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A study on digital twin role in industry 5.0 manufacturing

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A Study on Digital Twin Role in Industry 5.0 Manufacturing

A literature review on the current state and future.

Bachelor’s Final Thesis by Jorge Rubio Savall

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Abstract

Industry 5.0 is at its dawn, and with it, a new paradigm of the human-machine relationship has emerged. This new idea of industry states that humans, sustainability, and resilience should be the center of the production goals. This way, society could ensure that it manufactures according to human necessities. Industry 4.0 came with a strong development of automatization technologies and cyber-physical systems that will enable this change in approach. The Digital Twin (DT) falls within this group. DTs open up a new range of opportunities, especially regarding the human-centricity central pillar. This technology enables sharp modeling of systems, which then can translate into accurate predictions. Thanks to the DT application, human behavior, performance, and interaction factors could be better understood. As a result, industrial manufacturing can be enhanced, from planning production prioritizing the operator's human nature to increasing human and robot performance by establishing close collaboration. This work aims to investigate the current literature, examine this technology's trends within manufacturing and human centricity, and provide a structured technology state of the art.

1. Introduction

Rapid technological advancement characterizing the current age is leading to a new production paradigm: Industry 5.0. Parting from the intense focus on automation and cyber-physical systems (CPS) stage defining Industry 4.0, I5.0 aims towards human-centricity, sustainability, and resilience. Due to this transition feat's complexity, humanity must rely on I4.0 advancements and keep developing them along 5.0 goals. Digital Twin (DT) is one of those new advancements. Leveraging several I4.0 technology evolvements, DT involves the creation of virtual replicas of physical entities, presenting multiple benefits across industries. However, despite its applications, its role in the I5.0 new context and its relationship with human-centricity still need to be clarified.

DT merges the physical world with the digital one. They are a high-fidelity virtual model of a physical counterpart enabling real-time communication and correspondence (Bechinie et al., 2024). By live interchanging and analyzing data between both worlds, DTs can provide valuable insights into the analyzed entity's performance and state, whether a product, a process, or a system. DTs can accurately simulate, predict, and optimize them thanks to the recent improvement of sensors, data analytics, machine learning algorithms, artificial intelligence, and computational technologies (Fuller et al., 2020). This capability can translate into positive results, such as more efficient operations, better decision-making, and safer workplaces.

I5.0 shifts the focus from productivity to societal goals beyond growth to for a long-term sustainable industry. One of its key pillars is human-centricity, which prioritizes human needs and interests in industrial production (Xu et al., 2021). The human-centricity pillar underscores that humans and machines should work in synergic collaboration. This way, machines capable of perceiving human intentions and desires could support human creativity and will (Nahavandi, 2019). As a result, with the aid of technologies like cognitive ergonomics and AI assistants, Operator 5.0 could be aware of the actual situation, being able to prevent errors, be more efficient, and enhance productivity (Palazhchenko et al., 2024). In this context, DTs open a new window of possibilities, such as human-machine collaboration systems. Overall, DT plays the role of "glue," combining CPS technologies to implement the I5.0 paradigm (Palazhchenko et al., 2024).

Despite the numerous studies addressing DT applications, a comprehensive framework englobing the roles of DT in human-centric manufacturing has not been included in the available literature yet. Motivated by this fact, this work aims to explore DT's multiple roles within I5.0's human-centricity central pillar and provide a structured schema of DTs in manufacturing. Firstly, industry state-of-the-art and digital twin definitions and information will be provided to contextualize. Then, a systematic literature review will examine how digital twins can enhance human-machine relations, improve workplace safety, and contribute to sustainable and more effective industrial practices. Lastly, this project will outline DT's current trends and state-of-the-art and structure and discuss all the findings to provide an understanding of the present and future of this technology from a human-centric manufacturing perspective.

1.1 Industry State-of-the-art

Industrial Manufacturing has had many stages throughout its history, commonly categorized as the first, the second, the third, the fourth, and the upcoming fifth industrial revolution.

It all started in the late 18th century with the first Industrial Revolution, where industrial manufacturing was mechanical-based and powered by water and steam. Approximately a century later, the second industrial revolution emerged, introducing electricity and the mass production concept, exemplified by Henry Ford in the early 20th century (Tomac et al., 2019). However, although not human-powered, these machines were generally manually operated (C. Liu et al., 2018), and human-machine interaction was not collaborative (Zafar et al., 2024).

In the 1960s, the third Industrial Revolution brought the development of electronics and information technologies. This enabled higher automation and collaboration (Mourtzis et al., 2022b). Nevertheless, the current fourth industrial revolution's tools are the ones that will facilitate humanity to start achieving real human-machine collaboration. Technologies such as Digital Twins, the Internet of Things (IoT), Advanced Data Analytics, Artificial Intelligence, and Virtual and Augmented Reality will be the key to human-centric feats such as Human-Machine Interaction (HCI) (Zafar et al., 2024).

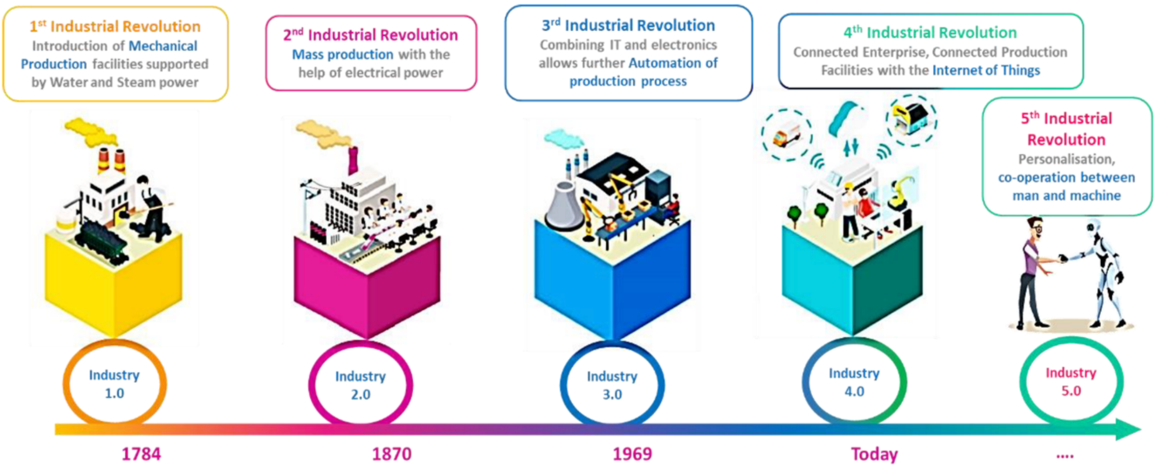


Figure 1. The Five Industrial Revolutions (Mourtzis et al., 2022b)

Industry 4.0 is a technology-centered concept that has enhanced production by establishing intelligent interfaces between machines and the physical world: Cyber-physical systems (CPS) (Xu et al., 2021). The adoption and development of technologies such as Digital Twins (DT), the Internet of Things (IoT), Advanced Data Analytics, and Artificial Intelligence have led to unprecedented productivity in all the stages of a product's life cycle (Opazo-Basáez et al., 2022; Radanliev et al., 2022). However, I4.0 could have detrimental effects on society in the long term due to its lack of focus on sustainability and humankind. This is why (European Commission, 2021) emphasizes moving from a profit-focused and technology-centered industry to a human-centered one that equally prioritizes sustainability, resilience, and profitability.

I5.0 considers three main pillars: sustainability, resilience, and human-centricity (van Erp et al., 2024). The sustainability pillar aims to preserve the planet, requiring a circular economy to enhance resource efficiency through reuse, repurposing, and recycling while reducing waste and mitigating environmental impact (Ben Youssef & Mejri, 2023). The second priority, resilience, is to develop solid industrial production that can withstand disruptions and support critical infrastructure during crises (Awouda et al., 2024). The human-centricity pillar states that humans should work in conjunction with robots, prioritizing human demands instead of the manufacturing process (Adel, 2022). Additionally, while the main focus in Industry 4.0 is on automation and other technological advancements, recent studies have highlighted the importance of placing the well-being of personnel at the center of manufacturing and utilizing digital technologies to achieve sustainable prosperity (Jeong et al., 2023). Aside from the benefits for human life, this human-centered approach presents production advantages such as maintaining human flexibility and natural senses (X. Li et al., 2023).

I5.0's human-centricity pillar stresses the importance of human skills and knowledge in manufacturing. Consequently, it seeks to balance automation and human action by combining human creativity and decision-making while leveraging machines' precision and efficiency (Pinto et al., 2023). Moreover, humans' inherent flexibility enables them to perform various tasks using different equipment, machines, and environments, leading to highly adaptable technology integration capabilities covering some of the drawbacks of automation (Jeong et al., 2023). These realities make sense of the human-machine collaboration (HMC) or human-robot collaboration (HRC) concepts. These propose the collaboration of humans and cobots (collaborative robots) within the same workspace (Mourtzis et al., 2022a). The abovementioned concepts will be delved into further in this work.

1.4 Digital Twins

Digital Twin (DT) technology is a dynamic simulation or model of physical entities: products, processes, or systems (Krupas et al., 2024; Semeraro et al., 2021). This technology combines various interdisciplinary, multi-physical, and multi-scale simulation processes, leveraging data from physical models, IoT sensors, and historical operations. It creates a virtual model that precisely mirrors and predicts the behavior and condition of its real-world counterpart by using the best available physical models, sensor updates, fleet history, etc. (Modoni & Sacco, 2023). Digital twinning allows for real-time monitoring of digital entities and operational indicators. Using data and AI, it mirrors the natural world, offering feedback to improve the physical realm. According to statistics, 85% of IoT-native devices rely on DT for information security. (Lv, 2023).

According to (Modoni & Sacco, 2023), the conventional digital twin model encompasses four critical elements: the digital model, the enterprise repository, factory telemetry, and the digital thread. The first element presents a conceptual asset classification, detailing its components, the logical relationships among those components, and a description of their behavior. The second is essentially a database that holds all information related to the organization's resource management. The third facilitates a two-way synchronization between the real-world artifact and its digital version. Lastly, the digital thread acts as the chronological component of the twin, documenting the digital twin's development by collecting and preserving real-world data.

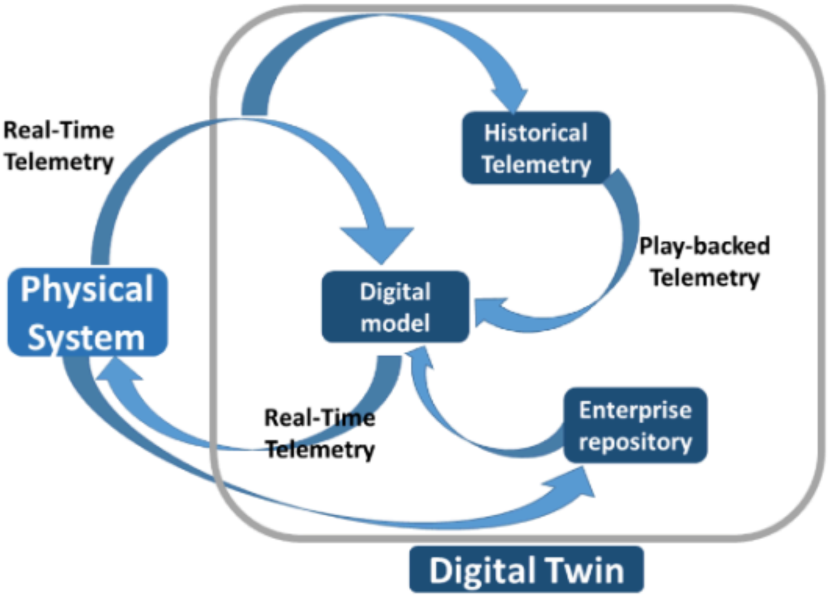


Figure 2. Data pipelines in the traditional DT concept (Modoni & Sacco, 2023)

DT History is relatively short, mainly due to technological limitations before I4.0 (Tao et al., 2019). The first publication treating DT and its uses was in 2011 (Tuegel et al., 2011). It discussed DT applications in aircraft structural life. A year later, NASA defined DT and predicted its uses in the aerospace sector (Glaessgen & Stargel, 2012). It was when applications to other fields emerged that the DT concept indeed developed. Moreover, the actual development of DT technology came hand-in-hand with other technology developments, such as IoT and AI (Tao et al., 2019). It is worth noting the crucial role IoT plays in DTs, as it contributes the data that DT systems then leverage for creating the dynamic, real-time models (Awouda et al., 2024). Additionally, IoT's improvement is contributing greatly to DT cost-effectiveness, making it accessible and profitable for many industries (Maddikunta et al., 2022). Other technological advancements enabling the useful implementation of DTs are edge and cloud computing, collaborative robots, and advanced networking methods such as 5G and 6G (Hu et al., 2023; Lv, 2023). Thanks to the development of these technologies, DT has become more widespread in recent years. As a result, DT technology is understood as an enabler of smart manufacturing (Nguyen et al., 2022), with uses such as human-centric scheduling (Sit & Lee, 2023) or HRC safety enhancement (Das et al., 2023).

