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Review paper

Human–machine interaction towards Industry 5.0: Human-centric smart manufacturing

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ABSTRACT

Since the concept of Industry 5.0 was proposed, the emphasis on human–machine interaction (HMI) in industrial scenarios has continued to increase. HMI is part of the factory's development towards Industry 5.0, mainly because HMI can help realise the human-centric vision. At the same time, to achieve the sustainable and resilient goals proposed by Industry 5.0, green, smart, and more advanced technologies are also considered important driving factors for factories to achieve Industry 5.0. Human-centric smart manufacturing (HCSM) factories that integrate HMI with advanced technologies are expected to become the paradigm of future manufacturing. Therefore, it is necessary to discuss technologies and research directions that may promote the implementation of HCSM in the future. In a smart factory, HMI signals will go through the process of being collected by sensors, processed, transmitted to the data analysis centre and output to complete the interaction. Based on this process, we divide HMI into four parts: sensor and hardware, data processing, transmission mechanism, and interaction and collaboration. Through a systematic literature review process, this article evaluates and summarises the current research and technologies in the HMI field and categorises them into four parts of the HMI process. Since the current usage scenarios of some technologies are relatively limited, the introduction focuses on the possible applications and problems they face. Finally, the opportunities and challenges of HMI for Industry 5.0 and HCSM are revealed and discussed.

1. Introduction

Artificial Intelligence (AI) has found its way into many aspects of daily life with applications like ChatGPT, Alexa and Face ID, but it has a much longer history in manufacturing. In the early 1980s, computer technology and automation began to be widely used in manufacturing. However, due to the limitations of computing power and hardware equipment, the ability to process data was relatively weak at that time [1,2]. Advances in these technologies lay the foundation for the realisation of smart factories. Smart factories have emerged with the rise of the Internet and the development of data storage technology. In the early 2000s, the industrial field began to adopt more advanced sensor technology and automation equipment, which meant that the datasets collected in the production process could be much larger and the data within them more accurate. Also, the development of cloud computing and big data technology provides a more optimal platform for processing and analysing these data [3,4]. Most previous smart factories focused on analysing process-related data. However, with the introduction of Industry 5.0, analysing human-related data to improve HMI may be a focus in future smart factories.

In 2011, the concept of Industry 4.0 was proposed at the Hannover Messe in Germany. It emphasises the interconnection of physical systems and digital systems. It realises a high degree of automation and intelligence in manufacturing through technologies such as digital twins, the Internet of Things, and data analysis [5–7]. This digital transformation improves production efficiency and flexibility and allows for personalised production, customised requirements and remote operation. This is inseparable from the development of smart factories.

Industry 5.0, however, takes the smart factory a step further and emphasises close cooperation between humans and machines, embracing human-centric, resilience and sustainability as core values [8]. It puts forward the vision of human-centric smart manufacturing (HCSM), advocates humanised smart manufacturing and focuses on human creativity, flexibility and professional knowledge [9]. This kind of manufacturing pursues human–machine collaborative work, combines the advantages of machines with human creativity, and promotes the sustainable development of industries.

To achieve the Industry 5.0 vision, it is essential to discuss human–machine interaction (HMI). This is because, in Industry 5.0, the role of

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many people within the factory/factories has changed and will continue to do so. This requires HMI to be better optimised to assist the operator efficiently. Machines will serve as extensions and assistants to help people make correct decisions and, at the same time, improve people's well-being through more humane assistance.

In Industry 4.0, the main research direction of HMI extended from the early automated psychological tests and knowledge acquisition to several major topics, including the distribution and allocation of tasks, trust and focus [10–15]. According to [16], the focal points and analytic approaches to HMI in Industry 4.0 focus on what can be divided into three taxonomies: human, machine, and interaction. Three-taxonomy focuses on the distinction of entities in the scene and the interactions between them. In the current paper, according to the process that HMI signals go through in manufacturing scenarios, HMI can be divided into four parts: (1) Sensors, where the signal is collected; (2) Data processing, where the signal and data are processed; (3) Transmission mechanism, how the data are transmitted, and (4) Interaction and collaboration. The purpose of adopting this classification is to better summarise the technologies involved in HMI rather than just focusing on research issues in the HMI field and the relationship between humans and machines. In Section 3, this paper will review the different types of technologies and research topics related to each part.

Although Industry 5.0 proposes a human-centric vision, the employees in the manufacturing scenario should be viewed from two perspectives [10]. First, people with professional capabilities will become the core of the HCSM factory. This is mainly because as the level of specialisation and intelligence of factories increases, the professional ability level of employees also needs to be correspondingly improved to operate these high-precision equipment. The HMI system should become their extensions and assistants, helping them better utilise their professional expertise and capabilities with a reduction (in areas) of physical aspects of work. On the other hand, the increase in integration and intelligence has also resulted in operators being unable to possess all manufacturing-related knowledge, meaning that they become "non-professional users" in some scenarios. Therefore, designing an empathetic, better interactive experience and personalised HMI system is the key to better serving these users. Key goals of HMI design in Industry 5.0 should be to reduce the burden on workers, improve their well-being and maximise their ability to realise their creativity.

Sustainability and resilience are the other two visions proposed by Industry 5.0, and they are also goals that the manufacturing industry has always wanted to achieve. In recent years, significant global factors such as pandemics and climate change have turned them into urgent issues and core values of Industry 5.0. The realisation of these visions cannot be separated from implementing new equipment and concepts. Developing optimal HMIs within this application domain and context is inseparable from these new technologies. VR and digital twins allow workers to monitor processes and perform operations anytime and anywhere, effectively improving the factory's resilience [17,18]. Machine learning (ML) and AI have greatly improved the efficiency of quality management, predictive maintenance, personnel planning and scheduling, thereby improving the sustainability of the factory. These all demonstrate the promotion of new technologies in manufacturing and HMI. The development of HMI in the future manufacturing industry will inevitably be inseparable from the application of these new technologies, and how these technologies optimally integrate with humans form the key focus points of the current article.

