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REVIEW OF HUMAN-MACHINE INTERACTION TOWARDS INDUSTRY 5.0: HUMAN-CENTRIC SMART MANUFACTURING

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ABSTRACT

Human-centric smart manufacturing (HCSM) is one of the essential pillars in Industry 5.0. Hence, human-machine interaction (HMI), as the centre of the research agenda for the advances of smart manufacturing, has also become the focus of Industry 5.0. As Industry 5.0 proposed three core concepts of human-centric, sustainable and resilient, the design orientation of HMI needs to change accordingly. Through understanding the state-of-the-art of HMI research, the technology roadmap of HMI development in the smart manufacturing paradigm can be shaped. In this paper, the focus is to review how HMI has been applied in smart manufacturing and predict future opportunities and challenges when applying HMI to HCSM. In this paper, we provide an HMI framework based on the interaction process and analyse the existing research on HMI across four key aspects: 1) Sensor and Hardware, 2) Data Processing, 3) Transmission Mechanism, and 4) Interaction and Collaboration. We intend to analyse the current development and technologies of each aspect and their possible application in HCSM. Finally, potential challenges and opportunities in future research and applications of HMI are discussed and evaluated, especially considering that the focus of design in HCSM shifts from improving productivity to the well-being of workers and sustainability.

Keywords: Human-machine interaction; Industry 5.0; Human-centric Manufacturing; Edge computing; Internet of things; IoT; Smart Manufacturing; 6G; Internet of Everything; IoE.

1. INTRODUCTION

In 2020, the European Commission proposed the concept of Industry 5.0. It focuses on the well-being of workers and complements Industry 4.0 with sustainable, human-centric and resilient industries [1]. Industry 5.0 is driven by six enabling technologies:(1) personalised human-machine interaction (HMI) technology that will combine the strengths of humans and machines, (2) using digital twins to visualise systems, (3) wide application of renewable energy technology to improve the sustainability of production, (4) application of artificial intelligence technology to realise the analysis and processing of big data and complex environment, (5) application of smart material and bio-inspired technologies in the sensor to enhance its function, and (6) data transmission, storage and analysis technologies, such as IoT [2]. Comparatively, Industry 4.0 focuses on automation and the productivity of machines [3], while Industry 5.0 focuses on providing customised, high-satisfaction products and a production environment that is more environmentally friendly and caring for workers by putting people at the centre of production [1]. Therefore, the core of Industry 5.0 in the manufacturing field, Human-centric smart manufacturing (HCSM), has gradually attracted people's attention.

According to the Smart Manufacturing Leadership Coalition (SMLC), smart manufacturing is defined as a data-driven, highly integrated collaborative manufacturing system that responds in real-time to changes in demand and environment [4]. In the context of Industry 4.0, there are two main driving factors for smart manufacturing, (1) the gradual replacement of mass production by individualised and customised production and (2) the popularisation of networked and intelligent equipment [5].

Therefore, the equipment based on the design concepts employed in current smart manufacturing cannot meet the human-centric demands of Industry 5.0. Since Industry 4.0, like the previous industrial revolutions, is technology-driven, while Industry 5.0 is positioned as value-driven [6], the most significant difference between them is the difference in design philosophy and focus, rather than technology. Thus, this difference is particularly evident in the field of HMI.

Since the 1970s, HMI-related research appeared, while automation start to be introduced into the engineering field. Some earlier research was dominated mainly by psychology and focused on psychological tests [7]. With the popularisation of new technologies, especially the widespread application of automation and digital equipment, research on HMI began to expand into more topics, such as knowledge acquisition, security research, time-sensitive (response within a specified time) tasks, human-machine task assignment, trust research. HMI research has generally developed from a single-domain static system (knowledge acquisition, psychological testing) to a multi-domain dynamic, intelligent system (task-oriented, emotional interaction) [8]. This development has also benefited from the proliferation of sensors and embodied, situated automated systems brought about by artificial intelligence (AI) [9]. Sensors allow machines to perceive the external environment, and AI ensures that these systems can be trained based on data to adapt and respond to the environment.