2. Literature Review (Prisma, mapping…)

As previously mentioned, the main goal of this research is to study the role of Digital Twins in manufacturing, especially regarding the human-centricity pillar of I5.0, to establish a structured state of the art on the matter. Given all the academic documentation currently available, a scoping literature review of it is necessary to understand the reach of Digital Twins. Adhered to the PRISMA method for ensuring the quality of results, the following literature review will delve into Digital Twins' current and future human-centric applications and their technological capabilities and barriers.

2.1 Research Methodology

Based on the initial research on I5.0 manufacturing, which was partly exposed in the introduction, literature research was started. This review followed an iterative process of search criteria definition, eligibility guidelines establishment, search, documentation filtering, sample refinement, and analysis of results. All this with the objective of providing a rigorous review of the current literature. The first step was selecting the most adequate platform to find relevant documentation. Because of its powerful search tool, its wide variety of English language literature, and its facilities for academic documentation and citation, Scopus was chosen as the best platform.

This research was performed using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) checklist to create a thorough and transparent systematic review ('McKenzie & 'Page, 2023). This method aims to aid authors in enhancing their reporting of systematic reviews and meta-analyses (Moher et al., 2009).

2.2 Eligibility Criteria

The literature eligibility criteria specified in Table 1 have been previously constituted to ensure a precise, unequivocal, and concise application. This careful definition pursues that the resulting documentation selection is not only relevant but also representative of the topic to analyze, simplifying an exhaustive, non-arbitrary, and precise content evaluation.

Eligibility criteria	**Condition**
Database	Scopus
Language	English

Publication period	2020-2024
Search Date	June 1st, 2024
Search within	Article title, Abstract, Keywords
Keywords and synonyms	Figure 3: Literature search outline
Subject area	-
Document type	Article, review, conference paper, and book chapter

Table 1: Literature eligibility criteria

Due to the abovementioned advantages, the Scopus database, which is part of the publishing company Elsevier, was chosen to perform the review. The selection of English as the only language in the results was due to the vast existence of academic literature in the language and the facility to work in it. As global reviews of the impact of digital twins on human centricity have not been done yet, reviews were included in the document type filter to include different views on the state of the art. Articles, conference papers, and book chapters were fundamental to constructing a formed idea of the topic. Considering the time period, I5.0 was introduced around 2020 (European Commission, 2021); Therefore, the recency of the matter to study justifies avoiding previously published papers.

2.3 Collection of Existing Literature

Regarding the search criteria, the research keywords included were considered critical for the correct review development. These words were: **Digital Twin, Industry 5.0, human centricity, and manufacturing**. Synonyms or acronyms such as “I5.0” were also included in the search to ensure that the available literature was complete and pertinent. Digital Twins and Human Centricity are the two main study topics related to this thesis. I5.0 englobes human-centricity and provides crucial context. Lastly, manufacturing was added to ensure that the literature was related to the industrial processes and added insight into Human-Machine Collaboration. DT was used to get more documentation relating to Digital Twins, and I5.0 was used to maximize the papers containing I5.0 material. As for the terms finished with asterisks, these were used to include all the possible words starting with the letters before them. For instance, “Human cent*” included “Human centricity” and “Human centered”. As a result, the following search framework (figure 2) was built.

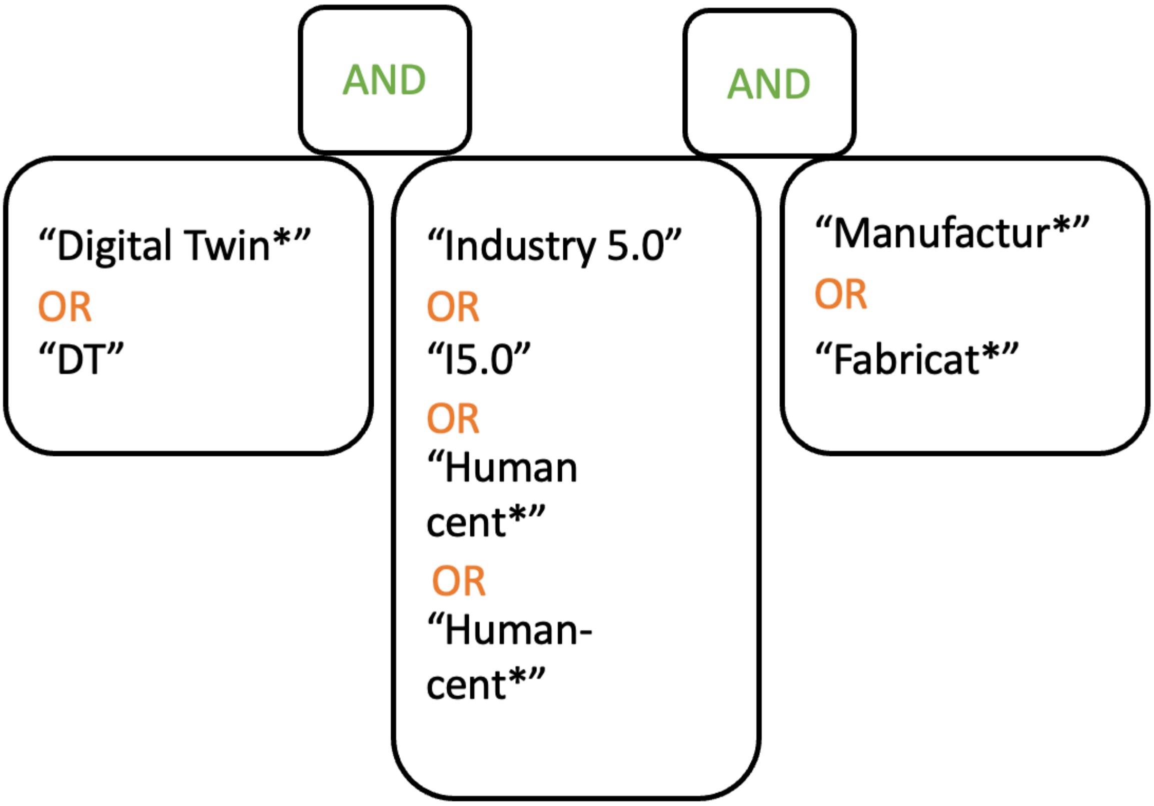


Figure 3. Literature search keywords and synonyms

The search equation was as follows:

(TITLE-ABS-KEY ("Digital Twin*") OR TITLE-ABS-KEY (“DT”) AND TITLE-ABS-KEY ("Industry 5.0") OR TITLE-ABS-KEY ("I5.0") OR TITLE-ABS-KEY ("Human-cent*") OR TITLE-ABS-KEY ("Human cent*") AND TITLE-ABS-KEY ("Manufactur*") OR TITLE-ABS-KEY ("Fabricat*))

Figure 4. Search equation

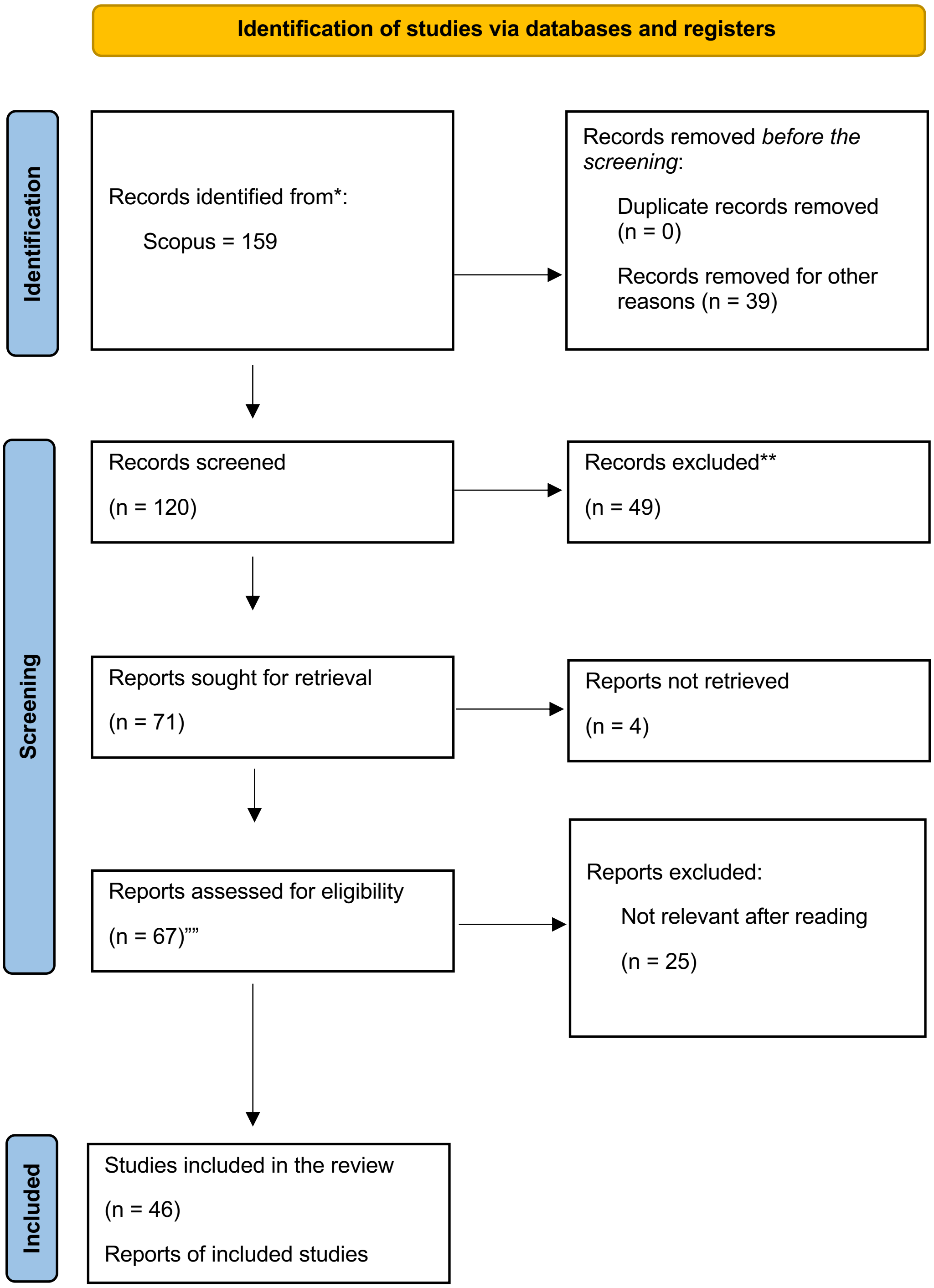


Figure 5. Prisma Search Outline

Figure 4 shows the publications related to the keywords used during the search over the years. As mentioned, the study field is relatively young, causing documentation to appear from 2020.

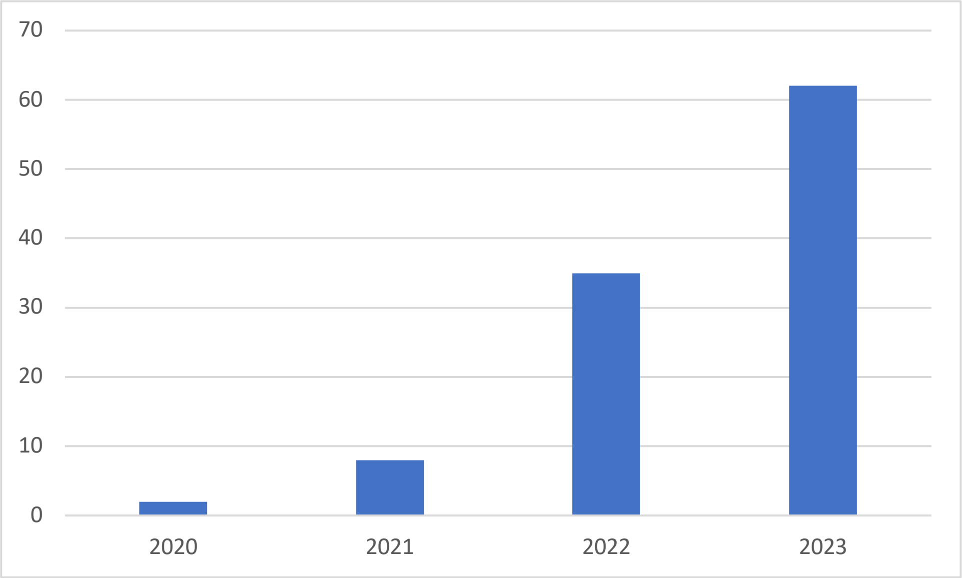


Figure 6. Number of released papers each year

This year's publication data have yet to be included as it is approximately half of 2024 when this work is being written. However, 52 more publications have been published by June 1st. Multiplied by 2, assuming that the year's second half will be similar, is 104. This shows signs of Digital Twins and I5.0 being an increasingly popular topic.

