotations directly onto the workspace. Validation in industrial environments confirmed improvements in assembly efficiency, usability, and operator satisfaction. In a more advanced application, Wang et al. [54] proposed an AR-based human-in-the-loop assembly simulation combining gesture recognition and dual geometric-physical constraints. Their approach allows for high-fidelity simulation of

assembly operations, enabling both process performance evaluation (e.g., time, continuity, parallelism) and human factor assessment (e.g., visibility, reachability, comfort) within the same AR environment. These results illustrate how AR can effectively bridge digital simulation and human execution, enhancing not only operational performance but also learning, safety, and human autonomy at work.

2.2.1.4 Challenges and Future Directions

Despite the rapid advancements, AR/VR applications still face several technological and human-centered challenges. Rueckert et al. [49] identified that current VR systems lack the capability to reproduce realistic physical feedback—such as weight or resistance—limiting the accuracy of virtual ergonomic evaluations. Tu et al. [51] highlighted issues of spatial registration, latency, and device tracking accuracy, which can compromise the precision of MR control interfaces. Similarly, Wang et al. [54] emphasized the need for adaptive gesture recognition and ergonomic evaluation to ensure natural and inclusive interactions. Addressing these challenges requires advancing multi-modal interfaces, adaptive visualization, and integration with AI-driven decision-support systems, ensuring that immersive technologies evolve into genuine tools of human empowerment rather than mere visualization instruments. As Industry 5.0 continues to merge the physical and digital realms, AR/VR systems will serve as critical enablers of human-machine collaboration, fostering environments where efficiency, creativity, and well-being coexist.

2.2.2 Digital Twin as Decision-Support Tool

The Digital Twin (DT) represents one of the most transformative technologies in modern production systems, enabling continuous interaction between the physical and virtual domains. A Digital Twin can be defined as a virtual counterpart of a physical system that maintains a bidirectional data connection to replicate, simulate, and predict the system's behavior throughout its lifecycle [55]. Unlike traditional simulation models, which operate offline and in isolation, a DT evolves dynamically by continuously assimilating real-time data from sensors, control systems, and external sources. This capability allows it to monitor operations, forecast performance deviations, and support decision-making in complex environments[55]. Within the Industry 5.0 paradigm, the DT assumes an additional role: it becomes a human-centered intelligence layer, designed to enhance the operator's understanding, autonomy, and ability to make informed decisions rather than to replace human judgment. In this

paragraph it is provided a complete overview on how to build a digital twin as decision support system by using a usecase scenario provided in [56].

2.2.2.1 Methodological Framework for Building a Digital Twin

Building a Digital Twin (DT) requires a systematic methodology that integrates both model-based and data-driven perspectives to ensure accuracy, interpretability, and adaptability. According to Monopoli et al. [57] and Semeraro et al. [58], a DT should evolve through iterative cycles of system definition, modelling, data acquisition, and knowledge extraction, enabling the creation of a digital entity that mirrors, predicts, and optimizes the behavior of its physical counterpart. The methodological framework can be articulated into eight interconnected stages, forming a closed and adaptive loop between the physical and digital domains (see Figure 2-1).

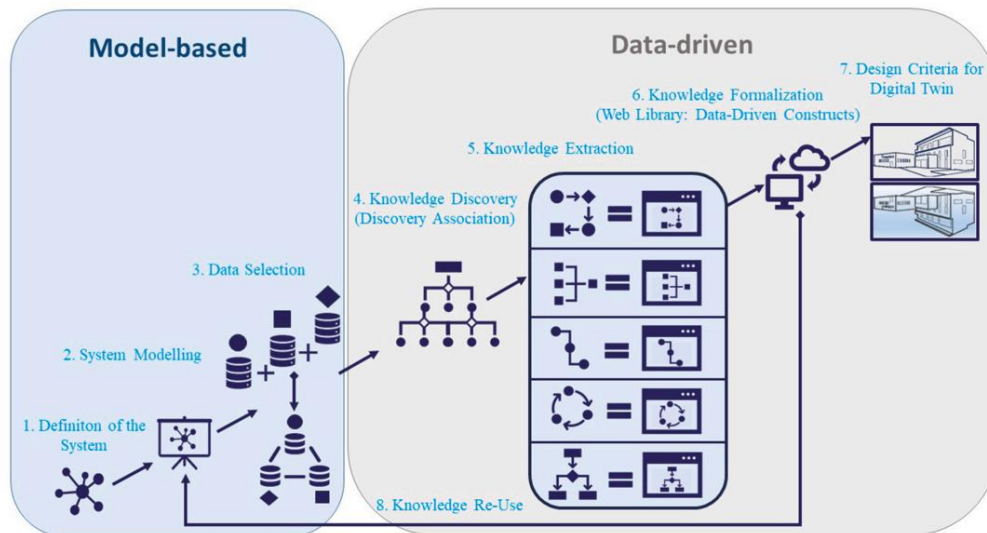


Figure 2-1 Digital Twin Methodology [58]

System Definition

The first step involves identifying the scope, boundaries, and critical variables of the physical process. This includes the decomposition of the system into subsystems, the recognition of its key performance indicators (KPIs), and the identification of critical-to-solution (CTS) variables that determine system efficiency and degradation trends. A clear definition of system boundaries ensures that only relevant parameters are considered for digital modelling, reducing redundancy and focusing the data collection effort.

System Modelling

In this stage, a model-based approach is applied to formalize the physical, functional, and behavioral structure of the system. Following the SysML, mathematical modelling or equivalent formal languages can be used to represent requirements, structural hierarchies, interconnections, and constraints through block, parametric, and state-machine diagrams. This representation provides the foundation for understanding system dynamics, defining cause–effect relationships, and preparing the digital model for later synchronization with real data. The outcome is a first-principles representation that encodes the physical laws (e.g., thermodynamic, electrochemical, or mechanical equations) governing the process.

Data Selection and Acquisition

Once the system model is defined, data collection becomes essential to parameterize and validate it. This stage defines the type, granularity, and sampling frequency of the data to be acquired, as well as the architecture of the sensor network and communication protocols (e.g., OPC-UA, MQTT). Data integrity is ensured through preprocessing operations such as filtering, noise removal, normalization, and merging from heterogeneous data sources (e.g., PLCs, MES, SCADA). A well-structured dataset enables both calibration of physical models and subsequent data-driven discovery of behavioral patterns.

Knowledge Discovery: Data-Driven Analysis

At this point, the focus shifts to data-driven analysis aimed at detecting recurrent behaviors and relationships between operating conditions and system performances. Techniques such as Formal Concept Analysis (FCA) and Relational Concept Analysis (RCA) are employed to identify correlations and derive association rules that describe the invariant relationships among CTS variables [57]. The discovery of such associations allows identifying invariant modelling patterns—recurrent behaviors that remain valid across contexts or time—thus representing the fundamental knowledge blocks for DT reasoning.

Knowledge Extraction and Pattern Formalization

Detected patterns are then interpreted and formalized to embed domain-specific meaning. Each pattern encapsulates a segment of process knowledge and is described by a standard structure including:

- Pattern ID and name

- Description of the modeled behavior
- FCA/RCA-based rule(s)
- SysML representation of its structure and dynamics
- Applicability criteria and operational range

Through this formalization, invariant patterns become reusable knowledge modules that can be combined and instantiated for various systems or processes. This modular approach drastically reduces modelling complexity and enhances the scalability and transferability of the DT design.

Architecture Integration

At this stage, physical and data-driven models are integrated into a coherent architecture. The digital layer includes three coordinated sub-models:

- a geometric model for visualization and operator interaction,
- a behavioral model for physics-based simulation, and
- a data-driven model based on invariant patterns for diagnostic and prescriptive reasoning.

This hybrid configuration ensures that the DT can simulate future behaviors while maintaining interpretability and physical coherence [57], [58].

Validation and Synchronization

The DT is continuously calibrated through a bidirectional feedback loop with the physical system. Predicted outputs are compared with real data, and discrepancies trigger model updates or re-weighting of data-driven rules. This ongoing synchronization enhances the fidelity and robustness of the DT, enabling it to reflect real-world conditions and maintain predictive reliability over time.

Knowledge Reuse and Continuous Learning

The final stage concerns the reuse and continuous evolution of the DT knowledge base. Recognized patterns and models are stored in a library, enabling their application to other systems with similar behaviors. This modularization supports transfer learning, enabling faster DT development and adaptation to new operational scenarios. As new data are collected, the DT refines its models and patterns, progressively evolving into a self-learning system capable of autonomous decision support.

2.2.2.2 Architecture and Core Components

The architecture of a Digital Twin (DT) is commonly conceptualized as a multi-layered system that enables continuous interaction between the physical and virtual domains through bidirectional data exchange. In accordance with the reference framework proposed in [57], as in Figure 2-2, the architecture is structured into three interconnected layers: Physical, Digital, and Connection, which collectively establish a closed information loop ensuring synchronization and real-time feedback between the twin and its physical counterpart. Each layer fulfills distinct but complementary roles: the Physical Layer is responsible for data generation and actuation, the Digital Layer interprets and models system behavior, while the Connection Layer ensures reliable and secure data transfer across the two environments.

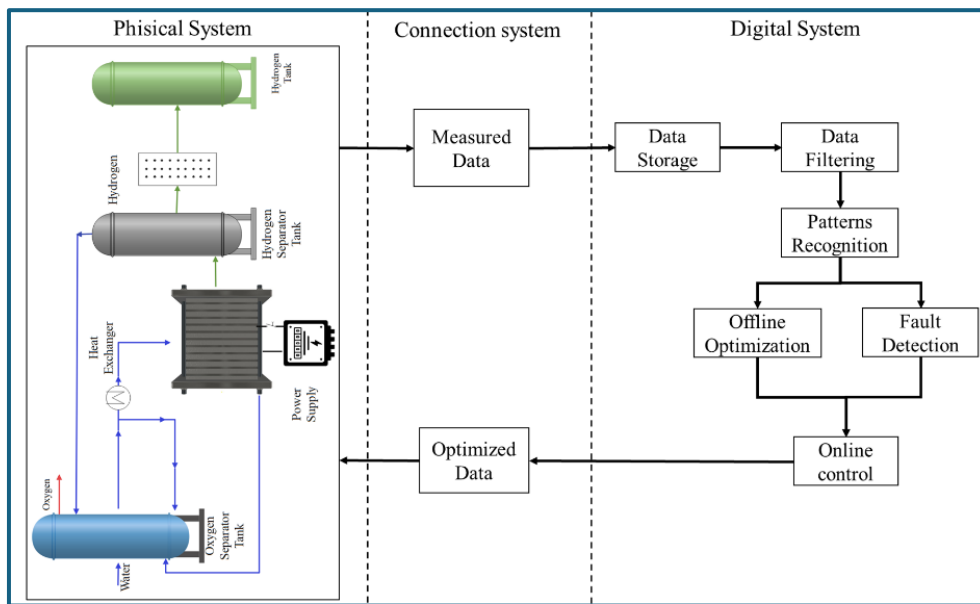


Figure 2-2 Digital Twin Architecture

Physical Layer

The Physical Layer represents the tangible part of the system, composed of all mechanical, electrical, and control components, as well as the network of sensors and actuators that enable real-time monitoring and control. Its primary function is to generate high-quality data streams describing the operational state of the system. For a PEM electrolyser, this includes temperature, pressure, water conductivity, flow rate, and stack current and

voltage [46]. Sensors convert physical quantities into digital signals and transmit them to the DT through industrial communication protocols (e.g., OPC-UA, Modbus TCP, or PROFINET). The layer also incorporates actuators — such as valves, pumps, and power supply controllers — which execute corrective actions derived from the DT's predictions or control algorithms. An example of physical system is provided in Figure 2-3.

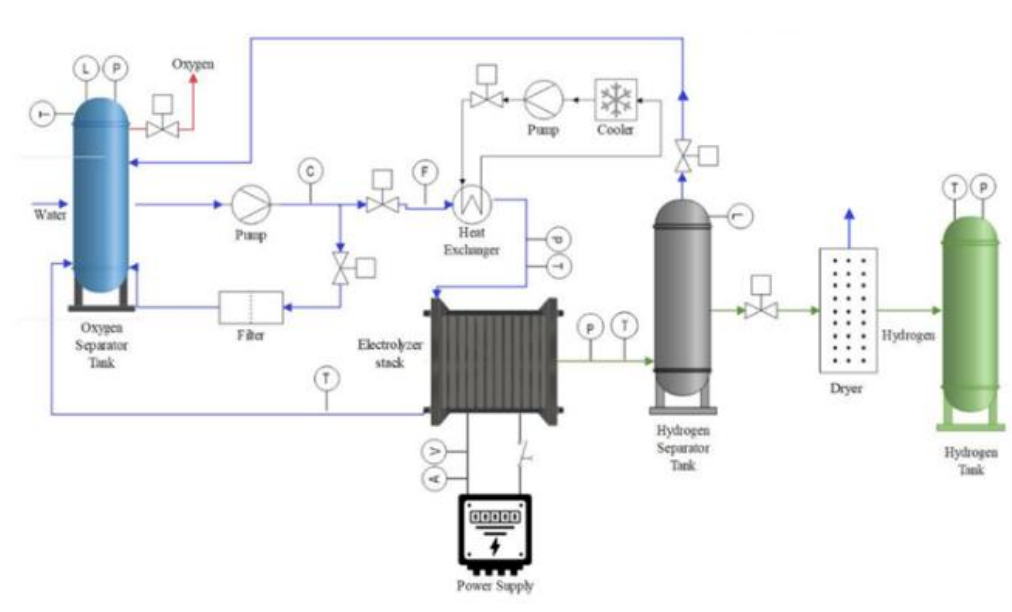


Figure 2-3 Physical system representation

At this level, system modeling plays a crucial role in understanding the interdependencies among variables and defining optimal operating ranges (see Figure 2-3 and Figure 2-4).

Monopoli et al. in [57] based on [59], [60], [61], [62] emphasize the use of multi-physics models encompassing:

- Electrochemical models, describing cell reactions, current distribution, and voltage losses (activation, ohmic, and concentration overpotentials);
- Thermal models, representing heat generation, dissipation, and the effect of stack temperature on efficiency and degradation;
- Mass and energy balance models, accounting for water flow, gas separation, and recirculation subsystems.

Through these models, the physical layer not only provides data but also constitutes the foundation for digital calibration and validation, ensuring that virtual representations remain physically consistent.

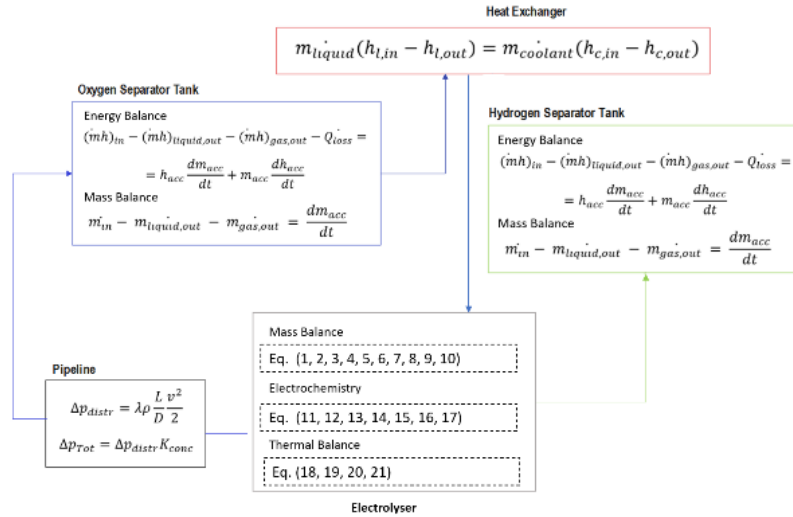


Figure 2-4 Physical system mathematical model

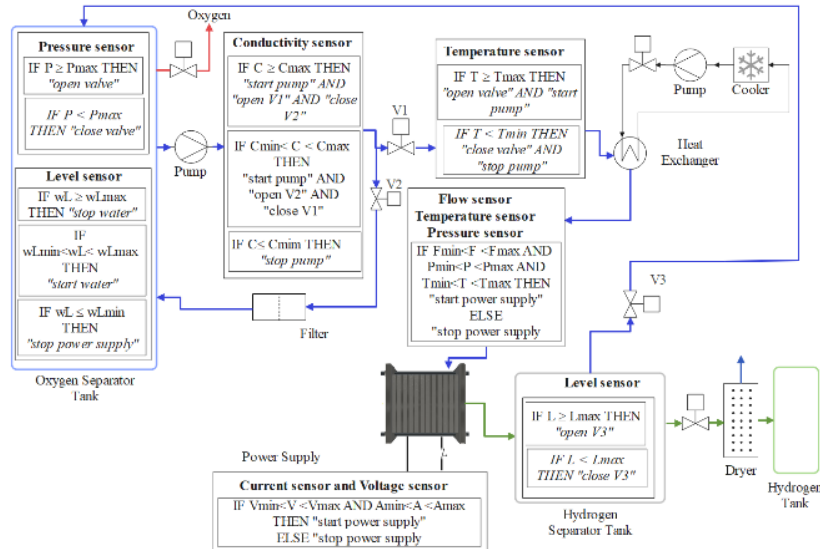


Figure 2-5 Example of control system

Digital Layer

The Digital Layer constitutes the cognitive core of the DT. It integrates and processes information collected from the field to generate insights, forecasts, and recommendations. It is composed of three complementary and synergistic subsystems:

Geometric Model – A 3D representation of the plant or system, developed using CAD or CAE tools (e.g., SolidWorks, CATIA, or Autodesk Inventor). This model provides an intuitive interface for operators, allowing them to visualize the current state of each subsystem in real time. Components are color-coded (green, orange, red) according to operational ranges, enabling immediate recognition of deviations or faults [46]. An Example of geometric model is provided in Figure 2-5. Beyond visualization, the geometric model also facilitates integration with augmented reality or virtual commissioning environments, enhancing operator awareness and training[63].

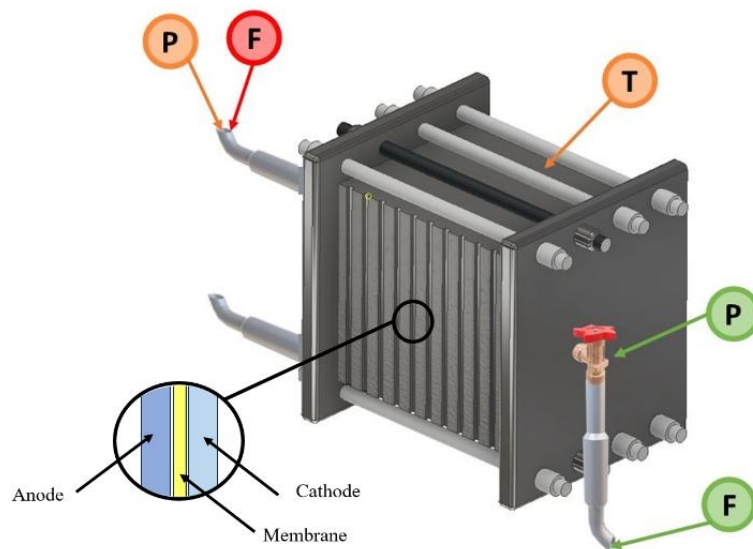


Figure 2-6 Geometric model

Behavior Model – A simulation environment derived from mathematical modeling. It uses physics-based equations to replicate the system's dynamic behavior under different operating conditions. This model enables *what-if* analysis, allowing engineers to simulate performance variations due to parameter changes (e.g., temperature, pressure, or current density) without interrupting real operations. Common software environments for this purpose

include MATLAB/Simulink, TRNSYS, or COMSOL Multiphysics. The fidelity of the behavior model directly affects the predictive accuracy of the DT and its usefulness in control optimization and failure prediction.

Data-Driven Model – This component captures latent knowledge that cannot be represented analytically. It relies on unsupervised learning techniques, particularly Formal Concept Analysis (FCA), to identify correlations and causal rules among process variables. FCA structures the system’s historical data into formal contexts of objects (observations) and attributes (parameters), generating concept lattices that highlight relationships among operating conditions and performance outcomes. From these lattices (see

Figure 2-7 and Figure 2-8), interpretable *if–then* association rules are extracted — for example:

IF stack voltage is average AND hydrogen separator level is high → THEN system efficiency is average (confidence = 100%) [46].

These rules enrich the decision-making process, enabling transparent reasoning that can be understood and trusted by human operators.

It is important to note that Formal Concept Analysis (FCA) is not the only approach available in the literature for extracting, formalizing, and reusing knowledge. Alternative approaches can be found in [64], [65], [66]. By combining physical knowledge (behavior model) and data-driven knowledge (FCA-based model), the digital layer achieves both *predictive* and *explanatory* capabilities, forming the backbone of the DT’s decision-support functionality.