However, the emergence of Industry 5.0 has brought new challenges to HMI, which are mainly reflected in two aspects: (1) the human-centred demand of professional users in manufacturing scenarios, and (2) the increasing number of non-professional users working in some domains [8]. Many HMI manufacturing scenarios have work and efficiency as the core objectives of the interaction, so the sensors and collected data in these scenarios often serve the manufacturing process [8, 10]. A lot of HMI studies struggle to meet the sustainable, resilient demands of Industry 5.0. Although some studies have focused on operator-focused topics such as safety and fatigue, these studies have not been widely used in HCSM [8, 11]. People-centeredness still lack effective research and practice. The rising promise and popularity of vehicles that can drive themselves have stimulated research on the interaction process of non-professional users [12], but this topic needs more work in the manufacturing field. With factory intelligence, automation, and the increasing amount of big data collected by sensors, it is unrealistic to expect future workers to understand all aspects of the whole system. Future HMI research needs to assume that workers may not acquire all the knowledge of the working machine and consider how to design interaction processes to help workers improve their interaction experience. Some researchers have begun to focus on using Extended Reality (Virtual Reality, Augmented Reality, Mixed Reality and other related technology) to provide users with a more accessible interaction model to understand and manipulate [13]. These studies offer new ideas for HMI in HCSM scenarios, but they also face many difficulties and challenges.

Thus, it is necessary to summarise and review the existing HMI-related research to predict and discuss the development of HMI under the framework of HCSM in the future. This paper analyses the current HMI research from the following five aspects: 1) Overall framework of HMI, 2) Sensor and Hardware, 3) Data, 4) Transmission Mechanism, and 5) Interaction and Collaboration. Industry 5.0 is not merely technology-oriented compared with Industry 4.0, so the analysis in this paper will focus on the shortcomings and differences in value orientation and design concepts and analyse potential challenges and opportunities in the future based on this theme.

The structure of this paper is as follows. The first section introduces the paper's background, motivation, and related knowledge. Then the second chapter introduces the research methods of this paper, such as how to select relevant studies. The third chapter introduces and analyses state-of-art research in HMI from multiple perspectives. Based on the existing research, Chapter 4 discusses the future development of HMI in the HCSM field from two aspects: challenges and opportunities. Finally, the conclusion and references are given.

2. METHODOLOGY

This section introduces the approach used to search and classify recent publications related to HMI in the HCSM. The papers are searched in two steps shown in Figure 1. In the first step, the search string ("Human-machine interaction" AND "smart manufacturing") is defined to find papers that include a connection between HMI and smart manufacturing. Then, the string is used to search the title, abstract, or author keywords in the journal papers among the mainstream database, including *IEEE Xplore*, *ScienceDirect*, *Springer Link*, *ACM*, *Scopus*, up until 1st January 2022. Publication time (after 2019) was the main criteria for filtering at this search step, mainly because this paper aims to introduce the latest technology. 50 relevant papers were identified; among them, 13 are review papers, which presented different enabling technologies of HMI in smart manufacturing, such as different sensor technologies, 5G, IoT. Therefore, a new round of retrieval is conducted using these enabling technologies as keywords combined with smart manufacturing/HMI. Under this step, papers are filtered according to the criterion that is directly explored enabling

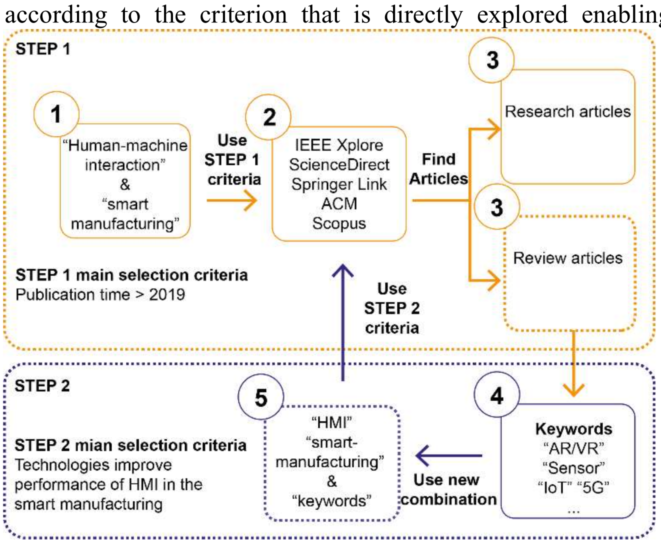

FIGURE 1: TWO STEPS PAPER SELECTION AND EVALUATION PROCESS

Reference	Research Objects	Related to aspects of HMI			
		Interaction & collaboration	Sensors & hardware	Data Processing	Transmission Mechanism
[1][6]	Industry 5.0				
[2][41][51]	Industry 5.0	√		√	
[3][13][50]	Industry 4.0	√		√	
[14]	Industry 4.0	√	√		
[4][5]	Smart manufacturing		√	√	
[53]	Smart manufacturing			√	
[55]	HCSM	√		√	√
[8][11][15][16][42][44][47][57]	HMI	√			
[48]	HMI	√	√		
[12][39][43][49]	Automated vehicles	√			
[17][19]	Visual sensor	√	√		
[18]	VR	√	√		
[20]	Multitouch sensor	√	√		
[21]	Smart sensor design	√	√		
[22]	Acoustic sensors	√	√		
[23]	Brain-computer interface	√	√		
[25]	Force sensors		√		
[37]	Wireless sensors		√		√
[26]	Wearable devices	√	√		
[27][28][31][38]	IoT			√	√
[29][30][52]	Cloud computing			√	√
[32]	Edge computing			√	√
[33][35][36]	Big data			√	√
[56]	Big data		√	√	√
[34]	PdM			√	
[40]	6G			√	√