This paper aims to explore and study the opportunities and challenges that may be encountered in the future development of HMI in the manufacturing industry by summarising the technologies and topics in the HMI field. Section 1 introduces the background and motivation of the research. Section 2 presents the research methodology. Section 3 provides a review of research and technologies in the field of HMI. Section 4 discusses the opportunities and challenges that HMI will face in Industry 5.0. The final Section 5 summarises the topics reviewed in this paper and provides an outlook on possible future research directions.

Table 1
Research question.

Research questions	Motivation
Q1: What are the main HMI-related technologies and research in the manufacturing field?	Analysing existing technologies and research can lead to a better understanding of their strengths and weaknesses.
Q2: What challenges will HMI face in HCSM and Industry 5.0, and how best to deal with them?	The human-centric concept is the core of Industry 5.0. Existing HMI equipment is still centred on efficiency, so it will inevitably face many new challenges.
Q3: What are the opportunities of HMI in HCSM and Industry 5.0?	As one of the important parts of realising the core value of Industry 5.0, the improvement and change that HMI can bring is one of the core issues we pay attention to.

Table 2
Research database websites.

Scopus	https://www.scopus.com
IEEE Xplore digital library	http://ieeexplore.ieee.org
ScienceDirect	http://www.sciencedirect.com
SpringerLink	https://link.springer.com
Google Scholar	https://scholar.google.com
ACM digital library	https://dl.acm.org

2. Methodology

To investigate the development of HMI in HCSM, this paper adopts a systematic literature review to identify and evaluate the relevant literature in this field. The overall approach is shown in Fig. 1. Our review process includes four main steps: defining research questions, identifying publication sources, identifying keywords, and paper selection. During the selection process, appropriate criteria are indispensable to ensure that papers provide a comprehensive overview of research in the field.

2.1. Research questions

This paper has three main research focuses: the current technologies and topics in HMI in manufacturing, the challenges that HMI will face in Industry 5.0, and the opportunities brought by implementing new technologies and concepts. To this end, we propose three research questions, as shown in Table 1.

2.2. The process of data collection

2.2.1. Search terms and resource identification

To better find research related to HMI in manufacturing, first, we need to determine the source of search resources and identify keywords.

The paper search is entirely done through the following scientific research databases: (see Table 2).

After identifying resource sources, we searched using keywords and included relevant literature references. There are two keyword searches. The first keyword search focused on an overview of HMI research in the manufacturing domain, thereby gaining a comprehensive understanding of the technologies involved. Search queries based on Boolean operators are as follows:

("Industry 5.0" OR "Industry 4.0" OR "Smart Manufacturing" OR "Human-centric Smart Manufacturing") AND ("Human–machine interaction" OR "human–robot interaction" OR "human–machine collaboration" OR "human–robot collaboration")

According to the results of this search, we added new keywords based on relevant review papers in this field containing terms that were not included within the original searches and conducted a second search. New keywords are HMI interface, Wearable Sensor, Computer

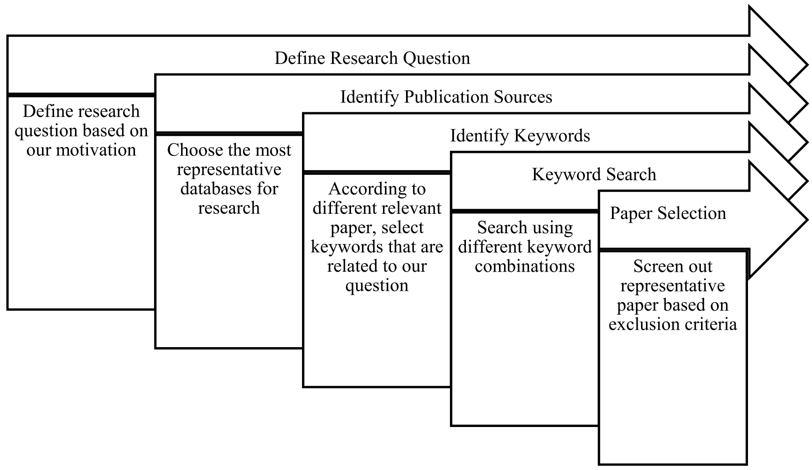

Fig. 1. Paper selection and evaluation process.

Vision, Optical Sensor, VR, XR, Hand-gesture Recognition, Acoustic Sensor, Speech Recognition, Anomalous Sound Detection, Bionic Sensor, Brain–computer Interface, Tactile Sensor, Motion Detection, Internet of Things, Internet of Everything, Big Data, Cloud Computing, Edge Computing, Cloud Computing Security, Machine Learning, Deep Learning, Wireless Sensor Network, Industrial Ethernet, 5G, 6G, data transmission, Function allocation, workload allocation.

2.2.2. Criteria for paper selection

The inclusion and exclusion criteria proposed within the systematic review were set based on the proposed aims and research questions.

Exclusion criteria:

1. Papers that topics are not relevant to the manufacturing field. If the technologies and research in a paper are completed in a manufacturing scenario and can be applied to manufacturing, this paper will be marked as 'relevant'. If a paper is not about HMI in manufacturing but its main content can be applied to manufacturing, it will be marked as 'less relevant'. If a paper is not about manufacturing solutions and its core idea and model cannot be applied to manufacturing, it will be marked as 'not relevant'.
2. The paper must be available in English.
3. For technology papers, the publication time should be after 2019. This is mainly because the concept of Industry 5.0 was proposed in 2020.

2.3. Paper selection

The first keyword search aims to comprehensively understand the relevant technologies in this field. A total of 47 relevant results were obtained. Based on papers in this research, we conducted a second search with new and original keyword combinations. We eliminated the duplicated results of the two searches and finally identified 234 relevant and less relevant papers. Then, We compared the relevance between papers and our research question and excluded papers that discussed duplicate issues. Finally, 152 papers were included in the review after all criteria were applied.