VOSviewer software was utilized to explore and map the link networks between the keywords and indexed terms in the Scopus database (Van Eck & Waltman, 2018). The search with the keywords above and relations resulted in three main clusters. The first of them englobing AI, IoT, cobots, edge computing, and other I5.0-enabling technologies related to DTs. The second included fields regarding human-centricity and manufacturing. Lastly, the third main cluster included augmented reality, human-robot collaboration, human digital twins, maintenance, and other fields related to operator 5.0.

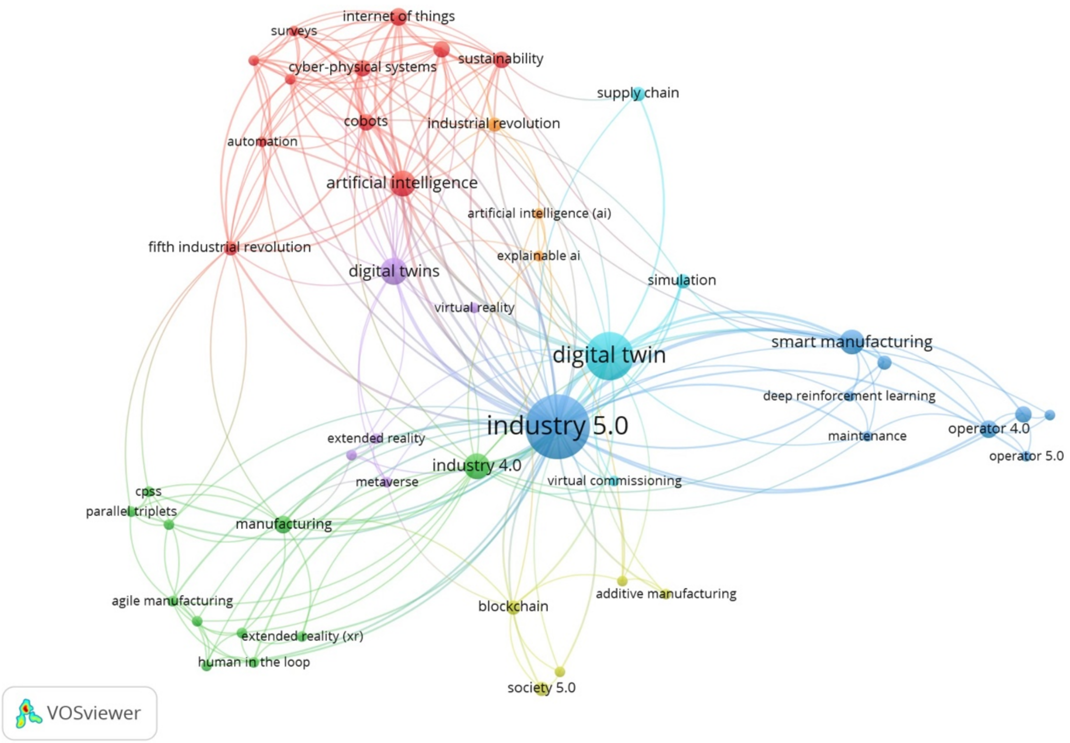


Figure 7: Cluster analysis results for the search performed.

As detailed in the PRISMA outline above, of the 159 documentation pieces resulting from the search, 113 were discarded. Papers between 2020 and 2024 were included due to the recency of the human-centricity, digital twins, and I5.0 topics. Earlier literature was discarded to avoid unnecessary information noise. Finalist documentation was selected based on its relevance to the research and contribution to understanding digital twins' role in human-centric manufacturing processes. After the various literature filtering stages (record screening, retrieval, etc.), a total of 46 articles remained.

Literature content was organized in a Microsoft Excel table to accurately categorize each piece of content based on the applications addressed. These topics or categories were explicitly selected to accurately reflect literature content, avoid redundancy, and form a structured outline valid for posterior content analysis. The selected categories, which are also the main topics addressed by the papers included in the review, are the following:

The chosen analysis categories were Human-Machine Collaboration (HMC) and Human-Robot Collaboration (HRC), Human Digital Twin (HDT), and Human-Machine Interfaces (HMI). It is worth mentioning that, due to DT’s interdisciplinary nature, some information subsets are shared across categories.

3. Results

As mentioned, the purpose of this review is to scope the current research on the possibilities DT can contribute to the Human-centricity I5.0 pillar in manufacturing and, then, to provide a state-of-the-art in terms of applications, technology, and future implications. This review covers the literature published between 2020 and 2024, focusing on DT, I5.0, Human-centricity, and Manufacturing. Articles were selected with the abovementioned criteria.

DTs can be categorized in multiple forms due to the technology's cross-functional nature. For instance, (Mendonça et al., 2023) offer a DT categorization in terms of the capacity to perform complex tasks. They distinguish the traditional Digital Twin (DT), the Hybrid Twin (HT), and the Cognitive Digital Twin (CDT). From the first to the last, they increase in computational capabilities until they are able to sense complex and unpredictable behavior. Despite this classification, for simplicity reasons and based on the aforementioned categorization, this work will first delve into the DT literature treating HMC as a global topic. Then, the more specific subjects are HRC and cobots (collaborative robots), HDT, and DT-based HMI systems. Overall, the following sections will provide a detailed synthesis of the findings.

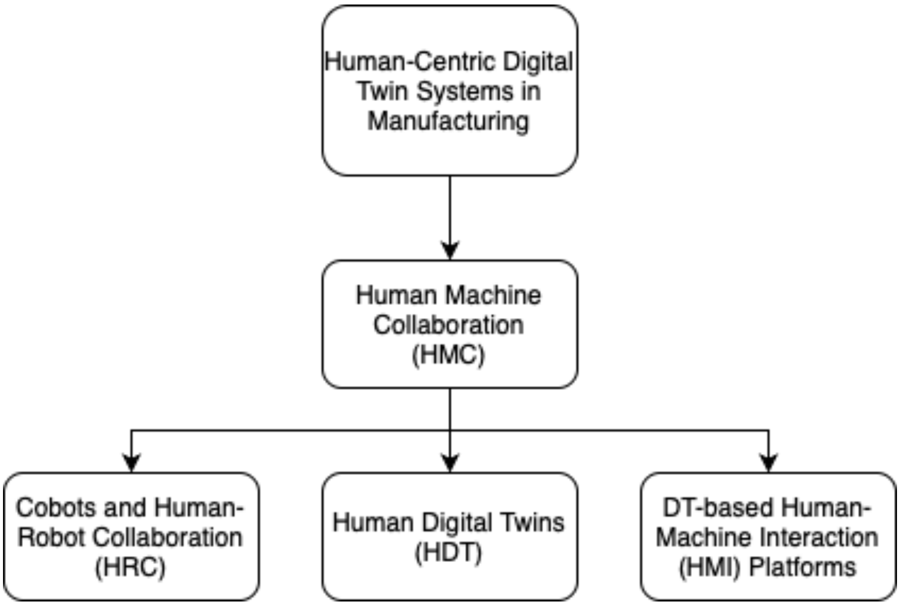


Figure 8 Distribution of results

3.1 Human-Machine Collaboration

Before the term I5.0 was created, the idea of HMC (Human-Machine Collaboration) emerged as a way to combine human and machine resources for better results. With the rise of I5.0, which emphasizes a human-centered perspective, machines will be required to directly work with human employees, reducing the physical and mental burden of difficult tasks for humans (Krupas et al., 2024). (Lv, 2023) describe the ideal I5.0 manufacturing in which operators and robots can cooperate in communication on the same workbench, as partners. This way the intrinsically human flexibility, creativity, and decision-making could synergically combine with the accuracy and efficiency of machines.

The Human-in-Loop concept adds to understanding HMC. (Bhattacharya et al., 2023) describe as a situation in which the operator operates or monitors the system. This is a situation in which a highly automatized process requires the action of a human operator. Therefore the Human-in-Loop and the HMC concepts are intrinsically related.

It is important to differentiate between human-machine interaction (HMI) and human-machine collaboration. According to (Krupas et al., 2024), while HMC is focused on synergy and combined effort, HMI refers to any situation when humans interact with machines and does not necessarily involve collaboration or working on a common goal.

Overall, HMC is a promising approach. According to (Raffik et al., 2023), over 79% of manufacturers in the US are currently using HRC or plan to do so in the near future.

3.2 Human-Robot Collaboration Systems and Cobots

Traditional manual processes are gradually evolving into hybrid systems, integrating humans and collaborative robots (cobots). One of the most mentioned uses of the DT technology is their applications for Human-robot collaboration (HRC). (Baratta et al., 2023) describes the I5.0 ideal HRC situation as that in which the robot is able to adjust its autonomy level depending on the operator's needs, instead of fully autonomous.

3.2.1 The Cobot Concept

Cobots, or collaborative robots, are designed to work hand-in-hand with human operators, in the same collaborative workstation. Unlike traditional industrial robots, the cobots interact with humans through sensors and other technologies, allowing them to notice and respond to human presence or movement. They are now employed in material handling, packing, assembly, and several other manufacturing processes (Raffik et al., 2023). The recuperation of the human worker role intrinsic in I5.0 brings more complex manufacturing application scenarios. Hence, Cobots must be able to flexibly adapt to different situations (Xiang et al., 2024). It is also critical for optimal HRC that operators and cobots work together smoothly, supporting each other with no interference to shorten the cycle and improve quality (Montini et al., 2023).

3.2.2 A General HRC Framework

(Montini et al., 2023) discloses a framework that can help overcome the existing limitations in current HRC applications. Being the inclusion of humans one of the main HMC-impeding factors, the framework aims to include all the relevant elements needed to increase efficiency and productivity while greatening flexibility, workers' comfort, and safety when working with cobots.

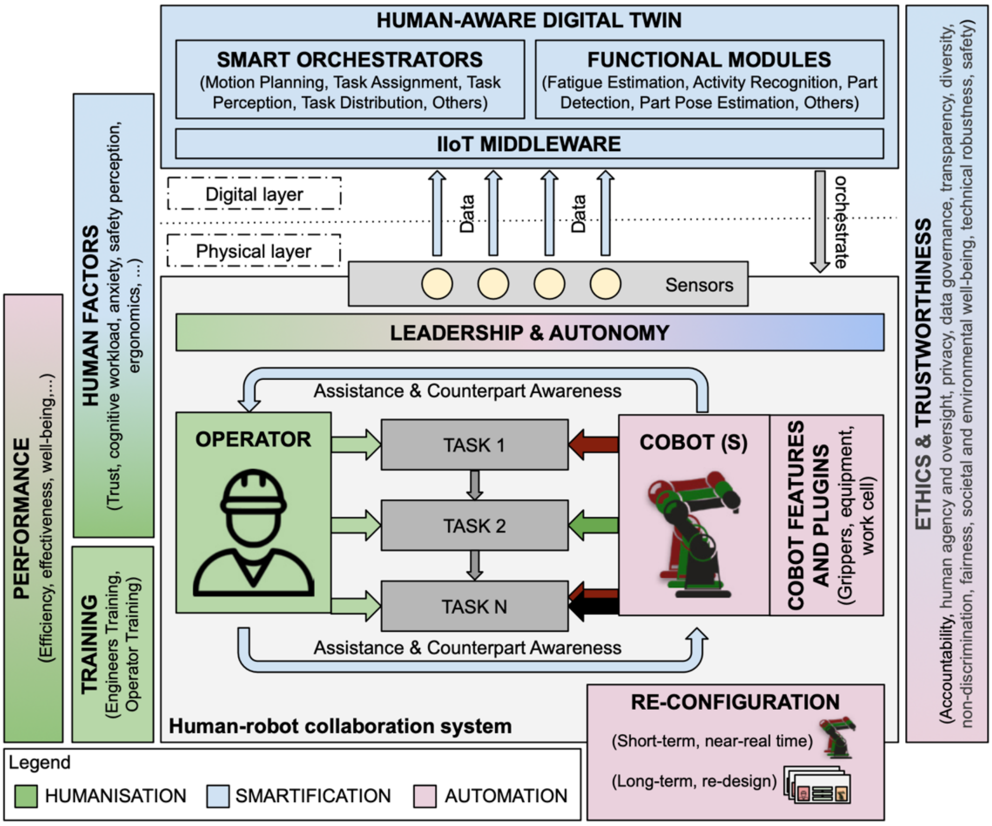


Figure 9. Framework for HMC systems proposed by (Montini et al., 2023)

(Montini et al., 2023) also mentioned the necessity of Human Digital Twins (HDT) for optimal humanization (including humans in the operations), which will be examined in a further chapter.