TABLE 1: LIST OF THE RECENT PUBLICATIONS OF HMI IN SMART MANUFACTURING

technologies to improve the performance of HMI in smart manufacturing. Additionally, since HMI is a field established in 1970, we examined the reference lists of the 50 papers to identify foundational papers in the past. Finally, the reviewed papers are classified based on four aspects: interaction and collaboration, sensors and hardware, data pre-processing, and transmission mechanisms shown in Table 1, which represents that the topics of reviewed papers are evenly spread over different HMI technologies.

3. STATE-OF-THE-ART OF HMI IN SMART MANUFACTURING

To better understand the current development of HMI in smart manufacturing, this paper proposes two classification methods for the current research in this field. The first method is based on the research of [14], which divides HMI into three top-level categories: Human, Machine, and Interaction. Humans and machines belong to different categories due to their different nature. Since interaction is the most dominant behaviour in the process, it is also classified as a separate category. As shown in Figure 2, each primary category contains several more detailed second-level sub-categories. This method is very effective in the context of Industry 4.0, as it can help researchers evaluate research results and associated factors better.

However, the disadvantages of this method are also prominent. Since it is not based on the interaction process but based on the research, it misses the problems faced by each process in HMI. Since this paper is to obtain HMI criteria suitable for HCSM through the analysis of existing HMI technology, it is necessary to study the design criteria and core elements in HMI according to the process. This paper aims to analyse the possible future development of HMI in HCSM by analysing each link in the process. Therefore, this paper will establish a process-centric HMI framework based on literature review and existing classification methods.

