REVIEW ON DIGITAL TWIN MODELLING APPLICATIONS TO SUPPORT HUMAN-CENTRICITY IN MANUFACTURING

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ABSTRACT

In today's manufacturing environment the Industry 5.0 (I5.0) paradigm has emerged and the concept of human-centricity started to be integrated enhancing workers roles, prioritizing their physical health, mental health and well-being. In particular, to support humans in their workplace, the Digital Twin (DT) paradigm can serve for designing and/or analyzing manufacturing environments that improve workers' well-being. Recently, this approach has evolved into the concept of Human Digital Twin (HDT) which aims at presenting a comprehensive representation of the human entity analyzing their behavior and understanding possible improvement approaches for workers status. The aim of this paper is to analyze, through a systematic literature review, DT solutions that support human-centric manufacturing systems, focusing also on the roles played by technological tools in assisting operators in their work environment. In this sense, attention will be devoted to improving human factors through modelling approaches and technological tools.

Keywords: manufacturing, human-centricity, digital twin, human digital twin, modeling.

1 INTRODUCTION AND OBJECTIVE

Manufacturing is continuously evolving from concept development to methods and tools available to produce goods for use or sale [1]. This evolution has led to high levels of production performance to satisfy increasingly demanding customers. Within this continuous evolution, which is also reflected in the technological advancement, the role of humans in production systems has been reconsidered. In the Industry 4.0 (I4.0) era, a new concept of manufacturing emerged, associated with the industrial automation and the integration of new production technologies to allow the improvement of work conditions, as well as increase productivity and quality [2]. The digitalization has supported the design of manufacturing systems in order to enhance workers' contribution. This can be noticed in the introduction of: *i)* robots to assist production [3] – which contribute to less physical effort for workers in performing their tasks as the routine jobs are assigned to machines, while what is left to the human are the cognitive decisions (e.g., planning and monitoring); indeed, new manufacturing environments where operators and robots collaborate are increasing and the humans and their relationship with collaborative robots in a factory is gaining much more relevance [4][5], – and *ii)* in the usage of technological tools – such as Augmented Reality (AR), Virtual Reality (VR), Artificial Intelligence (AI) - to allow an "augmented" human capability, in terms of decision making or training as examples, by having more timely and accurate information through the use of digital tools [6]. However, despite efforts in refining work environments, in I4.0 the primary focus remains on the improvement of productivity, while to workers' conditions is left a secondary importance. Nevertheless, the concept of I4.0, in recent years, has further evolved into the new Industry 5.0 (I5.0) paradigm which has recently emerged, especially since the European Commission announced its Policy Brief on Industry 5.0 in January 2021 [7], which increased the discussion on this topic in the research community [8]. It is expected that the concept of I5.0 will significantly increase manufacturing efficiency and create versatility between humans and machines, enabling responsibility for interaction and constant

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monitoring activities [9]. Indeed, at the core of I5.0 lies the concept of human-centricity, where the objective becomes creating a safe and inclusive environment to prioritize workers' physical health, mental health and well-being [10]. The digitalization and the technological tools introduced in the I4.0 become also relevant for supporting the human-centricity concept. In fact, I5.0 links to the I4.0 applications and focuses on the relationship between humans and the technological tools [9] and with other digital technologies such as digital twins and artificial intelligence. The human aspect becomes an essential dimension during design, deployment and operation of manufacturing systems [11]. Indeed, human help is fundamental not only to collect data and to turn them into added-value information, but also from a cognitive point of view, where machines in this sense cannot intervene as their role could just be a support to the decision-making.

I4.0 allowed the introduction of the Cyber-Physical System (CPS) concept [12] which supported the integration of physical systems with their digital reflection. A tool that is strictly linked to the CPS is the Digital Twin (DT), hosted in the digital counterpart of the CPS. DT, thanks to its ability of creating multidisciplinary models synchronized with their physical counterpart [13], played and continues to play a critical role in manufacturing; its application allowed the optimization of manufacturing environments through the support of various activities such as monitoring, maintenance and management. Traditionally, in the I4.0 era, the objective of implementation of DTs lied in the optimization of the production systems performances by modelling them and studying them in the virtual environment, while the human aspect was not considered as an integral part of the system to be optimized. Recently, consistently with the emphasis that the I5.0 brought on the human, technological tools are starting to be used to assess workers' status while performing work tasks and additionally it started to be agreed that in order to take the digital representation of the production system a step further, humans have to be included [11]. This expands the boundaries of production systems and besides the traditional CPS also the new concept of Human-Cyber-Physical System (HCPS) is starting to emerge and with it the concept of Human Digital Twin (HDT), which enables modelling approaches fed by dynamic and real-time data that allow a comprehensive representation of the human entity. The HDT places the human at the center of the manufacturing system and allows to predict worker's behavior through the analysis of historical data and psychophysiological status, with the aim of optimizing the processes and make better decisions based on workers' aspects [14]. This modelling approach can allow progresses of humans' wellbeing, but also optimized production systems, being the workers a fundamental part of it. In the I5.0 era the usage of the DT needs to be explored to assess how manufacturing systems can be adapted according to workers' conditions.