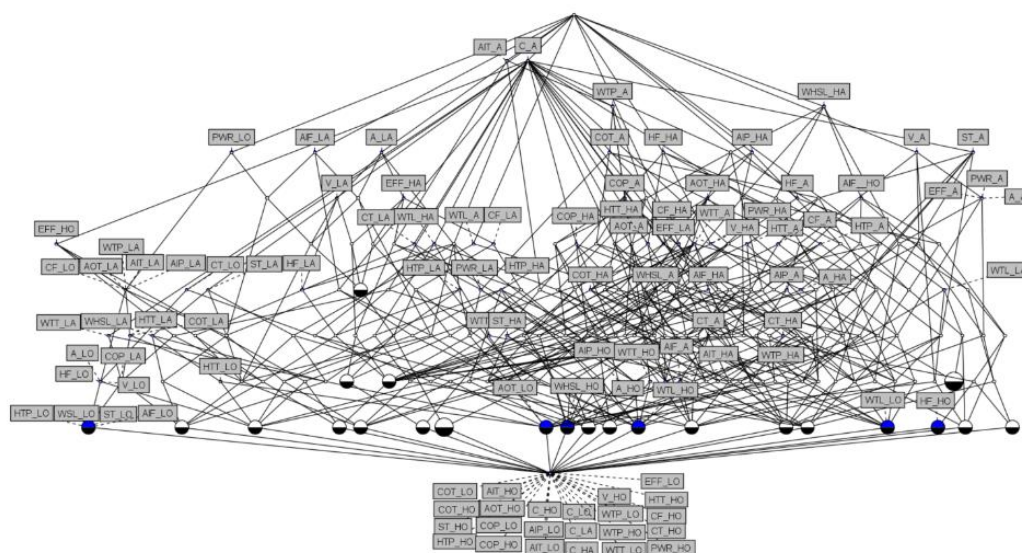


Figure 2-7 Association rules lattice

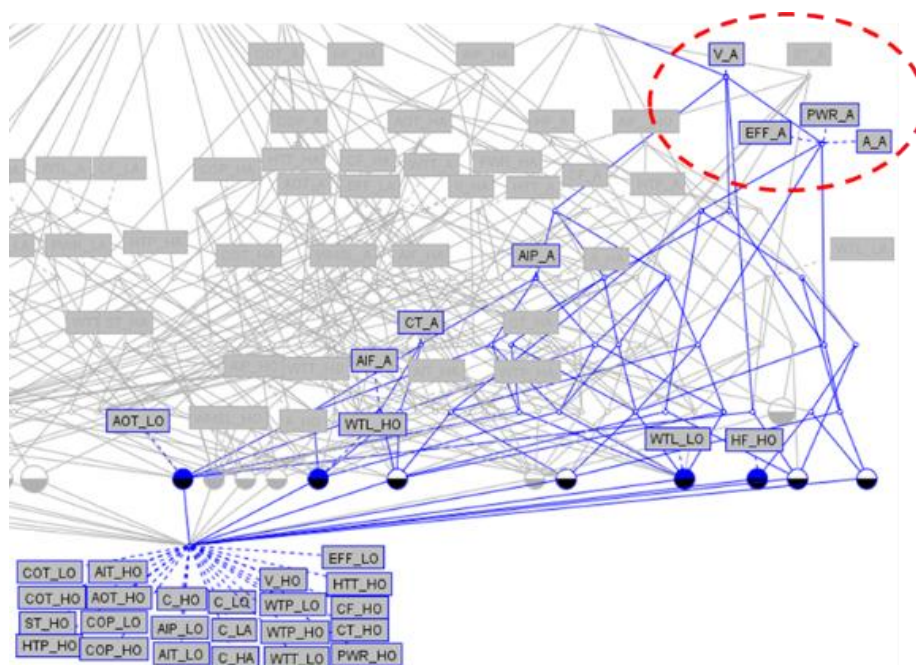


Figure 2-8 Detail of association rules lattice

Connection Layer

The Connection Layer acts as the communication backbone linking the physical and digital entities. It ensures that the data exchange between sensors, databases (see Figure 2-9), and simulation environments is continuous, secure, and synchronized. Depending on the application scale and latency requirements, different communication technologies may be adopted — from Bluetooth Low Energy (BLE) and ZigBee for local experiments, to Ethernet, Wi-Fi, LoRa, NB-IoT, or 5G for industrial-grade systems [46].

The connection layer typically includes (see Figure 2-10):

- Edge gateways for pre-processing and buffering raw sensor data;
- Industrial communication protocols such as OPC-UA or MQTT for interoperability;
- Data management infrastructures (databases, APIs, cloud or on-premises servers) to handle real-time streaming and storage.

In the DT loop, this layer closes the feedback cycle by transmitting analytical outcomes, optimized setpoints, or diagnostic warnings from the digital model back to the physical system. The fidelity and latency of this communication determine the DT's responsiveness and reliability as a real-time decision-support system.

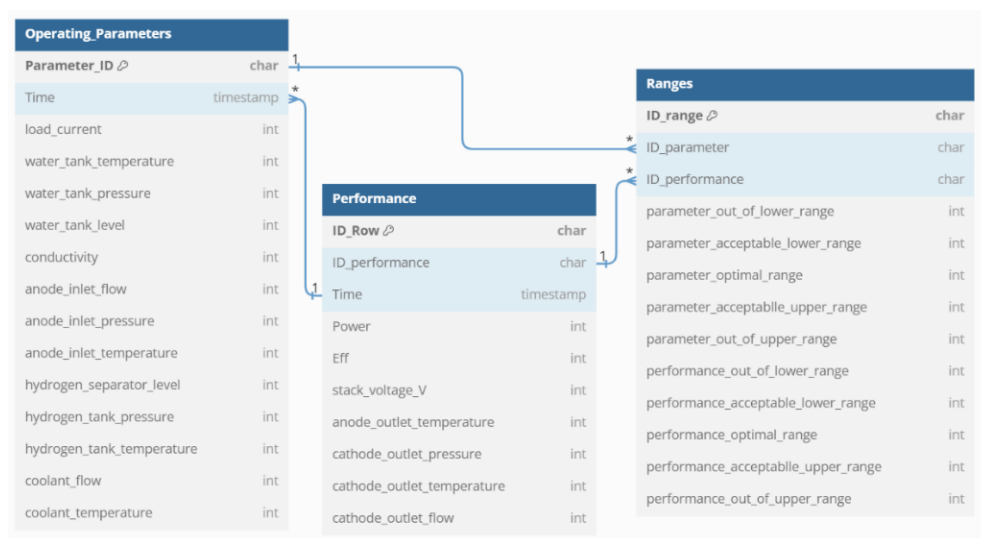


Figure 2-9 Example of relational databases

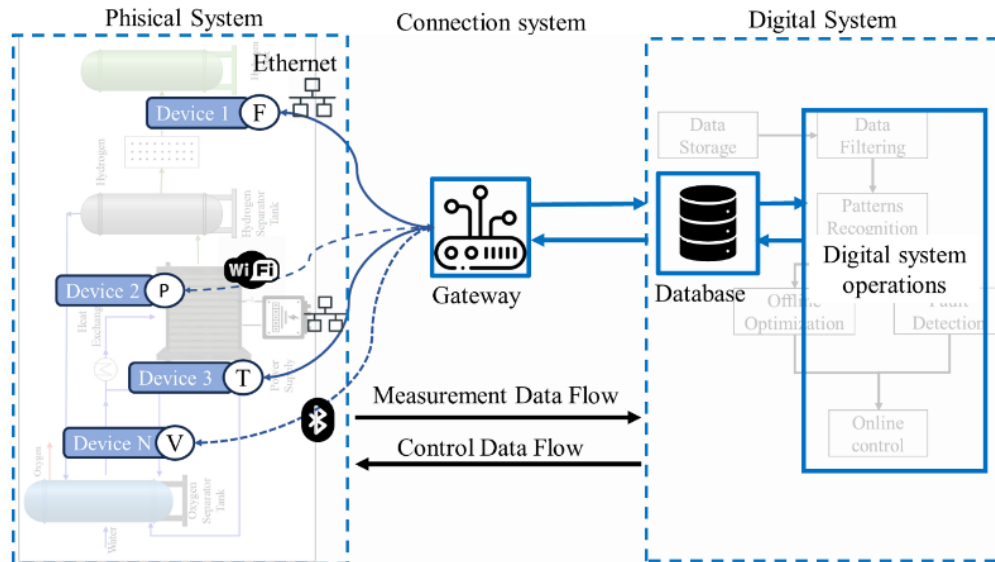


Figure 2-10 Example of communication layer

2.2.2.3 Decision-Support Functions

- Once deployed, a DT provides a variety of services that directly contribute to decision-making within industrial operations[67]:
- Monitoring and visualization – real-time representation of system states through dashboards or 3D interfaces, improving process transparency.
- Predictive maintenance – forecasting of component degradation and anomaly detection to prevent unexpected failures.
- Optimization and control – recommendation of optimal operating conditions using hybrid models that integrate data-driven analytics with physical constraints.
- Fault diagnosis and recovery – identification of abnormal behaviors and proposal of corrective actions in real time.
- Scenario simulation and what-if analysis – evaluation of alternative operational strategies before implementation.

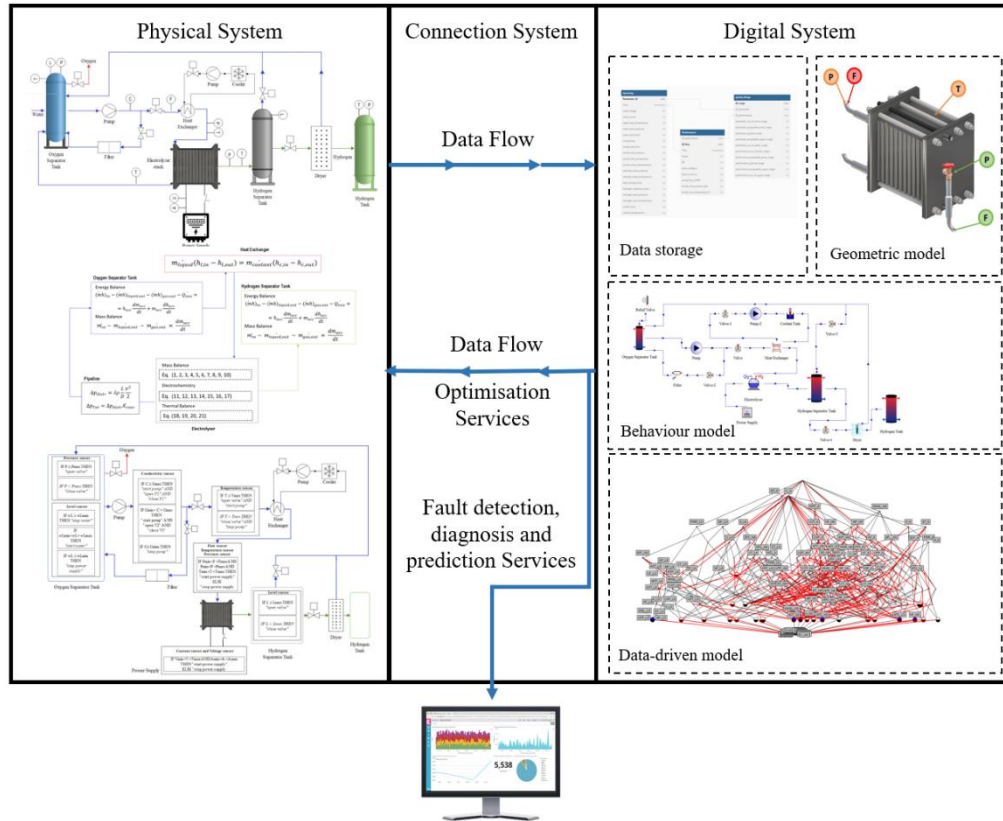


Figure 2-11 Complete Digital Twin Architecture

In the PEM-electrolyser case, Monopoli et al. [56] implemented a hybrid architecture combining physical equations with a data-driven reasoning layer based on Formal Concept Analysis. This combination enabled the DT to derive if-then rules from operational data, providing operators with transparent recommendations and enhancing trust in automated decision support. The final example of the architecture proposed is provided in Figure 2-11. By offering interpretable, traceable, and explainable outputs, the DT becomes an assistive system that complements human cognition rather than replacing it.

2.2.2.4 Linking Digital Twins to Human-Centered Technologies

The Digital Twin forms the cognitive core of the broader ecosystem of human-centered technologies in Industry 5.0. When integrated with other enabling tools—such as Artificial Intelligence, Augmented and Virtual Reality, and

collaborative robotics—the DT acts as the decision intelligence hub connecting humans, machines, and data [17], [44]. In combination with AR/VR technologies, DT data can be visualized immersively, allowing operators to explore system behavior, perform diagnostics, or simulate maintenance operations in real time [51]. When coupled with AI-based decision-support systems, the DT enhances reasoning capabilities, enabling adaptive and explainable decision-making aligned with operator goals. Within human-machine collaboration frameworks, the DT ensures transparency, trust, and explainability, promoting mutual understanding between humans and automation. Through these integrations, the Digital Twin evolves from a monitoring tool into an active mediator of human-machine collaboration, enhancing situational awareness, safety, and decision confidence. It thus embodies the principles of human-centricity by positioning technology as a partner that augments human expertise rather than substituting it.

2.3 THE HUMAN PERSPECTIVE

In order to understand how a human-centric production system can be improved through the adoption of human-centered technologies, it is first necessary to analyze the human system itself and the way it interacts with the machine system. The human being, throughout life, is constantly engaged in performing tasks. As stated by Normann[68], given a specific goal, in order to achieve it the individual follows a fundamental cycle composed of three primary operations: sensing the environment, elaborating information, and executing the planned actions. These steps, summarized as sensing, elaborating, and executing, are continuously repeated in a loop until the objective is reached. This general process is also followed when achieving the objective requires interacting with a machine, as shown in Figure 2-12. The sensing phase relies on the human sensory system—vision, hearing, smell, taste, and touch—which provides the necessary inputs from the environment. The elaboration phase is generally more complex, as it requires cognitive processing performed by the human mind[69]. It is assumed that before any task can be effectively executed, the individual must have undergone adequate training and learning, which represents a crucial aspect of human-centric systems: knowledge acquisition and preparation are indispensable prerequisites to proper task execution[70]. Finally, the execution phase is typically carried out through the human motor system, transforming planned actions into physical operations. This model highlights the intrinsic peculiarity of human-centric systems, where the effectiveness of task performance is not only determined by sensory and motor

capabilities, but also by the prior learning process that enables humans to adapt, improve, and operate efficiently in dynamic and complex environments.

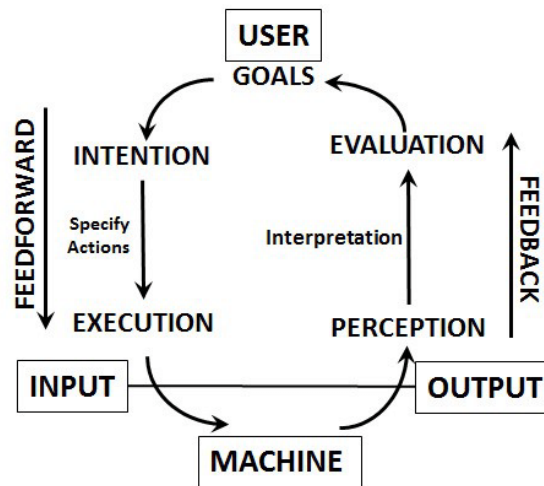


Figure 2-12 Norman's human machine interaction framework

2.3.1 The Human Cognition

Human cognition represents the complex network of mental processes that allow individuals to perceive, interpret, and interact with their environment. In the context of human-machine systems, cognition is the “central processor” that transforms sensory inputs into meaningful actions through perception, attention, memory, and decision-making. As shown in Figure 2-13, these processes are organized in a continuous perception-cognition-action loop, where each stage dynamically influences the next [71], [72].

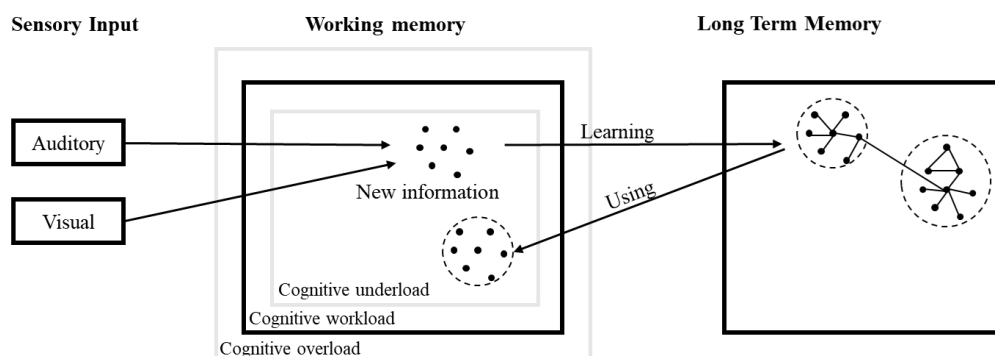


Figure 2-13 Human cognitive process

The cognitive cycle begins with perception, the process of acquiring and filtering sensory data. Neurophysiological evidence has demonstrated that perception is not a passive reception of stimuli but an active selection process that determines which information reaches consciousness[69]. The subsequent phase, attention, regulates this selection by allocating limited cognitive resources to relevant stimuli. Wickens et al. [71] suggests that humans possess several pools of attentional resources, divided across modalities (visual, auditory), processing stages (perceptual–cognitive vs. response), and codes (spatial vs. verbal). When concurrent tasks demand overlapping resources, cognitive overload and performance degradation occur.

Once perceptual information has been filtered and organized, it is processed within working memory, a temporary system for maintaining and manipulating information [73]. The multicomponent model of working memory includes the phonological loop, the visuospatial sketchpad, and a central executive, later complemented by the episodic buffer, responsible for integrating multimodal information. This framework enables the formation of situational representations that support reasoning and decision-making [73]. Working memory interacts continuously with long-term memory, where past experiences and procedural knowledge are stored and retrieved as needed.

The decision-making stage translates understanding into goal-directed actions. According to Parasuraman and Riley [74] this process involves the human evaluation of system states and automation feedback, which can lead to different interaction modes: use, misuse, disuse, or abuse of automation. The quality of human–machine collaboration therefore depends on the operator's ability to maintain an adequate level of situational awareness and to trust automation appropriately.

From a systemic perspective, [75] reinterpret cognition as an emergent property of joint cognitive systems, in which humans and machines cooperate as interdependent agents. In this view, cognitive functions such as monitoring, problem-solving, and adaptation are distributed across both components, emphasizing the need for transparency and shared control. Similarly, Norman [68] highlights the role of conceptual models and perceived affordances, through which users form mental representations of system behavior, guiding their interactions and expectations (see **Figure 2-13**).

In conclusion, human cognition constitutes the foundation of effective human–machine interaction. A deep understanding of cognitive processes enables the design of human-centered systems that align with natural perceptual and

reasoning capabilities. Technologies that support cognition—such as adaptive interfaces, augmented reality, or cognitive digital twins—should aim not to replace human decision-making, but to enhance it, maintaining an optimal balance between automation, workload, and human control.

2.3.2 Human Digital Twin

In recent years, the concept of the Human Digital Twin (HDT) has emerged as a key evolution of the digital twin paradigm, extending its focus from technical systems to the human element within cyber-physical environments. While traditional Digital Twins replicate machines, processes, or products, the HDT aims to create a dynamic and adaptive digital representation of the human being, capable of mirroring physical, cognitive, and even emotional states in real time. This transformation is crucial for realizing the human-centric vision of Industry 5.0, in which technologies are designed to enhance human capabilities rather than replace them [76].

The early conceptual foundations of this transition can be found in the Human–Cyber–Physical System (HCPS) frameworks. In [77] is proposed a Human Cyber-Physical System for “Operator 4.0,” highlighting the integration of sensing, modelling, and decision support around the human operator. Their architecture defines the operator as both a physical and cognitive agent in a continuous feedback loop with cyber and physical layers, anticipating many of the features that would later characterize the HDT. Similarly, Buerkle et al.[78] presented an adaptive human-sensing framework for Human–Robot Collaboration (HRC), combining physiological and task-performance data to infer cognitive load and enable robot adaptation. Although not explicitly framed as a digital twin, their approach represents one of the first data-driven attempts to close the human-in-the-loop feedback in collaborative environments.

A concrete step toward this goal was achieved by Maruyama et al.[79] , who proposed a Digital Human integrated in a DT-driven manufacturing system. Their model connected a biomechanical simulation of operator motion and fatigue with the scheduling and control of collaborative robots. This application demonstrated the feasibility of using a digital counterpart of the worker to optimize ergonomics and performance, introducing the first operational instance of a Human Digital Twin in a manufacturing context. These works collectively reveal how HDT research initially evolved from ergonomics and Digital Human Modeling (DHM), later expanding to cognitive and emotional dimensions [80].

A unified conceptual definition of the HDT was first proposed by Miller and Spatz in [81], who described it as a dynamic, adaptive, and bidirectionally coupled model of an individual human, continuously synchronized with real-world data to enhance system performance and human well-being. Their SysML-based architecture formalized the HDT as a component of Human Systems Integration, identifying its potential in design, training, and sustainment across the product lifecycle. He et al. [80] further clarified the transition from Digital Human Modeling (DHM) to Human Digital Twin, framing the HDT as the convergence of physics-based and data-driven human models under a human factors perspective. They introduced the notion of model–data hybrid simulation, merging traditional ergonomic modeling with machine learning to capture both physical and cognitive behavior.

Building upon these conceptual advancements, Lin et al. [82] offered a comprehensive survey of HDT research, identifying common architectural layers—physical world, digital world, and human–computer interface—and highlighting three dominant challenges: (1) lack of standardization, (2) limited interoperability, and (3) absence of holistic cognitive models. Chang et al. [83] addressed some of these gaps by developing a vision-enabled, fatigue-sensitive HDT that uses multimodal non-invasive sensing (video and physiological data) to evaluate worker fatigue in real time and adapt assembly scheduling accordingly. This contribution exemplifies the shift toward human-aware adaptive control in Industry 5.0 environments .

The field has also moved toward defining taxonomies and maturity levels. Gaffinet et al. [84] distinguished between Human Digital Model (static representation), Human Digital Shadow (unidirectional data mirroring), Human Digital Twin (bidirectional and adaptive), and Augmented Human Digital Twin (aHDT), which denotes a deep integration between human and machine intelligence. This classification clarified the conceptual evolution of HDTs and emphasized the importance of real-time feedback and explainability.

In industrial applications, several authors have implemented HDT-like frameworks focused on physical, cognitive, and hybrid modeling. Modoni in [85] and Bucci in [85], [86] explored HDTs within manufacturing, showing their role as ergonomic and cognitive gateways within human–cyber–physical architectures.

A major milestone in the formalization of the HDT concept is the comprehensive review by Wang et al. [76], which positions the HDT as the enabler of human-centricity in Industry 5.0. Their framework defines the HDT through four

interconnected layers—agent, data, inference, and implementation—and explicitly links it to Maslow’s hierarchy of needs, framing industrial roles (designer, analyst, decider, executor, user) according to progressively higher levels of human development. Wang’s model also distinguishes HDTs from machine-based DTs, emphasizing unique features such as human rights, well-being, upskilling, personalization, and safe environments. This perspective firmly anchors HDT within the humanistic and ethical dimensions of Industry 5.0, where technology must amplify human creativity and resilience rather than merely optimize performance.