3.1 Overall framework of HMI

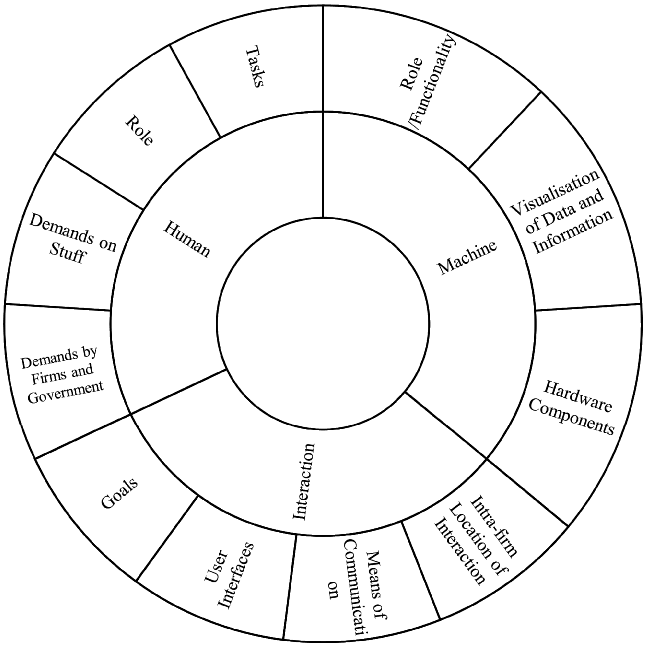

FIGURE 2: THREE TAXONOMY OF HMI RESEARCH

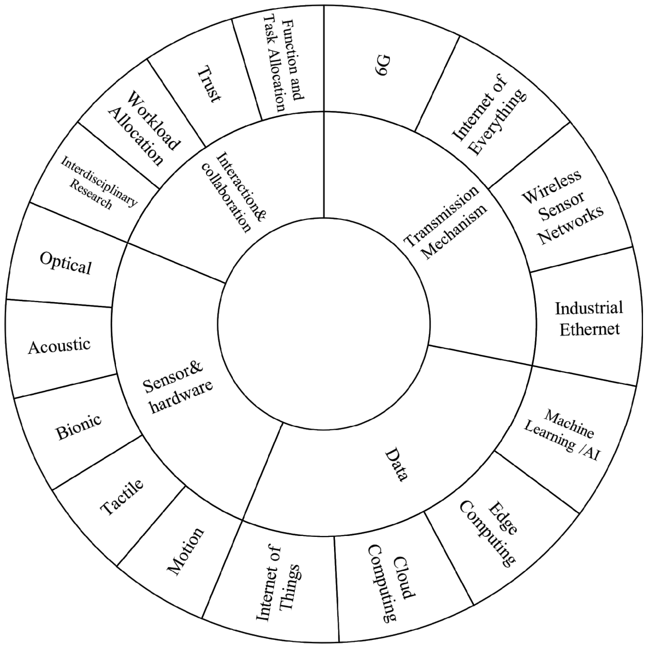

FIGURE 3: FOUR TAXONOMY OF HMI RESEARCH

As mentioned, HMI has begun to be widely used in dynamic, intelligent systems. Compared with the static research focused on a specific field in the early days, the current HMI system is often more complex and diverse. Especially with the popularity of machine learning enabling big data analysis, this further increases the complexity of HMI systems. However, the interaction process remained unchanged. Therefore, it is possible to analyse and study the HMI framework according to the process.

The process of HMI can be divided into the following four steps according to the collection, transmission and analysis of data: (1) the sensor collects the environment and input signals, (2) the signal is converted into data, (3) the data is transmitted to the processing centre. The process may include data pre-processing and screening (4) interaction and collaboration. As shown in Figure 3, current research contributions on HMI are grouped under these four main categories. Unlike the three-category approach, this framework will focus more on the technology and design goals used in the process. It can lay the foundation for predicting new applications and combinations of technologies after the design goals are changed in the HCSM scenario.

3.2 Sensors and Hardware

Smart manufacturing has been applied in many different manufacturing scenarios, so sensors in this domain are diverse. According to different design technology applied, these sensors can be divided into optical technology-based, acoustic technology-based, bionic technology-based, tactile technology-based, motion technology-based [15]. According to the different interaction objects, these sensor devices can be divided into two categories: one is to collect non-human signals, such as ambient temperature, brightness, working equipment status, and the other is to collect human signals, such as heartbeat, body temperature, vision Capture, motion capture [16].

Sensors based on optical technology are mainly camera-computer vision, LEDs and lasers also fall into this category, but they are used slightly differently. An optical HMI is ideal for use as a public interface because it does not require direct physical contact [15]. Camera - Computer Vision uses a camera to capture changes in the outside world and transmit this data to a processing device for processing. This technology has been widely used in domains such as gesture recognition, motion detection, and eye-tracking [17], and it has also been shown to have great potential in the realisation of virtual reality technology [18]. In smart manufacturing, it is indispensable in supply chain management and equipment/product positioning. In conventional manufacturing, increasing the number of cameras means increased regulatory work, so it is often seen as expensive, and the vast amount of data collected lacks effective means of analysis [19]. Nevertheless, the popularity of machine learning algorithms has laid the foundation for its large-scale application, and some research has begun to focus on using camera-computer vision to model workers for better real-time work and safety supervision.

LEDs and lasers are often used as replacements for camera-based HMIs because of their straightforward structure, limiting their applications [20]. They are often used in distance detection and touch sensors. Their future potential, therefore, lies mainly in complementing other sensors.

Acoustic-based sensors are mainly based on speech recognition and sonic detection [15]. As a well-developed technology, sonic inspection has diverse applications in manufacturing, especially in fault detection and environmental analysis [21]. Speech recognition is also widely used and proven effective in manufacturing robots and workers' interactions. Considering that such interactions will become more frequent in future HCSM scenarios, acoustic sensors will also be widely used. At the same time, acoustic myography, an interesting branch of acoustic sensors, has also been proven to have broad application prospects [22]. It measures the acoustic properties of muscles as they contract. These sensors enable the human body to become part of the interface, like skeletal sound detection.

Sensors based on bionic technology mainly detect biological signals for analysis through biology, computer science and robotics. This detection is often done through electrodes. For most sensors, the electrodes used were the same, with adjustments for the frequency of monitoring and level amplification [15]. These sensors are mainly divided into the electroencephalography-based brain-computer interface and the electromyography-based Myoelectric Interaction. There are also some studies based on electrooculography and electrocardiogram, but the proportion of these studies is relatively small. Brain-computer interfaces are the newest research in bionics and the most controversial, mainly due to the ethical and moral issues it may raise. The current brain-computer interface technology has realised the control of the robotic arm/wheelchair/mouse, and the bionic eye can restore vision for the blind [23, 24]. It is foreseeable that this will be a hot technology in Industry 5.0. Myoelectric interaction uses similar technology to the brain-computer interface, but its electrodes are mainly used to detect electrical signals from the muscles rather than the brain [22]. This technology has been used in human assistive limbs and exoskeletons in the industrial and is an essential part of caring for worker well-being. Sensors based on electrocardiogram and electrooculography have not been well used in the industrial field. Still, as the human-centred concept of Industry 5.0 begins to spread, they will also be used to care for and ensure workers' health.