In literature different studies are devoted to human centric-manufacturing systems and to HDT, such as in [8] where is provided a systematic literature review on human-centric smart manufacturing identifying the key I4.0 technologies that can enable the creation of such systems, in [15] where the concepts and ideologies of I5.0 and its respective technologies and the strategies of human centricity with the aim of achieving sustainable and resilient systems are proposed, in [16] which presents a comprehensive survey on HDT in the context of I5.0, summarizing the ongoing evolution, and proposing a proper connotation of HDT, and analyzing enabling technologies and industrial applications. Nevertheless, a consistent analysis on how DT and its extension in the HDT can be used to model and support studies on operators in their work environment is still lacking. To the best of the authors knowledge, studies on modelling approaches that can enhance workers' roles in manufacturing through DT usage are still limited. This paper wants to fill this gap by providing a systematic literature review that considers the human and the different modelling approaches at the center of the analysis. To this aim, after presenting a brief introduction on the roles of humans in manufacturing and the technological tools that can enhance their roles, Section 2 presents the systematic literature review analyzing the possible DT modelling approaches to support human centricity, while Section 3 provides the relevant results of the analysis. Finally, Section 4 proposes a brief conclusion together with the limitations and an outlook on future works of investigation.

2 SYSTEMATIC LITERATURE REVIEW

2.1 Methodology

In this section the objective is to provide an analysis of research that uses DTs to prioritize human-centered approaches in manufacturing by considering the relevant aspects for modelling. The systematic literature review has been guided by a research question (RQ) formulated as follows: *"What is the state-of-the-art of modelling approaches that enhance human-centric manufacturing systems?"*.

Considering that the HDT in manufacturing is a relatively new concept, it has been decided to not limit the number of research papers considering HDT as keyword. Indeed, by using both "human digital twin" and "manufacturing" as keywords in Scopus, it results that the first work mentioning HDT in manufacturing context dates back to 2019 in [17], and great part of publications started from 2021. Hence, to respond the RQ, both Scopus and Web of Science have been used as research literature databases considering papers published from 2021 to March 2024. This time span was selected to also explore the impact that the "Industry 5.0" concept had on research. Indeed, as reported in Section 1, the announcement of the Policy Brief on Industry 5.0 by the European Commission in 2021 has increased the discussion on I5.0 [8], therefore the authors agreed on the impact that such Policy had on research and aimed at exploring how the human aspect has been affected. In particular, the following keywords and logical connectors have been used:

("human" OR "industry 5.0") AND "digital twin" AND ("manufacturing" OR "production")

The first section of the search string aimed to include papers discussing the human aspect. Literature in the "industry 5.0" area is still not extensive, therefore also "human" has been included as keyword. Given that the focus of this paper is on digital twins in manufacturing, these concepts have been included as keywords respectively in the second and third sections of the search string.

The research resulted in a total of 307 papers from Scopus and 177 papers from Web of Science. After merging the results from both sources and after removing duplicates, a total of 371 papers have been considered. However, several papers needed to be excluded being not relevant for the purpose of the analysis. In particular, only papers considering DT solutions applied in work activities involving humans have been included in the analysis, while the exclusion reasons can be summarized as follows:

- 20 papers were not available in English, while 18 were not accessible.
- 142 articles did not consider the human centricity. The human aspect was rather included as an example, but the focus of the proposed research was not on this topic.
- 45 papers proposed solutions including the human aspect without referencing it to a manufacturing work environment.
- 119 papers were more theoretical, presenting overviews or reviews on the topic, without analyzing any specific solution.

As result, a total of 27 papers have been included in the analysis. Table 1 reports the analyzed papers with a short description under *Application purpose* and a brief presentation of the application benefits for both the human and the production system, when provided, under *Application benefits*, while the rest of the columns will be further analyzed in the next sections.

2.2 Modelling approach

The *Modelling approach* covers two different aspects: the *Modelling scope*, which describes the object that the DT aims to represent in the virtual world, and the *Type of model*, that describes the modelling methods and tools used to create the DT. Given the objective of analysis of the present paper, the modelling approaches considered have the aim of exploring human-centricity, therefore besides HDT solutions,

Table 1: Literature review – Papers' analysis.