Considering the manufacturing space as a whole is necessary to fully enable HRC. That is why (Montini et al., 2022) states that, in order to advance DT technology and achieve human-aware factories, it is necessary to develop DT frameworks englobing physical entities, processes, communications, and the DT itself. Consequently, they introduce a HDT reference model to make possible the mentioned, englobing all the physical attributes.

In addition, (Papacharalampopoulos et al., 2023) propose a computer-aided process planning (CAPP) in which a global DT or central entity receives and processes data from smaller DTs. This setup could help avoid collisions between autonomous mobile robots (AMRs) and workers thanks to IoT wearables with position-tracking capabilities, which will also be discussed in further sections.

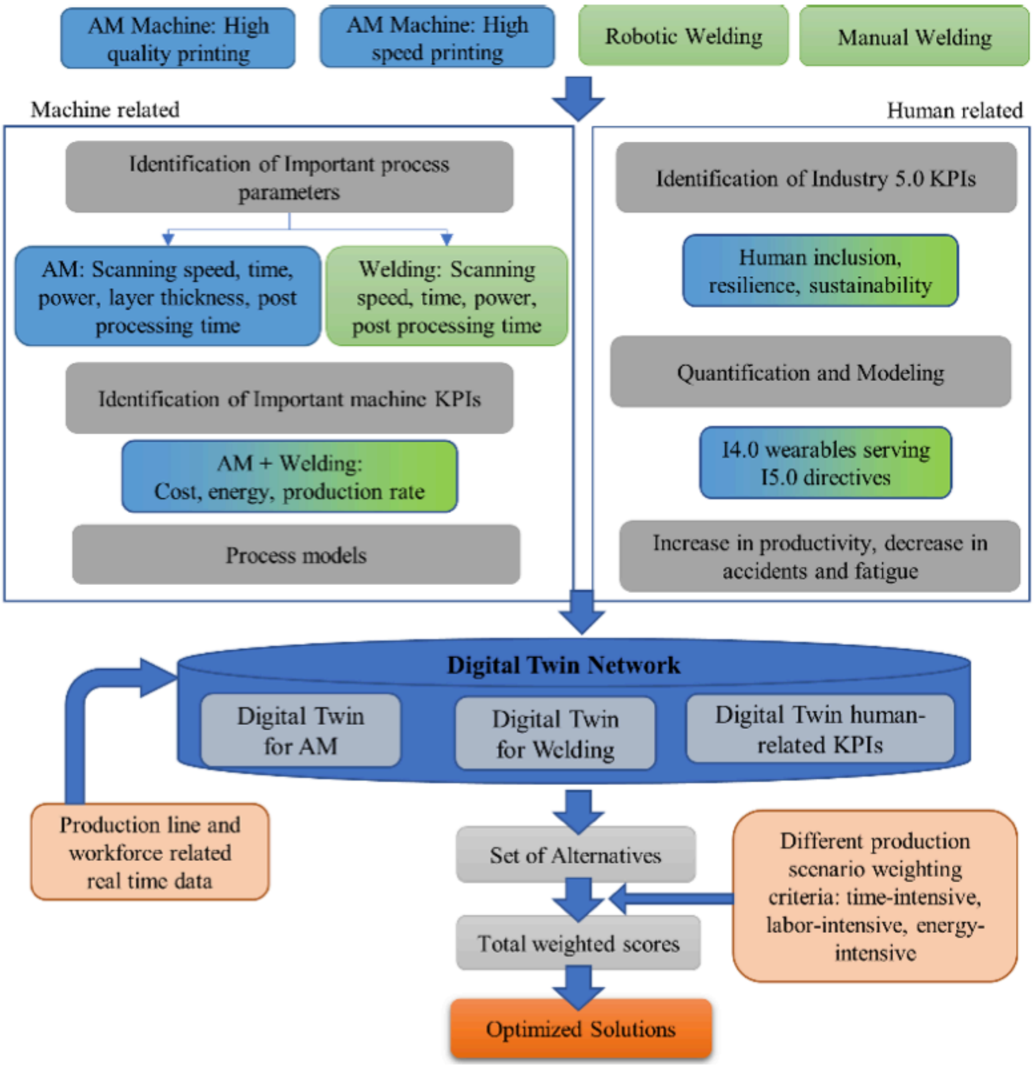


Figure 10. Global DT system proposed by (Papacharalampopoulos et al., 2023)

(Sit & Lee, 2023) gives another use to DT in manufacturing systems. They cover low volume high mix production optimization. They use a DT to do so. In their model, they study and optimize the combination of both human and robot roles. Combining this approach and human flexibility could help for a more human-centric manufacturing, with the benefit of enhancing mass customization to fully adapt to human customer necessities.

3.2.3 Cognitive Digital Twin in HRC

Due to the human-machine coordination criticality, authors in (Mendonça et al., 2023) and (Sharma & Gupta, 2024) introduce the Cognitive Digital Twin concept. With the inclusion of AI techniques such as machine learning (ML) and deep learning (DL), the DT model can dynamically adapt to the environment, resulting in fast analytics, system optimization, and prediction of situations. This concept is critical for HMC, as it is critical for the system to continuously improve due to the complex nature of the human-machine relationship. Because of this necessity, the idea pf an AI-enabled continuous learning DT will be present along the following section.

Considering the cognitive DT idea, multiple literature pieces propose collaborative manufacturing ideas on it. (Das et al., 2023) introduce a DT architecture that integrates a Neuro-Adaptive Controller (NAC) and edge computing technology. On the one hand, the NAC allowed advanced robot synchronization with its physical counterpart. On the other hand, edge computing enabled obstacle monitoring at the autonomous robot's workspace, leading the robot to an uncertainty-aware safe operation. Through experimentation, (Das et al., 2023) demonstrate that human-robot synchronization is achieved with low error. The experimental results indicate that NAC outperforms traditional controllers, allowing for more precise movements and a safer human-robot coworking space.

(S. Wang et al., 2024) also gives deep learning capabilities to the robot DT, which could be linked to the NAC and edge computing contribution made by (Das et al., 2023). As exposed during cognitive DT explanation, this DL approach continuously improves the system. Consequently, the system better detects and classifies human and robot movements, enhancing safety and reliability. Consisting of a robot DT, the physical system, the robot operating system (ROS), and deep learning and data generation layers, a deep learning DT framework was proposed by (S. Wang et al., 2024). The learning system could include both real and synthetic data, which, combined, created positive synergies regarding precision and consistency, as revealed by the performed experiment.

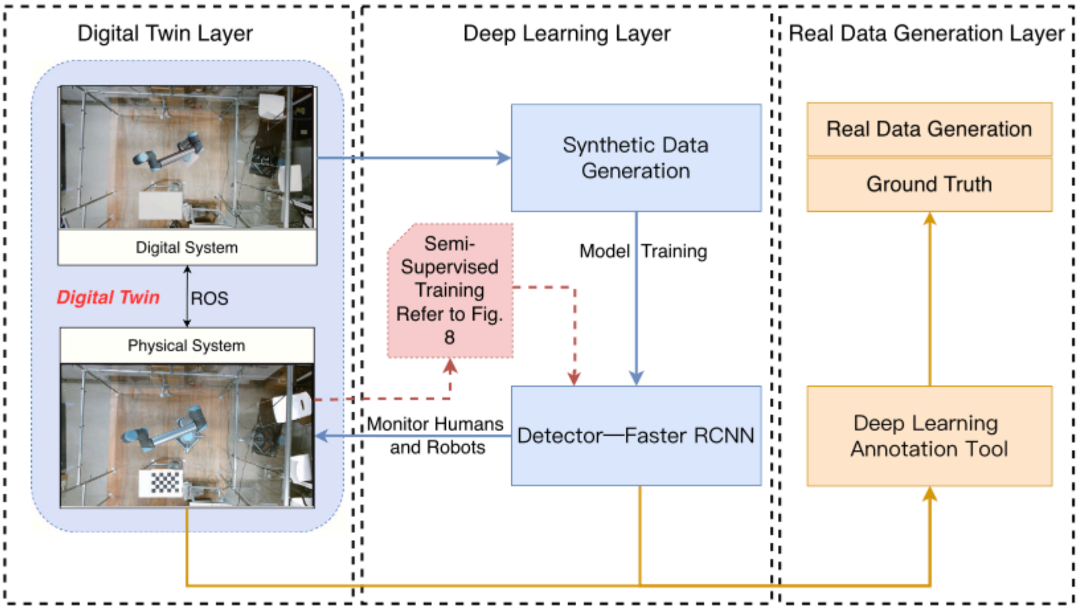


Figure 11. Theoretical framework of using deep learning and Digital Twin techniques for monitoring Cobots (S. Wang et al., 2024)

For the system's learning process, (Steed & Kim, 2023) propose DT human-in-loop simulations in which the operator participates to improve the process. However, compared to the previously mentioned deep learning systems, this approach seems less promising but complementary.

3.2.4 Sensors and Machine Vision Technology

In order for the DT to receive accurate information and provide the according insights to control robots for HRC, advanced sensing technologies such as IoT and AI-enabled Machine Vision have been proposed. Sensing technology is a pivotal part of intelligent manufacturing, enabling the robot to sense the environment though systems such as DTs and promote the development of human-machine integration (Lv, 2023).

(Borck et al., 2022) adds that smart sensors are critical in DT's quality consistency due to the importance of production data reliability, they propose of IoT-networked sensor systems and computer vision systems based on them as the keys for accurate DTs.

Continuing this trend, (H. Wang et al., 2023) leveraged machine vision technologies into a DT-based workshop concept which integrated real and virtual data with a certain set of rules to identify the workshop unsafe states and realize automatic reasoning of risk level and measurement accurately and unambiguously. In their system, workshop DTs were used to train the deep learning network in detecting dangerous situations, which could be especially useful in HMC situations.

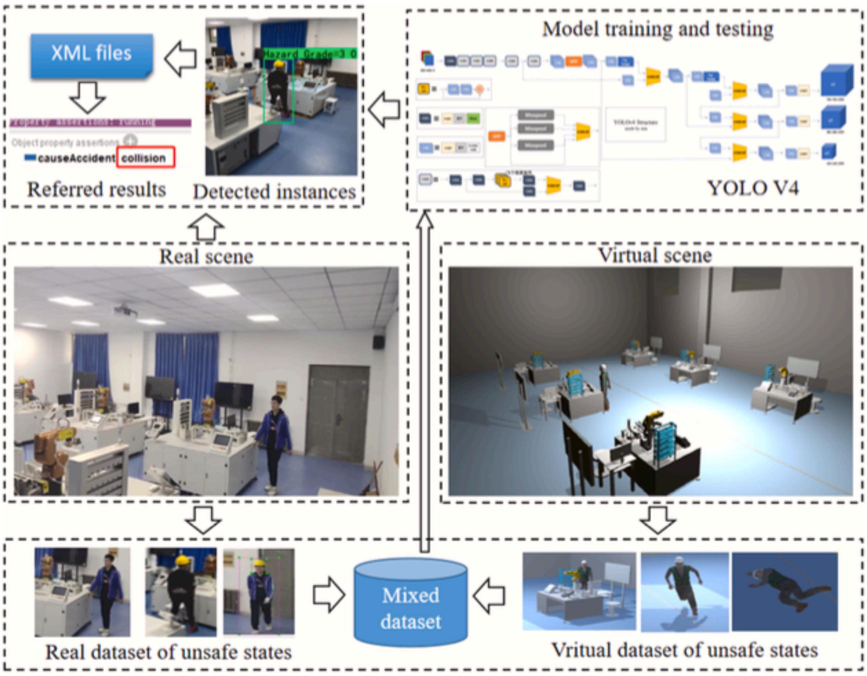


Figure 12. DT-based workshop safety management system using YOLO deep learning model proposed by (H. Wang et al., 2023)

(Fraga-Lamas et al., 2022) describes a thermal machine vision solution for collaborative robotics. Based on edge computing and thermal imaging, it enhances HMC safety, allowing for closer coworking, while keeping the DT system cost-effective.

Other authors such as (Lehmann et al., 2023) describe the physical system-sensor-DT information flow. (Awouda et al., 2024) adds DT-IoT frameworks and practical cases. However, none were specifically applied to HMC nor parts of it. As a result and seeking this thesis conciseness, these studies will not be looked into.