3. Human–machine interaction in smart manufacturing

3.1. Overall framework of HMI

As mentioned in previous sections, according to [16], HMI in Industry 4.0 can be divided into three categories: Human, Machine and Interaction. Due to the different attributes, Humans and Machines are separated, and Interaction is classified separately as it is one of the most important parts of this process. Fig. 2 presents this taxonomy and some of the subcategories within each category. This classification method is simple and intuitive. However, it can be found that each major category's subcategories are very different. For example, machines include psychological topics such as roles and functions and hardware and technology. Their commonalities are relatively small and cannot be compared when discussed. Each subcategory in this classification method needs to be more cohesive, and this classification method emphasises the differences rather than the connections. With more interdisciplinary research expected in Industry 5.0, this three-category taxonomy needs to be revised, as it fails to represent the HMI relationship in a highly integrated, closely connected smart factory.

To this end, we propose a framework to classify HMI according to the data transmission process in the factory, as shown in Fig. 2. Sensors are the first step in the HMI process in a smart factory, and signals are fed into the system through these devices. These signals and data are then sent to the data centre for processing and analysis, and humans in the data centre will make decisions with the help of machines. The input of data and the output of instructions are inseparable from the transmission mechanism, and this part also requires the cooperation of various hardware. Finally, after receiving the instruction, the device completes the interaction with the operator [19]. This paper briefly introduces the enabling technologies and related research designed in each part.

3.2. Sensor

Sensors in manufacturing scenarios can be divided into five categories according to different principles: optical-based, acoustic-based, bionic-based, tactile-based and motion-based sensors [19]. In smart factories, most sensors mainly collect the environment and process-related data. This is mainly based on two considerations. First, Industry 4.0 is efficiency-driven [8]. Second, collecting data related to people can easily violate workers' privacy.

To better understand the scenarios used by these sensors, the HMI interface must first be introduced. HMI interfaces in the industry can be divided into two categories [20]. The first category is the physical part of a machine that a user can see and touch, such as a computer interface. The other category is invisible natural user interfaces (NUIs), where users use intuitive everyday behaviours to perform interactions, such as gesture recognition [21]. Their difference is that physical interaction requires prior operator training, while NUI focuses on understanding user behaviours.

According to different interaction methods, HMI in smart factories can also be divided into five categories: gaze, voice, gesture, tactile,

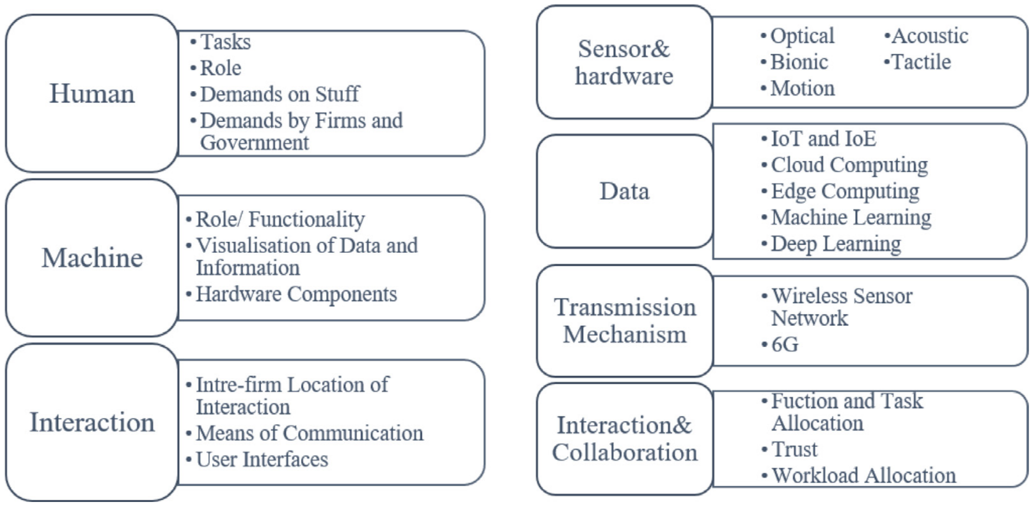

Fig. 2. HMI's three-category and four-category taxonomies.

and haptic interactions [2]. Gaze interaction mainly interacts with devices that detect human eyes [22]. Voice completes the control of the device by inputting voice information [23]. Gesture recognition can not only collect hand movement data through cameras but also collect data through wearable devices to complete the interaction [19,20]. Tactile is closely related to haptic interaction. Tactile refers to operators performing tasks through tablets and physical interfaces. In contrast, haptic recognition focuses more on nonverbal communication (sound, vibration, touch, and temperature) provided by wearable devices [2].

Next, we comprehensively introduce and discuss each sensor and its interaction interface and method.

3.2.1. Optical-based sensors

Optical sensors do not require physical contact and, as such, are widely used in public interfaces and NUIs [19]. LEDs, lasers and camera–computer vision are three of the most common types of optical-based sensors. LEDs and lasers are often used for position detection and recognition in traditional manufacturing, which makes them also applicable to gesture detection. They are also used in multi-touch sensors and displays [19,24]. Their structures are often relatively simple, with low cost and convenient deployment advantages. Fields such as motion detection, hand gesture recognition (HGR) and eye tracking are inseparable from the application of camera–computer recognition. It is also one of the technologies that enable extended reality (XR) (virtual reality (VR), augmented reality (AR), and mixed reality (MR)) [20].

Since the 1980s, VR glasses have been used to train pilots [25]. With the continuous development of technology in this field, VR head-mounted displays (HMDs) have been widely used in various fields [18,26]. As the demand for customised products continues to grow, the need for production processes and varieties also grows, further increasing the need for operators. The study found that in High-Mix Low-Volume (HMLV) assembly systems and Mixed Model Assembly Lines (MMALs), complex and variable operating systems and environments lead to a decline in worker efficiency and reduce worker satisfaction [27]. An effective way to solve this problem is XR. XR reduces the cost of understanding for workers and can better deliver effective information, making the workplace a 'small-batch, knowledge-driven place' [17,28]. However, some research results show that XR does not always assist workers in reducing workload in industrial scenarios [29]. The reasons for this problem can be summarised into four points: 1. XR cannot assist in low-complexity work [30]. 2. Current HMDs are still bulky and cannot be used long. Therefore, better results can often be obtained in spatial and projection-based XR applications [31]. 3. Interface also greatly impacts workers' understanding of the system, and NUI is considered to have lower learning costs in many cases [20,21,32]. 4. The information presentation mode will also affect the effect of XR, such as annotation, information availability and visual interference [31].