Reference	Application purpose	Modelling approach						Data acquisition		Technological tools		Human factors			Application benefits	
		Modelling scope	Type of model	Simulation	Data-driven	CAD	Other	Data type	Data processing	Type of tool	Interactive? [yes or no]	Ergonomic	Performance	Action recognition/ prediction	Benefits for the human	Benefits for the production system
[18]	HDT to evaluate human actions in human-robot collaboration disassembly scenario	HDT	Data-driven model	Motion	✓			Vision based data – Azure Kinetic RGB-D cameras	GPU server	Wearable devices	No	✓		✓	Safety (HRC), guarantee workers' correct posture	Optimized HRC
[19]	DT of a human-robot collaboration disassembly environment for EoL LIBs	DTwH	Dynamic model	Motion	✓		Dynamic	Vision based data – Intel RealSense depth camera	XML files to store the disassembly data	/	/	✓	✓		Safety (HRC)	Enhanced flexibility of disassembly operations
[20]	Assembly tasks – human-robot collaboration	DTfH	3D model		✓			Vision based data – Sensors to collect RGB and Skeleton data	/	VR headset	Yes			✓	Safety (HRC), training	Optimized HRC system
[21]	Assembly tasks – human-robot collaboration	HDT	Kinematic model	Motion				Vision-based data of human operator's tasks – RGB-D cameras	ResNet-50 backbone to extract the geometric features	/	/	✓		✓	Safety (HRC), training	Improved production rate, improved HRC
[22]	Analysis of human capabilities in human-robot collaboration	HDT	Kinematic model	Motion				Vision-based data, IMU – based motion capture.		/	/	✓			Physical load reduction, work balance (HRC)	Enhanced flexibility of assembly operations
[23]	Manual assembly job – Work fatigue estimation	DTwH	Data-driven model		✓			H-AAS data, Wearables to collect physiological data.	Physiological data recorded into the DT and queried by an AI model	Wearable devices – Detect physiological data	No	✓			Workers fatigue reduction	/
[24]	Assembly design for additive manufacturing	DTfH	3D model		✓			Data on assembly design acquired from digital prototypes VR to capture human assembly data	Python script	VR headset	Yes		✓		Training	Optimized assembly design
[25]	Assembly of a passenger vehicle through human-robot collaboration	DTfH	3D model		✓	✓		Sensors to get data on the workspace. CAD data – manufacturing system	/	AR wearable	Yes		✓		Safety, improved tasks performance (errors reduction)	Improved production rate
[26]	Human-robot collaboration assembly – Capturing of the 3-dimensional movement of humans and robots	DTwH	Kinematic model	Motion				Sensors: Vision-based – RGB-D depth image streams.	Data noise-reduction, CNN training data	/	/	✓			Safety (HRC)	Improved HRC assembly tasks – reduction of defects
[27]	Human-robot collaboration assembly system redesign considering safety guidelines for the operators.	DTwH	3D model			✓	Mathematical model	Sensor data-system's operational performance. Qualitative data – Observed data on human behaviors.	/	/	/		✓		Safety (HRC)	Optimized HRC system
[28]	Manual assembly tasks – Production of battery packs	DTwH	3D model	Motion		✓		CAD data, sensor data to detect data on humans, robots and assembled components presence and positions.	CAD data imported in Jupiter Tessellation (JT) format	/	/	✓			Safety (HRC), physical load reduction	Optimized HRC system
[29]	Human-robot collaboration in assembly tasks – Assembly process of mouse	DTwH	3D model	Process		✓		CAD data – human skeleton. Wearables – Operators tasks	/	Wearable devices – detect operators' tasks data	No	✓			Safety (HRC), physical load reduction	Improved HRC assembly tasks – reduction of defects
[30]	Human-robot collaboration assembly tasks – Pick-and-place	DTwH	Kinematic model	Motion				Sensor's data – HRI Sensors – IMU-based motion data. AI, Machine Learning – human actions intentions prediction	/	/	/	✓		✓	Work balance (HRC)	Improved HRC assembly tasks – reduction of defects
[31]	Human-robot collaboration – Assembly tasks	DTwH	Data-driven model		✓			Sensor's data – HRI	XML files to process assembly system's data	/	/	✓			Work balance (HRC), physical load reduction, safety	Optimized HRC assembly tasks
[32]	Human-robot collaboration – Assembly tasks	DTwH	Dynamic model	Motion	✓		Dynamic	Vision based data – Smart 3D camera	Optimization algorithm	/	/		✓		Safety (HRC)	Optimized trajectory, collision reduction
[33]	HDT model framework for modeling the human body – Human-machine interaction	HDT	Data-driven model		✓			Vision-based data – RGB-D camera. Sensors – IMU-based motion data. EMG sensors – Human muscles data	/	/	/	✓			Physical loads reduction, guarantee workers' correct posture	/
[34]	Human-robot interaction – DT to monitor the status of physical robot	DTfH	Kinematic model	Motion				/	/	AR wearable – allow human interaction with the robot in the DT	Yes			✓	Safety (HRC), training	Improved efficiency in HRC environments
[35]	Improved human-machine interaction	HDT	Data-driven model		✓			Sensors	/	/	/			✓	Safety (HRC)	Optimized HRC systems
[36]	Human-machine interaction (HMI) – Humans action recognition using CNN	DTwH	Data-driven model		✓			Sensors for vision-based data – RGB-D camera to get skeletal data	3D VGG and 3D-ResNet for video data analysis	/	/	✓		✓	Safety (HMI)	/