From a cognitive and philosophical standpoint, Yao in [87] introduced the concept of Human–Machine Co-Intelligence, rooted in the idea of human–machine symbiosis. His Symbols–Meaning–Value (SMV) space formalizes a shared perceptual–cognitive–action framework that merges human and machine reasoning. The paper defines co-intelligence as the “third intelligence,” emerging from the interaction of human and machine intelligences, guided by three principles: unified oneness, division of labor, and co-evolution. This theoretical vision directly complements the technical frameworks by Wang et al.[76] and Miller [81], offering a cognitive foundation for future empathic and symbiotic systems.

Overall, the literature shows a clear evolution from Digital Human Models (DHM) focused on physical representation, to Human Digital Twins (HDT) incorporating cognitive and affective states, and now toward symbiotic human–machine systems capable of reasoning and learning in context. The convergence of these trends—architecture [76], cognition [88], and symbiosis [87]—indicates that the next step in this progression is the development of Human-Centered or Empathic Machines, systems that not only sense and replicate the human but also understand, predict, and act in harmony with the human’s goals, states, and values[89].

This trajectory positions the HDT as the missing bridge between the digital twin of a process and the human-centered machine of Industry 5.0, where both human and digital entities co-evolve in a shared cognitive loop.

2.3.3 The Human Machine perspective

As previously discussed, the aim of this work is to understand how machines can effectively support human operators, with a particular focus on those tasks that cannot be fully automated. Within this perspective, machines can provide valuable assistance by enhancing human capabilities in one or more phases of

the aforementioned framework: sensing the environment, elaborating information, and executing tasks. By reinforcing these stages, technology does not replace the human role, but rather augments it, enabling operators to perform complex activities more efficiently, safely, and with reduced cognitive or physical workload. The discipline that addresses these aspects is known as human–machine interaction (HMI), which originated alongside the development of the first computers. Initially, the focus was primarily on designing interfaces that could enable humans to communicate effectively with machines. However, with the rapid evolution of digital technologies and the progressive increase in machine intelligence, the foundational principles of traditional HMI have started to reveal their limitations[41], [43]. In particular, the growing complexity of socio-technical systems has highlighted the need for new paradigms capable of ensuring not only usability, but also adaptability, trust, and effective collaboration between humans and machines. The following section discusses the current challenges in achieving seamless and reliable human–machine collaboration.

2.3.4 Human Machine Collaboration challenges

The prevailing perspective envisions the development of work cells composed of two interacting entities, human and machine, each capable of fully expressing its respective strengths. The primary challenge in human–machine collaboration arises from the **communication process** between these entities [90] particularly in the exchange of actions, intentions, and information. Intending to improve human-machine collaboration, several authors have reported on the difficulties encountered in achieving the goal. These have been collected in **Table 2-1**. The changes required of human beings are mainly concerned with training and education. Knowledge and understanding of the machine are the primary enablers for predicting machine behavior [30]. Indeed, if the machine behaves as expected, it is readily accepted by the human [41]. Similarly, the machine must learn to understand the human operator by developing behavioral models that capture individual characteristics and preferences, thereby enabling it to recognize human limitations, anticipate behavior, and adapt its actions accordingly. [91].

Table 2-1 Human Machine Collaboration Challenges

Type	Challenge	Description /Rationale	Reference2
Social Challenges	Technology acceptance and trust	Man perceives the machine as practical, easy to use, and reliable	[27], [29], [40], [41], [42], [43], [47], [92], [93], [94]
	Change of team Dynamics	The man accepts that his role within the production may change	[42], [43], [46], [47], [70], [92]
	Ethics and Privacy	The man acknowledges that the machine will use his data for good and will not be passed on to third parties.	[29], [37], [40], [43], [47], [93]
	Lifelong learning	Man accepts that training will be continuous	[27], [41], [42], [43], [46], [47], [91], [93]
Technical Challenges	Human Centric, personalized and adaptive	The machine adapts to man's physical, cognitive, and emotional conditions and allows the customization that operators prefer.	[29], [40], [41], [42], [43], [46], [47], [70], [91], [92]
	Transparency and Explainability	The machine acts transparently, showing its intentions.	[27], [40], [41], [43], [47], [91], [93]
	Performances Measures	The performances to be monitored are not only those related to the production process but also those concerning the well-being of the operator and the quality of collaboration.	[41], [43], [47], [92], [94]
	Interaction modes	The machine allows new and different modes of interaction depending on the task, role performed, and characteristics and preferences of the human being.	[40], [41], [42], [43], [47], [91], [93]

Starting from the challenges that hinder the realization of fully collaborative human-centered systems, as summarised in **Table 2-1**, the functional

requirements in Table 2-2, which are that the machine must be collaborative, empathetic, and intelligent, were derived.

2.3.5 Human Machine interaction Framework

As highlighted in [30], achieving these objectives and addressing the challenges summarized in **Table 2-1** requires the establishment of a symbiotic understanding between human and machine, enabling the system to attain optimal performance in both action and decision-making. In the same study, the authors propose a three-component framework to conceptualize symbiotic collaboration between humans and machines. Within this framework, the goal decomposition level defines the sequence of steps necessary to accomplish a task; the decision level identifies the most suitable alternative to achieve the objective; and finally, at the action level, the human and the machine cooperate to execute the developed plan. A related concept is discussed in [95], where the authors argue that a machine must possess both Know-How (KH) and Know-How-To-Cooperate (KHTC) in order to achieve maximum efficiency and flexibility in production. Within their proposed framework, KH and KHTC constitute the foundation for constructing the behavioral models of both entities, which are essential for supporting decision-making processes aimed at optimizing performance at the strategic, tactical, and operational levels. Although these contributions represent an important step toward enhancing human–machine collaboration, they fall short of considering the human being in a holistic sense, as they overlook aspects related to cognitive and emotional well-being. Moreover, they provide limited guidance for practitioners seeking to implement collaborative human–machine systems in real industrial contexts

This section represents an initial effort to conceptualize intelligent and empathic collaborative systems for production environments, designed to promote the physical, cognitive, and emotional well-being of human operators through a reference-based approach. In this work, empathy is defined as a communicative process through which one understands and appropriately responds to the feelings and emotions perceived in others [94].

As illustrated in **Table 2-2**, the functional requirements include keywords that reflect the core functions to be performed by the main subsystems of the collaborative, intelligent, and empathic machine. Specifically, the system will comprise four fundamental subsystems: sensing, understanding, prediction, and action.

Table 2-2 System Requirements for collaborative empathic and intelligent machines.

N	System Requirement	Ch. Add.	Ref.
1	Humans shall be trained and educated on machine Limits	1,2,4,	[29], [70], [93]
2	Humans shall be trained and educated on machine use and Behavior	1,2,3,4	[29], [70], [91], [93]
3	Humans shall be educated on Privacy concerns and cybersecurity issues	3	[43], [70]
4	The machine should adapt itself to Human's skills	1,2,4	[90], [96][22]
5	The machine should adapt itself to Human's preferences and behavior	1,3	[27], [43], [96], [97]
6	The machine shall be able to train the user	4	[91]
7	The machine shall sense Human Physical, Cognitive, Emotional load	5	[78], [94], [95], [98]
8	The machine shall understand Human Physical, Cognitive, and Emotional Limits	5,6	[22], [78], [95], [98], [99]
9	The machine shall understand Human intentions and Behavior	5,6,8	[27], [90][91][95][99][97]
10	The machine shall understand Human Skills, Expertise and Working preferences	5,6,8	[22], [27], [90], [91]
11	The machine shall communicate with the human	5,6,8	[27][90][95], [99]
12	The machine shall evaluate human well-being performances	7,8	[78], [94] [35][100][97]
13	The machine shall evaluate the collaboration quality performances	7,8	[27], [101][100]
14	The machine shall evaluate process performances	7,8	[95], [99], [100]
15	The machine shall behave according to the Human Physical, Cognitive, and Emotional load	8	[22], [27], [78], [97]
16	The machine shall behave according to Human Behavior	8	[27], [78], [91], [97]
17	The machine shall behave according to the Skills, Expertise and Working preferences	8	[7], [8], [18], [20]
18	Machines shall have different working modes according to human and process performances	8	[22], [27], [46], [90]
19	The machine shall have different interaction roles	8	[96][22][46]

The findings summarized in **Table 2-2** confirm what has been found in the literature regarding conceptualizing enhanced human-machine collaboration. It also adds some components to the frameworks presented by [30], [95]. To achieve symbiotic understanding and know-how-to-cooperate, the machine must be able to collect and process the information required to construct behavioral models of the human operator. This necessity underscores the inclusion of a sensing subsystem within the framework. After acquiring relevant data on the operator's intentions, preferences, skills, and physical, cognitive, and emotional states, the system employs this information within the understanding subsystem to build an individualized operator model. It is important to emphasize that such models are generally valid only for the specific operator from whom the data were collected, owing to the high degree of subjectivity inherent in this information. Through this modeling, the machine can infer, for instance, whether the worker is experiencing fatigue or boredom, and accordingly determine whether a change in the operational mode is required. These evaluations occur within the predicting subsystem, where the system assesses whether potential adjustments align with the predefined production objectives. Finally, the acting subsystem executes the selected action. It should be noted, however, that the detailed implementation of the sensing, understanding, and predicting components required to accomplish this process lies beyond the scope of the present work. The complete framework is shown in **Figure 2-14**.

2.3.5.1 Sensing subsystem

This subsystem is designed to capture the operator's state, including the physical, emotional, and cognitive conditions of human workers. It is responsible for collecting signals and information directly from the operator. According to requirements 7 and 8, the system must account for the operator's physical, cognitive, and emotional workload. In general, assessment methods for these dimensions can be grouped into three main categories: subjective methods, observational methods, and direct measurement techniques [102].

Regarding physical workload, the measurable characteristics typically allow kinetic and kinematic analyses of body movements. For instance, Lorenzini et al. [103] employed seventeen inertial measurement units to capture full-body motion, complemented by a force plate to record applied loads. Similarly, Tirupachuri et al. [104] performed real-time physical load assessments using accelerometers and innovative sensor-equipped footwear. Additional examples can be found in [101]. Cognitive workload, on the other hand, has been widely investigated through the measurement of physiological parameters and

behavioral indicators. The most commonly employed physiological signals include electrodermal activity (EDA), electroencephalography (EEG), and heart rate variability (HRV), whereas behavioral indicators often encompass eye tracking, gesture analysis, and voice analysis. Planke et al. 2021 [97] use a system capable of receiving EEG, cardiac activity analysis, eye movement analysis, and voice analysis to assess the operator's cognitive state. Jo et al. 2022 [98] use sensors for EEG analysis, cardiac analysis, and electrodermal activity as physiological measurements, eye analysis, facial expressions, and mouth control to perform behavioral assessments. Finally, Lagomasino et al. [92] use two subsystems for cognitive analysis: a kinematic tracking system for gesture analysis to assess body language, evaluating, for example, hyperactivity or self-touching, and attention tracking by head positioning in addition to measurements of physiological parameters such as EEG, EDA, and HRV. Emotional load is another factor to consider in improving human-machine collaboration [105]. Methods of measuring and assessing emotional load include those based on measures of physiological parameters, e.g., those derived from EEG measurements. In [105], [106] they use measurements derived from 12 sensors placed on the operator's head to measure emotional responses in different scenarios.

2.3.5.2 Understanding subsystem

According to [30], achieving the highest standards of human-machine collaboration requires that each entity within the system understand the other and be capable of predicting its behavior prior to taking action. Once the operator's physical, cognitive, and emotional signals have been acquired, the machine must possess reference patterns against which these signals can be compared in order to adapt and modify its behavior accordingly. The machine, therefore, must contain the static and dynamic models representative of the operator with whom it is working [76], [78], [100]. Some examples of static models of the operator concern the biographical characteristics, skills possessed, personality, and physical dimensions. As for the dynamic ones, we have the dynamic and kinematic characteristics, physical, cognitive, and emotional fatigue [22], [107]. For example, in [104] they use a kinematic and dynamic geometric model of the human body consisting of rigid bodies connected by joints to estimate the load and optimize the robot's actions. In [101] on the other hand, the geometric model is constructed by the vision system based on the mutual positioning of the markers worn by the human being. In [97] an Adaptive Neuro-Fuzzy Inference System, calibrated offline, allowed the data to be clustered into four different states characterizing the operator.

Subsequently, the model can accurately predict the operator's state in real time. An innovative approach was proposed by Lagomarsino et al. [92], who combined physiological parameters with behavioral indicators—such as hyperactivity and self-touching—to construct comprehensive behavioral and cognitive models of the operator. With regard to emotional modeling, it is important to note that only a limited number of practical applications are reported in the literature. One such example is presented by Ardito et al. [106]. In general, machine learning, deep learning, and neural network techniques are the most commonly employed approaches for developing these models.

2.3.5.3 Predicting subsystem

This subsystem employs the models generated in the previous stage to formulate operational decisions that precede the actions executed by the subsequent subsystem. In order to make informed decisions, the system must possess knowledge of the objectives to be achieved, the task to be performed, and the characteristics of the human operator [108]. Objectives can be related to productivity performance, quality, operator welfare, and environmental and economic sustainability [22], [99]. Lemoine et al. [95] strategic, tactical, and operational sub-blocks. In the strategic one, objectives are defined, possible alternatives are formulated, and the best alternative (tactical and operational plan) is selected through prediction. According to [27], the decision is made considering several dimensions: the capabilities, availability, welfare, preferences of the worker, and the requirements of the process. Simulations, optimizations, and predictive algorithms are mainly used to realize this subsystem.

2.3.5.4 Acting/Interacting subsystem

At this stage, the system must act to achieve the defined task objective. Depending on the nature of the task, the action may take place either in the physical domain or in the informational domain. In both cases, the system produces a variation in the environment—whether through a physical operation or by generating and communicating information—and these actions occur at the human-machine interface. An example of an application in which the machine interprets the user's intentions and adapts its behavior accordingly is presented in [109]. The authors present an assisted milling tool that enables inexperienced users to manufacture artifacts from a block of Balsa Foam. The tool incorporates the geometric model of the desired artifact and automatically adjusts the spindle rotation speed as the physical model approaches the target geometry. Moreover, the machine is equipped with force sensors that allow it to interpret the user's intentions and, when necessary, override its own predefined

recommendations. For example, [100] shows the design of an intelligent wearable robot to support physical assembly operations. The robot placed on the shoulders of the worker contains the models of the task and the operator. The robot should be able to minimize worker fatigue by reallocating task steps and respecting process constraints. Another fascinating work by Eyam et al. [110] involved using a cobot to complete assembly operations. The system employs EEG signals to classify the operator's emotional state and subsequently adjusts the robot's movement speed and task delay times to restore the operator's emotional condition to acceptable levels. Depending on the specific task, the appropriate technologies may vary: augmented reality or I/O interfaces can be used to provide information and guidance to the operator, while collaborative robots, exoskeletons, or robotic arms can execute physical operations.

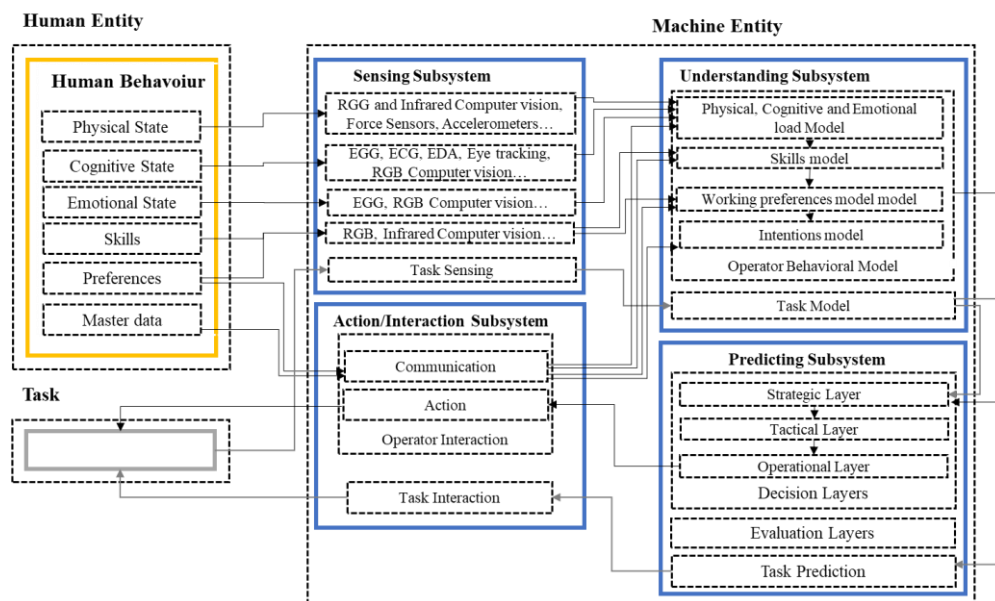


Figure 2-14. Sensing, Understanding, Predicting, Acting Framework

2.3.5.5 Use case scenario

An example is presented in this section to illustrate the practical application of the proposed framework. Consider the case of a flexible production process in which a plate must be drilled at a specific axial angle and depth, with each hole requiring different parameters. At the initial stage, the machine has no prior knowledge of the operator; therefore, it must collect data during task execution

through the sensing subsystem and use this information to build models within the understanding subsystem.

For simplicity, let us assume that the training phase of the machine—namely, the creation of the models within the understanding subsystem—has already been completed. During the operation, the operator holds the drill, supported by a robotic arm, and positions it at the drilling site. Through the sensing and understanding subsystems, the machine determines that the operator is in optimal condition, sets targets for maximum productivity, and transmits information on movement speed to the predicting subsystem. Strategically, the machine knows that the drilling sequence, as well as the angle and depth of each hole, must be defined. In this configuration, the human operator decides which hole to drill first, while the machine determines the correct axial angle and depth, verifies that the working parameters are accurate, and executes the operation through the action subsystem.

As the task progresses, the operator may experience physical, cognitive, or emotional fatigue. The machine, by continuously monitoring the operator's state, can detect these changes and adjust its objectives to help restore the operator's optimal condition. Consequently, it adapts its own behavior—for example, by reducing the feed rate or overriding decisions that appear suboptimal—thereby demonstrating how a human-centered machine acts adaptively to sustain both performance and operator well-being.

2.4 PARALLELISM BETWEEN THE DIGITAL TWIN AND THE HUMAN-CENTERED MACHINE

The conceptual model of the Human-Centered Machine (HCM) can be regarded as an evolution of the traditional Digital Twin (DT). While the DT establishes a bidirectional connection between the physical system and its digital counterpart, the HCM extends this paradigm by including the human being as an intrinsic part of the physical layer. In this configuration, the machine does not merely mirror the state of a technical system but also captures and interprets the operator's behavior, intentions, and physiological state, integrating them into the digital representation. In the HCM framework, the Sense–Understand–Predict–Act architecture mirrors and extends the DT layers as follows:

Sense – Physical layer

The sensing subsystem continuously acquires data from the human operator—such as posture, gestures, workload, and stress level—together with process data from the surrounding environment. This corresponds to the physical layer

of the DT, but enriched by human-related information that reflects the operator's state and interaction with the system.

Understand – Digital layer

The understanding subsystem elaborates the sensed data, updating the digital models that describe both the process and the operator. It captures the operator's skills, preferences, and cognitive state, integrating them into a coherent digital model. This process is equivalent to the DT's data and model management layer but extends it to include human cognitive and behavioral models.

Predict – Digital layer

The prediction subsystem uses the updated models to forecast future states of the human-machine system, identifying possible deviations, risks, or opportunities for improvement. In the DT analogy, this represents the simulation and analytics functions, which in the HCM are oriented toward anticipating human needs and optimizing collaboration rather than only process performance.

Act – Physical/Interface layer

Finally, the acting subsystem delivers the outcomes of the prediction either through interfaces (e.g., Augmented Reality guidance, adaptive visualizations, auditory or haptic feedback) or through physical actuators that modify the environment or machine behavior. This corresponds to the service/control layer of the DT, but with the explicit goal of closing the loop with the human, supporting decision-making and action in a context-aware and empathic manner.

In this sense, the HCM can be interpreted as a "human-augmented digital twin", where the traditional physical twin is replaced—or complemented—by the human operator, and the digital twin evolves into a cognitive partner capable of sensing, understanding, and predicting not only system states but also human states.

2.5 CONCLUDING REMARKS

This chapter has outlined the evolution from Industry 4.0 to a human-centric Industry 5.0, arguing that value in modern production systems emerges from symbiotic human-machine collaboration rather than substitution. Building on the Operator 5.0 and H-CPS perspectives, we identified AR/VR/XR and Digital Twins as enabling technologies that augment human capabilities across the

lifecycle—from immersive design and monitoring to assembly guidance and data-driven decision support. We translated open challenges (trust, transparency, adaptivity, performance, privacy) into actionable system requirements and proposed a Sensing–Understanding–Predicting–Acting framework to operationalize them. In doing so, the Digital Twin serves as the cognitive nucleus that connects data, models, and human intent, while AR/VR provides intuitive, context-aware interfaces on the shop floor. The next chapters leverage these principles to (i) analyze the human system and its interaction with machines, (ii) instantiate the framework into a human-centered machine design, and (iii) empirically validate effects on performance, well-being, and collaboration quality.

CHAPTER 3



Methodology and Experimental Validation

This chapter is extensively based on the following publication:

Monopoli, D., Caggiano, M., Semeraro, C., Dassisti, M. (2025). Towards a Human-Centric Industry 5.0: Exploring Team Roles to Improve Human-Machine Collaboration. Communications in Computer and Information Science, vol 2373. Springer, Cham. https://doi.org/10.1007/978-3-031-80775-6_21

3 METHODOLOGY

3.1 FROM CONCEPTUAL FRAMEWORK TO EXPERIMENTAL VALIDATION

The conceptual framework developed for Human-Centered Empathetic Intelligent Machines (HCM) represents an operational evolution of the Digital Twin paradigm, in which the human operator becomes an integral component of the physical layer. Within this architecture, the machine perceives human behavior and state through its Sense subsystem, processes and updates this information in the Understand and Predict subsystems located in the digital layer, and finally generates adaptive responses through the Act subsystem, which communicates with the human via multimodal interfaces or physical actuators.