It is worth noting that part of the system's sensing could come from extended reality (XR) devices wore by the operators coworking with the robots. Section 3.4 will delve further into it. Additionally, in section 3.3 more detail on operator detection will be provided.

3.2.5 DT for Assembly Monitoring and Quality Inspection

(X. Zhang et al., 2021) unveiled a DT model consisting of 3 modules: A process control module controlling multiple robots receiving feedback from sensors, cameras, and the quality inspection model. A parallel quality inspection module judging with deep learning whether the product qualifies or not the requirements. This last offering a human-monitoring module with a 3D DT display. Contributing to the topic, (Thangavel et al., 2024) proposes a DT-based system to assess and predict welding quality in manufacturing. This would aid operators in inspecting and preemptive decision-making when HMC. Lastly, (Pang et al., 2023) propose a multi-layered digital twin system for verification-oriented, part-focused assembly monitoring. An algorithm was used to detect if the goal layer matched the actual entity layer. The information was provided to operators through an interface for manual assembly assistance.

Additionally, (Jeong et al., 2023) describe a set of smart tools that operators can use to increase productivity and quality. These smart tools are capable of sending their position to the DT and a tool-blocking system to ensure correct assembly. The author describes this use in the aircraft assembly process, which is particularly complex, both for the quantity of parts involved and the quality needed. Moreover, because of the intricacy of the process, human-labor flexibility is necessary, demonstrating the importance of human-centered technology development.

3.3 Human Digital Twins

Human digital twins (HDT), also known as operator digital twins (ODT) in the context of manufacturing, are digital replicas of real humans. They encapsulate crucial information, including physical, physiological, and psychological models. Beyond capturing human personality and traits, they also encompass human-machine and human-environment interactions, providing comprehensive representations. The applications of HDT are diverse, spanning from the customization of human-centric prototypes to the enhancement of human-robot collaboration (B. Wang et al., 2024).

As (Montini et al., 2023) argue, HDT is an important part of achieving efficient I5.0 HMC. However, the variability and inconsistency of human behavior pose a significant challenge (Ramírez-Gordillo et al., 2024). (Modoni & Sacco, 2023) states that DT solutions available are almost entirely on physical assets and not on human operators, which is a shortcoming of the current DT state-of-the-art.

(Picone et al., 2024) described the minimum capabilities that should describe an ODT in manufacturing are:

Representativeness and contextualization:	*Shadowing:*	*Augmentation:*
▪ The ODT must accurately represent its physical counterpart within its physical context, including properties, actions, events, and relationships.	▪ It is essential for the ODT to keep updated. ▪ Achieved by accurately mapping and computing the critical attributes, characteristics, and capabilities of the real operators in a synchronized manner (e.g., heart rate and steps).	▪ Continual development of insights and deepening of analysis. ▪ These new analysis capabilities allow manufacturers to accurately understand the physical, cognitive, and even emotional states of workers, which could have a positive impact on the well-being and productivity of workers.

Table 2. HDT necessary characteristics (Picone et al., 2024)

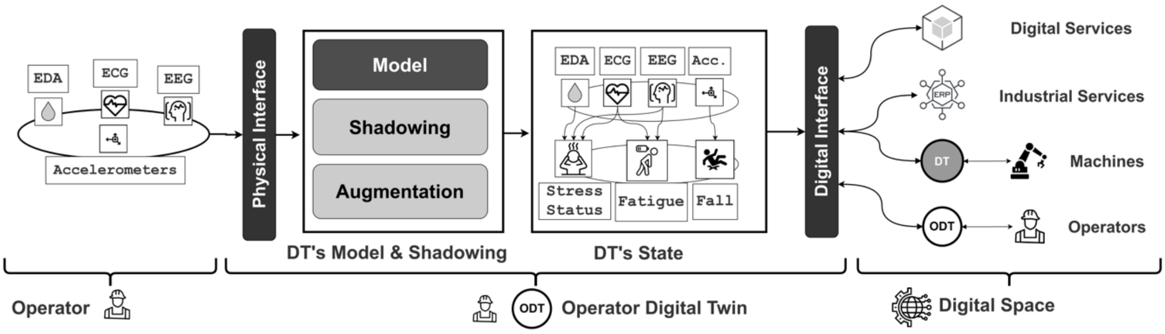


Figure 13 Schematic view of the scenario proposed for ODTs (Picone et al., 2024)

Adding to this, (X. Zhang et al., 2024) defend that to develop a high-quality ODT, it's essential to integrate a variety of modeling techniques and to balance its cost and utility. Thus, enabling an economically feasible HDT that encapsulates the entire spectrum of human performance.

Literature found exposes two main Human Digital Twin applications: Human modeling for enhancing HMC and human modeling for operator human-centric management.

3.3.1 Human Digital Twins for Human-Machine Collaboration Enhancement

Motion recognition

(Fan et al., 2023) designed an HDT model aimed at improving worker well-being and, especially, enhancing safety in HRC. Created and trained with visual RGB-D and complimentary depth data, it is able to depict, predict, and visualize human posture, action intention, and ergonomic risk in HRC scenarios. In Figure 14, the system's continuous control loop is described.

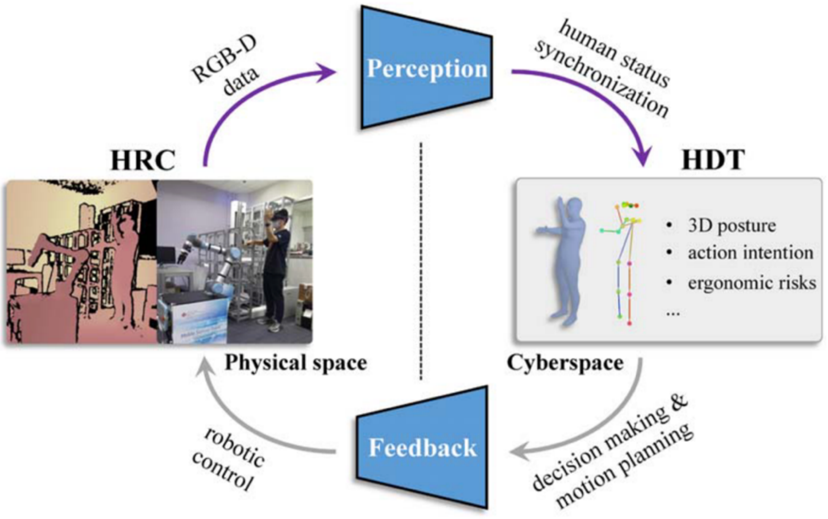


Figure 14. Overview of the HDT-based HRC system proposed by (Fan et al., 2023)

(Fan et al., 2023) then depicted their adaptive motion control strategy involving the following steps:

- A decision-making step is responsible for selecting robotic action missions, such as picking up an object, along with the associated task specifications, such as the pick-up position.
- In this approach, the task assigned to the robot for proactive help is determined by predicting the intention behind human actions.
- Upon startup, the robot will initially assume the standby state. This state serves as the default mode, to which the robot will revert immediately after finishing any other actions.

Additionally (T. Liu et al., 2023) details a 3D human body modelling and recognition system which could be also employed in robot's operator detection. Based on a project to develop Aerospace Defense devices on which any careless activity could cause critical harm, this method could help monitor tasks for higher safety. Their approach has already shown clear advantages in keeping the operators more careful and more responsible. For RGB+D, this system features optimally achieve up to 86.62% accuracy.

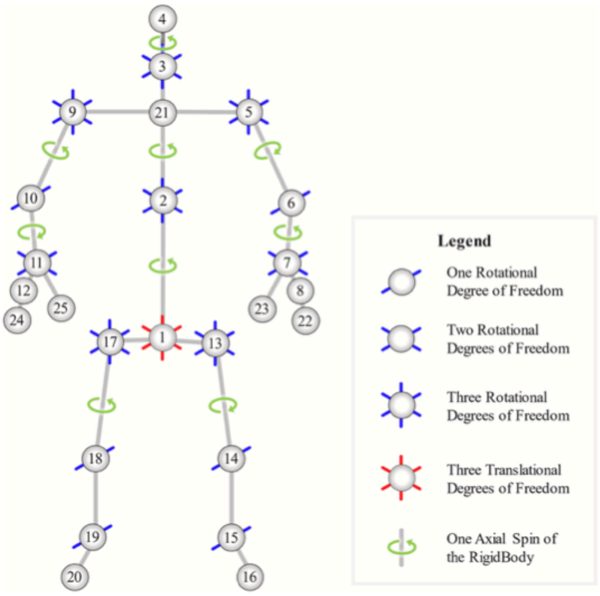


Figure 15. Frame of human skeleton model by (T. Liu et al., 2023)

(Maruyama et al., 2021) also developed a HDT scoping to improve HMC. Aside from the DT interaction modules and a system schema similar to Figure 8, they described the HDT's representation of the operator's actual body. Consisting of a node layer and link structure describing general movement possibilities and a deformable skin surface adding volume to the model. The sensing camera used marker-based optical motion as the sensing submodule, where 3D marker positions are captured by multiple cameras arranged in the environment. This is an improvement compared to the RGB-D proposed by (Fan et al., 2023), as this type of sensor is limited to the worker moving in a limited area, i.e., within the field of view.

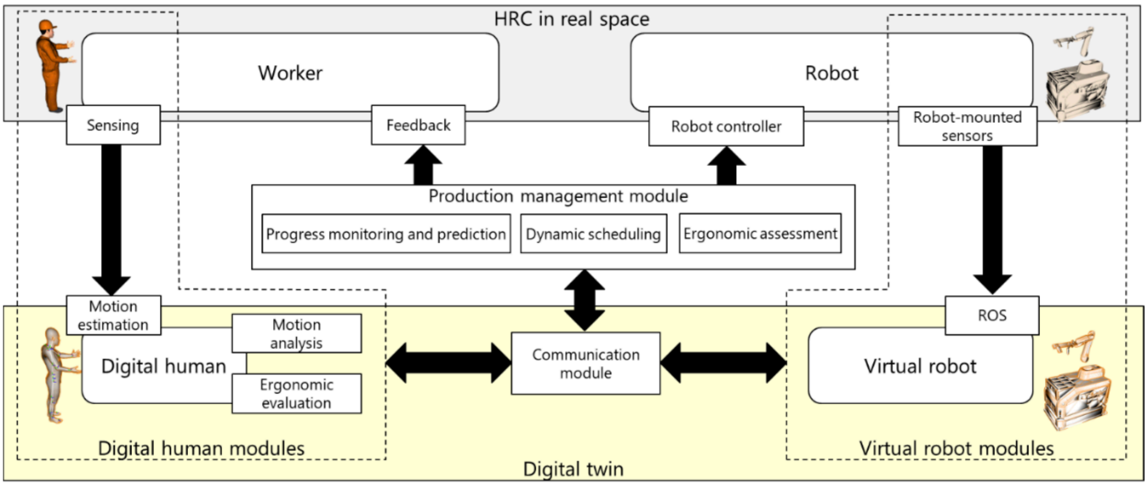


Figure 16. General HDT-Based HMC system architecture (Maruyama et al., 2021)

Following the neural network usage described in section 3.2.3, (Ji et al., 2023) use neural networks to represent human body parameters from images. They robust their model by feeding the system with partial and augmented data. (Ji et al., 2023) also proposes to construct separate DT models of humans and robots, integrating them in a workspace simulation to reduce movement prediction inaccuracies.

Emotion recognition

It is vital for HMC that robots can recognize human intentions and patterns. (Baratta et al., 2023) defined a DT-based module for emotion recognition in HRC. Their system would examine facial expression, body gesture, and vital parameters through neural networks, machine vision, and sensors (temperature, biometric, electroencephalography, etc.). Emotion classification modules leveraging ML were proposed. By performing simulations within the DT, predictive and corrective can be taken, guaranteeing the maximum physical and cognitive ergonomics. The module would work within a DT reflecting the collaboration process. Nevertheless, this system presents limitations as the analysis dimensions required are significantly numerous and have innumerable degrees of freedom.