[37]	DT in offshore oil platform context for operators' training	DTfH	Data-driven model		✓			/	/	VR headsets – training scenes	Yes		✓		Safety, training	Reduction of time and defects, optimized process
[38]	Implementation of automated process selection and scheduling	DTfH	Data-driven model		✓			IoT wearablles – data on work environment, pulse and body temperature	/	AR glasses	Yes		✓		Safety, operator effectiveness: support in tasks execution	Optimized reconfiguration of production system
[39]	Dynamic scheduling of jobs	HDT	Kinematic model	Motion	✓			Sensors – IMU-based motion data (MoCap – motion capture data)	Robot Operating System (ROS)	/	/	✓			Physical load reduction, guarantee workers' correct posture, work balance	/
[40]	Reconfiguration of production system based on workers characteristics and capabilities	DTwH	Optimization model				Mathematical model	/	/	/	/	✓			Safety (HRC), physical load reduction	Optimized reconfiguration of production system, increased productivity
[14]	Assessment of human behavior in working environment – Human-cobot	HDT	Data-driven model		✓			Qualitative data – Surveys, questionnaires (operators' information on age, sex, skills)	/	Wearable devices – detect physiological data	No	✓			Safety (HRC), Physical load reduction	/
[41]	Assembly Line Worker Assignment Balancing Problem – Assist fatigue worker job rotation/reallocation scheduling	DTwH	Data-driven model		✓			Sensor's data – workers parameters: pulse rate, tasks repetition	/	/	/	✓			Reduction of worker's fatigue rate, physical load reduction	Improved production rate, reduction of defects
[42]	DT for human-centered product development -Human interacting with a product	DTwH	3D model		✓	✓		Sensor's data – elements in the workspace	/	/	/		✓		Operator's effectiveness: improved task execution	/
[43]	Assessment of biomechanical fatigue caused by repetitive manual material handling	HDT	Kinematic model	Motion	✓			Sensors – IMU-based motion data (MoCap – motion capture data)	/	/	/	✓			Physical load reduction	/

Legend: "HDT" – digital twin of the human or human digital twin, "DTfH" – digital twin for the human, "DTwH" – digital twin with the human, "/" – information not available.

applications concerning DT of work environment connected to operators' roles are included as well in order to have an overview on all the impacted humans' aspects in the different modelling approaches.

Modelling scope

This feature relates to the boundaries of the system represented by the DT according to an increasing degree of detail and human-centricity. Three different levels are considered:

- DT *with the human:* the production system or workstation, including both automated machines, robots and workers, is modelled. In this sense, the human is modeled as part of a complex system, where he/she performs his/her production tasks, but the focus is not only on the human. In [19] is proposed the DT for Human-Robot Collaboration (HRC) disassembly and considers also the operator's tasks, in [23] is provided a DT of an assembly system which includes also humans. Here the DT serves to monitor the worker well-being and for tasks assignment between the human and the robot. In [26][28][29][30][31][32][40] DTs of workspaces including the human and robots in collaborative environments are considered. In [27][41] are presented DTs of assembly systems including the operators. In [36] is considered a DT to analyze Human-Machine Interaction (HMI) system and includes human actions and skeletal data to represent the human body. Finally, in [42] is proposed a DT that monitors product development in a human-centered production system and includes in the model also the human interaction with the product.
- DT *for the human,* consisting of the DT of a production system which allows the operator to interact with it through wearable devices and/or Virtual Reality (VR) and Augmented Reality (AR) devices. However, the human is not replicated in the DT. In [20] is provided a DT that simulates an assembly workflow of an industrial workstation, in [24] the DT models the physical assembly design system, in [25] is considered a DT of a shopfloor, in [34] is presented a DT of a production system that monitors the status of a physical robot, in [37] is proposed a DT of the workspace in offshore oil platform context, in [38] is considered a DT network of a production system, including the DT for additive manufacturing, DT for welding and the DT of human related KPIs.