While the previous work [89] presented in **Chapter 2** focused on the conceptualization and functional decomposition of such empathic machines—defining requirements, subsystems, and technological enablers—this doctoral research extends that framework toward its experimental validation. However, rather than constructing a fully functional prototype, the study adopts a simulation-based approach to reproduce the behavior of an HCM in a controlled environment.

In particular, the experimental study [111] on human–machine roles and collaboration dynamics can be interpreted as a first practical instantiation of the HCM concept. The “machine” under test was not a physical system, but a virtual human-centered assistant, whose perception, reasoning, and action modules were simulated through an interactive interface developed in Unity 3D. This virtual platform emulated the subsystems of the conceptual framework: the Sense subsystem was represented by the system’s capacity to receive task data and monitor operator inputs; the Understand and Predict subsystems were embodied in the system’s apparent ability to analyze, interpret, and anticipate the operator’s actions; and the Act subsystem was reproduced through visual and auditory feedback guiding or correcting the operator’s behavior.

To make the interaction realistic, the experiment employed the Wizard of Oz methodology, in which a hidden human operator simulated the system’s autonomous reasoning and responses in real time. This approach was instrumental in reproducing the dynamics of a human-centered intelligent machine—capable of perceiving, understanding, predicting, and acting—without the need to build a complete physical or AI-based system. By doing so,

it was possible to investigate how different role configurations between human and machine (executor, supervisor, collaborator, negotiator) influence performance, workload, and system acceptance, while maintaining ecological validity and experimental control.

In summary, the experimental setup represents a simulated embodiment of the Human-Centered Machine framework: the conceptual subsystems were not physically implemented but virtually enacted through the Wizard of Oz simulation. This methodological bridge allowed testing the cognitive, social, and ergonomic implications of human-centered collaboration before developing an actual intelligent system—thus validating, in a controlled yet realistic way, the principles established in the conceptual design.

In this context, the literature review reveals that few studies on improving human-machine collaboration in Industry 5.0 are based on real industrial cases, particularly in exploring the roles within human-machine teams [112]. With reference to the previously discussed challenges, this work presents a preliminary study to evaluate different roles within human-machine teams by simulating various collaborative scenarios. Specifically, this study aims to identify the most appropriate roles for humans within human-machine teams and the best interaction strategies to improve process performance and operator well-being. To achieve this, in this work, the operators' workstations were enhanced with several components, such as cameras, displays, and speakers, remotely controlled through an interface developed in Unity. Operators were asked to perform their tasks under different collaborative scenarios. In particular, in this chapter, **paragraph 3.2** provides a brief literature review on measurement metrics, **paragraph 3.3** examines the literature regarding various roles within human-machine teams, **paragraph 3.4** outlines the testin methodologies used in similar context, **paragraph 3.5** complete methodology and experimental setup applied in a real industrial case. The experimental results are presented in **paragraph 3.6**.

3.2 MEASUREMENT OF HUMAN-MACHINE INTERACTION

As the Industry 5.0 paradigm shifts toward a human-centric approach, understanding and optimizing Human-Machine Interaction (HMI) becomes critical to achieving seamless collaboration between operators and technology [113]. The interaction between humans and machines lies at the core of this new paradigm, in which machines act not only as tools but as collaborative partners designed to support and enhance human capabilities. In this context, such interactions must be carefully designed to minimize operators' cognitive

load while safeguarding their well-being and maintaining high levels of productivity. Human-machine interaction concerns the ways in which humans engage with machines to perform tasks and how these interactions influence the operators' cognitive state. Although technological advancements can significantly improve efficiency, they may also introduce unintended consequences such as cognitive overload [114]. Therefore, optimizing HMI requires the design of intuitive and adaptive interaction modalities that alleviate, rather than amplify, these cognitive stresses. This approach aligns with the Industry 5.0 vision, fostering both operator well-being and overall system performance.

Evaluating human interaction with technology, however, is inherently complex. Unlike machines, whose performance can be measured with straightforward metrics, human interaction involves unpredictable behaviors and subjective experiences.

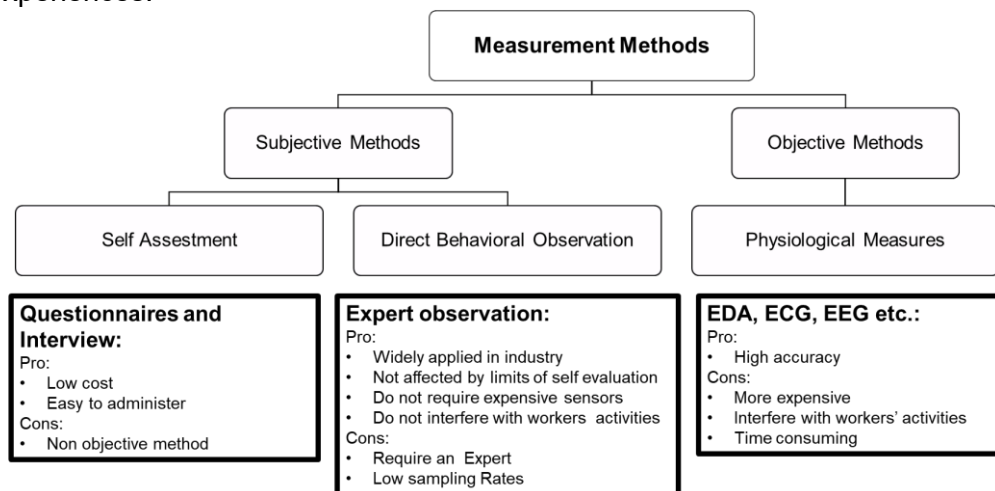


Figure 3-1 HMI measures taxonomy

A widely recognized tool used in HMI studies to assess these aspects is the NASA Task Load Index (NASA-TLX) [115]. This instrument is intended to evaluate the cognitive workload experienced by operators. It is widely employed to assess the mental, physical, and temporal demands imposed on users during interaction with machines. The NASA Task Load Index (NASA-TLX) enables a multidimensional assessment of task demands, providing meaningful indications of how different HMI configurations affect operator performance and overall well-being..

Given the complexity of human responses to technology, it is essential to adopt a holistic approach to the evaluation of Human–Machine Interaction, integrating tools such as the NASA-TLX with complementary assessment methods. A comprehensive literature review was conducted to examine a range of techniques and instruments for evaluating HMI, highlighting their crucial role in the design of effective and truly collaborative work environments. According to Sim and Loo [116], there are four evaluation methods used for human studies in HMI as depicted in Figure 3-1:

- Self-Assessments Subjective Evaluation/ Questionnaire [117]
- Behavioral measurements/ Direct Observation [118]
- Psycho-physiological measures [119].
- Task performance metrics [120].

Within this taxonomy of measurement methods, questionnaires, expert observations, and performance assessments represent traditional and widely adopted tools that have been extensively discussed over the years. A more innovative approach is offered by physiological measurements, which are gaining increasing importance across various scientific domains. A preliminary review of these approaches can be found in Section 2.3.5.1, dedicated to sensing methods for human operators.

3.3 HUMAN MACHINE INTERACTION DIMENSIONS

Following the literature review, several assessment models and frameworks were analyzed, such as the one proposed by Gervasi et al. [121], Grerkiat et al. [122], and Marvel et al. [123]. The proposed HMI evaluation method draws inspiration from existing frameworks, revisiting and extending them to better capture the dynamics of interaction. It differentiates the key variables of human–machine interaction that can be modified through design and examines how these variables influence operator performance and experience. The framework is schematized in Fig. 3-2. Among the modifiable variables are the dimensions concerning the exchange of information, team organization, and adaptivity and training. The first dimension, information exchange, refers to the medium and format through which communication occurs between the machine and the operator. Human input may be conveyed through direct modalities such as voice commands, typed text, or physical gestures, as well as through user interfaces including touchscreens, keyboards, or other interaction devices.

Similarly, machines can communicate with humans using various means, such as voice, text, or visual outputs [124]. Information exchange can be assessed

using the communication medium and format [121]. The communication medium refers to the senses (e.g., sight, hearing, touch) [124], while the communication format refers to the tools used for this exchange. In this evaluation framework, particular attention is given to the directionality of information flow. Interaction can be unidirectional, in which the user provides input and the machine simply reacts, or multidirectional, where both the human and the machine exchange inputs and feedback continuously, forming a dynamic and reciprocal communication loop [125]. The "team organization" dimension refers to the agents involved in the human and machine interaction. The team's structure is identified to define the right balance. Following this, it is important to define each team member's role (e.g., supervisor, operator, teammate, mechanic, and spectator) according to the taxonomy proposed by Scholtz [126], [127].

The final modifiable variable is adaptivity and training. Adaptivity refers to the machine's ability to modify its behavior based on external factors, such as learning from experience. From an industry 5.0 perspective, especially in the social domain, adapting machine behavior to human characteristics and context is a crucial aspect [128]. The concept of adaptivity is linked to the morphology of the machine. Machine morphology refers to the machine's design, which can encourage or discourage collaboration between humans and machines. The morphological features of a robot are significant, as they influence people's expectations and willingness to collaborate [129]. Finally, the training of both machines and operators is considered. Machine training involves teaching the machine to perform a specific task [130], while operator training refers to preparing operators for tasks involving machine use. Variations in these factors impact the dimensions of Operator Well-Being and Operator Satisfaction.

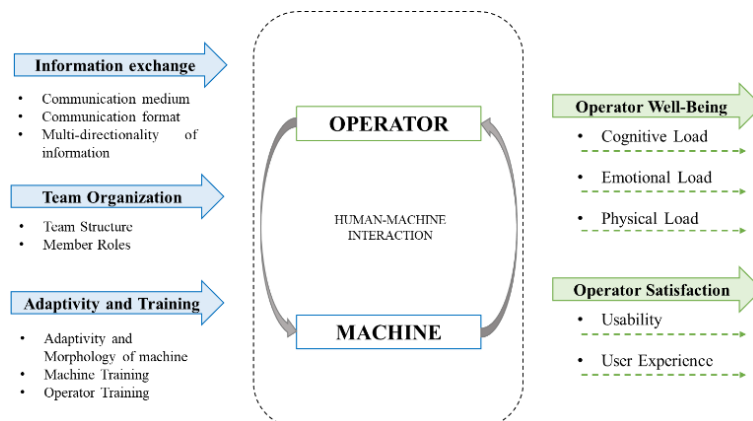


Fig. 3-2. Dimensions of Human-Machine Interaction and Operator Effects

Operator well-being is determined by the interplay of cognitive load, emotional load, and physical ergonomics. Cognitive workload refers to the mental effort perceived by the user during task execution and is largely influenced by the complexity of the task and the quality of the system's design [131]. Cognitive load tends to increase as task complexity rises; however, this relationship does not fully account for individual differences in skills and cognitive capacity. Physical ergonomics, on the other hand, focuses on the anatomical, anthropometric, physiological, and biomechanical characteristics of human work, which collectively determine the operator's physical load and influence comfort, efficiency, and long-term well-being [132]. This subdimension examines repetitive movements, postures, material handling, and force application in collaborative work. Cognitive and physical loads also affect the operator's emotional load [133]. Regardless of task design or ergonomic optimization, operators possess individual traits and attitudes that shape their perception of work. Another key aspect affected by the variables discussed is operator satisfaction, which is closely linked to the usability of the system and the overall user experience. According to the standard definition, usability refers to *"the extent to which specified users can use a product to achieve particular goals with effectiveness, efficiency, and satisfaction within a defined context of use"* [134]. User experience refers to "a person's perceptions and responses resulting from the use and/or anticipated use of a product, system, or service" [134]. This concept encompasses the user's feelings, preferences, perceptions, and reactions before, during, and after interaction with the system. From the individual user's perspective, usability also involves perceptual and affective components that are closely associated with the overall user experience. User experience can, in turn, be evaluated through established usability criteria. In this study, several of these aspects were analyzed to identify the optimal configuration for effective human-machine interaction.

3.4 HUMAN AND MACHINE ROLES

A key element in the design and analysis of human-machine collaborations is the clear definition of respective roles (**section 3.2**): it is necessary to establish precisely which tasks fall to the human and which to the machine, to determine the level of decision-making authority given to the technology, and to identify the point in the decision-making process at which the machine is called upon to intervene. To study role allocation, several taxonomies offer descriptions of what tasks the "human operator" and the "computer" are assigned within a collaboration [135]. Typically, levels of automation range from fully manual to fully automated [136], [137]. Fully manual describes a situation where the

human is completely in charge. In contrast, fully automated indicates that the human operator is completely out of the loop and, therefore, obsolete [138]. In general, automation refers to a state in which a technical system performs a task previously done by a human or part of a human. In performing this task, the machine operates autonomously, without the need for direct intervention by a human operator [138]. In the context of human-machine collaboration, the level of automation describes the extent of machine contribution to joint performance. It is essential to determine whether, and to what extent, humans remain 'in the loop' for both action and decision-making [139]. These taxonomies focus on human-machine interaction, where the level of automation depends on variations in task assignment. Consequently, these taxonomies describe the different role allocations between humans and technical systems, asking the fundamental question: who does what?".

Designing human-machine collaboration requires careful determination of which tasks to automate and to what extent [138]. Thoughtful design decisions depend on a thorough understanding of task allocation. For example, focusing on the impact of fatigue in human-robot collaborative tasks and how it may affect task assignment, Hu et al. [140] modeled human fatigue as a Markov decision-making process in continuous time, capturing stochastic uncertainties about fatigue dynamics under different task assignments and proposing a Petri net to model production processes and linear programming to solve task assignment in an assembly context. Focusing on human factor needs, humans should be retained in the decision-making cycle to avoid phenomena of complacency, loss of skill, and loss of situational awareness [141]. However, some empirical studies on human-robot interaction indicate that human control and decision making are not always desirable regarding process efficiency and subjective satisfaction [142]. This can be partially explained by the increased workload from decision-making authority and human responsibility in the supervision of autonomous systems [143].

To formalize the roles of human and machine, two leading roles that both human and machine operators can assume in the context of collaboration were considered: the role of executor and the role of supervisor. The machine can act as an autonomous performer, performing tasks and making operational decisions without direct human intervention, or it can support the operator in repetitive tasks, leaving the operator in control of decision-making. The human operator, on the other hand, can be an autonomous performer when it manages the entire process independently, playing an essential role in contexts that require creativity and flexibility [144]. Another crucial role is that of supervisor: in this case, the operator monitors the machine's activities, intervening only

when necessary to ensure correctness and efficiency of the process [145]. This concept of machine/human as leader/supervisor can be integrated with the concept of Level of Robot Autonomy (LORA) [146], which describes how the functions of perception, planning/decision-making, and action (Sense, Plan/Decide, Act) can be divided between human and machine within a team.

As shown in **Table 3-2**, human and machine roles can be organized along a continuum from fully manual control to fully automated control. At the lowest levels of automation, as in the case of manual control or teleoperation, all key functions—perception, planning, and action—are handled primarily by the human operator. In these configurations, the machine acts as a mere performer or physical assistant, with no autonomous capabilities for perception or decision-making. Progressing to intermediate levels, we observe forms of shared control in which humans and machines contribute to the three functions to varying degrees. For example, machines can sense and analyze the environment in decision support, but humans remain responsible for decision-making and command. In more advanced configurations, such as shared control with machine initiative, the machine not only perceives and acts autonomously but can also prompt human intervention in case of difficulty or to redefine goals and plans. At higher levels of autonomy, such as in executive or supervisory control, the machine gradually assumes responsibility for cognitive and operational functions, reducing direct human involvement to monitoring or exceptional intervention. Finally, in the case of full autonomy, the machine handles all phases—perception, planning, and action—without any direct human intervention. Based on the literature review, we can outline two key roles that emerge within the collaborative work between humans and machines. The operator or machine can be an *executor*. In this case, autonomy and decision-making control may vary [144]. The machine can be an autonomous executor, meaning completely autonomous, able to take control of certain operations and make operational decisions without direct operator intervention. The operator intervenes only in special or emergencies. Or the machine performs repetitive and automated tasks, supporting the operator in operations that require precision or continuity. In this case, the operator retains decision-making control. In contrast, humans can also be autonomous executors when they manage and complete specific tasks without machine assistance. In this role, the operator has entire decision-making and operational autonomy and can intervene directly at any stage of the production process.

Table 3-1 Human-Machine Role Configurations According to Levels of Autonomy

LORA	Sense	Plan/ Decide	Act	Supervisor		Executor		Description
				Leader	Follow er	Leader	Follow er	
Manual	H	H	H	H	/	H	/	Human Supervisor and Executor
Teleoperation	H/M	H	H/M	H	/	H	M	Human Supervisor and Executor / Machine Assistant Executor
Assisted Teleoperation	H/M	H	H/M	H	M	H	M	Human executors and a supervisor machine assistant
Batch Processing	H/M	H	M	H	/	M	/	Human Supervisor /Machine Executor
Decision Support	H/M	H/M	M	H	M	H	/	Human Supervisor and Executor /Machine Assistant Supervisor
Shared Control with human initiatives	H/M	H/M	M	M	H	M	H	Human supervisor and assistant Executor Machine Executor
Shared Control with Machine initiatives	H/M	H/M	M	M	/	H	M	Human Assistant Executor and Supervisor Machine Executor
Executive Control	M	H/M	M	M	H	M	/	Human assistant, Supervisor, Machine Supervisor, and executor
Supervisory control	H/M	M	M	M	/	M	H	Human assistant executors, Machine Supervisor, and executors

This is especially the case in situations where adaptability, intuition, or creativity are required, qualities that the machine cannot replicate—the executive assistant role for the human overlaps with that of the *supervisor* [145]. When the human operator assumes this role, his main task is supervising the machine's work, monitoring that operations proceed correctly, and intervening only when necessary. In this case, the human does not directly perform operational tasks but aids in the form of monitoring and correction, ensuring that the system runs efficiently and error-free.

The machine can also assume the role of human work supervisor in advanced automation contexts, especially in Industry 5.0, where human-technology collaboration is more integrated. In this case, the machine uses sensors, algorithms, and artificial intelligence to monitor the activities performed by the human operator, providing support, suggestions, or even reporting errors or inefficiencies in human work. The machine can offer real-time feedback, suggest improvements or changes in operations to optimize the operator's performance, or monitor the quality of the work performed, detecting anomalies or defects that may not be visible to the human eye.

Therefore, machines and operators communicate and make decisions in this context. Underlying this scenario emerges two fundamental theories: negotiation and game theories [145]. These theories provide the conceptual basis for understanding and optimizing the dialogue between machines and humans, enabling shared decisions, optimal solutions, and greater synergy between human capabilities and technological potential. The models describe how humans and the automated system negotiate decisions based on options. The goal is to agree on a joint decision through a bid exchange mechanism at specific times [147]. Each agent, whether human or machine, evaluates the offers it receives based on a utility function representing the value or preference for a given offer. As the negotiation proceeds and approaches the deadline, agents are willing to make concessions by reducing their target utility, that is, by accepting less advantageous offers than they would have accepted at the beginning of the negotiation.

A significant example is shared control systems, such as those in semi-autonomous vehicles, where the human operator and the machine actively cooperate to decide on the most appropriate driving actions. Similarly, in robotic collaboration, humans and robots should cooperate to complete complex tasks to optimize efficiency and reduce errors. Even in automated decision-making systems, such as in financial trading or air traffic management, human-machine synergy is crucial: the human supervises the operations performed by the

machine or collaborates directly with it to make decisions that require rapid and accurate evaluation [148].

Decision logic and heuristics criteria for human-machine role allocation

In the experimental validation presented in this work, the different human-machine collaboration modes were predefined and kept fixed throughout each experimental scenario. This choice was intentional and aimed at isolating and comparing the effects of distinct role allocations under controlled conditions. However, within the proposed human-centered framework, these collaboration modes should be interpreted as states of a potentially adaptive system rather than as rigid configurations. Transitions between modes may be driven by a decision logic based on a combination of human-related and system-related indicators. Typical examples include variations in operator cognitive workload, task performance degradation, error rates, or confidence levels associated with automated decision support. For instance, an increase in operator workload beyond acceptable thresholds may trigger a transition toward higher machine autonomy, whereas situations characterized by low automation confidence or unexpected system behavior may require a shift toward increased human supervision.

To increase the technical clarity and implementation readiness of the proposed framework, the allocation of roles between human operators and machines can be expressed through a set of simple heuristic decision rules. These rules are not intended as optimized control laws, but as interpretable criteria that link observable system states to collaboration mode selection. In particular, role allocation may be driven by indicators such as operator cognitive workload, task performance metrics (e.g., execution time, error rate), and automation confidence. For example:

- *If operator cognitive workload exceeds a predefined threshold, then the system may shift toward increased machine execution or assistance.*
- *If task performance degrades despite high machine autonomy, then human supervision or intervention may be reinforced.*
- *If automation confidence is low or unexpected system behavior is detected, then control authority may be transferred back to the human operator.*

These heuristic rules allow the collaboration modes defined in this work to be interpreted as decision-dependent states of a human-machine system.

Although such adaptive transitions were not implemented in the current experimental setup, their conceptual definition represents a key element of the

proposed framework and provides a foundation for future real-time implementations.

After detailing these roles and scenarios, the upcoming case study assesses the enhanced collaboration model by evaluating cognitive stress and performance across the different scenarios.

3.5 TESTING METHODOLOGY

Designing and evaluating effective human-machine interaction (HMI) has long been a central theme in Human-Computer Interaction (HCI). Over the years, various prototyping and testing methods have been developed to assess usability, user satisfaction, and task efficiency, particularly in systems characterized by fixed interfaces and deterministic behaviors.