Tactile-based sensors are the only HMI sensors requiring physical contact and including all operable keys. Telerobot hand pressure and other force sensors are prime examples in the industry [25]. At the same time, as the centre of smart manufacturing begins to shift to human-centricity, tactile sensors will be better served by workers in work environments, especially given the role they can play in virtual reality.

Motion technology-based sensors mainly utilise gyroscopes and accelerometer needles to detect motion during HMI processes. They are usually used in conjunction with other sensors. For example, it can be combined with the camera-computer vision sensors to fully model interaction objects. These sensors are mainly used in wearable devices [26].

In the conventional smart manufacturing scenario, sensors that collect non-human signals still occupy the mainstream position. This is mainly because these sensors are designed for production efficiency and product quality. However, with the introduction of HCSM, human signals will become the most valued data in production scenarios, and these related sensors can also be promoted and applied.

3.3 Data Processing

After the signals are collected by sensors, they are converted into data and transmitted to end devices for analysis. However, these raw data often contain much noise and need to be pre-processed. At the same time, although data pre-processing can filter out irrelevant data, the amount of retained data is still colossal. For this, suitable data analysis methods are required.

In the late 1990s, academics at the Massachusetts Institute of Technology proposed the concept of the Internet of Things (IoT), the main goal of which is to digitise the real world, thereby creating a centralised network that can collect and process information [27]. There are three leading enabling technologies: (1) Radio Frequency Identification (RFID) and Near Field Communication (NFC) technology, which ensure the reception and transmission of data. (2) Wireless Sensor Networks (WSN) technology, which collects data and processes, analyses and transmits information through the extensive use of a large number of sensors; (3) Data Storage and Analytics, which makes it possible to generate and exchange large amounts of data through cloud storage [28]. IoT builds a system that can interconnect smart devices that integrate different communication technologies.

To process the large amount of data stored in IoT, cloud computing was introduced into IoT architecture. Cloud Computing (CC) is a process of analysing and processing data from different devices in the cloud, and it aims to provide services to users in the cloud through data processing [29]. CC services can be divided into three categories: (1) Software as a service (SaaS), where users access apps and services provided by cloud service providers through the Internet, (2) Platform as a service (PaaS), where users rent from service providers Virtualized servers, which allow users to run their applications and provide computing power and capacity, (3) Infrastructure as a Service (IaaS), which allows users to manage and control software and hardware resources [27]. It has the advantage of accessing all relevant facilities and services anytime, anywhere.

IoT and CC together lay the foundation for big data analytics. However, with the increasing number of connected devices in the IoT architecture and the increased timeliness requirements of manufacturing scenarios, this analysis method has ushered in its limitations. As the number of devices increases, the CC becomes less efficient, and the time required for data transfer cannot meet the real-time response requirements in many manufacturing plants [30]. Therefore, edge computing was introduced into IoT to solve this problem.

Edge Computing (EC)is a technology that focuses on decentralising data processing from the cloud to the endpoint. In many industrial scenarios, the requirement for the response result of part of the data processing is real-time, so it is unrealistic to put this part of the data on the cloud for processing [27]. For example, in fault detection in the production process, if the machine waits for data to be transmitted to the cloud and then returns a response signal, the fault may have caused a series of severe consequences. At the same time, reliability, security and privacy considerations have also resulted in some data not being put into the cloud for analysis [31]. EC can effectively solve these problems because the calculation is done at the device terminal and is not transmitted to the cloud. Another benefit of EC is that it can effectively reduce network load, thereby improving the efficiency of CC. In smart manufacturing, edge computing has been used in many scenarios, especially those equipped with processing chips. Some well-designed smart manufacturing processes can even achieve self-optimisation that relies entirely on equipment [32].

In EC and CC computing, machine learning is one of the most used methods. Because the data collected in the smart manufacturing environment has the characteristics of multi-dimensional, intrinsic correlation and high complexity, machine learning is the most suitable method for analysing the manufacturing environment data [33]. The use of conventional machine learning algorithms in manufacturing is already familiar. In recent years, deep learning has also begun to have small-scale research and applications in manufacturing. However, since the prediction process of deep learning is still a "black box" for humans, it is challenging to meet the requirements of controllability and safety in industrial scenarios. For example, in some Predictive Maintenance (PdM) studies, although a deep learning algorithm is used to establish a failure prediction model, periodic human inspection and maintenance are still necessary [34].