Vision-based HGR uses cameras to capture scene information and machine learning to analyse gesture features. Such systems generally consist of three components: detection, tracking and recognition. In the detection phase, the camera captures images of hand gestures and segments them from the background [33,34]. In the tracking process, the computer will continuously analyse the characteristics of the hand to realise real-time dynamic recognition [35]. Finally, through machine learning algorithms, the computer recognises and classifies gestures [36]. Generally, ordinary RGB (red, green and blue) cameras on the market can complete the HGR task. However, the improvement of the quality of the camera can not only improve the recognition accuracy but also require the device to have better computing power [34]. Therefore, selecting the most suitable sensor according to the task is also a major issue that needs to be considered when designing the HGR system. Kinect and Leap Motion are widely used products with high reliability and complete functions in vision-based HGR design. Kinect achieved an average recognition ability of 95% and 98.9% in recognising numbers and letters written in the air [34,37]. Leap Motion has been experimentally verified to improve the accuracy of intelligent systems and robot interactions [38].

Over the years, many researchers have continued to improve visual sensors to make them perform better, be more portable, and be suitable for more scenarios. Part of the research mainly focuses on reducing the burden on people who have existing equipment through new materials and designs. Nanoparticles, nanowires, carbon nanotubes (CNTs), and graphene have been used to build new types of XR devices [18]. They are characterised by strong stretchability, flexibility, and low load, so they can effectively solve the problems of bulky and poor flexibility of many HMDs [39]. In addition, smart contact lenses are also a topic that shows great potential [19]. In terms of medical treatment, it has been used in vision aids [40], corneal temperature detection [41], intraocular pressure detection [42], blood sugar level detection [34] and other fields, and has shown good results. It is used in medical, visual aids, near-eye displays and other fields and has great eye-tracking potential. In addition, it may be an effective solution to the damage to vision caused by VR HMDs.

3.2.2. Acoustic-based sensors

In Industry 4.0, acoustic sensors are widely used in machine status detection, fault detection, and voice recognition [19,43]. Compared with contact sensors such as probes and temperature sensors, acoustic sensors have the advantage of low cost and do not require physical contact with the sensor. However, due to the large amount of noise in most industrial environments, the use or quality of the signals and data produced by this type of sensor is limited. Abnormal sound detection is the basis of machine status and fault detection [44]. However, since the abnormal sound data is relatively small compared with the overall data (data imbalance problem), and these data are various, it is not easy to put these data into the machine learning algorithm for training [45]. For this reason, some researchers have adopted a multi-microphone serial combination system to suppress noise and reverberation [46]. In addition to reducing the impact of noise by adding sensors, algorithms such as Autoencoder-Based [43,45], Gaussian Mixture Model-Based [47] and Outlier Exposure-Based [48] anomaly detection are also used to eliminate noise and improve data imbalance problems.

Speech recognition technology has greatly progressed with AI development [49]. A speech recognition system consists of acoustic hardware sensors and speech recognition software [44]. Condenser microphones are one of the representatives of acoustic sensors. They use capacitance differences, such as voltage changes, to detect sound signals [50]. However, this sensor has disadvantages such as instability, short recognition distance, high power consumption, and low sensitivity. A piezoresistive microphone detects sound through a change in resistance. Its advantage over capacitive sensors is that they can still detect sound at high temperatures because the resistance is temperature-dependent [51]. The advantage of a triboelectric sensor is that it does not require an external power supply [44,52]. However, due to electrostatic phenomena, such sensors are easily affected by humidity and temperature. Flexible piezoelectric sensors that mimic the structure of the human cochlea are considered suitable candidates for speech recognition due to their high sensitivity and recognition rate [51]. It has a self-powered structure and can perform well in complex environments due to bionic concepts and flexible film materials [53]. The sensor has proven 97.5% accurate in recognising speech [44].

3.2.3. Bionic-based sensors

Bionic sensors detect biological signals through computer technology and biotechnology, and they generally have the characteristics of ultra-sensitivity, self-adaptation, and low power consumption [19]. Bionic materials, bionic structures, and functional bionic are three bionic strategies for sensors [54]. Bionic materials are components in sensors that use materials that mimic the structure of natural materials [55]. This gives these sensors unique properties. Bionic structures mean sensors realise certain functions and characteristics by imitating and learning biological and natural structures. The waterproof super-hydrophobic film is obtained by imitating super-wet biomimetic materials [56]. The difference with functional bionics is that it mainly improves sensor detection capabilities by imitating biological senses rather than focusing on adding new functions [19].

Generally, collecting biological signals by bionic sensors is completed through electrodes. The electrodes can collect different signals by changing the monitoring frequency and level amplification [19]. According to different sources, these biological signals can come from the brain, muscles and movements [57]. The electroencephalography-based brain–computer interface and the electromyography-based myoelectric interaction are two of the more common ones. Electrooculography and electrocardiograms have also received continuous attention in recent years [19,54]. Brain–computer interface is one of the most concerned studies in this field, but due to ethical and moral issues, research in this field is somewhat controversial. In the industrial field, brain–computer interfaces can already be used for robotic arm control [58]. This technology will play an important role in HCSM because it can meet the needs of Industry 5.0 for sensors to serve humans. Like the brain–computer interface, the electromyographic interaction completes the control process by detecting the muscles' electrical signals. A major application direction of this technology is exoskeleton and auxiliary limbs [59].

3.2.4. Tactile-based sensors

Tactile sensors include all sensing devices that require physical contact, such as operable buttons, tablet computers (tactile), and non-verbal communication (haptic) provided by wearable devices. According to different principles, these sensors can be divided into capacitive, piezo-resistive, piezoelectric and optical tactile sensors [60]. The difference in principle determines the difference in the materials they use. Among them, the material of the optical tactile sensor must have optical transparency and elasticity.