Historically, low - and medium-fidelity prototyping methods have played a fundamental role in interface testing [149]. Techniques such as pretend mode, paper prototyping, and staged prototyping have been widely used in early design phases [150]. Pretend mode involves simulating system behavior with no real backend, allowing users to interact with mock interfaces while the evaluator manually triggers visual or navigational changes [149]. Paper prototyping similarly focuses on interface layout and flow, relying on printed mock-ups manipulated by facilitators. These traditional methods are highly effective for evaluating visual design, navigational flow, and usability principles, but they prove inadequate when applied to intelligent systems [43]. In particular, they lack the flexibility to respond dynamically to user inputs, cannot simulate autonomy or probabilistic reasoning, and fail to elicit critical user perceptions such as trust, cognitive load, or shared control [151]. These dimensions are essential when the system under evaluation includes artificial intelligence or adaptive behavior [40]. In recent years, modern methodologies have emerged to bridge this gap, offering new ways to simulate, supervise, or co-operate with intelligent systems. Among them, three approaches are particularly relevant: Wizard of Oz, Ghost in the Machine, and Human-in-the-Loop simulation. Simulation-based methods such as Wizard of Oz, Ghost in the Machine, and Human-in-the-Loop have proven highly valuable in the early prototyping stages of human-machine systems. These approaches enable realistic user interactions without requiring a fully functional backend, allowing researchers to explore how users behave, decide, and react in scenarios involving artificial intelligence or automation. Through these controlled yet ecologically valid setups [152], designers can capture rich insights into operator preferences, preferred interaction modalities, cognitive workload, and usability patterns [153].

Moreover, they offer a window into social dynamics, such as trust calibration, perceived system agency, and willingness to delegate or supervise decisions. These methods also help uncover latent factors that are difficult to predict through traditional usability tests, such as emotional responses, coping strategies under uncertainty, levels of perceived control, and user adaptation over time. Collectively, these insights inform the design of collaborative technologies that are functional, acceptable, empowering, and aligned with human cognitive and social needs.

Table 3-2 Comparison of Testing Methodologies for Autonomous Systems

Methodology	Pros	Cons	References
Wizard of Oz	High realism, flexible, valuable behavioral insight	Logistically complex, ethically sensitive, not scalable	[155], [159], [160]
Ghost in the Machine	Low intrusion, safety net, suitable for monitoring	Does not simulate autonomy, limited insight into user trust	[156]
Human-in-the-Loop	Realistic collaboration, supports learning, enables trust evaluation	Requires a functional system and human resources	[157], [158], [161]
Traditional Methods	Fast, low-cost, ideal for early UI/UX feedback	No intelligence simulated, not suitable for dynamic testing	[43], [149], [150]

The Wizard of Oz involves a hidden human operator who simulates the responses of an AI system. The user believes they are interacting with an autonomous agent, which allows researchers to study realistic interactions without requiring a fully functional backend [154], [155]. In contrast, Ghost in the Machine involves a human observer who supervises a partially autonomous system, stepping in only when necessary [156]. The user is usually aware of the human's presence, and the primary goal is to ensure task completion or safety rather than to simulate autonomy while still gathering experimental insights [156]. Finally, Human-in-the-Loop simulation involves a real AI system that

interacts with the user in a shared control setting [157]. The human contributes actively to the decision-making process, and the system may learn from or adapt to human input. This approach is commonly used in safety-critical domains where trust, accountability, and adaptability are paramount[158]. These methodologies differ in their assumptions, user awareness, and interaction dynamics. Table 2 provides a comparative overview.

3.6 EXPERIMENTAL VALIDATION: A CASE STUDY

To validate the methodology presented in the previous sections, a case study was conducted within a real industrial environment. However, due to the numerous production constraints typical of aerospace companies, as well as the practical impossibility of performing experimental activities within an aerospace facility, a different industrial context was selected for the validation of the proposed approach.

The case analyzed in this work concerns a company operating in the textile sector in southern Italy, specialized in the design and production of medium- to high-end sofas. This production process is strongly human-centric, as human intervention is required at every stage to meet strict quality standards.

In its current as-is configuration, the production process consists of several key phases. It begins with the acceptance of incoming materials, followed by the digitization of the leather hides. During this phase, operators scan each hide to capture information regarding potential defects. The process then advances to the nesting phase, where pattern placement is optimized through dedicated software. The boundaries of these patterns define the cutting paths for the machine tools. Finally, the workflow concludes with the quality control and upholstery stages.

The subphase identified as most representative of the research objectives of this thesis is the scanning and digitization of the hide. This phase is considered critical for two main reasons. First, it requires extensive tacit knowledge: operators must possess years of experience to perform the task effectively. Second, the high value of the raw material means that operators play a decisive role in determining both the amount of material discarded and the overall quality of the finished product. During this stage, operators must identify and digitize defects while categorizing different quality zones. Some defects may remain acceptable if they are located in hidden or tensioned areas of the final product.

A further challenge relates to operator fatigue. Workers report increasing difficulty in detecting defects during the final hours of their shifts, suggesting the

presence of cognitive and visual overload. To perform this task, the operator uses a workstation equipped with a sliding table on which the leather hide is placed, a computer with input/output devices for communication with the system, a digital pen for defect acquisition, and a projection system that displays the operator's ongoing actions. The complete actions are shown in **Table 3-3**. Upon proceeding to the next area (operation number 8), steps 3 through 7 are repeated until the hide is fully completed. The workstation is shown in **Figure 3-3**. Instead, **Fig. 3-4** shows an example of defect classification (a) and the output of the scanning phase (b).

Table 3-3 As is Process

Op. No.	Description	Performer and tool
1	Place hide on sliding table	Operator
2	Insert information about the hide	Operator + keyboard
3	Place orientation tracker	Operator + Digital Pen
4	Detect and assign defect position	Operator + Digital Pen
5	Assign defect shape	Operator + Digital Pen
6	Assign defect type	Operator + Digital Pen
7	General check	Operator
8	Move to the next area to scan	Operator + Pedal
9	Place orientation tracker	Operator + Digital Pen
10	Overall check	Operator
11	Save changes	Operator + keyboard
12	Remove the hide from the sliding table	Operator



Fig. 3-3 As is set up

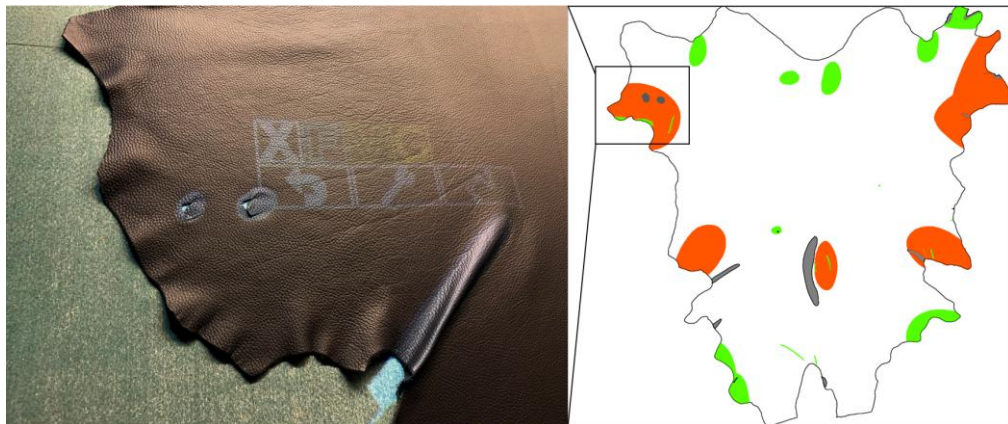


Fig. 3-4 (a)Example of defect detection and classification (b) Results of Scanning task

The difficulties operators encounter in carrying out the sub-process identified as critical can be overcome by adopting innovative AI-based tools. On the other

hand, as explained earlier, numerous challenges concerning the interaction modes do not allow these systems' complete adoption and use. For this reason, different modes of human-machine interaction will be explored in this section, defining different working roles in the human-machine team.

Four scenarios were identified in the literature search conducted in the previous chapters to achieve this. The next section will outline the different experimental procedures, the experimental setups implemented for each scenario, the participants, and the measurement methods. In each scenario, operators will have to perform the defect scanning task as in **Table 3-3** on the workstation that will be suitably modified for each scenario.

3.6.1 Experimental Methodology

Given the objective of our study—namely, to evaluate how human operators perceive and respond to different AI collaboration configurations—we adopted the Wizard of Oz methodology. This approach allowed us to simulate realistic and dynamic interactions with a system that appeared autonomous to participants but was controlled by researchers behind the scenes. All system responses, including defect classifications, feedback messages, and confidence indicators, were manually generated in real time by observers in a separate control room. In detail, the observer's team was composed of a task expert with more than 30 years of experience on the job and technicians. Furthermore, participants remained unaware of this setup throughout the experiment. This allowed us to investigate cognitive workload, trust formation, and configuration preference under conditions that closely mimic the expected behavior of an intelligent system, without requiring its actual implementation. The Wizard of Oz technique thus provided an optimal balance between experimental validity, experimental control, and feasibility, making it the most appropriate choice for our research context.

3.6.2 Experimental Setup

The experimental setup was built upon the company's existing defect scanning workstation, which was adapted to simulate various configurations of human-AI collaboration. The base station (as shown in **Figure 3-5**) includes a rolling table, a digital pen for defect annotation, a main display for interface navigation, and a foot pedal for progressing between hide areas. This setup was modified for the experiment by adding external tools to simulate intelligent system behavior. These included a secondary display, an audio speaker, and a camera mounted above the station to stream the operator's actions to a remote-control room in

real time. The user interface and feedback system were developed using the Unity 3D engine, enabling dynamic visual and auditory communication between the simulated AI and the operator. The simulation platform supported four collaboration scenarios by altering the distribution of roles between the human operator and the AI system.

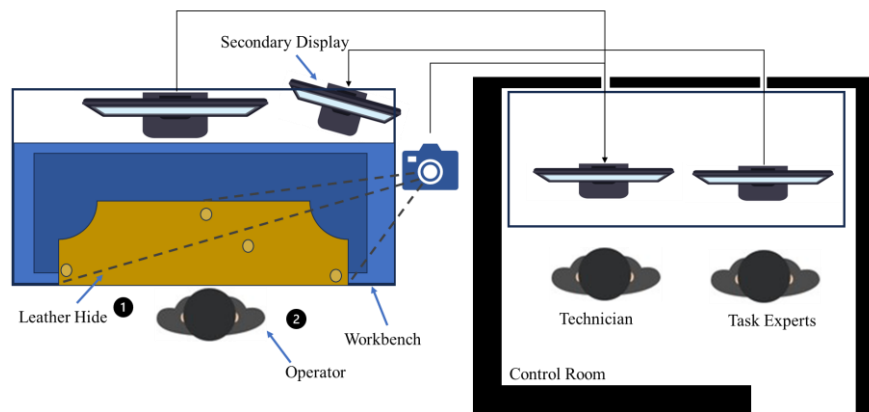


Figure 3-5 Experimental Setup

The operator performed the same hide scanning task in each scenario but received different support and feedback.

3.6.3 Experimental Procedure

Each experimental session lasted approximately 90 minutes and was conducted individually with each participant. The procedure was structured in several phases to ensure proper familiarization and accurate data collection, as shown in **Figure 3-6**. Initially, participants underwent a theoretical training session where the experimental goals and functionalities of the system were explained. This was followed by a practical training phase to familiarize the operators with the task execution and the tested collaborative configurations.

Before each of the four scenarios, participants were presented with a brief explanation of the system's intended behavior in that configuration. They were told that the AI system had been designed and trained to support defect detection and classification through visual and cognitive analysis, and that it would take on different roles, such as executor, supervisor, or decision-maker, depending on the scenario. This step was essential to reinforce the AI's perceived realism and ensure that participants approached the task with the belief that they were interacting with a functional intelligent system. This measure contributed to increasing the ecological validity of the Wizard of Oz

approach by minimizing suspicion and promoting natural behavior. Once the scenario introduction was completed, participants performed the hide defect detection task using the adapted workstation. The order of scenarios was consistent across participants. During each session, an overhead camera monitored the operator's actions in real time. At the same time, the system's responses were manually generated by researchers and task experts located in a separate control room, using a Wizard of Oz configuration.

At the end of each scenario, participants completed questionnaires to assess perceived cognitive workload and system acceptability. In addition, short interviews were conducted to collect qualitative feedback and subjective impressions. This structured and repeated procedure allowed for consistent data collection and multi-dimensional user experience evaluation across all experimental conditions.

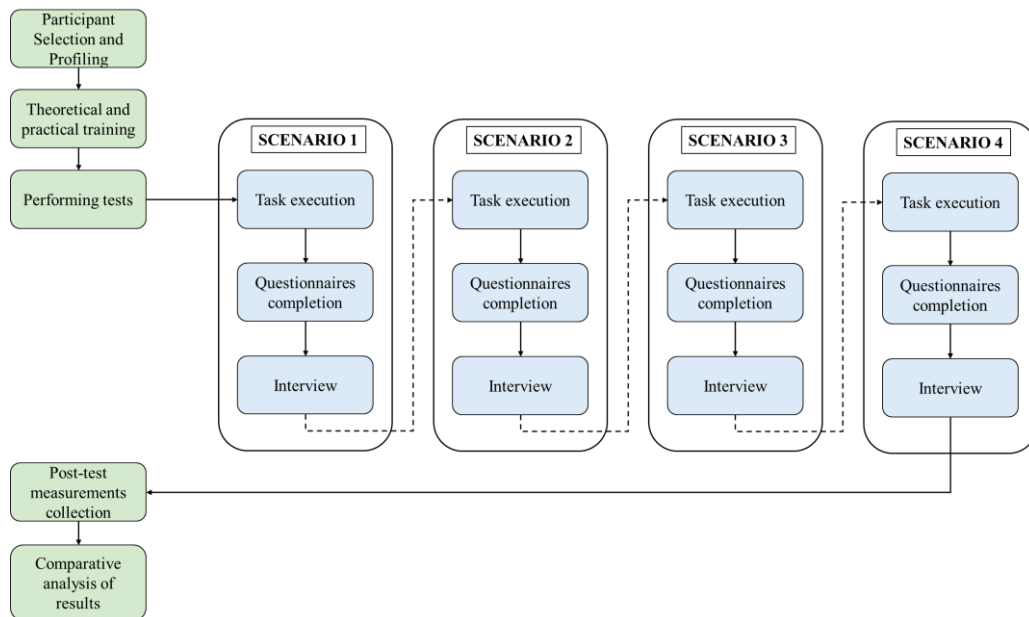


Fig. 3-6. Experimental procedure

3.6.4 Participants

The participants involved in the experimental study were two operators employed at the company where the case study was conducted. One was a 41-year-old male with approximately one year of experience in defect detection and classification. At the same time, the other was a 24-year-old

female with about one month of experience in the same task. This intentional variation in experience levels allowed the study to explore how different degrees of familiarity with the process influence the perception and effectiveness of human-AI collaboration. Both participants were selected in agreement with company managers, based on their availability and operational compatibility with the testing schedule.

The experimental study involved a limited number of participants due to practical and organizational constraints related to the industrial environment in which the experiments were conducted. In particular, the availability of qualified operators and the need to avoid disruptions to ongoing production activities prevented the inclusion of a larger experimental sample.

Nevertheless, this limitation was considered acceptable in light of the exploratory nature of the present study. The primary objective of the experimental validation was not to achieve statistical generalization, but to perform a preliminary assessment aimed at understanding whether the proposed human-machine collaboration setup is suitable and potentially beneficial for the targeted application context. The experiment was therefore conceived as a proof-of-concept and feasibility study, designed to observe trends, identify critical behaviors, and evaluate the qualitative impact of different collaboration configurations on performance and cognitive workload.

3.6.5 Experimental Measures

The A mixed-methods measurement strategy was adopted to evaluate the impact of different human-AI collaboration configurations comprehensively. The selected instruments allowed for the collection of objective performance data and subjective user feedback, which aligns with the human-centric principles of Industry 5.0. Objective measures included execution time, which was recorded for each scenario to assess task efficiency, and error rate, which was calculated as the number of misclassifications or omissions during the defect detection task. These indicators were systematically compared across scenarios and against the company's as-is process to detect performance differences related to varying role distributions. Subjective measures focused on the operator's experience and perception. Cognitive workload was assessed using the NASA Task Load Index (NASA-TLX), a validated instrument that evaluates mental, physical, and temporal demands and perceived effort, frustration, and performance. System acceptance and usability were assessed through a custom questionnaire developed by a team of occupational psychologists. This instrument included dimensions derived from the Technology Acceptance Model

(TAM), such as perceived usefulness, perceived ease of use, and behavioral intention to use. It was further enriched with constructs from contemporary models, including technostress creators, technology anxiety, attitude toward the system, and technology dependence. Additionally, post-scenario interviews and direct behavioral observations were conducted to gather qualitative insights, capturing operators' impressions, emotional responses, and perceptions of trust, control, and usability during each interaction. This multi-layered measurement approach enabled a robust and human-centered assessment of the collaborative configurations.

3.6.6 Experimental Scenarios

This section describes all the identified and tested collaborative scenarios

3.6.6.1 Human Executor Machine Supervisor

The collaboration mode identified in [162] is explored in this scenario. The operator is asked to perform the task of scanning the hide independently and without assistance. Each time a defect is identified and classified, the operator will receive feedback via a second display on the workstation. The interface through which the operator obtains auditory and visual feedback was developed in Unity. Throughout the execution of the test, the operators are filmed in real time by a camera positioned above the workstation. The real-time images are sent to the control room, where supervisors and an expert operator analyze the task in real-time. For each defect detected and classified, the worker under the test receives feedback regarding the correctness or incorrectness of the operation. If the operation is correct, the operator continues; if it is wrong, he has to repeat it. The sequence of operations performed is shown in Table 3-4, and the station design is shown in Fig. 3-7.

Table 3-4. To be processed: First Scenario

Op. No.	Description	Performer and tool
1	Place hide on sliding table	Operator
2	Insert information about the hide	Operator + keyboard
3	Place orientation tracker	Operator + Digital Pen
4	Detect and assign defect position	Operator + Digital Pen
5	Assign defect shape	Operator + Digital Pen
6	Assign defect type	Operator + Digital Pen
7	Check Defect Position, Shape Position	AI System
8	Move to the next area to scan	Operator + Pedal

9	Place orientation tracker	Operator + Digital Pen
10	Overall check	Operator
11	Save changes	Operator + keyboard
12	Remove the hide from the sliding table	Operator

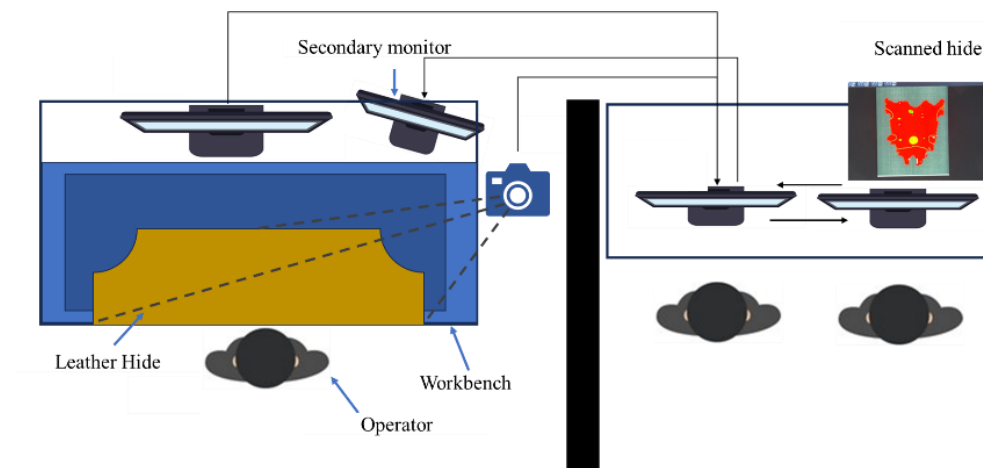


Fig. 3-7. Experimental Setup Scenario 1

In this setup, the operator has high autonomy and decision-making power as they independently perform scanning and classification tasks. Conversely, the machine is a supervisory tool, providing feedback and verification support without directly influencing the operator's decisions.

3.6.6.2 Human Supervisor Machine Executor

In the second collaborative scenario, the roles are reversed from the first scenario. The Artificial Intelligence system plays the role of the executor by localizing the defects, their shape, and classification. The human being controls the machine's work by conducting supervisory operations. The as-is workstation is augmented with a second screen on which the image of what the finished product should look like once the scanning is complete is projected. The operator then compares the scanning work done by the intelligent system with the actual coat. If disagreeing with what is shown, the operator modifies the scan manually. Again, images of the finished product are provided from the experienced operator's previous scans. The station design is shown in Fig. 3-8. The sequence of operations remains the same, but the roles change from the previous scenario (Table 3-5). The AI System performs activities 4, 5, and 6, while the Operator performs activity 7 with a digital pen. In this scenario, the AI

system possesses a high degree of autonomy and decision-making power in performing defect scanning and classification tasks. The human operator's supervisory role involves reviewing and adjusting the AI's work. The workstation is equipped with a second screen that displays the scanned image of the finished product, with which the operator can compare. The operator's main responsibility is to validate and correct the AI results, ensuring the quality and accuracy of the final results.