However, deep learning can be expected to play a significant role in HCSM. As some human-related data begins to be collected in manufacturing scenarios, the analysis of this data will inevitably use deep learning. At the same time, due to the high fault tolerance rate of these human data, the requirements for controllability are relatively low, so the prediction model based on deep learning can be put into practical application faster. Also, the prediction model based on deep learning can be better trained for more changeable and personalised manufacturing scenarios, which meets the needs of Industrial 5.0 for resilience.

3.4 Transmission Mechanism

IoT, CC and EC solve the processing problem of Industrial Big Data (IBD). However, collecting and transmitting data in WSN reliably and efficiently is another great challenge in smart manufacturing. In industrial scenarios, the environment is often complicated, and many factors such as electromagnetic interference, noise, signal attenuation, and high temperature will have a massive impact on the transmission quality. Therefore, an efficient and reliable data transmission mechanism is necessary.

There are two main data transmission mechanisms in smart manufacturing, wired and wireless networks. The wired network "Industrial Ethernet" is the most widely used transport network in manufacturing environments [35]. It has the advantages of fast speed, high efficiency and strong anti-interference ability. However, this technology requires many connector devices, which leads to high maintenance costs, high failure rate and low scalability while taking up a lot of workspaces [36]. Therefore, as a representative of wireless technology, WSN has been adopted by many factories in recent years. A WSN usually consists of several wireless sensors that can collect various data in the environment and wirelessly transmit them to Data Terminal Equipment (DTE), such as cloud computing terminals or PCs. Although WSN can solve many problems in the wired network, the current WSN still has many deficiencies. Limited resources make it challenging to deploy in harsh environments, and security risks and privacy risks are four frequently discussed issues [37].

Therefore, the Internet of Everything (IoE) was proposed. IoE is a concept built on IoT, and it is an intelligent connection between people, processes, data and things, not just between devices [38]. IoE attempts to treat all parts of the entire environment as an intelligent whole, enabling optimisation and adjustment of resources and connections.

The optimisation of the data transmission mechanism in smart manufacturing by IoE can be divided into two categories, hardware and software. In terms of hardware, it is mainly the application of EC in WSN. Simple data analysis and storage can be done on microchips or regional computing nodes [39]. This method effectively reduces the amount of data transmission in the network and the pressure on the central processing centre and improves transmission's privacy and security. Software optimisation is combined with hardware optimisation. For example, with machine learning algorithms, data transmitted by different sensors in industrial scenarios can be classified and clustered, thereby reducing energy consumption and improving efficiency [33].

As one of the enabling technologies of Industry 5.0, 6G will also bring new opportunities for the data transmission mechanism in smart manufacturing. Compared with 5G, 6G can provide ultra-high bandwidth, flow rate, reliability, ultra-low latency services, which will lay a solid foundation for integrated HCSM [40]. Although 6G also faces shortcomings such as short transmission distance and being susceptible to interference from obstructions, these problems will be solved by deploying EC equipment and applying artificial intelligence optimisation. Another considerable advantage of 6G is that it can improve the sustainability of production with advanced energy management schemes [41], thus satisfying industry 5.0 new demands on manufacturing.

3.5 Interaction and collaboration

Interaction and collaboration have always been the core goals and themes of HMI. In traditional HMI analysis, three research themes have been discussed, human-machine function and task allocation, trust and workload allocation. It is foreseeable that these topics will still receive continued attention in the HCSM scenario. Therefore, discussions on these topics are essential. At the same time, based on our understanding of HCSM scenarios and requirements, this paper will also discuss several topics that are expected to play an essential role in implementing HMI in HCSM.

Since the introduction of automated equipment and machines into industrial production, the assignment of tasks and functions between humans and machines has been emphasised. The original intention of introducing automated equipment and machines was to perform highly repetitive tasks. However, as the level of automation increases, in many industrial scenarios, they are responsible for most tasks, while human operators are only responsible for supervision and some crucial determinations. However, an important problem with introducing automation is the "irony of automation", which means operators change work strategies and behaviours in an automated environment [42]. Some drivers experience prolonged visual distraction prior to an accident [43]. As the number of non-professional operators grows, it is foreseeable that this misallocation of tasks may also occur in HCSM. Especially under the guiding ideology of human-centred, it is necessary to let human operators understand their tasks and responsibilities quickly and efficiently.