- DT *of the human*, which may be strictly considered as the HDT, which models the human movements, behavior and actions in the space-time. In [18] is proposed a vision-based HDT model for highly dynamic HRC applications, in [33] is considered a framework for building a HDT model based on multimodal data to represent the human body in the human-machine collaborative environment, in [21] is proposed a vision-based fine-grained HDT modelling scheme of a human operator where human posture is reconstructed and is recognized the spatial-temporal human behavior intention recognition, in [35] is presented an approach to realize a HDT considering data of individuals and their role in production and intralogistics. In [22] is constructed a human model for an individual in the physical space, which is geometrically, kinematically and dynamically precise. In [39] the DT replicates human operators in manufacturing systems to enable dynamic scheduling of jobs by continuously monitoring workers' parameters through an ergonomic digital platform. In [14] is proposed a meta-model that supports the modular composition of tailored HDT with the aim of assessing the human's behaviors in their workplace. Finally, [43] proposes a HDT in order to assess the biomechanical fatigue of workers caused by repetitive manual material handling.

Type of model

The following types of modelling have been determined.

- Data-driven model is a type of modelling technique based on input data collected from observations and measurements – in [18] is considered a data driven model, where a deep learning-based architecture is considered to process RGB-D data and to perform various perception tasks such as human body posture and 3D mesh. In [23][30][31][41] data on the assembly tasks are gathered to create the data-driven model, in [33] is proposed a data-driven model where data are collected to create the human body, while in [14][35] are built the HDT considering a data-driven model to model operators' skills and behavior respectively in the working environment and during their interactions with machines. Finally, in [42] is considered a data-driven model to replicate the interaction between a user and a product in product development.
- Kinematic model which can describe the motions of operators, equipment and in some cases robots – In [21] this type of modelling approach is used through a deep learning model that reconstructs the fine-grained 3D mesh and skeleton points of the human body and considers the human pose and shape parameters, in [26] the 3D kinematic model represents the postures of the human operator and deep data are used to generate human operator's skeleton coordinates. In [22] DhaibaWorks software is used to represent the human 3D kinematic model. In this sense the motion of the human model is represented as the time sequence of the position and posture of the kinematic model. In [34] the kinematic model of a robot is created for motion planning and collision detection in the Human-Robot Interaction (HRI) context. In [30] is considered a 3D kinematic model to incorporate human motion capture systems that include full-body, finger and eye movements. In [43] the 3D kinematic model studies the human body movements during manual material handling tasks. It involves the analysis of joint angles, range of motion, angular velocities and acceleration to understand the biomechanical fatigue of the operator. Finally, in [39] the DT is created considering a 3D dynamic model which allows real-time monitoring of human motion and behaviors during work activities.
- Dynamic model – In [19] is proposed a 3D dynamic model that replicates dynamic production process and enhance the flexibility of a HRC disassembly operations. The virtual space combines geometry, physics, behavior and rules of disassembly and specifically, the disassembly scene is recreated through semantic relations by combining the actions of workers and robots. In [32] the DT represents the motion capabilities of the robot and the forces involved in its interaction with the environment, including the human operator.
- 3D model – In [24][27][25] are proposed 3D CAD models that represent the assembly systems, in [28] through CAD model are represented the components and workstation of the considered system and is included a digital human mannequin of the human worker to conduct ergonomic evaluations, in [29] is represented the 3D model of the assembly system including the human and the robot in HRC context,

in [20] is proposed a 3D model to replicate the assembly system and its components. Finally, in [42] a CAD model to represent the considered product geometry is considered.

- Other types of modelling approaches include mathematical models presented in [27] to evaluate safety measures and in [40] that proposes an optimization problem with the aim of assigning operation tasks between operators and robots.

2.3 Data acquisition

When creating a DT, model data flows and communication should be considered, as should the architecture and logical structure of the system and the technical requirements to implement the solution [44]. *Data acquisition* describes the types of data used by the DT - *data type* - and the approaches adopted to process them to create or feed digital models - *data processing*.