Table 3-5. To be processed: Second Scenario

Op. No.	Description	Performer and tool
1	Place hide on sliding table	Operator
2	Insert information about the hide	Operator + keyboard
3	Place orientation tracker	Operator + Digital Pen
4	Detect and assign defect position	AI System
5	Assign defect shape	AI System
6	Assign defect type	AI System
7	Check Defect Position, Shape Position	Operator + Digital Pen
8	Move to the next area to scan	Operator + Pedal
9	Place orientation tracker	Operator + Digital Pen
10	Overall check	Operator
11	Save changes	Operator + keyboard
12	Remove the hide from the sliding table	Operator

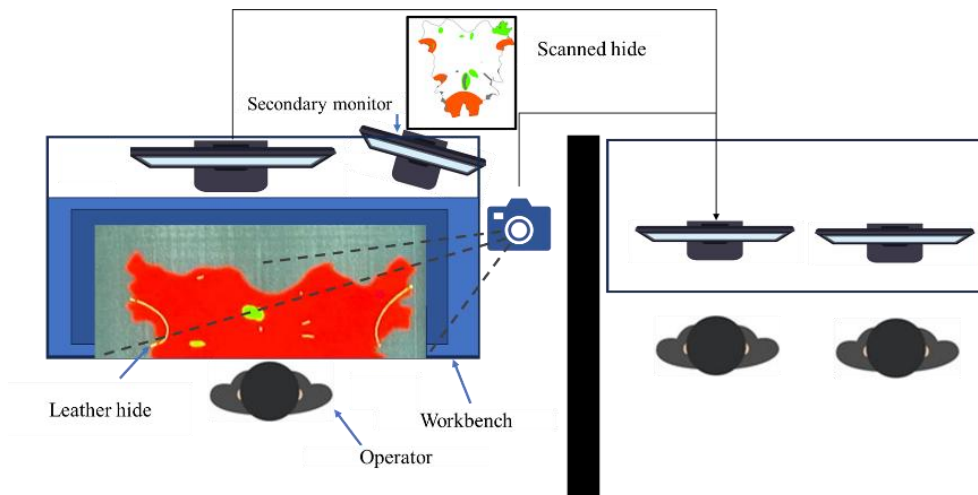


Fig. 3-8. Experimental Setup Scenario 2

3.6.6.3 Human Coexecutor/Supervisor Machine Coexecutor

The third collaborative scenario involves co-executing the scanning task, i.e., the machine identifies the location and shape of the defect (operation 4) while the operator classifies the defect (operation 5). As in the previous scenario, information about the position and shape of the defect is provided to the operator via a second screen located at the workstation. Again, the images of the hide to be shown to the operators during the execution of the task were scanned by an experienced operator who was asked to perform the task by assigning the same defect type for each defect detected. The sequence of operations performed is shown in Table 3-6, and the station design is shown in Fig. 3-9. The AI system detects the defect position and shape, while the operator is responsible for classifying the defect type and verifying the accuracy of the defect details. The operator retains significant decision-making authority, particularly in the classification and verification stages. This collaborative approach ensures that the AI system's strengths in data processing and the operator's expertise in classification and oversight are effectively utilized.

Table 3-6. To be processed: Scenario 3

Op. No.	Description	Performer and tool
1	Place hide on sliding table	Operator
2	Insert information about the hide	Operator + keyboard
3	Place orientation tracker	Operator + Digital Pen
4	Detect and assign defect position	AI System
5	Assign defect shape	AI System
6	Assign defect type	Operator + Digital Pen
7	Check Defect Position, Shape Position	Operator + Digital Pen
8	Move to the next area to scan	Operator + Pedal
9	Place orientation tracker	Operator + Digital Pen
10	Overall check	Operator
11	Save changes	Operator + keyboard
12	Remove the hide from the sliding table	Operator

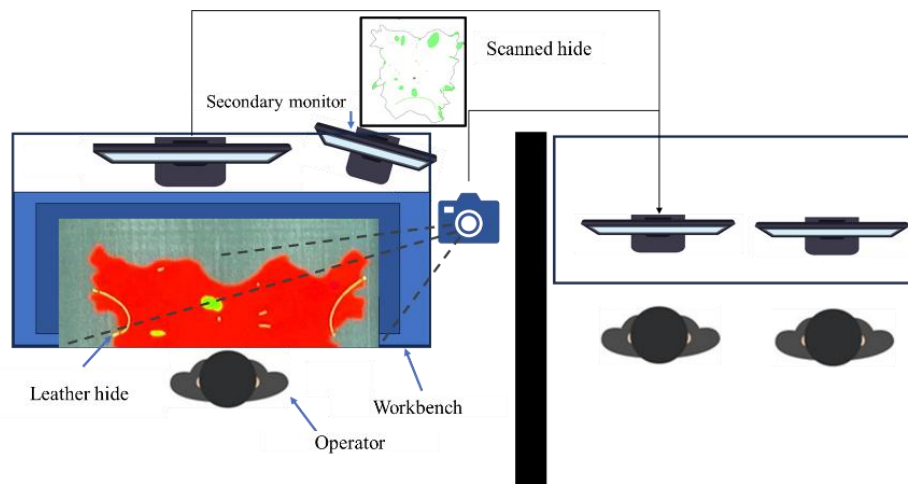


Fig. 3-9. Experimental Setup Scenario 3

3.6.6.4 Human-Machine negotiation

The machine provides information about the location, shape, and type of defect, as in scenario 2 (operations 4, 5, and 6), and the percentage of reliability of the prediction made (operation 7). In this way, the worker can have more information about the machine's task performance and thus better fulfill its supervisor function. The sequence of operations performed is shown in Table 3-7, and the station design is shown in Fig. 3-10.

Table 3-7. To be processed: Scenario 4

Op. No.	Description	Performer and tool
1	Place hide on sliding table	Operator
2	Insert information about the hide	Operator + keyboard
3	Place orientation tracker	Operator + Digital Pen
4	Detect and assign defect position	AI System
5	Assign defect shape	AI System
6	Assign defect type	AI System
7	Provide Prediction accuracy	AI System
8	Check Defect Position, Shape Position	Operator + Digital Pen
9	Move to the next area to scan	Operator + Pedal
10	Place orientation tracker	Operator + Digital Pen
11	Overall check	Operator

12	Save changes	Operator + keyboard
13	Remove the hide from the sliding table	Operator

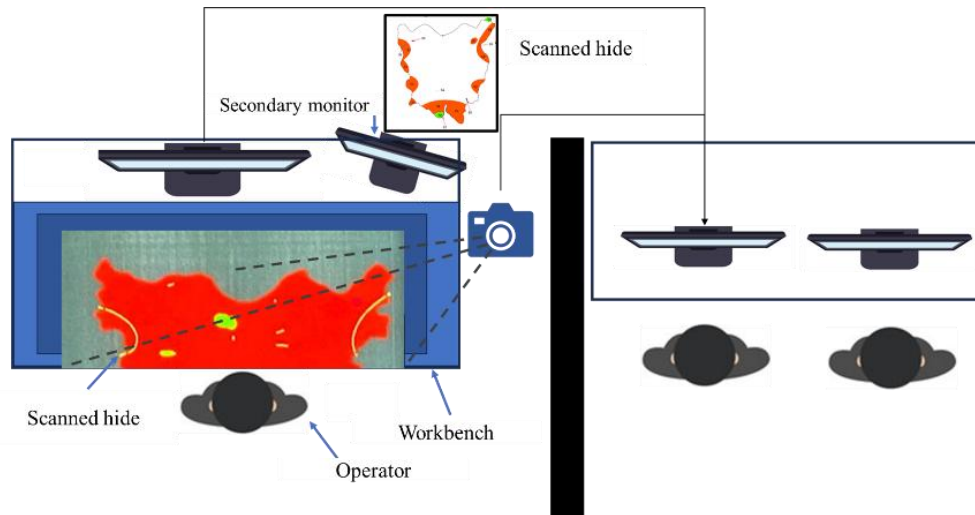


Fig. 3-10. Experimental Setup Scenario 4

In this scenario, the AI system plays a comprehensive role in managing detection and classification and providing feedback on the accuracy of the prediction. The operator's role is to supervise and verify the machine's output, using the reliability information provided by the AI to improve the effectiveness of its supervision. This configuration aims to improve the overall efficiency and accuracy of the task by integrating detailed feedback on machine performance into the operator's decision-making process.

3.7 RESULTS AND DISCUSSION

As a result of the experiments, the outcomes presented and analyzed in this section were obtained. Specifically, performance metrics were collected, including execution time and task errors, along with subjective assessments of the operator's condition and impressions gathered through questionnaires and interviews. Due to the limited number of participants, inferential statistical analyses aimed at population-level generalization (e.g., ANOVA) were not considered appropriate for this study. The experimental validation was designed as an exploratory, proof-of-concept assessment to identify trends and to

evaluate the potential usefulness of the proposed collaboration setups in a realistic industrial context.

3.7.1.1 Performance

The two operators considered, representing an inexperienced operator and a moderately experienced operator, displayed notably different results. As illustrated in Fig. 3-11, operator 1, with less experience, generally benefited from using the system, resulting in reduced execution times and fewer errors. In contrast, the improvements for operator 2 were significantly less pronounced. Specifically, operator 1 achieved the fastest execution time in scenario 2 and the slowest in scenario 1. This is because, in scenario 2, where the operator oversees the machine, they only focus on areas of the task where they disagree with the AI system. However, when the AI system takes on the supervisory role, conflicts can arise in the event of operator error, which the human operator is reluctant to lose. Regarding errors, the inexperienced operator made the most mistakes in the "as-is" scenario and the fewest when the machine was the supervisor, as seen in scenario 1. In contrast, for the moderately experienced operator, task execution time increased slightly compared to the "as-is" scenario, while the error rate showed a modest decrease.

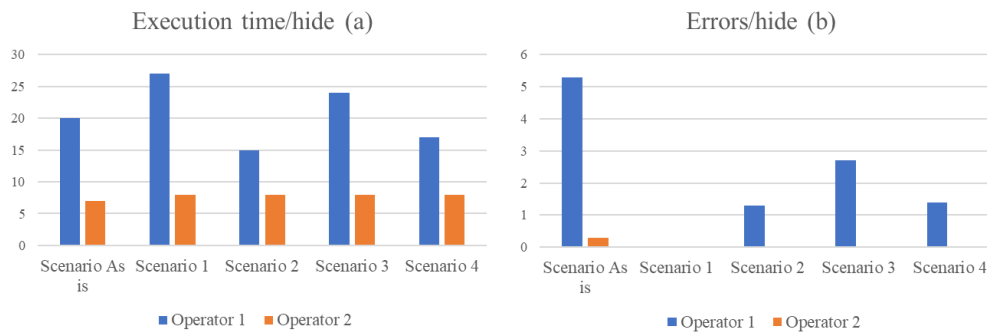


Fig. 3-11 Execution times (a) errors (b)

3.7.1.2 Questionnaires

After completing each scenario, cognitive load and operator satisfaction and preferences were assessed using questionnaires provided to the operators. In terms of cognitive load, measured through the NASA-TLX, the use of the AI system reduced the task's cognitive load for both operators compared to the "as-is" scenario, particularly for the inexperienced operator. As shown in Table

3-8Table 3-8, scenario 4 resulted in the lowest cognitive load for both participants, as the AI system not only provides defect classification but also the reliability of its prediction. Therefore, the operator has more information to make an informed decision.

Table 3-8 Nasa TLX scores

	Operator 1	Operator 2
As is scenario	82	62,5
Scenario 1	53	55
Scenario 2	48	65
Scenario 3	63	56
Scenario 4	50	30

The results regarding the acceptance and usability of the optimal system configuration are presented in the radar charts shown in Fig. 3-12. Operator 1 consistently preferred the AI system over the as-is system, as the additional task support was beneficial given their inexperience. Among all scenarios, it was favored scenario 1, where the positive auditory feedback from the AI system encouraged faster and more enthusiastic task performance. In contrast, Operator 1 found scenario 2 less useful, as their limited experience made it difficult to supervise the AI system's work. The prediction reliability provided in scenario 4 aided the decision-making process. On the other hand, Operator 2, being more experienced and having used the as-is system for a year, did not observe significant improvements with implementing the AI system. However, they acknowledged the value of the AI system's scan defects and their reliability as a useful support for the scanning task.

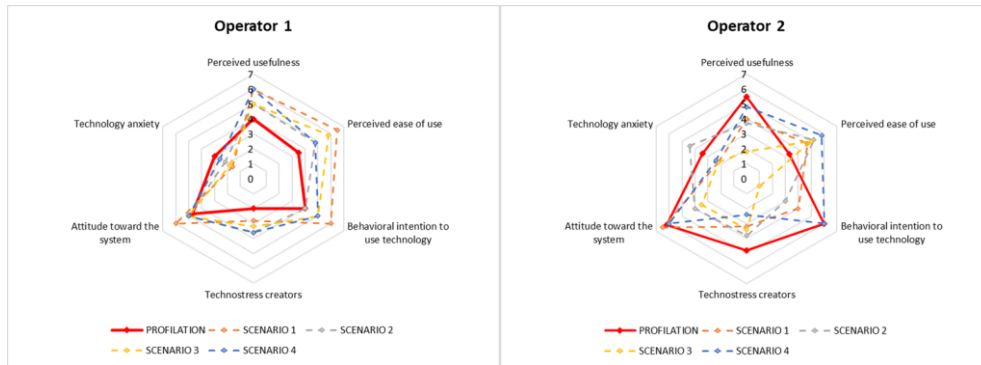


Fig. 3-12 Ad hoc questionnaire results

3.7.1.3 Qualitative observations

Post-scenario interviews and direct observation yielded additional insights. The inexperienced operator expressed enthusiasm for scenarios where the system acted as a guide or mentor, appreciating its support in difficult classification cases. However, they also showed signs of over-reliance in scenarios where supervision was required. The experienced operator, while generally skeptical of automation, recognized the added value of confidence-based feedback in Scenario 4 and acknowledged its potential to improve inspection consistency. These findings suggest that AI support is particularly beneficial for inexperienced operators, who prefer guidance and structured feedback, while experienced workers favor supervisory roles where transparency and control are preserved. The combination of performance metrics, workload data, and subjective impressions supports the hypothesis that different operator profiles require tailored collaboration models for effective and acceptable human-AI interaction.

3.8 FINAL REMARKS

This section explored the human-centric approach of Industry 5.0, emphasizing the integration of advanced technologies, with sustainability and worker well-being. The literature review suggests that the adoption of innovative technologies may negatively impact operator well-being. This study addresses the challenges identified in the literature (section 2.3.4) that could hinder effective collaboration between humans and machines. The experimental setup explored various human-machine team configurations, with each entity assigned roles such as supervisor, executor, or assistant. The optimal configurations for performance and operator well-being were evaluated through direct observation, questionnaires, and interviews. Tools such as the NASA-

TLX, which measures cognitive workload, or ad hoc questionnaires were useful in assessing the demands placed on operators in these interactions. The research results highlight how the operator's experience level impacts the system configuration. More experienced operators used the system as an assistant while assuming a supervisory role, whereas the less experienced operators relied on the system as a guide for task execution. Therefore, technologies should be adaptable to the operator's experience level and preferences. Moreover, understanding the accuracy of AI system predictions improves system acceptance and ease of use. The findings presented in this study should be interpreted in light of several assumptions and limitations related to statistical generalizability. Due to the limited number of participants and the exploratory nature of the experimental validation, the observed results cannot be directly generalized to the broader population of operators. The study assumes that the selected participants, representing different levels of expertise, are indicative of typical operator profiles involved in activities. Moreover, the experiments were conducted under controlled conditions and within a specific application scenario, which may not capture the full variability of real operational environments. Consequently, the results are intended to provide indicative trends and qualitative insights into the effects of different human-machine collaboration configurations, rather than statistically generalizable conclusions. Larger-scale experimental campaigns involving a wider range of operators and repeated trials in diverse industrial settings are required to validate and extend the findings reported in this work.

Additionally, the study only examined a limited range of collaborative scenarios, meaning the full spectrum of human-machine interaction possibilities remains unexplored. Future research should aim to validate these preliminary results with a more extensive and diverse sample to increase the robustness of the findings. Moreover, expanding the experimental setup to include more complex and varied collaborative tasks could provide deeper insights into the dynamics of human-machine interaction. Further developments should focus on refining operator profiling tools, allowing for a more tailored adaptation of technologies to human factors such as experience level, personality traits, and individual cognitive load capacities. This will help identify the best collaboration strategies and ensure that Industry 5.0 systems are both effective and supportive of operator well-being.

This chapter presented the experimental methodology designed to evaluate human-centric machines, which was validated through an empirical study conducted within an industrial context different from the aerospace sector. This choice was motivated by the numerous constraints that limit the implementation

and testing of such solutions in aerospace environments. In the following chapter, the focus shifts to an aerospace company, where a criticality analysis is carried out to identify the main challenges both from a programmatic perspective and in terms of operator well-being. Finally, potential solutions are proposed, outlining feasible directions for future implementation.

CHAPTER 4

The Company Case Study

4 INDUSTRIAL CASE STUDY

4.1 THE COMPANY CONTEXT

SITAEL S.p.A. is an Italian company, headquartered in Mola di Bari and part of the Angel Holding group, operating in the field of aerospace research and technological development. The company is primarily specialized in the design and manufacturing of avionics systems for satellites, minisatellites, and microsatellites, as well as in the development of electric propulsion technologies.

Since 2012, SITAEL has participated in international space missions, such as NASA's Mars Science Laboratory, which achieved the landing of the Curiosity rover on Mars. A major national program led by the company is PLATiNO (mini Piattaforma spaziale ad Alta TecNOlogia), funded by the Italian Space Agency (ASI), which focuses on the development of advanced small satellite platforms.

In November 2022, a contract was signed between SITAEL and the Luxembourg-based SES for the provision of a PLATiNO platform within the framework of the ESA EAGLE-1 project. The aim of this initiative is to develop and validate the first satellite system enabling Quantum Key Distribution (QKD).

On December 1, 2023, the MicroHETSat satellite—entirely designed and manufactured by SITAEL—was launched on board a SpaceX Falcon-9 vehicle from the Vandenberg Space Force Base in California. The satellite, controlled by SITAEL's Mission Control Center located in Forlì, represents the first fully electric satellite ever built in Italy and the first of its class in Europe.

The company's involvement in the PLATiNO program, as well as in other aerospace initiatives, reflects its strategic role in reinforcing Italy's position in the international space sector. Furthermore, SITAEL contributes to the advancement of state-of-the-art technologies and to the consolidation of national expertise in this highly strategic domain.

The IRIDE program represents the most significant initiative for the industrialization of the Italian aerospace sector, with SITAEL having signed the contract on 11 April 2023 to develop four PLATiNO hyperspectral satellites. This project, entirely realized in Italy through the collaboration of large companies and SMEs, fosters both technological innovation and the consolidation of a national aerospace industrial ecosystem.

4.2 THE COMPANY PRODUCTION PROCESS

Satellites are generally classified as complex products. Their complexity arises from multiple factors, including the large number of components, the variety of engineering disciplines involved in the design, and the stringent dimensional tolerances that impose several constraints during the manufacturing process. For these reasons, it is not feasible to produce all components in-house, and companies must rely on suppliers and sub-suppliers. This operational model, while essential for the completion of an aerospace project, introduces an additional variable related to the control and management of the supply chain. To mitigate these challenges, during the contracting phase and the assignment of work packages, not only the technical designs but also the manufacturing processes are subject to validation by both the supplier and the prime contractor, that is, the final customer. Typically, these processes are developed and qualified according to the reference standards, most notably the ECSS regulations specific to the aerospace sector. While this approach ensures high levels of quality, it simultaneously imposes rigid constraints on production processes, which inevitably limits their flexibility and resilience.

Once the make-or-buy policies have been defined and all components and equipment have been allocated to the various subcontractors, the responsibility for the final Assembly, Integration, and Testing (AIT) of the product lies with the prime contractor. The AIT phase is of central importance in the satellite lifecycle, as it ensures the correct integration of all subsystems, validates their functionality under representative operational conditions, and minimizes the risks associated with launch and in-orbit operations. The focus of this work is therefore placed on the satellite AIT process.

4.3 PRODUCTION PROCESS DESCRIPTION

As previously discussed, the AIT phases are strictly governed by rigorous procedures and frequent intermediate quality inspections. The production flow is defined in the AIT Plan, a document that outlines the logical sequence of both mechanical and electrical integration activities. In general, all materials entering the production cycle must first pass incoming quality control before being stored in the warehouse, awaiting retrieval for integration into the satellite platform. The satellite integration flow, as described in the AIT Plan, is further detailed in specific integration procedures, whose purpose is to provide operators with all the necessary information to correctly perform each activity in compliance with the prescribed quality requirements.

The entire integration process can be divided into several macro-phases, which can generally be classified as either mechanical or electrical integration activities. The first phase concerns the preparation of the external panels that constitute the satellite's thermo-structural body. The second phase involves the mechanical integration of the units onto the panels. This is followed by the preliminary routing and the execution of electrical integration. Finally, once the lateral panels are closed and the routing is completed, the platform is ready to undergo functional testing.



Figure 4-1 Satellite AIT phases

As previously mentioned, each of these macro-phases is further detailed into sequences, sometimes described step by step to guide the operators. An additional overview of the process is provided in **Figure 4-2**.

The analysis methodology involved the identification, for each defined phase, of the production factors: operators' skills, tools, materials, and information (methods). This step was necessary during the definition phase to identify the inefficiencies and critical issues discussed in the following section.

The tables below (**Table 4-1, Table 4-2, Table 4-3, Table 4-4, Table 4-5**) report some examples of assembly phases: one related to the Panel Preparation phase, one concerning the Unit Integration phase, and one referring to the Harness Routing and Panel Closure phase.