As the second most-appreciated topic in the HMI area, trust is often discussed with incorrect use and confusion. According to [44], interaction and collaboration in HMI can be divided into four scenarios, use, misuse (over-dependence and over-trust), disuse (do not use, do not trust) and abuse (do not consider the impact of introducing machines," irony of automation"). These four ways will affect the operator's trust in the device to varying degrees, affecting the interaction and collaboration process. Meanwhile, the second big problem faced in HMI is confusion. For example, in a power plant, since the power generation system is highly complex, part of the equipment is always in a state of maintenance, so the factory will always be in a state of multiple modes in parallel, and this will cause workers to work in a confusing mode. Requirement [45]. Such situations will also occur frequently in HCSM, so it is necessary to build appropriate confusion models to help workers understand and respond to work conditions [12].

Workload distribution is the third HMI area of most significant concern. In traditional HMI analysis, the primary purpose of rational workload allocation is to avoid underload and overload [46], thus ensuring work efficiency and production quality. A study of work environment alerts found that when the level of automation increases, operators are less sensitive to explosiveness [47]. This type of load research often ends up in attention management. As people replace work efficiency and work quality as the focus of industry 5.0, establishing a close partner relationship between any machine and focusing on worker fatigue and health will receive more attention.

In addition to these topics studied in the HMI field for many years, with the advent of HCSM and industry 5.0, it is expected that some new topics will also receive increasing attention. Interdisciplinary research is one of the focuses of the next phase. The combination of psychology, engineering and computer science can better analyse and model workers' state and this will have a wide range of applications in HCSM [48]. Regulation and explainability are considerable challenges for the next phase of HMI, especially the black box problem brought by artificial intelligence and machine learning algorithms [33]. With the shift of the focus of work brought about by industry 5.0, how to change these unknown factors in the existing system and take into account the previously ignored factors to adapt to the new needs are the breakthroughs for the next stage of research.

Moral and ethical considerations and humane improvement are also the focus of industry5.0. With the increasing proportion of automated devices in decision-making, how to design moral and ethical considerations into programs so that these decisions conform to human values should also be studied in more depth [49]. The humanisation improvement will mainly focus on the design of human-computer interaction pages. At the same time, the introduction of automation should also ensure that workers realise their creativity and value, rather than raising the level of automation blindly.

4. TOWARDS HUMAN-CENTRIC SMART MANUFACTURING: CHALLENGES AND OPPORTUNITIES

4.1 Challenges

Figure 4 shows the correlation between different HMI topics/enabling technologies and HCSM expectations in four aspects: technical, worker wellbeing, moral and security. The colour scale ranges from 0 (white) to 1(black). 0 (White) represents the HMI topics/enabling technologies that do not correlate with HCSM expectation, and 1(black) means that HMI topics/enabling technologies are highly correlated with HCSM expectations.

There are still many challenges in applying HMI in HCSM. These challenges are mainly divided into four aspects: 1) some enabling technologies are still not widely used in industrial production, such as brain-computer interfaces, 6G, 2) the human-centred design concept has not been widely used in the existing HMI design, 3) How to train workers to adapt to the new work environment and mode, 4) Issues in existing HMI such as work assignment, trust. There have been lots of studies on these issues, but more research is required.

Although the popularity of smart manufacturing has enabled most of the enabling technologies of Industry 5.0 to appear in the industry, there are still many new technologies in the experimental stage that have not been applied in practical scenarios [50]. First, because the cost of promoting and applying new technologies is relatively high, enterprises must consider economic issues as well as disruption to operations. Since the focus of Industry 5.0 is human-centric, sustainable and resilient, the application of new technologies should be seen as a long-term investment, often without short-term benefits [51]. In

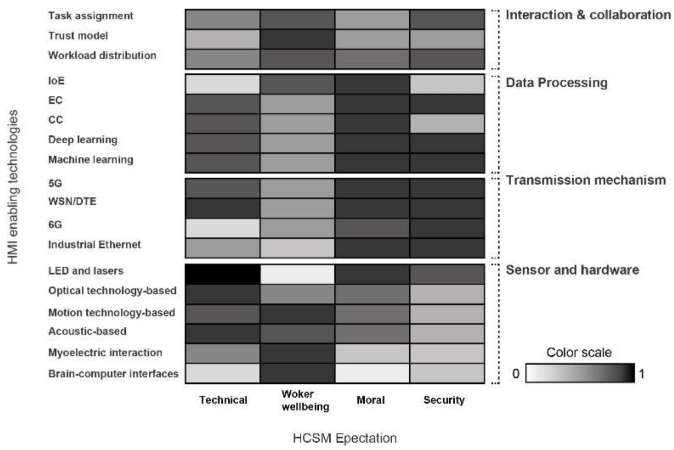

FIGURE 4: THE CORRELATION HEATMAP BETWEEN DIFFERENT HMI TOPICS/ENABLING TECHNOLOGIES AND HCSM EXPECTATIONS

addition to this, ethical and moral issues are also a challenging point for many technological applications and need careful consideration, especially applications like brain-computer interfaces and virtual reality [8]. These new technologies should consider not only humanisation and convenience but also the privacy of workers and businesses [52]. Security issues are the third important consideration in the application process, especially in HMI. As the level of automation increases, the work of workers and machines in manufacturing environments will be redistributed, which will bring new safety hazards and considerations.