The main purpose of tactile sensing is to obtain information about the environment and objects to manipulate them [61]. Therefore, much of the early research on this type of sensor was focused on the medical field. For example, compared with traditional surgery, tactile sensor-based surgery involves smaller incisions, less blood loss, and is safer overall [62]. However, the performance of these devices depends on the accuracy of the tactile information collected [61]. In the manufacturing industry, the force sensor represented by the Telerobot hand pressure sensor is one of the main application scenarios of the tactile sensor [19]. In recent years, as robots have become more and more intelligent and anthropomorphic, basic sensory system simulation is also a research direction that has attracted wide attention. By implementing simulation of basic perception systems, robots can become more like humans and have stronger empathy, which is more conducive to human–machine collaboration. In the robot grasping problem, the combination of tactile and visual information is a problem many researchers pay attention to [63].

Tactile sensors are also the basis of wearable devices. In VR devices, these sensors can collect haptic information such as vibration, touch, and temperature to provide users with more realistic and sensitive feedback [2,33,34]. In addition, these tactile sensors have become smaller and more sensitive through the combination with bionic technology, making them have a wider range of application scenarios [54].

3.2.5. Motion-based sensors

Motion sensors in HMIs, such as accelerometer pointers and gyroscopes, are often used in wearable devices to detect the motion of objects [19]. The function and structure of these sensors are relatively simple. Some studies have used them as an alternative to optical sensors because of their lower space requirements [64]. Most studies use a combination of gyroscopes, magnetic needles, and accelerometers to determine the 3D position of the object of interest — including humans [65,66]. A recent review paper [65] concludes that healthcare is the most common application area for inertial motion sensors. These sensors improve human physiological conditions by collecting data on human movement [64]. Although some studies used two types of motion sensors to analyse 2D planar data, most studies used 3D data. In the industrial field, motion sensors have been used in equipment and production line detection [67].

As one of the most important parts of HMI, sensors are responsible for collecting information and signals and completing interactions. The design of these sensors not only affects the efficiency and ability to collect signals but also affects the operator's experience. A good sensing system should be able to collect valid data, be easy to use, and not place additional burdens on workers.

3.3. Data processing

Since the sensor(s) collects only raw signals, these signals must be processed to obtain the desired results. The original dataset collected by the sensor cannot be processed directly because the quality and quantity of the data may not meet the requirements of the data analysis algorithm [5]. In this case, the original data set must be pre-processed. Reduced noise data, feature extraction, and data fusion are common methods for processing and integrating data in some industries [68]. Taking appropriate processing methods can improve the data's validity and the model's accuracy.

Three types of problems may occur in the data collected in the industry: too much data, too little data, and fractured data [68]. Too much data is very common in the manufacturing industry. This is mainly because the current manufacturing environment is often equipped with many sensors, which will collect a large amount of data. However, not all of this data is valid. Noise, irrelevant, and categorical/numerical mixed data exist [69]. When splitting the dataset, too little data may be caused by missing attributes or uneven distribution of features [68,69]. In this case, the reliability of the model is very low. When data comes from multiple sources and platforms, it may lead to fractured data due to incompatibility. In addition, the different weight levels of data in the model and repository may also cause this problem [68,70].

After collecting the data, we first need to determine the appropriate preprocessing method based on the problems in the data. Reducing noise data is a method that most original datasets need to adopt. Binning, regression and clustering are three common methods to reduce noise data [69]. Binning can replace data with smoother interval discrete values to reduce observation errors [68,71]. Regression uses machine learning to predict variance and bias variables to improve accuracy. Robust regression, Gaussian process regression, support vector regression, polynomial regression, linear regression and decision trees are some common regression analyses. Clustering analyses the intrinsic connections between data and groups them to exclude noise and irrelevant data. Some common clustering methods are k-means, spatial clustering based on noise applications, and mean shift [68]. In addition, feature extraction can also be used to filter data. The features of data collected in the manufacturing industry include process features, process features, personnel features, etc. [70]. Statistical and regression analysis, dimensionality reduction analysis, text mining and image processing are common feature extraction methods [70,72]. Data fusion can solve the fractured data problem and increase the size of the data set, so it is also an important processing method in the manufacturing industry. Bayes 'Rule, Probabilistic Grids, The Kalman Filter, Sequential Monte Carlo Methods and Alternatives to Probability are common multi-sensor data fusion methods [73]. Bayes 'Rule infers changes in environment and state values by building a probabilistic model. Probabilistic Grid is a method that implements Bayesian data fusion through mapping. The Kalman Filter is a Bayesian filter that uses a recursive function to calculate changes in continuous values. Sequential Monte Carlo Methods can convert probability distributions into weighted samples in space for calculation. Interval calculus, fuzzy logic and evidence reasoning are common Alternatives to Probability methods. They can solve the complexity, inconsistency, uncertainty and precision problems in probabilistic modelling [73].

After the data pre-processing, the smart factory will analyse the data set and build a model to achieve predictive maintenance and condition monitoring goals. In this analysis process, most industrial scenarios have relatively high requirements for real-time instructions, so there are requirements for the factory's data transmission and processing capabilities. Here, smart factories need suitable data processing solutions. This section will start with the Internet of Things (IoT) and introduce cloud computing (CC), edge computing (EC), and machine learning and their place in smart factories.

3.3.1. Internet of things and internet of everything

The concept of IoT can be traced back to the late 1990s. Its main goal is to control processes by connecting devices, sensors and software [74]. By connecting various devices to the network, not only can we realise functions such as predictive maintenance, production monitoring, supply chain optimisation, energy saving, inventory management, and quality tracking, but also, the data collected in the factory can be effectively integrated to maximise the use of the potential of this data [7]. IoT has three enabling technologies [75]:

- Radio Frequency Identification (RFID) and Near Field Communication (NFC) technology
- Wireless Sensor Networks (WSN) technology
- Data Storage and Analytics technology

RFID technology guarantees real-time traceability, controllability and visibility of personnel, materials and equipment [1]. NFC is built based on RFID, which ensures the transmission and reception of short-distance data [75]. WSN will be introduced more specifically in the next section. Data Storage and Analytics technology development is inseparable from CC, machine learning and the establishment of big data platforms [19]. These technologies are necessary to extract useful information from collected big data.