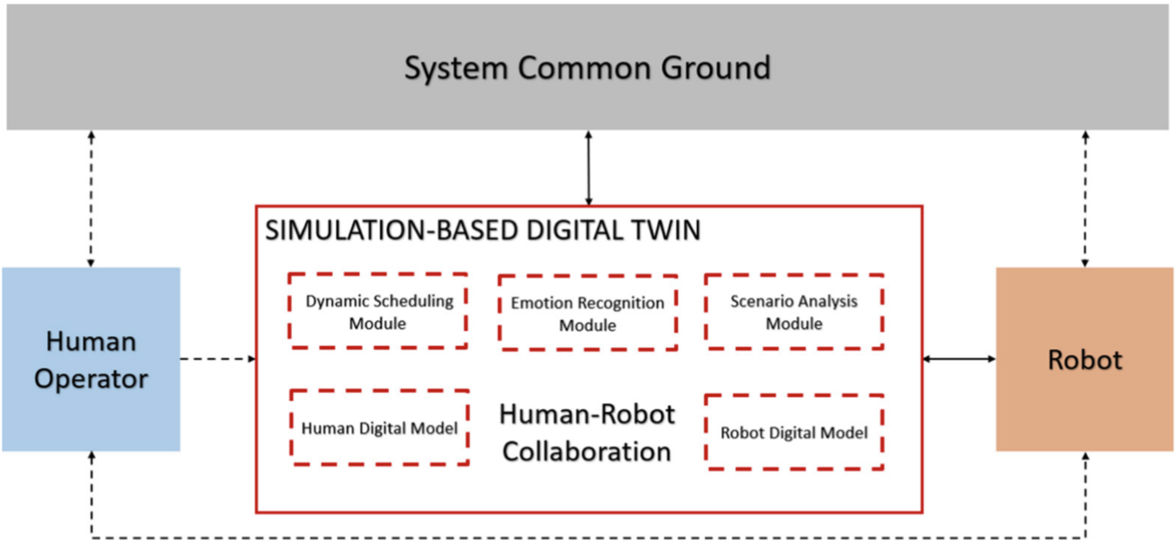


Figure 17 (Baratta et al., 2023) proposal for emotion recognition.

3.3.2 Human Digital Twins for a Human-centric Workforce Dynamic Scheduling

In (Maruyama et al., 2021), they include a dynamic scheduling function in the system to prevent human operators from injuries caused by physical overload. The system estimates current working progress (calculated with motion analysis of the worker), future working progress (predicted based on the worker's time cycle), and physical strain (computed with kinematics/dynamics analysis). This function introduces this section, in which HDT uses for scheduling within a human-centric paradigm are discussed.

The work of (Berti et al., 2023) describes an HDT architecture with a different scheduling approach. Focused on avoiding hazardous situations in the workplace and comparing it to the predictive maintenance concept, they argue that modeling workers' posture and habits with a DT system can avoid jeopardy to operators' health. (Zafar et al., 2024) backs this position, arguing that HDTs in HMC can notice bad postures, decreasing the risk of operator injury. The architecture system (Berti et al., 2023) propose, evaluates fatigue and other risk states in real-time and modifies the schedule strategy accordingly.

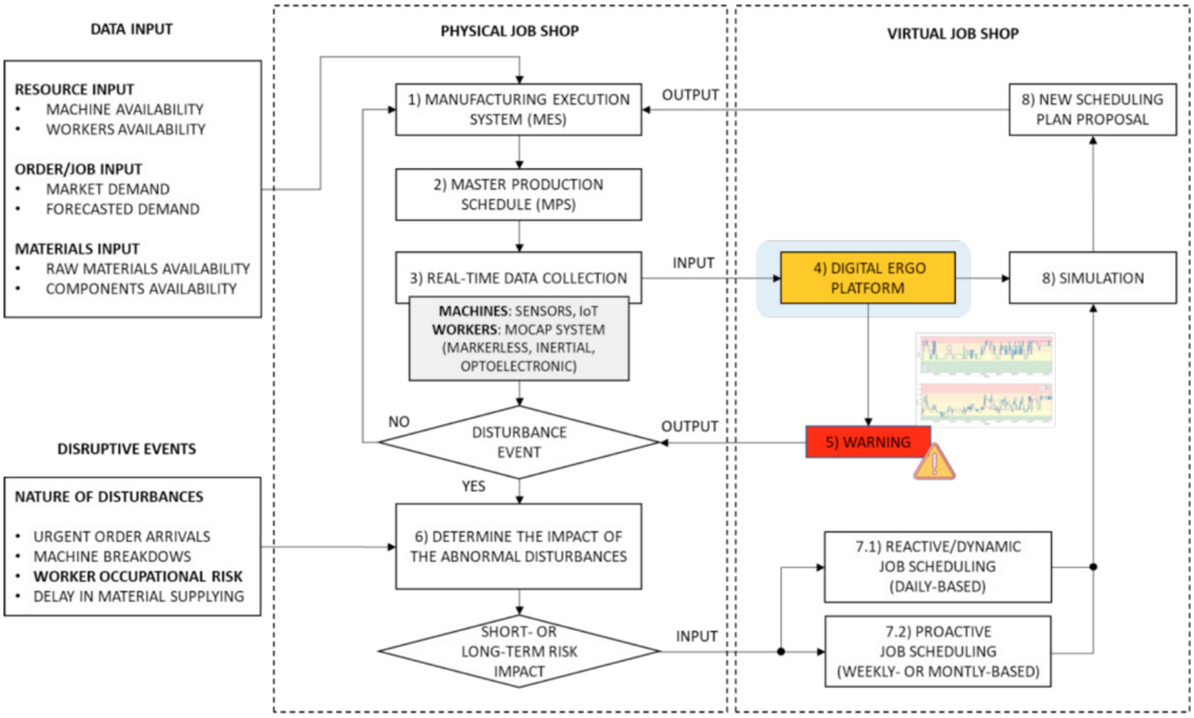


Figure 18. HDT architecture designed by (Berti et al., 2023).

In their architecture, (Berti et al., 2023) describe two modes for responding to risk when task rescheduling:

- Reactive: The production line manager receives a warning message whenever hazardous postures and/or high levels of occupational risk are present in one or more workstations. This approach is useful for peak production periods when urgent orders do not allow a long-term rescheduling plan.
- Proactive: Adopts time-weighted occupational risk grading to monitor, simulate, and predict risk levels.

(Modoni & Sacco, 2023) adds a new dimension to the HDT concept: a Skills Virtual Model (SVM). This provides a description of the needed worker skills in order to perform certain production stages. Combined with a Digital Factory Model (DFM), it would contribute to human-centric operator scheduling.

Despite the abovementioned benefits for HMC and safety, (Berti et al., 2023) raise concerns despite the clearly visible benefits. They argue that, although employee monitoring and biomonitoring have been around for a while, they could cause polemic regarding workers' rights, privacy, and trust. Especially in fields such as data protection, with biometric data collection probably crashing head-on with data protection regulations. (B. Wang et al., 2024) mentions additional HDT challenges. The increasing complexity of algorithms can cause a decrease in decision transparency from a human-centric perspective. Furthermore, as current DT systems are not so human-centered, the switch to using HDT can be complex, involving changes from technology standardization to resource organization. (Montini et al., 2022) agree, adding that HDT must have stricter privacy measures, again, due to the storage of operator’s sensitive information.

Regarding HDT feasibility, (Picone et al., 2024) argue that HDTs can be doable computation-wise after experimenting with the ODT-IoT interaction. (Fan et al., 2023), is also positive about this application’s future, describing the results of their HMC experiments as promising. (Maruyama et al., 2021) experimenting proves that movement-wise, it is possible to model humans with sufficient accuracy to integrate human and machine effort. However, (Berti et al., 2023) and (Maruyama et al., 2021) also refer to the technology as potentially being applicable to many industries but still in the development phase. Budget and scalability reasons are mentioned.

3.4 DT-based Human-Machine Interaction Platforms

I5.0 places a big emphasis on the importance of human-machine interaction (Raffik et al., 2023). According to (C. Zhang et al., 2023), human-cyber-physical systems (HCPS) with reality are able to enhance the sensing and cognition capabilities in humans. In this mission, the duo of digital twins and extended reality plays a crucial role.

According to (Bechinie et al., 2024), developing human-centered assistance systems that are adaptable to different expertise levels and, also, able to enhance operator's capabilities (from sensorial and cognitive to physical) is crucial for optimized human-machine system performance.

3.3.1 Extended Reality and Digital Twins

According to (C. Zhang et al., 2023), DT and extended reality (XR) can help in driving the human-cyber-physical fusion. By integrating the physical environment with the physical one, this duplet elevates real-world entities with computer-generated information that contributes to multi-functional flexible assembly technology (Mincă et al., 2022). (Mourtzis et al., 2022b) describe and divide extended reality into the following categories:

- Augmented Reality (AR): Combines physical and virtual, interactive in real-time, and registered in 3D.
- Mixed Reality (MR): Physical and virtual worlds are displayed within the same display. Virtual and real objects can be interacted with at the same level, making MR a step further than AR. Headsets with an integrated computer, translucent glass, and sensors are required in these applications. Microsoft's HoloLens is an example of these headsets.
- Virtual Reality (VR): The use of real-time computers to generate a simulation of an alternate world or environment. This is the DT world.

According to (S. Li et al., 2024), manufacturing MR integrates DT models with an AR environment. While AR primarily focuses on visually merging objects with the physical world, MR goes further by analyzing the physical state of systems, simulating future conditions using DT models, and then presenting this simulation information through AR.

Proposed Architectures and Uses

Multiple publications propose use cases and frameworks for a synergic combination of DTs with XR. The literature resulting from the search will be studied below.

(C. Li et al., 2023) worked on a DT-XR interactive system contributing to HMC. They state that, by wearing AR devices, operators can both monitor the status of the physical robot and the robot's DT, which would provide a control/planning interface, within their field of view. The DT's display would allow the operator to preview the robot's motion, lowering the chances of collisions and enhancing cognition in safety and control. Moreover, adding safety zone indications to the operator's field of vision could also help the operator to be aware of the robot's operating range and speed, also improving safety.

Besides safety, (C. Li et al., 2023) include another use of AR-DT systems: Visual work instruction software. This allows workers to receive and analyze stream manufacturing information and provides them with suggestions for the optimization of their tasks in terms of productivity and quality through MR glasses.

(Liao & Cai, 2024) design and propose a system for improved human-machine interaction in HMC. The proposed system has three layers.

- The robot's DT: real joint states, trajectories, collisions, sensor data, and other physical messages are transmitted to the virtual counterpart, allowing for real-time monitoring, visualization, and diagnosis.
- Two-way communication channels between the physical and virtual robots. Goal positions, limitations, desired joint angles, and some system commands can be sent to the physical counterpart.
- Human involvement is introduced, and human intelligence is utilized to control and optimize the robot's operation, such as collision avoidance and trajectory optimization through the AR interface.

The framework is composed of three primary components: robot-AR headset communication, intuitive interface design, and implemented algorithms (spatial anchor, object recognition and tracking, and robot kinematic model).

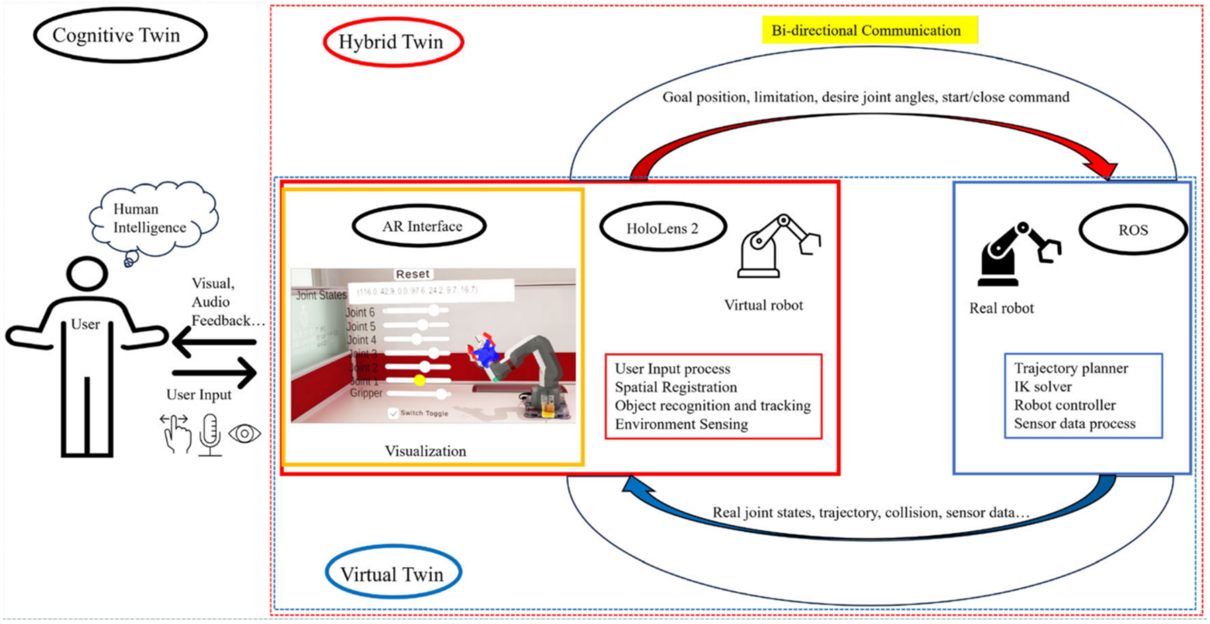
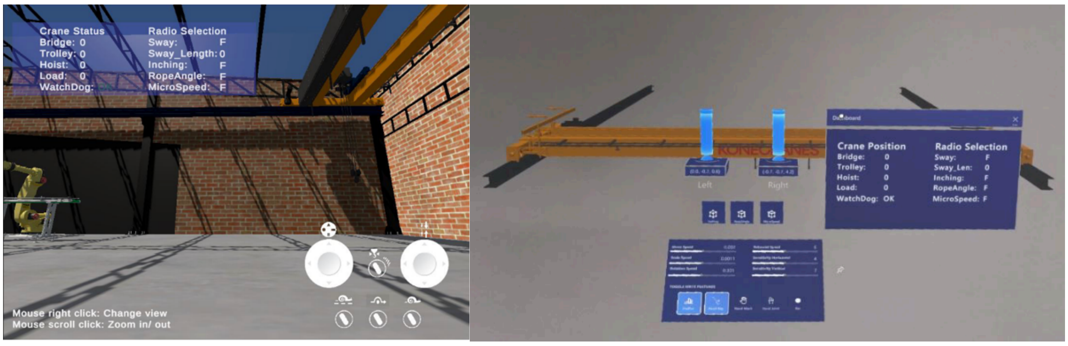