Data type

The following data types have been reviewed:

- Sensor data which allow the collection of:
  - vision sensor-based data – in [18][21][26][33][36][31] RGB-D kinetic cameras are used to capture data on human actions, skeleton dynamics and positions while performing work tasks, in [29] 3D camera is used to detect the distance between human and machines, while in [32] the 3D camera captures real-time data on the presence and movements of the human operator within the workspace. In [19] the IntelRealSense depth camera is used to collect environmental data. This depth camera has strong depth sensing capabilities and is suitable for extracting depth values as the position and attitude of the operator, in [20] motion capture sensor is used to capture skeletal data and RGB data were collected through two "Logitech C920" cameras,
  - data on elements in the workspace through sensors [22][25][42][27]. Specifically in [29] sensors are used to evaluate machines status, while in [35][41][30][31] sensors are used to obtain data on human parameters (e.g., actions, behaviors, task repetition, pulse rate), additionally, in [30][31] sensors collect data on robot actions and human-robot interactions,
  - small electrical signals by human muscles through Electromyography (EMG) sensors [33],
  - motion data by attaching Inertial Measurement Units (IMUs) devices into human body [22][30][33][39][43].
- CAD data are considered in [25] to detect the components of the manufacturing system, and in [28] to represent the components of the assembly environment.
- In [24] data on the physical assembly lines have been acquired from digital prototypes. Specifically, the assembly time and assembly displacement error were gathered from a VR simulation and support volume data from third-party software.
- Qualitative data: in [14] it is mentioned the usage of surveys and questionnaire to collect information on operators, such as their age, sex and skills, while in [27] are considered observed data on human behaviors.

Data processing

Among the analyzed papers, few of them provide details on the applied data processing methods. In [18] the gathered data are sent to a Graphic Processing Unit (GPU) server to allow updating the HDT, in [23] the physiological data are recorded into the DT and queried by an AI model that estimates the worker's fatigue level, in [24] the experimental data are processed using an in-house Python script, in [31] data on the assembly system are processed through XML files, while in [19] XML file allows the storage of disassembly information. In [32] an optimization algorithm uses the data gathered to optimize the robot trajectory. In [21] the RGB-D images of the human operator are processed by a ResNet-50 backbone network to extract all the human's geometric features, in [28] it is used Tecnomatix Process Simulate (TPS) to import CAD data in Jupiter Tessellation (JT) format, in [26] collected data are noise-reduced to prevent the interference of light and vibration to obtain more accurate skeletal data, additionally a Convolutional

Neural Network (CNN) is trained to allow locating the human subject at the middle of the image and facilitate the acquisition of the full range of human feature without missing any limb parts. In [36] data are processed through 3D VGG and 3D-ResNet which allow the analysis of the video data on human actions and positions. Finally, in [39] it is proposed the use of Robot Operating System (ROS) to allow processing and using the collected data.

2.4 Technological tools

In *Technological tools* the aim is to evaluate the roles that technological devices have in supporting modelling approaches within human-centric manufacturing systems. Specifically, technological tools such as wearable devices serve to gather data on human movements and body posture during tasks performance ([18][29][30]) and to collect physiological data ([23][14]). These data can be used to support the modelling phase.

Moreover, as highlighted in Table 1, it is relevant to explore the cases where technological tools provides an interface, enabling human interaction with the virtual system when the DT of the work environment is provided (therefore in the case of *DT for the human* modelling scope). This interaction facilitates optimization strategies for manufacturing systems based on human characteristics. Additionally, this allows assessing operators' behaviors within the system without the need to model them. In this sense, in [20] operators are equipped with VR headsets allowing them to move freely in a 3D space while interacting with the workstation. In [24] VR technology creates an immersive and realistic environment to allow the human interaction with the assembly design system. Similarly, in [37] VR headset supports the operator in a virtual reality training scene, allowing him/her to dive into a virtual reality while enhancing his/her psychological engagement. In [34], AR wearable enables human interaction with the robot within the DT environment, while in [25][38], AR wearables prevent humans from dangerous behaviors and support them in taking safer decisions within the system.

2.5 Human factors

This feature describes the main human-related aspects involved in or impacted by the DT solutions. The following human factors have been determined:

- Ergonomics, it allows studying human's efficiency in their working environment by considering their physical, physiological and behavioral aspects. – In [18] the human status is analyzed including the 3D human posture and ergonomic risk, in [19] human movements guided by robots are analyzed with the aim of assessing worker's fatigue rate during disassembly tasks execution, in [21] is analyzed the motion in HRC considering the full-body human skeleton, in [22][23] the physical load and physical capabilities of the human are considered, in [26] a precise capturing of the three-dimensional movements of humans and robots is considered and to this aim a camera-based human recognition system for accurate prediction of key points for human skeletons model is used, in [29] the human skeleton during HRC assembly tasks is analyzed, in [30] it is captured the full body of the human and the motion data for the analysis of the operator's interaction with the robot are considered, in [31] the work balance between human and robot is considered through the evaluation index on tasks properties, human capabilities and robots capabilities, in [33] are conducted experiments for human motion pattern recognition, in [36] the aim is to analyze tasks that could bring physiological issues to workers, in [40] is optimized the reconfiguration process of manufacturing system with human-robot collaboration and to this aim data on humans' physical limitations are considered, in [14] is proposed a HDT to analyze humans' ergonomics, in [41] is considered a dynamic solution for an assembly line fatigue worker job rotation with an analysis of workers' stress and fatigue during their work tasks, in [28] the digital human mannequin of a human worker is integrated to conduct ergonomic evaluations in HRC system. In [39] the DT solution enables dynamic scheduling of jobs by continuously monitoring workers' parameters through an ergonomic digital platform. Finally, in [43] the biomechanical fatigue analysis allows the assessment of ergonomic risks associated with operators' movements during their work tasks.

- Human action recognition/prediction. – In [20] labeled data are generated by the DT for human action recognition based on deep learning, in [30][35][36] predictive models for action prediction and recognition in HMI are considered, in [34] operators are provided with VR headset to allow them interact with the virtual robot assessing all the movements and actions trajectory. Finally, in [42] is investigated the concept of coupling a geometrical model of an operating table with a cognitive digital user and the interaction of the user with the physical product is analyzed.
- Performance, to assess how well the individual performs a task or responsibility. – In [24] the VR headset allows the human to familiarize with the assembly process leading to improved performance. In [25] the interaction with flexible mobile robot workers is considered. AR is integrated with the DT and allows human operators to train in order to reduce errors in performing the tasks. In [27][32] are proposed guidelines for the design of a safe human-robot collaborative assembly system to allow the operators working efficiently and safely. In [28] is explored the opportunity of using a DT to address the complexity of collaborative production system and the focus is devoted to the roles of the operators in this system, in [37] is proposed a structured on-the-job training strategy for operators' non-routine tasks. While in [38] is considered a scheduling problem integrated with users' interaction with the system and to allow the assessment of operators effectiveness in such systems.

3 RESULTS OF THE ANALYSIS

The systematic literature review enabled the assessment of DTs application in the context of human-centric manufacturing at different scope levels. A critical aspect of the modelling process involves the identification of data sources and collection methods. Additionally, the appropriate modelling approach depends on the required levels of analysis which depend on the humans' factors needed to be addressed. As analyzed, human factors include ergonomics, psychological status in terms of human actions prediction or recognition, and work performance. Specifically, the findings reveal that most research is dedicated to human's ergonomics aspects, as seventeen papers propose solutions in this area, while only eight papers focus on human performance analysis and seven address action recognition and/or prediction studies.

In particular, considering a physical system – or physical twin (PT) – different DT modelling approaches can be used, and as also presented in Figure 1, the systematic literature review revealed that:

i) *DT with the human* is a broad modelling approach that includes both the human and his/her working environment, though maintaining a system's perspective. To model such system effectively, information on both workspace and the humans - specifically, their physiological, skeletal and motion data – need to be integrated. Thirteen analyzed papers adopt this modelling scope. This approach enhances the following human factors: ergonomics, performance and action recognition/prediction. Indeed, modelling both humans and their work environment supports the analysis on humans' interactions in the workplace, allowing the simulation of different scenarios for both operators and work environment. This enhances benefits in terms of humans' postures analysis while they perform certain tasks, their fatigue rate, their effectiveness in performing the tasks (in terms of time and defects) and additionally, in the context of HRC or HMI can assess the safety of the work environment by simulating and improving respectively human-robot interactions or human-machine interactions.
ii) *DT for the human* is a modeling approach aimed at supporting human operators in their activities, strictly linked with the usage of interactive technological tools. In this case the DT models the work environment (i.e., workstation or the production system), while the human operators interact with it using technological tools such as wearables, AR or VR headsets. Six of the analyzed papers propose solutions in this area. Literature revealed that combining such tools with the DT enables studies on the human interaction with virtual objects, allowing them to be part of the simulated system and perform tasks accurately, such as monitoring, maintenance and decision-making [45], without the need to model the humans directly. This approach impacts human factors in terms of performance and action recognition/prediction. Additionally, it can improve operators' safety – through the assessment of the

rate of danger for some work tasks such as in the context of HRC – and enhance tasks execution effectiveness through the training activities that this type of modelling approach can assist.