There are six main functional elements of IoT: semantics, identification, sensing, services, computational and communication [76]. Among them, identification realises the naming and matching of elements in the network. Subsequently, the sensing element collects data and sends it to the computing centre. The key to realising digital services for different objects is communication. The computational and semantics functions provided by both hardware and software ensure that the system can send signals and instructions to various components in real-time to achieve the ultimate goal of IoT: to provide services for anyone at any time.

After years of development, IoT has been widely used. These applications mainly focus on five areas: Smart City, Internet of Medical Things (IoMT), Smart Grid, Internet of Vehicles (IoV), and Industrial Internet of Things (IIoT).

IoT-based smart cities collect data through different sensors and identification technologies and implement energy management, road maintenance, water supply systems online, crime prevention, community planning and other functions based on these data [77,78]. IoT-based smart cities can provide more timely, intelligent and high-quality services than the current urban management system. However, since these data often involve residents' privacy, data security is a major issue in smart city deployment.

The rapid development of IoMT and travel restrictions brought about by COVID-19 are inseparable. IoMT enables medical professionals and hospitals, more generally, to understand patients' data in real-time through remote devices and wireless medical devices to provide timely medical treatment [79]. The often very small wearable device(s) can transmit the patient's heartbeat, blood oxygen, blood pressure and other health data to the medical centre, which enables people to receive continuous health monitoring support. However, personal health data breaches will hit 45 million worldwide in 2021, tripling in just three years, according to a report by cybersecurity firm Critical Insights [76]. Since patient information and their identities are closely linked in the IoMT, these leaks can greatly impact patients' treatment, prognosis and lives.

The concept of the Smart Grid is summarised as "encapsulating the entire power generation and distribution system in a single frame" [76]. It makes the whole system cleaner and smarter through intelligent control systems, renewable energy, smart switchboard and other facilities. Supervisory control and data acquisition (SCADA), energy management system, grid communication system and distributed energy resources (DER) are the four components of a smart grid [80]. Among them, SCADA is often attacked because it contains many user data. In 2010, a SCADA system at a nuclear facility in Iran was targeted [81]. There are also data security issues and user privacy in smart grid systems. In 2015, three electricity distribution companies in Ukraine were hacked, causing 225,000 customers to lose power for over three hours [82].

IoV – also called intelligent transportation or connected vehicles [76,83] – helps the transportation system improve road safety, space utilisation, traffic congestion, control costs, and reduce environmental impact by integrating road and vehicle data. By adopting this technology, smart factories realise optimised management of raw material transportation and the Internet of Things. The IoV network contains vehicle-to-sensor, vehicle-to-infrastructure, vehicle-to-pedestrian, vehicle-to-vehicle, and vehicle-to-network communications implemented via cellular, Bluetooth, and Wi-Fi. Through the seamless integration of these communications, each vehicle can be helped to plan the optimal route. However, some cyberattacks can steal the way by modifying data [84]. Fast network authentication frameworks are currently used to defend against attacks [76].

The Industrial IoT (IIoT) and smart manufacturing are closely related. Smart manufacturing focuses on the manufacture of products, while IIoT refers to the exchange of data between machines, systems and people [85]. The Industrial Internet of Things is the basis for realising smart manufacturing. Due to the industry reliability, security and timeliness requirements, many wired transmissions are often involved in the Industrial Internet of Things [74,75,86]. This is mainly because industrial scenarios are often complex, so there is a lot of interference, and wireless transmission cannot meet the demand. 5G is seen as a solution for the Industrial Internet of Things. However, it lacks licensed frequency bands and business models [87]. EC-GSM-IoT and LTE Cat M1 (LTE-Advanced Pro) are two industrial 5G cellular spectrums currently under development [85]. Bluetooth Low Energy (BLE) is a low-power solution with disadvantages such as high latency, volume and distance limitations [88]. Some researchers solve these problems using connectionless schemes and optimising output distribution [89,90]. The industrial Internet of Things has four main challenges: energy efficiency, real-time performance, limited spectrum, and security [85]. Many IIoT devices run on batteries, so effective energy-efficient designs are necessary. Achieving real-time response in an industrial environment with multiple disturbances is a must for IIoT. The channel congestion and resource allocation problems caused by using many wireless devices in the limited spectrum are also difficulties in industrial Internet design. Data security and privacy issues are also some elements that must be considered in the design. 6G is considered one of the effective solutions to the difficulties of the Industrial Internet of Things, but it is still in the research stage [91,92].

The Internet of Everything (IoE) concept is built based on IoT, which connects people, data, processes, and things rather than just focusing on things [86]. This concept was first proposed by CISCO in 2012. IoE focuses more on intelligent network connections and technologies, while IoT focuses on physical devices and network infrastructure [93]. IoE has received more attention in Industry 5.0 because the core of Industry 5.0 is people, and IoE pays more attention to the connection between people and things. The connection that IoE focuses on is realised through HMI. Therefore, IoE and HMI are inseparable from each other.

The core of IoE is the process [86]. The entire system can become a whole through the flow of people, things, and data. It can analyse and extract the collected information in real-time and provide more precise assistance and improvement without IoT's environmental interference [87]. The development of IoE faces challenges similar to those of IoT. However, the difference is that since IoE also connects people, it requires people to have a consensus on the entire system. This is the basis for realising IoE.

3.3.2. Cloud computing and edge computing

The United States National Institute for Standards and Technology (NIST) defines Cloud Computing (CC) as "a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction" [94]. This technology is not new. Since 2000, commercial CC services have appeared on the market [95]. This technology enables remote management and sensor miniaturisation and is an indispensable part of HMI in smart factories. After years of development, it has become a mature product and has been applied in the industry to a certain extent. CC models are mainly divided into four categories [19,95,96]:

• Software as a Service (SaaS): Service providers provide software and applications to users.

• Platform as a service (PaaS): The service provider provides a platform on which users can use their own software and the provided computing power.

• Infrastructure as a Service (IaaS): Users can control all the rented software and hardware anytime and anywhere.

• Container as a Service (CaaS): Similar to PaaS, the applications developed by users are independent of the platform.