As one of the cores of Industry 5.0, human-centric is not considered enough in the existing HMI design. Current smart manufacturing is still oriented towards work efficiency and production without always giving enough attention to the well-being of workers [2]. For example, production-related data is still the key focus in data collection, which leads to the lack of data support for HCSM [41, 53]. In industrial scenarios, the existing sensors are mainly based on monitoring the environment and equipment, and the sensors in the next stage need to pay more attention to workers and their conditions [54].

Training workers' skills and ideas are and always will be a crucial challenge as will the extent to which training works over extended periods of time and how it transfers (or not) to other areas. In the HCSM scenario, workers are both professional and non-professional. Due to the high degree of automation and intelligence of the system, workers will be freed from daily work to do more creative work and enhance personal development and professional capabilities. At the same time, they should not be expected to have all the knowledge to understand the operation of the entire complex system [55]. Therefore, designing suitable training courses and guiding work to help workers adapt to the work environment and improve themselves will be the focus of future research.

The three major themes in the HMI field, task distribution, workload distribution, and trust will continue to receive attention in HCSM. However, as the design concept changes, new problems will inevitably arise in these fields. Creating a safe and inclusive work environment for workers will be the new goal. Therefore, rationally distributing tasks and workloads and establishing trust between workers and machines to ensure safety and sustainability will still be challenges for HMI applications in HCSM [48].

4.2 Opportunities

As seen in Figure 4, some HMI enabling technologies introduced in this novel review paper already meet the demands of HCSM, however, some are not, and need forces more in future studies (Figure 4). Therefore, the emergence of HCSM will bring many opportunities for HMI, divided into the following three perspectives: 1) The application of new technologies and interdisciplinary research brought by the introduction of the human-centric concept and HMI design focus on sustainability and resilience. 2) Improvement of workers' well-being. 3) Improve the relationship between human and machine collaboration.

Interdisciplinary HMI research has already emerged in Industry 4.0, but these are often machine-led. As people become the centre of production, these studies will focus on understanding human states and intentions. For example, by collecting data related to workers to build a state model of workers, machines can better cooperate with humans. At the same time, through the analysis of external human behaviour signals, the machine can better understand the short-term and long-term intentions of workers. In the design of the HMI interface, humanised design can also better bring closer the relationship between humans and machines. These require researchers to comprehensively combine cognitive science, engineering, psychology, computer science and other fields. As sustainability and resilience become the focus of the subsequent research phase, the guidelines and approaches to HMI design will also change. These designs will incorporate more renewable energy technologies and smart materials to enhance the capabilities of sensors while making them more energy-efficient and recyclable [2, 56].

The well-being of workers will be a new opportunity in HCSM, and workers will move from being seen as a "cost" to an "investment" [57]. This change means that the future HMI technology will consider the needs and diversity of workers. This adjustment can better protect workers' rights while also helping workers better utilise their expertise and creativity.

In HCSM, HMI will also aim to establish a closer cooperative relationship, from the old task distribution model to a collaborative intelligence model. Many years ago, with the breakthrough of artificial intelligence technology, some researchers believed that AI would take workers' jobs [58]. However, research in recent years has found that the system's capabilities can be better improved when AI and humans collaborate intelligently. Therefore, the HMI in HCSM will establish the relationship of intimate partner between man and machine through more humanised and intelligent design, such as empathy machine.

5. CONCLUSIONS

In this novel review paper, we have demonstrated different enabling technologies of HMI towards HCSM. We illustrated a new classification framework to analyse the HMI based on the collection, transmission, and analysis process. We then discussed and analysed the state-of-art technologies in each process of the classification framework, such as sensors and other hardware, data and related transmission technologies, and different interactions and collaborations technologies. Through our analysis, we detected the gap between current HMI technologies towards the requirements of HCSM in Industry 5.0, which leaves a number of challenges and opportunities in the new era of HCSM, such as enhancing the security, efficiency, and privacy (including ethical considerations) in the HMI. By handling these new issues and challenges through rigorous research efforts – and especially utilising multidisciplinary approaches to research challenges – a more optimal HCSM system could reach a result that can benefit all aspects of Industry 5.0.

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