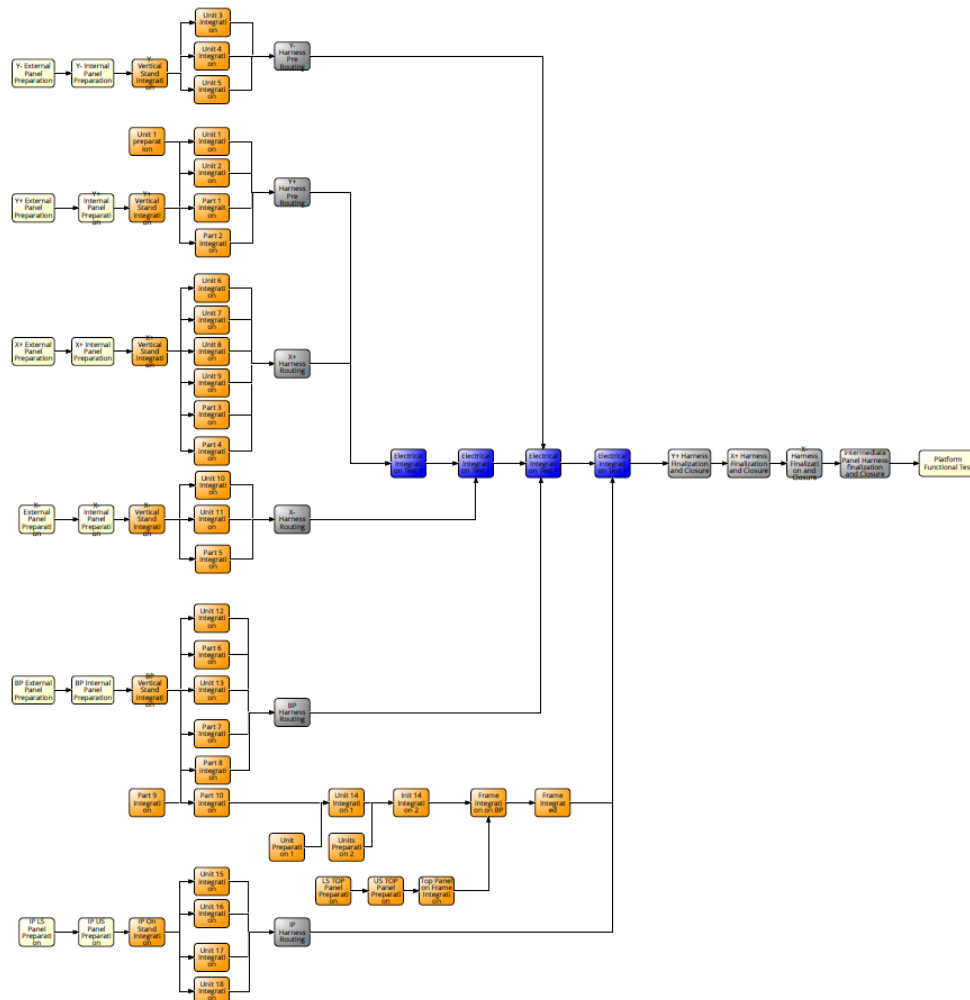


Figure 4-2 Satellite AIT Flow

4.4 PRODUCTION PROCESS ANALYSIS

With the aim of identifying the most critical processes from both performance and human operator perspectives, several analyses were carried out focusing on production performance in terms of operation execution times, downtime, and operator well-being. The analytical methodology presented in [163], was mainly based on execution time measurements, direct observation, interviews, and questionnaires administered to operators on the shop floor. In particular, once the theoretical execution time had been established—first through the identification of value-added operations, and subsequently through the classification of non-value-added operations—the critical operations and

bottlenecks were identified. A separate consideration was dedicated to aspects related to operator well-being. Among the observed operations, those that were highly repetitive, demanded high precision, involved significant physical effort, or required elevated cognitive load were classified as critical. The analyses were structured according to the following categories:

- Activity execution times
- Human-Centered analysis
 - Cognitive load
 - Detection time
 - Processing time
- Physical load
 - Operation repetitiveness
 - Physical effort
 - Operation precision

For all analyses, it was assumed that a single operator was able to autonomously carry out the assigned tasks.

4.4.1 Time Analysis

The completion times of each macro-phase described above were analyzed. For confidentiality reasons, the execution times are here reported as percentages with respect to the total process duration.

It can be observed that the bottleneck phase corresponds to the harness routing activities. Moreover, if the harness finalization phase is also considered—whose nature and working methods are substantially identical to those of the preliminary routing—the time required to complete these two operations accounts for 40% of the overall satellite platform integration process, and 56% when only mechanical operations are considered (see **Table 4-1**).

Table 4-1 Activity duration

Phase	Duration(%)
Panel preparation	12.1
Units Integration	16.3
Harness Routing	24.2
Electrical Integration	15.7
Routing finalization and Panel closure	12.7
Functional Test	18.7

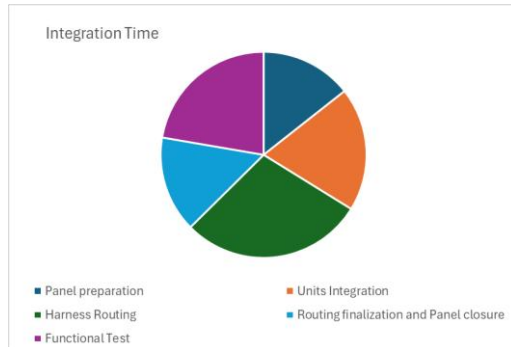


Figure 4-4 Total integration time

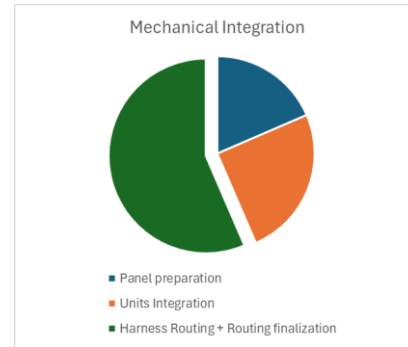


Figure 4-3 Mechanical Integration time

For the purposes of this analysis, the Electrical Integration and Functional Test phases were excluded, as these activities are performed automatically through the EGSE system.

To better understand the causes and underlying rationale behind the distribution of these times, a more detailed analysis was conducted at the level of individual operations, as illustrated in the figure above. Execution times were collected for each fundamental operation with the objective of distinguishing value-added activities from non-value-added ones, thereby identifying potential sources of inefficiency and waste.

For confidentiality reasons, the specific durations are again presented in normalized form. In particular, a common time unit was defined as the least common multiple of all operation durations, assigning a base value of 0.5 to the shortest operation; all other operations were then expressed as multiples of this reference value.

Table 4-2 Panel Preparation

N.	Phase	Operation	Description	T	R	A	Tt
10	Preliminary checks	Scratch inspection, tool calibration, material kit preparation, climatic chamber conditions	Visual inspection of materials and equipment	5	1	5	
20	Panel positioning on workbench		Retrieve panel from warehouse, place spacers on the	1	1	1	

			workbench, and position the panel			
30	Mask creation with Kapton Tape	1:1 panel mask printing	Print and position 1:1 mask on the panel			0
40	Mask creation with Kapton Tape	Preparation of bonding areas	Use Kapton tape to delimit the bonding area	1.5	5	7.5
50	Support preparation	Support abrasion	Use sandpaper to prepare the support for bonding	1	5	5
60	Support preparation	Cleaning supports and bonding areas	Use vacuum cleaner and isopropyl alcohol	1	5	5
70	Adhesive preparation	Adhesive material mixing				0
80	Adhesive preparation	Preparation of test sheet for adhesive		1		0
90	Support bonding	Adhesive deposition on bonding area	Use spatula to spread adhesive on bonding area	1	5	5
100	Support bonding	Support placement	Place the support on the adhesive	1	5	5
110	Support label bonding	Support ID identification	Use CAD to identify the support			0
120	Support label bonding	Label creation and application	Write ID on Kapton tape and attach the label	1.5	5	7.5
130	Adhesive curing waiting time					12
140	Panel installation on VS	Install bottom panel on vertical stand	Position centering pins			0
150	Panel installation on VS		Place bottom panel on vertical stand			0
160	Panel installation on VS	Tighten screws to torque		1	4	4
170	Panel installation on VS	Record running torque		1	4	4
180	Panel installation on VS	Install bonding strap		3	1	3
190	Panel installation on VS	Bonding test		4	1	4
200	Mask creation with Kapton Tape	1:1 panel mask printing	Print and position 1:1 mask on the panel			0
210	Mask creation with Kapton Tape	Preparation of bonding areas	Use Kapton tape to delimit the bonding area	1.5	23	34.5

220	Support preparation	Support abrasion	Use sandpaper to prepare the support for bonding	1	23	23
230	Support preparation	Cleaning supports and bonding areas	Use vacuum cleaner and isopropyl alcohol	1	23	23
240	Adhesive preparation	Adhesive material mixing				0
250	Adhesive preparation	Preparation of test sheet for adhesive		1		0
260	Support bonding	Adhesive deposition on bonding area	Use spatula to spread adhesive on bonding area	1	23	23
270	Support bonding	Support placement	Place the support on the adhesive	1	23	56 23
280	Support label bonding	Support ID identification	Use CAD to identify the support			0
290	Support label bonding	Label creation and application	Write ID on Kapton tape and attach the label	1.5	23	34.5
300	Heater installation	Measure initial resistance values	Use multimeter	3	3	9
310	Heater installation	Identify bonding position and apply heater		3	3	9
320	Heater installation	Measure final resistance values	Use multimeter	3	3	9
330	Heater installation	Record resistance values	Write measured values on the procedure	0.5	3	1.5
340	Thermistor bonding	Measure resistance values	Use multimeter	3	3	9
350	Thermistor bonding	Prepare bonding area	Sand the surface			0
360	Thermistor bonding	Adhesive preparation	Mix adhesive materials	3	1	3
370	Thermistor bonding	Preparation of test sheet for adhesive		1	1	1
380	Thermistor bonding	Adhesive deposition on bonding area	Use spatula to spread adhesive on bonding area	1	5	5
390	Thermistor bonding	Support placement	Place the support on the adhesive	1	5	12 5
400	Thermistor bonding	Measure final resistance values	Use multimeter	3	3	9
410	Thermistor bonding	Record resistance values	Write measured values on the procedure	0.5	3	1.5

420	Reinforcement points application	Prepare adhesive	4	1	4
430	Reinforcement points application	Apply adhesive	3	3	9
440	Visual inspection		10	1	10

Table 4-3 Units integration

N.	Phase	Operation	Description	T	R	A	Tt
10	Preliminary checks	Scratch inspection, tool calibration, material kit preparation, climatic chamber conditions, satellite SN	Check product and project documentation, facilities, and tool conditions	10	1		
20	Unit integration	Positioning of centering pins		1	1		
30	Unit integration	Cut thermal filler		5	1		
40	Unit integration	Position thermal filler		1	1		
50	Unit integration	Prepare unit for installation		2	1		
60	Unit integration	Position unit		2	1		
70	Unit integration	Place screws and washers near the holes		1	12		
80	Unit integration	Tighten screws to contact		1	12		
90	Unit integration	Record running torque		0.5	12		
100	Unit integration	Torque check after 5 minutes		1	12		
110	Unit integration	Record 5-minute torque value		0.5	12	1	
120	Unit integration	Torque check after 1 hour		1	12		
130	Unit integration	Record 1-hour torque value		0.5	12	24	
140	Unit integration	Torque check after 24 hours		1	12		
150	Unit integration	Record 24-hour torque value		0.5	12		
160	Unit integration	Prepare adhesive		5	1		

170 Unit integration	Apply a drop of adhesive for testing		0.5	12	
180 Unit integration	Bonding strap installation	Shape the bonding strap	3	1	
190 Unit integration	Bonding strap installation	Place the bonding strap	0.5	1	
200 Unit integration	Bonding strap installation	Tighten to torque	1	2	
210 Unit integration	Bonding strap installation	Record torque value	0.5	2	
220 Unit integration	Bonding strap installation	Apply a drop of adhesive for testing	0.5	12	
230	Thermistor installation				
240 Thermistor bonding	Measure resistance values	Use multimeter	3	3	9
250 Thermistor bonding	Prepare bonding area	Sand the surface	0.5	3	1.5
260 Thermistor bonding	Adhesive preparation	Mix adhesive materials	3	1	3
270 Thermistor bonding	Preparation of test sheet for adhesive		1	1	1
280 Thermistor bonding	Adhesive deposition on bonding area	Use spatula to spread adhesive on bonding area	1	5	5
290 Thermistor bonding	Support placement	Place the support on the adhesive	1	5	12 5
300 Thermistor bonding	Measure final resistance values	Use multimeter	3	3	9
310 Thermistor bonding	Record resistance values	Write measured values on the procedure	0.5	3	1.5
320 Thermistor bonding	Apply reinforcement points – prepare adhesive		4	1	4
330 Thermistor bonding	Apply reinforcement points – apply adhesive		3	3	9
340 Visual inspection			10	1	10

Table 4-4 Preliminary harness Routing

N.	Phase	Operation	Description	T	R	A	Tt
10	Preliminary checks	Scratch inspection, tool calibration, material kit preparation, climatic chamber conditions, satellite SN	Check product and project documentation, facility, and tool conditions	10	6		60
20	Cable identification on CAD			7	114		798
30	Cable routing			5	114		570
40	Apply cable ties			4	114		456

Table 4-5 Final Harness routing

N.	Phase	Operation	Description	T	R	A	Tt
10	Preliminary checks	Scratch inspection, tool calibration, material kit preparation, climatic chamber conditions, satellite SN	Check product and project documentation, facility, and tool conditions	10	6		60
20	Cable identification on CAD			7	61		427
30	Cable routing			5	61		305
40	Apply cable ties			4	61		244

Once the total duration for each phase had been determined, these cumulative times were considered as the sum of the value-added operations. They were then compared with the planned calendar times of the corresponding production activities. This comparison revealed the actual production efficiency, highlighting the gap between theoretical process performance and real operational execution.

Table 4-6 Activity efficiency

Attività	Efficiency= VA/(VA+NVA)
Panel preparation	9.2 %
Units Integration	13.6 %
Harness Routing	3.7 %
Electrical Integration	28.7 %
Routing finalization and Panel closure	3.4 %
Functional Test	31.2 %

From the table above, it immediately emerges that overall production efficiencies are relatively low. Nevertheless, when compared with the efficiency levels typically observed in the sector—particularly in companies operating under a job-shop production model—these values appear to be only slightly below the average.

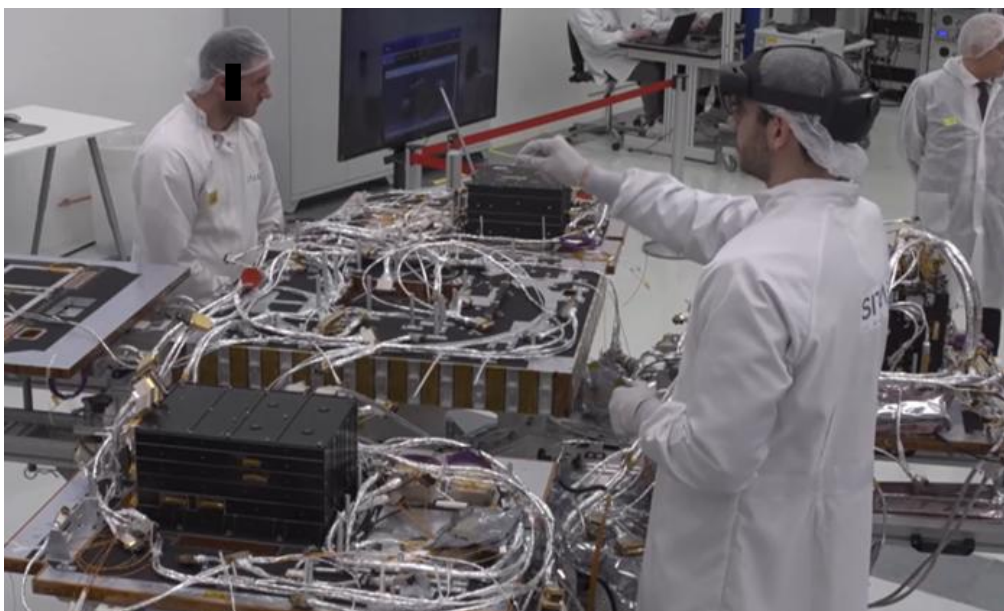


Figure 4-5 Preliminary routing phase

Another relevant observation is that the lowest-efficiency operations are those related to cable positioning and fastening, which show an efficiency of approximately 3,5 %. As discussed in [164] the most common causes of efficiency loss include waiting times due to material unavailability, tool unavailability, non-conformities, and rework activities.

A more detailed analysis of the sources of inefficiency, and therefore of the reasons for such extended idle times, reveals several contributing factors. First, operators are required to perform their activities by strictly following written procedures. For each procedural step, the operator must read and understand the instruction, gather the necessary tools and materials, complete the task, and record the outcome. Once a step is completed, the operator may either proceed to the next activity or be required to wait, depending on the nature of the process.



Figure 4-6 Final routing phase

For instance, as shown in the table, after bonding or screwing operations, the operator must set a timer and wait for a prescribed curing period before resuming work. In other cases, subsequent operations must be performed within a specific time window: for example, after cleaning a surface with alcohol, bonding must start no earlier than 15 minutes and no later than 45 minutes; once the adhesive is prepared, it must be applied within 45 minutes, otherwise the preparation must be repeated. All these temporal and procedural constraints place the operator in a condition where performing parallel operations is not allowed, in order to avoid procedural errors and ensure process compliance.

4.4.2 Human Centered Analysis

After assessing the overall performance of the production system and identifying the main process-related programmatic issues, the next step—aligned with the objectives of this work—is to analyze the human-related criticalities that impact system performance. As discussed in the previous chapters and in the state-of-the-art review, a human-centered analysis requires observing and measuring the operators' physical and cognitive states.

During the present study, both direct observations and questionnaires were conducted to capture conscious and unconscious manifestations of operator behavior, with the aim of identifying which operations are the most critical from a human perspective and should therefore be prioritized for improvement.

Regarding the data collection methodology, questionnaires were administered to the operators immediately after the completion of each task. The selection and assignment of activities were performed randomly to minimize potential bias in subjective evaluations. Each operator performed each of the three selected activities once, ensuring uniform task exposure across participants.

Following questionnaire completion, open interviews were conducted with each operator to collect qualitative insights and contextual observations. The following sections present the results of the measurements and analyses obtained during this phase.

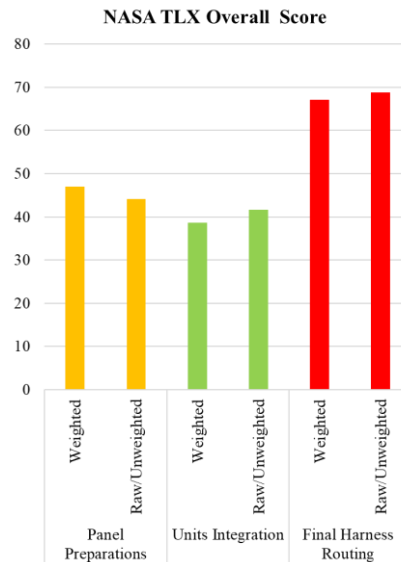


Figure 4-7 NASA TLX Scores

The results of the questionnaires indicate that the operation perceived as the most demanding by the operators is the Final Harness Routing, which obtained an overall NASA-TLX score of approximately 70 points. This is followed by the Panel Preparation phase, with about 45 points, and the Units Integration phase, with roughly 40 points (**Figure 4-7**).

When analyzing the individual dimensions measured by the NASA-TLX, the Panel Preparation phase shows the lowest level of mental workload, while the physical and temporal dimensions exhibit higher values. This result is likely related to the high repetitiveness of the operations involved in this phase, which tend to induce a more mechanical execution behavior among operators. These findings were also confirmed through open interviews, where operators described this phase as repetitive and physically fatiguing but not cognitively complex.

In the Units Integration phase, the mental and temporal demand dimensions were the most significant. Operators explained that this activity requires managing multiple heterogeneous tasks while maintaining awareness of time constraints and precedence relationships among operations.

Finally, the Harness Routing phase—which recorded the highest overall NASA-TLX score—is characterized by a dominant mental workload component, followed by slightly lower but still considerable levels of physical demand, effort,

and frustration. These results suggest that this operation represents the most cognitively and physically challenging phase within the process.

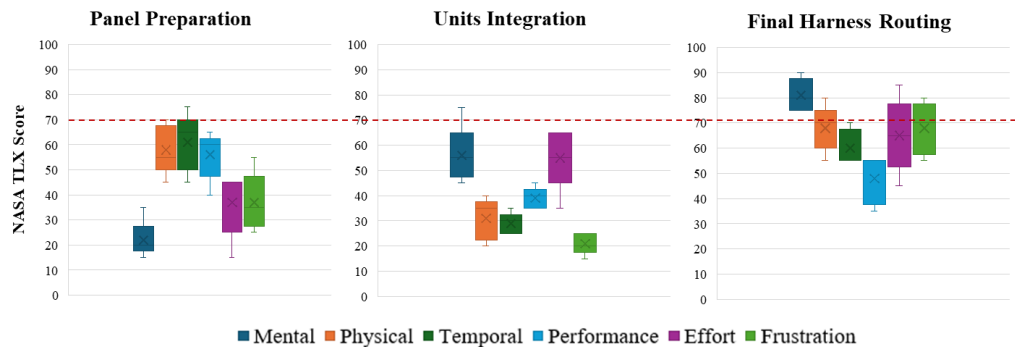


Figure 4-8 NASA TLX Scores per dimensions

From the interviews and direct observations, several difficulties were reported by the operators regarding the interpretation of the CAD drawings used to support the operation. As summarized in **Table 4-4**, **Table 4-5**, the activity primarily consists in identifying the correct cable based on the label code.

This step alone is already critical, as the real working environment is highly cluttered due to the large number of cables and labels present on the product. The cables may belong to different categories: the simplest point-to-point cables, characterized by a single connector at each end, and the more complex multi-input/multi-output cables. In some cases, a single cable can include over 40 terminals, each with its own individual label.

Once the correct cable is identified, the operator must locate it within the CAD model and trace its routing path. This phase is also highly demanding, as it requires frequent viewpoint changes to visualize each section of the cable to be routed. Another major source of cognitive load lies in the need to mentally simulate the intermediate states of the operation. The CAD drawing, in fact, displays only the final configuration of the harness, whereas the operator must infer all the intermediate routing stages required to reach that configuration. The success of the task therefore depends largely on the operator's experience, spatial reasoning, and creativity.

Once the routing of an individual cable is completed, the operator proceeds to secure it along the defined path using cable ties, ensuring that the harness does not interfere with restricted or sensitive areas. Another recurring issue reported during the interviews concerns the physical accessibility of certain routing

points, especially after some panels have been closed, which often forces operators to work in non-ergonomic postures.

For a complete understanding of the activities described and spatial constraints, reference can be made to **Figure 4-9**.