Figure 19. AR-DT integration for enhanced HMC (Liao & Cai, 2024)

Additionally, (Yang et al., 2022) propose a framework for digital twin-based smart industrial facilities, exemplified with a crane. The DT-based framework combines AR with Microsoft HoloLens with a dynamic data-driven DT to intermediate and exchange data between the physical model and the simulation model. (Kuts et al., 2022) also work on augmenting the usual operator-machine interaction by combining DT and virtual reality (VR) technologies instead of the usual human-machine interaction with a keyboard and mouse.



Crane Status
Bridge: 0
Trolley: 0
Hoist: 0
Load: 0
WatchDog: OK

Radio Selection
Sway: F
Sway_Length: 0
Inching: F
RopeAngle: F
MicroSpeed: F

Mouse right click: Change view
Mouse scroll click: Zoom in/ out

Dashboard

Crane Position
Bridge: 0
Trolley: 0
Hoist: 0
Load: 0
WatchDog: OK

Radio Selection
Sway: F
Sway_Len: 0
Inching: F
RopeAngle: F
MicroSpeed: F

Figure 20. Virtual model of the control model prototyping and of the MR actual application with HoloLens proposed by (Yang et al., 2022)

(C. Li et al., 2023) state that robots can use AR devices to better perceive worker information and relevant environmental information. This is, using AR headsets as motion/positioning sensors for distance-speed control, obstacle avoidance motion planning, protective stops, etc.

(Papacharalampopoulos et al., 2023) adds that the tracking capabilities of AR glasses can prevent dangerous behaviors, support workers in making better decisions that require more experience and prevent important errors. Moreover, since a digital twin will be responsible for monitoring, storing, and analyzing the aforementioned data, it could be much easier to not overlook an error that caused an accident and to successfully detect the cause of a problem. Without the use of wearables, manual data input and inquiry are required, whereas the use of wearables enables automated learning and prediction.

Re(Tu et al., 2023) presented TwinXR, which is a platform that serves as the foundation for DT-XR systems. It is designed to work across various applications (e.g., robotic arms, cranes, etc.). As it is applicable to many situations, it improves interoperability across industrial machines, DTs, and XR platforms.

(S. Li et al., 2024) presented an MR-enabled mutual-cognitive HRC architecture consisting of ergonomic collaboration in physical spaces, virtual reasoning modules and DTs, and cognitive services.

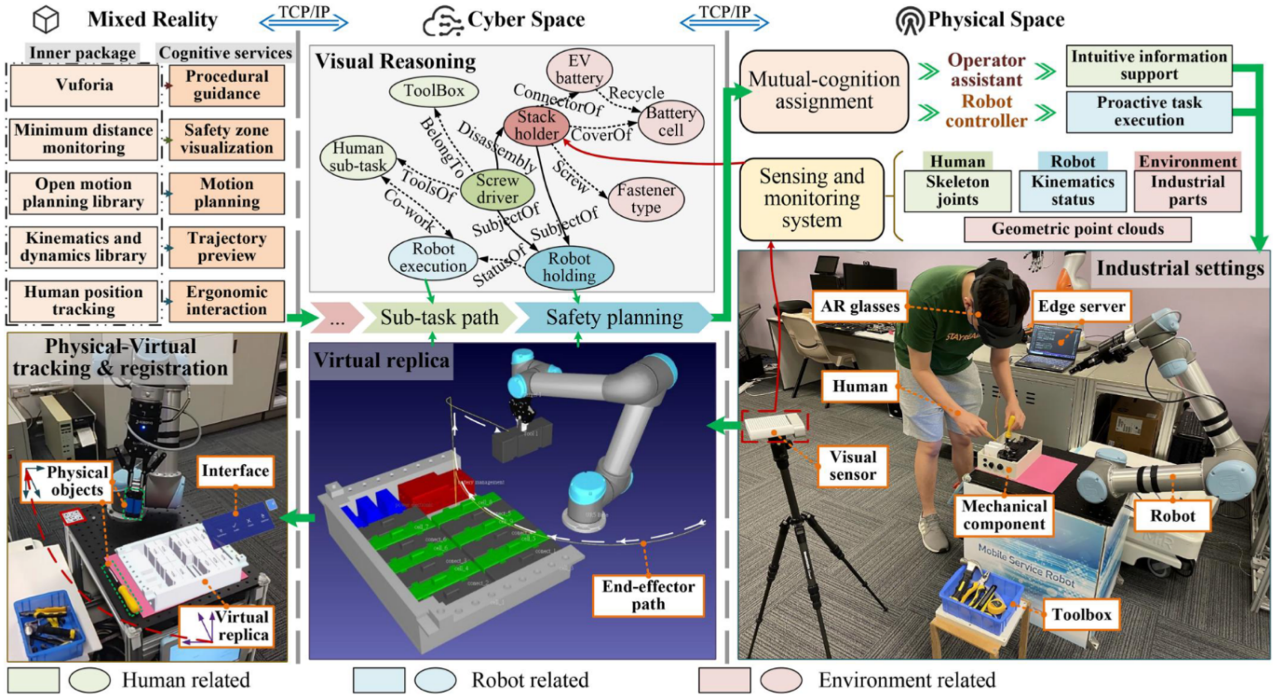


Figure 21. HRC architecture based on MR and DT technologies (S. Li et al., 2024).

The mutual-cognitive intelligence in Proactive HRC systems stands for empathic understanding between human-robot teams. They divide their system in two attending to the necessary bi-directional information flow for task cognition:

- For improved human cognition the proposed MR loop enables active communication within the HRC system. The MR system provides the human operation with insights and suggestions to enhance their performance.
- Regarding robot cognition, it interacts with humans in accordance with ergonomic rules such as handover position and orientation, improving the overall human wellbeing.

The MR-enabled visual reasoning-based method advances mutual-cognitive HRC systems, leading to human-centric smart manufacturing. Apart from the above advantages, precision of coworking strategy generation can be improved with further experimental tests, for example, such as addressing the sample imbalance via data-augmented techniques. In ergonomic tests, there are two reasons why a few human skeleton models fail to meet requirements. One part is visual estimation errors of human skeleton points in models such as the one proposed by (T. Liu et al., 2023), whereas the other one is human movement uncertainty when moving towards a position. It is in this second part where works in the HDT section could play a crucial role.

Application Results

(Kuts et al., 2022) experimentally compared the DT interfaces to the physical ones. Regarding execution time, it decreased significantly with the newer. However, in terms of the subjective survey they performed, the DT solution created more anxiety for operators and was more demanding than the real robot cell. Nevertheless, the DT solution did not generate more physiological stress than the traditional solution. Additionally, eye-tracking data revealed that concentration levels were higher in the newer approach, mainly linked to an increase in safety perception.

Regarding AR results, (Liao & Cai, 2024) tested the effectiveness of their AR-DT system for their robotic arm. The outcomes also demonstrated an improvement in the operation times and quality compared to the traditional one. Moreover, user satisfaction and perceived ease of use were higher. The following figure compares their AR system's quantitative results against normal 2D interfaces.

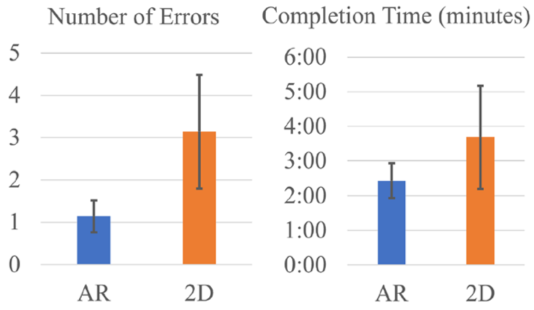


Figure 22. results on DT-AR systems HMC (Liao & Cai, 2024)

Regarding (Liao & Cai, 2024) qualitative results, they reveal that there is no significant difference between the levels of physical demand in traditional systems and their proposed one. However, AR outperforms in all the interactional aspects, especially regarding efficiency and willingness to use this system.

(Modoni & Sacco, 2023) performed an experiment more focused on assembly instruction software with similarly positive results. They demonstrated that all workers, independently from their experience, could perform tasks faster with fewer mistakes with the DT and AR-based instructions during their assembly activities. Furthermore, operators' qualitative results were also positive: 71% felt more confident with the new assistance, 80% believed the solution offered clear support along the assembly steps, and 90% argued that the solution provided better guidance than previous systems.

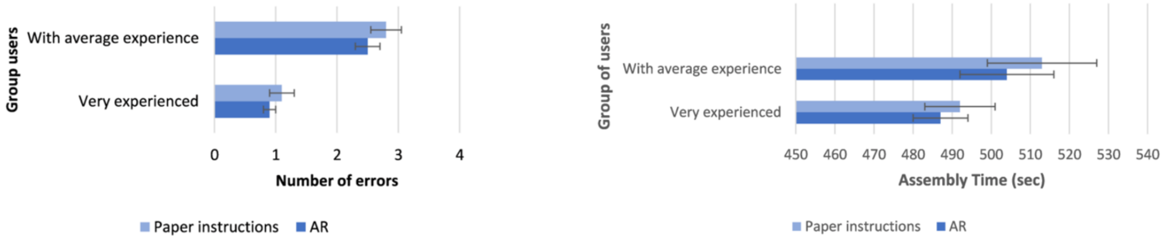


Figure 23. (Modoni & Sacco, 2023) experiment results on AR for assembly instruction software

4. Discussion

This literature review has exposed the main applications of DT technology for human-centric manufacturing. As previously mentioned, a structured outline of this field is lacking in the available literature. The following is an overview of the state of DT and its role in manufacturing.

4.1 Summary of Key Findings

As shown, the results were divided into three interrelated applications, which englobed different DT fields. All of the three mentioned fields had the objective of improving Human-Machine Collaboration or Human-Robot collaboration and, consequently, enhancing workers' well-being, security, production quality, and efficiency.

Overall, DT acts as an information exchange, analysis, prediction, and optimization platform in a manufacturing context. From the literature review, it can be extracted that DT's major contributions to Human-centric Manufacturing can be canalized through HMC, as DT improves it. The following insights extracted from the literature prove so:

- DTs improve robot control, which is strictly necessary for HMC.
    - Facilitates humanization (Montini et al., 2023) thanks to HDTs, body recognition (T. Liu et al., 2023), wearables (C. Li et al., 2023), etc.
    - Manufacturing space DT aids in avoiding collisions (Papacharalampopoulos et al., 2023).
    - Continuous robot control improvement thanks to the proposed AI-enabled cognitive systems by authors such as (Das et al., 2023) and (S. Wang et al., 2024).
- DTs enable easier Human-Robot-System communication, which is also critical for HMC.

The subsequent HMC benefits justify DT's potential for Human-centric manufacturing:

- Lower physical and mental strain (Krupas et al., 2024). Enhanced worker well-being.
- Increased manufacturing flexibility (Montini et al., 2023), (Jeong et al., 2023) while maintaining quality and efficiency.
- Inclusion of human will and creativity (Lv, 2023).

Moreover, DT, especially HDT, eases in-depth analysis of unprecedentedly measured human metrics such as stress, emotional state (Baratta et al., 2023), or fatigue (Berti et al., 2023). As a result, groundbreaking measures can be taken to lead to human-centric scheduling or health hazard avoidance (Zafar et al., 2024).