iii) *DT of the human* (*HDT*) is a modelling approach that focuses more specifically on the human operators, enabling in-depth analysis of their status and behaviors. Modelling humans is a complex task since the human being is a multifaceted entity and can be characterized by many different dimensions, each of them requiring a dedicated model [14]. Such dimensions include operators' experience, knowledge, skills, capabilities, wellbeing, and performance indicators and all these elements could be comprised in their digital representation. In the conducted systematic literature review, eight papers consider this modelling approach. In particular, sensors support the extraction of vision-based data and motion data from humans to replicate their shapes, movements and behaviors. This approach impacts mainly the following human factors: ergonomics and human action recognition and/or prediction. Focusing on these factors, the application of HDT contributes to the following benefits for the human: safety in the context of HRC as simulating humans' actions can support robots in perceiving the human body, physical load reduction and guaranteed workers correct postures which is supported by humans' ergonomics studies.

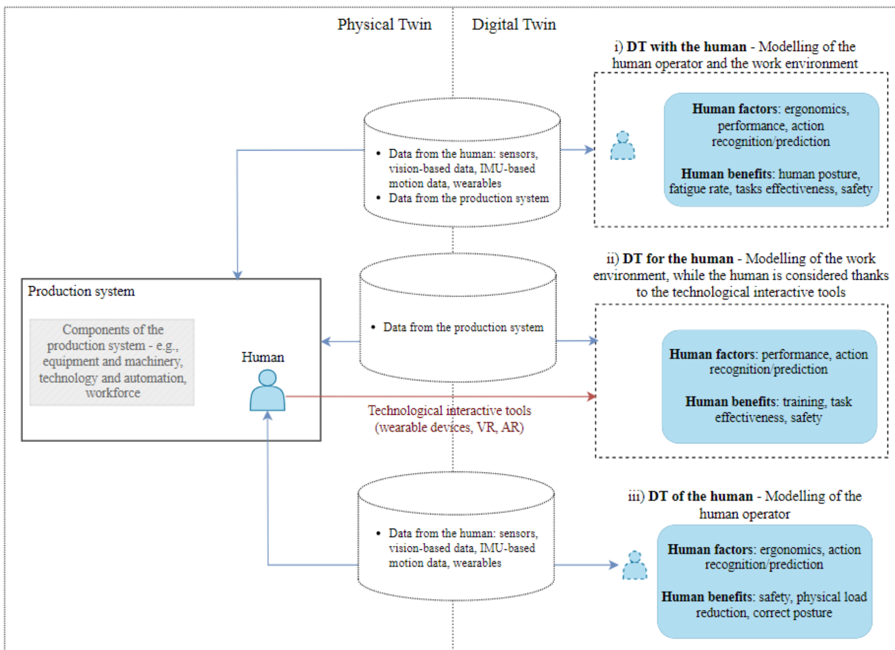

Figure 1: DT modelling approaches in human-centric manufacturing systems.

4 CONCLUSIONS

The application of DT in the I4.0 era usually had the objective of optimizing production system's performance (e.g., in terms of production rate, production times, reduction of defects), however recently the roles of the operators has been reconsidered and the concept of human-centricity has started to be valued, especially starting from the emergence of the I5.0 concept. This article focuses on the roles of humans in manufacturing by providing an overview on the importance of improving their well-being and on the roles that digital technologies have in supporting them in manufacturing environments. In particular, the paper explores the state-of-the-art of the different DT modelling approaches that support human-centricity in manufacturing. From the analysis it has been possible to assess that:

- Besides HDT, which allows to specifically model humans and analyze their behavior and psychophysiological status, modelling human's workplace is relevant as it allows building and/or improving working environments considering the roles that humans have in that system. In this sense, literature revealed the existence of the following modelling approaches which depend on different levels of analysis: DT with the human, DT for the human and DT of the human (HDT).

- To study and model a human-centric system through DT it is necessary to define the human factors that want to be studied and the related human benefits that want to be obtained. Based on this, it will be possible to assess the required level of analysis and therefore the required modelling approach and the needed data to be extracted from the real system (or physical twin).

Despite the promising results, some limitations of this work must be highlighted. The review of the literature only considers the works published in a limited time frame, which could result in excluding some works related to HDT published before the emergence of the Industry 5.0 paradigm. Furthermore, the analysis is not considering relevant issues as privacy and ethics to better focus on technological aspects of HDT.

Future works should discuss the correlation between the modelling approaches, the technologies adopted, and the benefits realized, in order to deliver more detailed recommendations to scholars and practitioners. In fact, on the relevant examples discussed in the literature this could not only allow a better understanding of the concept of HDT, but it could also support its development and application.

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