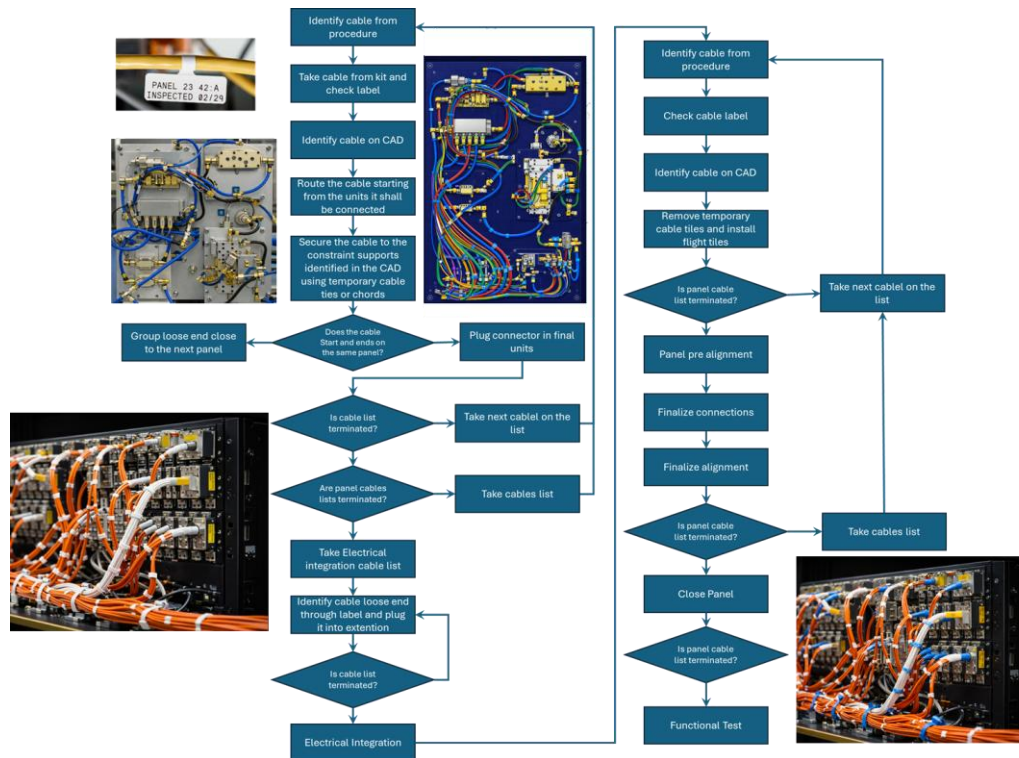


Figure 4-9 Complete harness routing Description

4.5 CONSIDERATIONS ON ANALYSIS

In this chapter, the company's production process was presented and analyzed. The technological assembly cycle was first described in terms of its macro-phases and subsequently detailed down to the level of individual fundamental operations. For each operation, performance analyses were conducted: execution times were measured, and a Value Stream Mapping (VSM) was performed to evaluate the impact of idle times on the product's overall lead time.

The performance analysis revealed that the production efficiency is slightly below the average values typically observed in job-shop manufacturing systems, yet it remains generally low and therefore improvable. Several non-value-added operations were identified, particularly those related to the

completion of procedural steps, which require operators to record the outcome of each execution and measurement activity.

A further analysis focused on the human operators. Through direct observations, interviews, and questionnaires, the most critical operations were identified, as well as the specific elements that make each of them challenging from a human-factor perspective. In particular, the repetitive and mechanical operations in the Panel Preparation phase were found to be critical due to their monotonous nature and physical effort.

In contrast, during the Units Integration phase, operators reported difficulties related to the high variability and heterogeneity of the activities, many of which can be carried out in parallel provided that the start–end dependencies between tasks are respected. While this parallelization could theoretically reduce idle times and improve overall performance, it would also increase cognitive load, requiring operators to keep track of multiple concurrent operations and their respective constraints.

Finally, the most critical task—cable identification through labeling—was perceived as highly demanding due to the cluttered and information-dense work environment. Another relevant issue concerns the discrepancies between the CAD representation of the harness and its real physical configuration, which often appear significantly different and complicate operator interpretation and execution.

4.6 PRODUCTION PROCESSES IMPROVEMENTS

In light of the criticalities identified in the industrial case study, and with the aim of defining a technological tool to support operators during the execution of assembly operations, this section presents the requirements that such a system should fulfil in order to effectively address the observed issues. An example list of system requirements that the future collaborative system should satisfy is presented in the following table.

Table 4-7 Systems requirements

N.	Requirements
1	The system shall help the operator in cleaning and preparing the surfaces
2	The system shall help the operator in gluing surfaces
3	The system shall help the operator in placing supports
4	The system shall inform the operator about expire time for cleaning and gluing
5	The system shall be assign tasks to operator

-
- | | |
|----|---|
| 6 | The system shall accept task information completion by operator |
| 7 | The system shall provide information about operation time constraints |
| 8 | The system shall help the operator in finding and identifying parts label |
| 9 | The system shall provide information regarding part location on the product under assembly at every assembly step |
| 10 | The system shall provide the path for parts placing |
| 11 | The system shall provide parts positions constraints |
| 12 | The system shall check curvature constraint for each part |
-

4.7 IMPROVEMENT SCENARIOS

The analyses presented in the previous sections highlighted that, although the current production system ensures high quality and compliance with ECSS standards, it suffers from limited flexibility, long execution times, and a significant cognitive and physical workload for operators. In particular, the Harness Routing and Final Harness Routing phases account for approximately 40% of the total integration time (and up to 56% considering only mechanical operations) and were identified as the most demanding activities in terms of mental and physical effort.

These results indicate that the AIT process, while technically robust, presents several opportunities for improvement through the introduction of human-centered technological solutions aimed at supporting operators during task execution and reducing non-value-added time.

4.7.1 Root Causes of Inefficiency and Human Workload

The identified inefficiencies can be traced back to two main sources:

Process-related constraints:

Operators are required to follow rigid procedural steps and specific time windows (e.g., adhesive curing, torque checks, or bonding sequences). These constraints prevent task parallelization, generating long idle periods and low overall efficiency.

Human-related cognitive and physical challenges:

Operators must interpret static CAD drawings that represent only the final configuration of the harness, while the actual routing task involves a sequence of intermediate states that are not explicitly documented. The high density of cables and labels, combined with difficult accessibility to certain areas, increases both cognitive load and physical strain.

To address these limitations, the following improvement strategy is proposed, based on the development of a collaborative, human-centered technological system.

4.7.1.1 Digitalization and Activation of Procedures

The first improvement concerns the transformation of current static paper-based procedures into interactive digital workflows. By implementing digital or augmented-reality interfaces, each operator would:

- receive the current operational step with the corresponding instructions;
- be automatically notified of time constraints (e.g., adhesive expiration, waiting times);
- be able to confirm task completion directly on the system interface.

This approach reduces the non-value-added time dedicated to manual transcription and procedure consultation, while simultaneously decreasing mental and temporal workload, particularly critical during the Units Integration phase.

4.7.1.2 Support for Part Identification and Localization

The second improvement addresses the most frequently reported source of inefficiency: the search and identification of cables and components in a highly complex and information-dense environment. The proposed system should:

- assist the operator in identifying the correct part or cable by filtering the Bill of Materials and displaying only relevant items (Requirement 8);
- provide visual and spatial information on the exact location of each part within the assembly (Requirement 9).

Through these functionalities, the system would minimize search times and reduce cognitive load during Harness Routing operations, which were shown to be the most demanding phase in the human-centered assessment.

4.7.1.3 Guidance for Cable Routing and Constraint Management

Once the correct cable is identified, the operator must perform the routing by translating the final CAD representation into a set of intermediate steps. The system should therefore provide real-time guidance on routing and positioning, including:

- the path to be followed for each part (Requirement 10);
- the positional constraints defining the allowable routing areas (Requirement 11);

- the verification of curvature constraints for each cable (Requirement 12).

These functionalities would transform the operation from a cognitively demanding task requiring interpretation and planning into a guided execution process, improving both accuracy and efficiency.

4.7.1.4 Time Dependency and Parallelization Management

Another critical issue identified in the analysis concerns the mandatory waiting times (e.g., adhesive curing, torque verification) that prevent continuous task execution. The proposed system could actively manage these temporal dependencies by:

- monitoring elapsed times and notifying operators when a waiting period has expired;
- suggesting alternative low-risk tasks that can be performed concurrently;
- preventing process delays due to timeouts or expired materials.

Such a mechanism would enable a more balanced workload, reduce idle time, and improve process efficiency while maintaining procedural compliance and operator safety.

4.7.1.5 Collaborative Robotics for Repetitive and Ergonomically Demanding Operations

Among the operations analyzed, the gluing and positioning of structural supports in the Panel Preparation phase was identified as one of the most repetitive and physically fatiguing tasks. This activity requires operators to perform a long sequence of highly standardized manual actions—such as adhesive preparation, deposition, and support placement—often in constrained or non-ergonomic positions.

From a human-centered perspective, such repetitive manual work is not only a source of physical fatigue but also a potential cause of attentional lapses and micro-errors, particularly when precision and adherence to curing times are critical.

To mitigate these limitations, it is proposed to integrate collaborative robotic systems (cobots) to assist operators in these phases. Cobots can execute repetitive or precision-driven subtasks—such as dispensing the correct amount of adhesive, placing supports in predefined positions, or holding components steady during curing—under the supervision and guidance of the human operator.

In this hybrid configuration, the operator would retain responsibility for process control and verification, while the cobot would perform repetitive, low-value-added actions with higher consistency and reduced physical strain. Such human–robot collaboration would provide several benefits:

- Improved ergonomic conditions, by reducing prolonged static postures and manual handling;
- Enhanced process repeatability, ensuring uniform adhesive deposition and support alignment;
- Reduction of cognitive and physical fatigue, allowing operators to focus on higher-value tasks such as inspection, decision-making, and process verification;
- Increased production efficiency, through the parallelization of manual and robotic activities within the same workstation.

Before implementation, it is recommended to simulate the collaborative layout using the same human-centered modeling methodologies described earlier, to evaluate the optimal degree of task sharing and ensure safe and effective human–cobot interaction.

4.7.1.6 Simulation and Validation through Human-Centered Modelling

Before the technical implementation of the system, it is recommended to conduct simulation and validation activities to evaluate the effects of the proposed collaboration modes on operator performance and well-being. As discussed in Chapters 3 and 4 [165], [166], these simulations can be based on Human Digital Twin (HDT) methodologies, allowing the assessment of:

- the impact of task fragmentation and information density on cognitive load;
- the balance between system guidance, robotic assistance, and operator autonomy;
- the expected improvement in process efficiency and human comfort.

The simulation phase would thus enable the identification of optimal collaboration configurations, reducing the risk of cognitive overload and ensuring that technological support effectively enhances, rather than hinders, operator performance.

4.7.2 Expected Benefits

The introduction of the proposed collaborative system is expected to yield the following benefits:

- Reduction of non–value-added time related to manual documentation and procedural verification.
- Improved process efficiency, particularly in routing and integration phases.
- Lower cognitive and physical workload for operators, enhancing well-being and safety.
- Improved ergonomics and reduction of repetitive strain through cobot-assisted operations.
- Increased process traceability and compliance with aerospace quality standards.
- Greater process flexibility, enabling dynamic adaptation to resource and time constraints.

In summary, the proposed approach aims to transform the satellite AIT process from a rigid, document-driven workflow into an interactive, human-centered, and knowledge-supported environment.

By integrating simulation, digital guidance, collaborative robotics, and real-time feedback mechanisms, the system would serve as an intelligent collaborator, capable of assisting the operator in complex tasks, improving both process performance and human well-being.

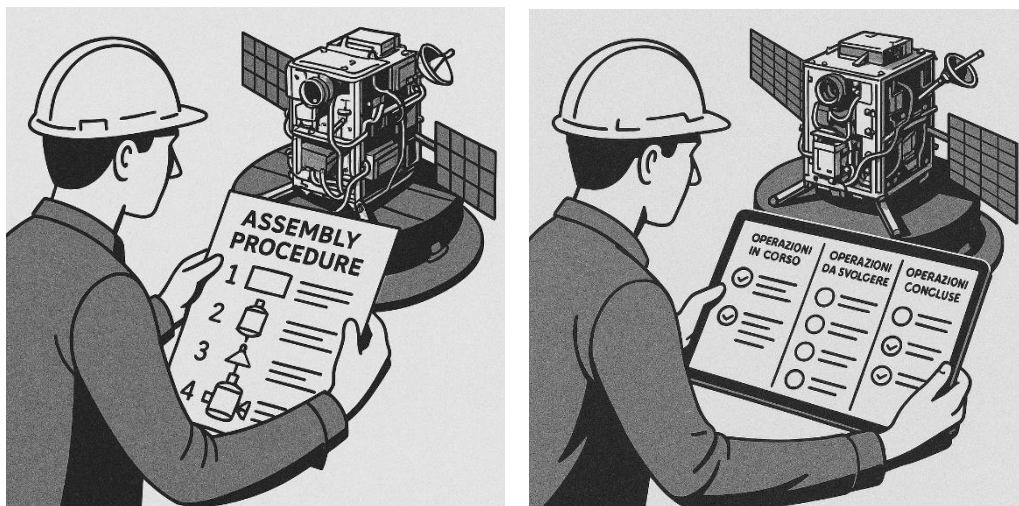


Figure 4-10 As is vs To be process Step 1

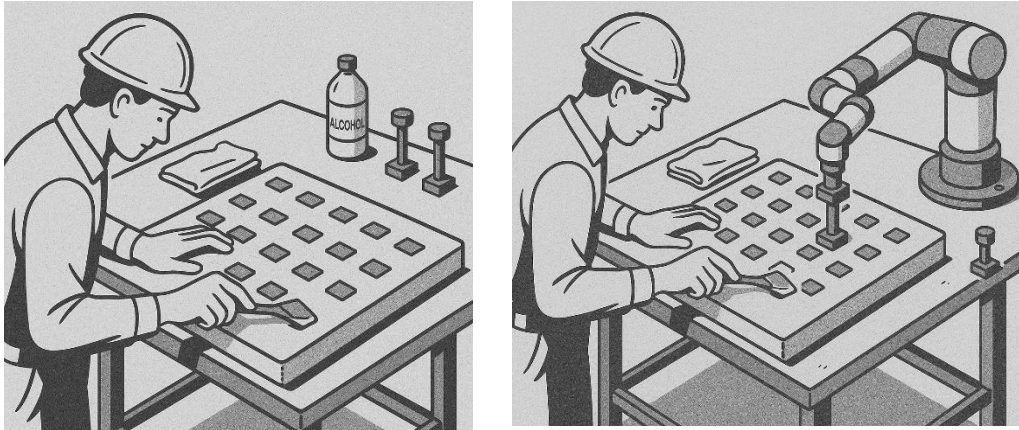


Figure 4-11 As is vs To be process step 5

CHAPTER 5

Conclusions

5 CONCLUSIONS

5.1 GENERAL CONCLUSIONS

This doctoral work set out to explore how aerospace manufacturing — a domain traditionally dominated by high precision, strict regulation, and strong human expertise — could evolve toward a new form of productivity that remains authentically human-centered.

The research began by recognizing a fundamental tension: while the aerospace industry is rapidly digitalizing, it still relies on manual knowledge, craftsmanship, and procedural rigor that cannot simply be automated. The central question, therefore, was not how to replace humans with machines, but how to empower human work through technology — preserving the value of experience and creativity while reducing complexity and inefficiency. Throughout the thesis, this idea was examined from both theoretical and experimental perspectives.

In the first part, a comprehensive review of the literature and industrial context traced the evolution from Industry 4.0 to Industry 5.0, highlighting how the latter places people, sustainability, and resilience at the heart of industrial transformation. Within this conceptual frame, the aerospace sector appeared as a particularly relevant testing ground: its high requirements for reliability, precision, and traceability make it a frontier where digital transformation and human centrality must coexist rather than compete.

From this background, the research identified two key technological enablers — Augmented Reality (AR) and Digital Twins (DT) — as potential bridges between human knowledge and digital systems. These technologies were not treated as ends in themselves, but as tools to support the cognitive and collaborative dimensions of production: helping operators visualize complex data, follow integration procedures, and understand the impact of their actions in real time.

The second part of the thesis translated these conceptual insights into an operational and experimental methodology. A framework was designed to study human-machine collaboration within production processes, combining digital-process analysis with human-factor evaluation. Indicators were defined to capture both technical performance (lead time, rework rate, error frequency) and human performance (cognitive workload, engagement, situational awareness).

This framework was then applied to a real industrial case study conducted at SITAE S.p.A., one of the leading European companies in satellite manufacturing. The AIT process was examined in depth, mapping every phase from mechanical integration to electrical testing. Bottlenecks, redundancies, and information asymmetries were identified, and possible human-centered improvements were proposed. The analysis showed that digital assistance systems, when carefully designed around the operator's workflow, can reduce ambiguity, enhance task coordination, and shorten decision loops, thus improving overall productivity without diminishing human responsibility.

Finally, the work proposed a set of principles for human-centered industrialization, grounded in both empirical evidence and conceptual reasoning. These principles include: (1) empowering operators through accessible and contextualized digital information; (2) ensuring that automation remains transparent and adjustable; (3) valuing human adaptability as a core asset rather than a variable to minimize.

Through these findings, the thesis contributes to the ongoing debate on how the aerospace industry can embody the values of Industry 5.0: sustainability, resilience, and human-centricity.

5.2 ANSWERS TO THE RESEARCH QUESTIONS

RQ1. How can digital technologies be designed to understand and support complex production processes?

The first research question was addressed through the development of a Digital Twin (DT) framework designed to model, monitor, and optimize complex production systems. The proposed methodology demonstrated how a DT can act as a cognitive representation of the production process, capable of integrating heterogeneous data sources—from sensor measurements to process documentation—to create a continuously updated virtual replica of the physical system.

By decomposing the system into its functional layers (physical, connection, digital, and service), the framework enables the dynamic synchronization between real and virtual entities, supporting both operational control and decision-making.

In the aerospace context, this architecture proved capable of capturing process variability, identifying inefficiencies, and formalizing the relationships between resources, tasks, and constraints. The integration of data-driven

models (for prediction and anomaly detection) and knowledge-based rules (for procedural consistency) allows the DT not only to describe the current state of the process but also to understand its behavior and support operators and engineers through actionable insights.

Ultimately, this research showed that digital technologies, when designed around structured and interoperable models, can transform complex aerospace processes into knowledge-rich ecosystems. These systems enhance traceability, reproducibility, and scalability while preserving the human role as the ultimate decision-maker.

RQ2. How can human–machine collaboration evolve toward adaptive systems that respect and enhance human capabilities?

The second research question was explored through the conceptualization of Human-Centered Empathetic Intelligent Machines (HCM) within the Industry 5.0 paradigm.

This framework extends the Digital Twin concept by embedding the human being as an integral part of the system's physical layer. The HCM is composed of four interconnected subsystems—Sense, Understand, Predict, and Act—that enable the machine to perceive, interpret, and respond to the operator's physical, cognitive, and emotional states.

The study identified a comprehensive set of functional requirements for intelligent collaborative systems, covering both technical and social dimensions: from adaptability and explainability to the measurement of well-being and collaboration quality. The resulting model demonstrated that effective human–machine collaboration requires not only data and automation, but also mutual understanding between the operator and the system.

Through multimodal sensing, adaptive modeling, and transparent feedback, the HCM can adapt its behavior to the operator's skills, workload, and preferences—thus evolving from a deterministic tool into an empathetic partner capable of cooperation and co-decision-making.

In essence, this research demonstrated that adaptive human–machine systems must go beyond mere ergonomics or automation efficiency. They should be designed as cognitive ecosystems in which technology amplifies human capabilities while maintaining operator autonomy, engagement, and trust.

The proposed HCM framework provides the methodological foundation for this evolution, defining how empathy, transparency, and adaptability can be translated into measurable system functions.

RQ3. How can the effectiveness and social sustainability of these human-centered systems be experimentally assessed in real industrial environments?

The third research question was investigated through an experimental study on human–machine collaboration, focusing on the distribution of roles between humans and intelligent systems.

In this work, a collaborative workstation was developed to simulate different interaction scenarios—ranging from human execution with machine supervision to shared control and negotiation—using the Wizard of Oz methodology. This approach allowed researchers to emulate the behavior of an intelligent human-centered system without requiring a fully autonomous implementation.

The results provided empirical evidence on how different role configurations affect both process performance and operator experience. Objective data (execution time and error rate) and subjective measures (NASA-TLX workload index and technology acceptance) revealed that collaboration success is strongly influenced by the operator’s expertise and perception of control. Less experienced operators benefited most from assistive configurations, which provided structured guidance and reduced cognitive effort, while more experienced operators preferred supervisory modes that maintained autonomy and transparency. These findings confirm that human-centered technologies must be evaluated not only in terms of productivity but also through multi-dimensional metrics encompassing cognitive, emotional, and social factors.

The Wizard of Oz simulation proved instrumental for this purpose, allowing the measurement of user trust, workload, and system acceptance in realistic conditions without the complexity of a fully operational prototype.

Overall, this study validated the social sustainability and practical applicability of the human-centered design approach proposed in the conceptual framework. It demonstrated that experimental assessment—grounded in controlled yet ecologically valid environments—is essential for translating human-centered principles into effective industrial technologies.

5.3 FINAL REMARKS

In conclusion, this thesis demonstrates that the industrialization of aerospace production does not require dehumanization. On the contrary, the path to higher efficiency and quality lies in recognizing human expertise as a critical element of system intelligence. By embedding digital technologies within a human-centered design philosophy, it is possible to achieve smartness without losing meaning.

From a scientific perspective, the work contributes to defining the theoretical and methodological bases for Human-Centered Production Systems in high-precision industries. It bridges the gap between engineering and human factors, showing how collaboration, cognition, and technology can be jointly optimized.

From an industrial standpoint, it provides actionable insights for the New Space Economy: the aerospace sector can scale up production while safeguarding the role of humans as decision-makers, learners, and innovators.

Ultimately, the research suggests a paradigm for the future of manufacturing, one where efficiency and humanity coexist, and where progress is measured not only by what machines can do, but by how much better humans can become when empowered by them.

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