Customers can choose suitable model(s) for use according to different needs. However, although CC already has mature models, it still has one of the biggest problems: data security. The statistic [96] shows that in the CC field, cloud security has seven main problems:

- Data model IaaS concerns
- Data synchronisation issues
- Secured communication between two parties
- Data confidentiality and availability
- Data storage security concerns
- Data intrusion threats
- Data tampering and leakage

Among them, data tampering and leakage problems concern customers the most [90]. Some cloud service providers have recently introduced blockchain technology into the cloud service system to reduce the probability of hacker attacks [97,98]. But this inevitably leads to another problem: the timeliness of data. To reduce latency, many manufacturers need to redesign sensor systems within the factory to ensure the lowest physical latency [96]. Even so, for some tasks with very high timeliness requirements, CC still cannot meet their needs. Therefore, EC was introduced to solve the data tampering and leakage problem.

EC is the opposite of CC. Its main goal is to disperse computing to the network's edge, thereby solving the delay problem caused by transmission [74]. This method can reduce latency and data channel load, effectively reduce energy consumption and ensure data security [4]. EC is usually located between the cloud and end devices and consists of five parts [74,99,100]:

- Authentication and Authorisation: Determine system control rules.
- Offloading Management: Design the offloading scheme and define the information type.
- Location Services: Map physical locations.
- System Monitor: Provide information such as workload and usage to other parts.
- Resource Management: Responsible for resource allocation.
- VM Scheduling: Design the optimal strategy.

EC has the characteristics of wide distribution, relatively small capacity, low energy consumption, low cost, and low delay, which are determined by its nature [101]. EC has been widely used in smart grids, smart cities, smart homes and other fields [74]. In IoT, EC also plays a very important role. For example, facial recognition and motion detection algorithms can be implemented through EC [68,96]. Although EC avoids leakage during data transmission, it still has data security problems. This is because devices at the edge often do not have sufficient capabilities to perform complete security verification [74,102]. Therefore, both physical and virtual measures must be used to ensure information security.

3.3.3. Machine learning and deep learning

The analysis of big data in the industry is inseparable from machine learning and deep learning algorithms. This is because the data in the manufacturing scenario is large and has many characteristics that correlate with each other [19]. They are also the cornerstone of data analysis in CC and EC. The application of conventional machine learning algorithms in areas such as predictive maintenance is not new [103]. Deep learning has also begun to be applied in manufacturing scenarios in recent years. However, due to its "black box" (the specific operations and processes performed in the model cannot be described) characteristics, it cannot fully meet the industry's safety and controllability requirements. As a result, the use of deep learning in many industrial scenarios is limited [5,104].

Machine learning can be divided into three categories: unsupervised learning (discovering information from data), supervised learning (given data, predicting the label of the data), and reinforcement learning (given data, choosing actions to maximise long-term reward). Research on reinforcement learning has received much attention because it can continuously optimise the model and give more accurate results. Commonly used unsupervised learning algorithms in industry include SVM/SVR, Bayesian Networks, Naive Bayesian Networks, K-nearest Neighbours, Artificial Neural Networks, Multiple Linear Regression, Decision Tree/ Regression Tree, Addictive Models, Logistic Regression, Bag of Words, Locally Weighted Training. Supervised learning algorithms include Kmeans and Self Organising Maps, and reinforcement learning algorithms include PILCO and SMART [104].

Generally, deep learning is divided into unsupervised and supervised learning as a subcategory of machine learning. Commonly used supervised learning algorithms in the industry include Convolutional Neural Networks, Recurrent Neural Networks, Restricted Boltzmann Machines, Multiple Linear Perceptron, and YOLOv2. Unsupervised learning algorithms include Auto Encoders, Convolutional Neural Networks, Recurrent Neural Networks, Restricted Boltzmann Machines, and CAMP-BD [104,105]. Deep learning has been used in image recognition, anomaly detection, natural language processing, and high-dimensional data processing. Compared to machine learning, deep learning is often used on large amounts of data. Applying deep learning to small data sets can result in high variance and low accuracy. Deep learning has imposed higher requirements on hardware, and at the same time, the computational cost is relatively higher.

In recent years, with the continuous improvement of machine learning and deep learning algorithms, the manufacturing industry has seen an increasing application of them. Machine learning and deep learning in manufacturing have three main development directions: task, technology, and industry-centred [106]. Task-centred machine learning research focuses on using algorithms to solve specific tasks, such as defect detection in additive manufacturing [107], process improvement [108], and optimising production processes [109]. Technology-centred research focuses on specific technologies that integrate machine learning algorithms, such as processing monitoring systems [110], using soft computing to improve processing performance [111], and using image recognition to monitor production processes [112]. In addition, the transformation of industrial data to big data is also a research focus in this direction [113]. Industry-centred research focuses on how machine learning affects manufacturing development from various perspectives, such as Industry 4.0, Industry 5.0, and smart manufacturing. New technologies such as augmented reality, data mining, the Internet of Things, intelligent supply chain management, cyber–physical systems, intelligent robots, smart factories, virtual manufacturing, and cloud systems are inseparable from the development of machine learning [114]. In addition, deep reinforcement learning, deep learning combined with big data digital transformation, and industrial artificial intelligence are also research focuses that have received much attention [115]. Deep reinforcement learning has the principle of trial and error and can continuously optimise itself in interacting with the environment. Therefore, it has self-adaptation advantages, strong flexibility, and high time efficiency, which can better meet smart manufacturing requirements [116]. The application of this technology in the manufacturing industry is still lacking in sufficient research [117]. The deep integration of deep learning and big data technology provides new technical support for the digital transformation of factories. Deep learning ensures factories can make more intelligent and sustainable decisions and deployments during digital transformation [118]. Industrial artificial intelligence will become the brain of future smart factories, making decisions on the deployment and arrangement of factories [115].

In future smart manufacturing scenarios, a major change is expected to occur. Human and environment-related data will become one of the focus areas of data analysis to optimise the HMI experience. These two types of data are areas where deep learning is suitable. Their requirements for timeliness are not so high, so even in an environment with low computing power and high latency, deep learning can be used to offer a suitable response. In addition, deep learning has shown great potential in human-related fields such as social media and medical practice, so it has become promising as an effective tool for assisting people in industrial contexts. To meet the needs of individualisation in the future, factories need to adopt algorithms with self-optimisation effects to improve the factory's ability to manufacture different products.