The following is a holistic schematic view of the integration of the different DT modules proposed in the available literature:

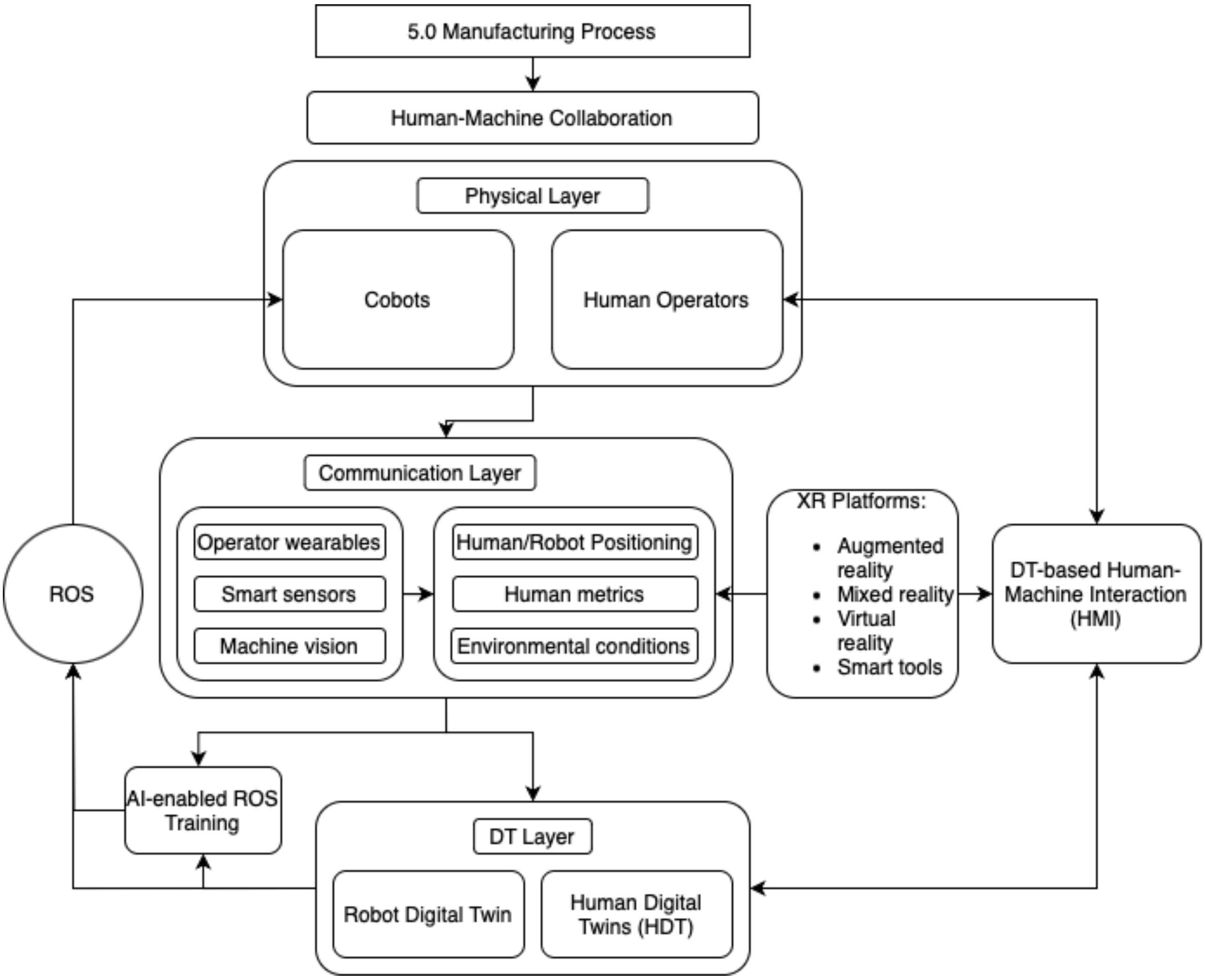


Figure 24. Possible architecture integrating discussed DT-based technologies. Arrows represent information flow.

4.2 Control and Collaboration

Robot control is a critical factor in HMC. Thus, its evolution is crucial for HMC's evolution. Aside from pure control, this category includes human-awareness modules, robotic action fit within the production chain, robot operating system (ROS) training, machine vision and sensors, and quality assurance. All these DT-improvable applications could enhance manufacturing results in terms of safety, human well-being, quality, and efficiency.

Both (Montini et al., 2023) and (Montini et al., 2023) propose general DT-based HRC frameworks that could allow for reaching I5.0 goals on human-centricity. Although they cover the micro and the macro scale of HRC, (Montini et al., 2023) support the necessity of HDT for truly effective human-robot coworking.

The HDT description (Picone et al., 2024) clearly defines how HDT could contribute to HRC. The three minimum HDT capabilities of representativeness and contextualization, shadowing, and augmentation are necessary for the ROS to understand and determine with which movements to proceed. To accurately portray the human body, (T. Liu et al., 2023) defined a framework for creating those models. (Maruyama et al., 2021) add an emotion-recognizing DT based on machine vision, biometric data, sensors, etc. Regarding the HDT integration within the HRC system, it is covered by (Fan et al., 2023) control loop/strategy. This would interact with an HDT combining the concepts of (T. Liu et al., 2023), (Maruyama et al., 2021), and (Baratta et al., 2023) and, attending to postures and ergonomic states, the ROS would receive predictions on human intention and act accordingly.

An advantage of having 3D body models and other human information about the workers in the HDT is that it is possible to schedule according to these. (Berti et al., 2023) describe an HDT-based architecture that does so. Attending to sustained postures, fatigue patterns, and sensor information, the system would organize the operator’s timetable. As a result, unnecessary strain, injuries, and hazards could be avoided, increasing human well-being and safety. This approach matches with (Papacharalampopoulos et al., 2023) and (T. Liu et al., 2023). This model could include the emotion recognition system proposed by (Baratta et al., 2023) in order to better notice stress or other impactful emotional states.

However, (Montini et al., 2023) argue that the variability and inconsistency of human behavior make digitally twinning a human challenging. This is where the augmentation is needed. (Das et al., 2023) and (S. Wang et al., 2024) propose cognitive DT with continuous improvement capability. This is a DT capable of generating synthetic data, combining it with real data, and, through deep learning techniques, improving the ROS to enhance the robot’s motion, ergonomic adjustment, and overall interaction with humans.

Regarding HDT feasibility aspects, experiments by (Picone et al., 2024) and (Fan et al., 2023) suggest it is promising and computationally doable. (Maruyama et al., 2021) experimenting proves that movement-wise, it is possible to model humans with sufficient accuracy to integrate human and machine effort. However, (Berti et al., 2023) and (Maruyama et al., 2021) also refer to the technology as potentially being applicable to many industries but still in the development phase. Budget and scalability reasons are mentioned. Nonetheless, no scaled manufacturing uses were described, revealing potential gaps in the field.

Although technical feasibility aspects are crucial for the development of HDTs, privacy, and moral concerns also arise. Due to the storage of sensitive information, (Berti et al., 2023) raised preoccupation on rights, privacy, trust, and regulation compliance. (B. Wang et al., 2024) add to the trust argument, suggesting that HDT usage could lead to a lack of transparency, and (Montini et al., 2022) assert that it would be necessary to impose stricter privacy measures.

4.3 Human-Robot-System Communication

The main DT-based Human-Robot-System Communication tool is XR. (C. Zhang et al., 2023) mention that XR implementation could drive the human-cyber-physical fusion sought in the I5.0 paradigm. Through these tools, operators can visualize real objects while keeping up with simulations and being cautious of their surroundings. Overall, these technologies can potentially elevate or augment human worker's perceptions. Therefore, both safety and performance can be notably enhanced.

(C. Li et al., 2023) proposed a system that enhanced, as mentioned, the operator's view by previewing the robot's motion, among other visualizations. XR systems can also help in providing assembly or operations instruction and suggestions.

XR devices can also serve as a base for whole HRC systems. (Liao & Cai, 2024) proposed a system in which the HRC cornerstone was the XR, in this case, AR, a device worn by the operator. (Yang et al., 2022) did the same with a crane instead of the robotic arm used in the previous work. Proving that this approach is usable in multiple situations. Moreover, XR devices have been primarily theoretically introduced as a substitute for keyboard-mouse setups (Kuts et al., 2022).

XR devices for locating human operators in the workplace, thanks to sensors and other technologies, create synergies leading to better HMC. These synergies are represented in the HRC architecture presented by (S. Li et al., 2024), which complements the abovementioned. In the system, the author's focus is on mutual cognitive intelligence, standing for empathic understanding between human-robot teams, and establishing bi-directional communication through MR.

Experimental results are promising, with lower execution times and the number of errors in the XR-assisted systems. These results were present in studies both in HRC with robotic arms (Liao & Cai, 2024) and in advanced assembly instruction (Modoni & Sacco, 2023). Nevertheless, in (Kuts et al., 2022), the subjective perception of the surveyed was that these systems increased their anxiety. However, when using quantitative measuring methods, this was not the case, proving that it may have been a result of the lack of habit.

Finally, (Papacharalampopoulos et al., 2023) contribute by adding that XR wearables' tracking capabilities could help avoid hazardous actions. This links well with (T. Liu et al., 2023) human detection system, which tracks operators' movements in order to grant safety in potentially disastrous manufacturing situations. The work (Papacharalampopoulos et al., 2023) can also relate to posture or habit prevention through HDT, which has been discussed earlier.

Other interaction platforms, such as smart tools, have been discussed (Jeong et al., 2023). Still, the main focus within the available literature is XR applications. Due to the potential synergies between XR applications, smart tools, and DTs, a promising gap in this regard appears. Furthermore, despite already having efficient XR devices, such as the aforementioned Microsoft HoloLens, and also having the technology to develop precise DTs, such as edge computing and AI, a real-world scalable holistic HMC DT is still non-existent. The next step would be to physically integrate the available technology and know-how for comprehensive DT systems that make the most out of the likely synergies between the approaches described in this paper.

5. Conclusion

This paper has introduced, reviewed, and discussed Digital Twin's prospective role in Human-centric manufacturing. Based on a PRISMA methodology for literature reviews, a conscious and systematic approach was done. Thus, existing literature could be consistently examined, ensuring an accurate perspective of the knowledge in the field. All of this with a focus on human-centricity and manufacturing.

One of the primary manufacturing areas in which DT technology can be applied is human-machine collaboration. This technology's data exchange and augmentation capabilities suggest that it will be a key enabler of HMC. Regarding the data augmentation capacity, through AI techniques, DTs can improve data quality by combining it with other records and by creating synthetic data capable of training the system. Data-exchange-wise, DTs improve the information flow, providing insights to human operators and enhancing their vision, and also acting as a central station connecting all the modules in the different HMC architectures.

HDTs could play a vital role in coordinating robot's and human's actions. They could enable human intention based on patterns, emotional states, etc. By doing so, ROS could better understand human coworkers and act accordingly, avoiding collisions, enhancing ergonomics for humans, and improving overall efficiency. Additionally, authors describe another use for HDTs. As HDTs allow for better recognition of the physical and psychological state of operators, they can enable systems for human-centric scheduling. This is scheduling workers strongly focused on their well-being. Nevertheless, privacy, trust, and law compliance issues could arise with HDTs, creating another research gap in the field.

The last main DT usage exposed in the scoping is their application to XR and other interactive platforms. As described, I5.0 focuses on human involvement in industrial activity. To enable this within such advanced and automated processes, it is necessary to have advanced interaction systems augmenting human cognition. This is what XR does by including crucial insight into the operator's field of vision or through similar means. Early-stage tests suggest significant productivity and operator cognition enhancements. The role of DTs here would be to bi-directionally share information with the XR system. As a result, the whole HMC, or even the whole manufacturing site, could make use of the wearables' information to enhance safety, efficiency, human well-being, and quality in the production process.

However, collaborative robotics and HMC have not been fully applied as described above. The most used sort of DT currently are DTs representing systems or material entities, which are easier to model and help with multiple tasks such as predictive maintenance and resource assignment. Due to the complexity inherent to their physical counterparts and the computational limitations, HDT is still a premature technology. However, the potential advantages they could create make HDT worth the watch. This fact induces the necessity of further investigation on the topic, aiding to develop more insight into this promising technology.

Finally, an architecture that combines the three main areas studied by the authors was proposed in this work. In this architecture, HMC, HDT, and XR could synergically be used within the same system, united by different DTs, improving data exchange, quality, and utility. Nevertheless, this is a theoretical approach. As most of the literature studied was based on theory and only experimental systems have been tested for such holistic systems, a future research direction is to seek the integration of these systems into the real world in a useful and scalable way.

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