3.4. Data transmission mechanism

Data transmission sends and receives data and signals between sensors and data processing centres. The data transmission mechanism in the manufacturing field can be divided into wired "Industrial Ethernet" and wireless WSN according to the connection method [19]. In addition, according to different wireless spectrums, the transmission mechanism can also be divided into 5G, 6G, etc. [91]. Different mechanisms have different properties and are suitable for different industrial environments. In an industrial environment, the security issue during data transmission in HMI is one of the most important issues [74,96–98,102]. In WSN, many studies have pointed out security issues due to wireless transmission [119–121]. In addition, because industrial scenarios are often complex and have multiple interfering signals, the use of WSNs is also limited [19]. "Industrial Ethernet" is currently the world's most successful and widely used wired communication architecture [103]. After years of development, Industrial Ethernet has the advantages of fast transmission speed, high adjustability of network scale, and convenient parallel connection with other networks. But it also has disadvantages. These data transfer devices were not designed for the harsh environment of a factory, so the extra expense was spent on protective enclosures and add-on equipment to keep them functioning properly. Second, it has an inherent non-deterministic nature, which makes it unable to meet the time requirements of some industrial equipment and models [122].

WSN will be one of the most important enabling technologies in Industry 5.0 because it can better meet the sustainability and human-centric demands of Industry 5.0. In addition, 6G will also help WSN to accomplish these goals better as it can efficiently improve the data transmission speed and coverage. Therefore, this section will mainly introduce these two technologies, the challenges they face and the opportunities they bring.

3.4.1. Wireless sensor network

WSN refers to a series of sensor nodes dispersed in space and connected by wireless transmission [123]. These sensor nodes measure fluctuations in the surrounding environment, process the information, and send it to designated devices [124]. Through the cooperation of multiple sensors, WSNs can monitor a wide range of counterattacks. In recent years, with the continuous development of technology, these wireless sensors have achieved characteristics such as miniaturisation, low cost, and high sensitivity, so they have expanded from the military field to industrial, medical, maritime exploration, environmental monitoring and other fields [125].

WSN consists of four parts: WSN hardware, WSN communication stack, WSN Middleware, and Secure Data aggregation [75]. WSN hardware includes a power supply, transceiver, processor, and sensor interface. These hardware generally consist of multiple A/D converters that can communicate in the same frequency band, ensuring the network's versatility. The WSN communication stack utilises topology, routing and MAC layer to realise the connection between the WSN subnet and the Internet. WSN Middleware is a platform-independent middleware used to isolate and access resources between different sensors. The main goal of Secure Data aggregation is to ensure the system's security and provide self-healing capabilities.

The basic feature of WSN is intra-network transmission, which does not transmit original data but integrates them instead [126]. In recent decades, WSN has played an important role in supply chain management, manufacturing process control and automation [127,128]. By integrating WSN and existing networks, smart factories reduce the labour force, improve automation levels, and increase revenue [120]. WSN is also widely used in wearable sensors, which promotes the development of HMI [2]. Whether it is a wearable device based on VR or a smart glove that remotely controls a robot, WSN is indispensable [26,32,64]. However, as mentioned above, there are still some difficulties and challenges in applying WSNs. The biggest concerns are those about data and security [120]. With the explosive growth of the total amount of data in the industry, it is difficult for factories to manage such a large amount of data in a timely manner [129]. Difficulties with system updates also contribute to the problem. Because these devices are often distributed across various factory parts, the amount of work and disruption needed to upgrade the equipment is dramatic. This leads to a relatively weak anti-attack negligence of the whole system. Sensors deployed in some vulnerable environments become weak points of the overall system. Also, the risk of being attacked is aggravated because the supply chain system is often connected to the external network or cloud system [130]. Finally, the limited resources of WSN make it unable to respond to changes in external conditions effectively. This resource limitation is reflected in two aspects. The energy limitation makes the sensor unable to switch between working and sleeping modes flexibly, and the Internet integration is not high enough due to the restricted movement [131]. Researchers hope to solve the current problems of WSNs by deploying 6G in the future. Therefore, developing WSN devices with sufficient computing power, low energy consumption and low cost in 6G is also a major challenge in Industry 5.0.

3.4.2. 5G/6G

5G has become one of the most popular technologies in recent years. It extends the connection between people to people and things so that popularising a series of technologies requiring high data transmission speed, including unmanned vehicles, smart medical care, autonomous manufacturing, and remote operations, is no longer restricted [132]. Compared with 4G, 5G has been significantly improved in many aspects. However, it still has shortcomings such as power consumption, secure connection, latency, dense connection, and global coverage. Therefore, academia and industry have begun to focus on 6G research. The main goal of 5G is to realise the "Internet of Everything" (IoE). And 6G hopes to achieve intelligent IoE by integrating AI technology. The biggest difference between 6G and 5G technology is that 6G not only includes communication technology. 6G will combine communication and sensing technologies to enable a series of functions, such as positioning, sensing, and communication, to be realised through it [133]. [91] summaries the future development of 6G as a six-F trend: full spectrum, full coverage, full dimension, full convergence, full photonics, and full intelligence. Another research [133] described the goal of 6G as "global coverage, all spectrum, full applications, all senses, all digital, and strong security".

6G expects to achieve global coverage communication services by integrating various communication networks (e.g. unmanned aerial vehicle (UAV) communication, ground ultra-dense communication network, maritime communication, satellite communication, and underground communication). This service will incorporate remote areas and special scenarios into the communication system [132]. Full spectrum can not only solve the problem of band spectrum congestion caused by the explosive growth of the number of devices but also provide higher data transmission rates. Sub-6 GHz, centimetre wave (cmWave), mmWave, THz [134], and optical wireless bands [135] will all be used in 6G [133]. 6G's ultra-short-distance communication, wireless data centre, and nano-Internet cannot be realised without the support of THz's ultra-high bandwidth and ultra-fast transmission rate. Optical wireless bands have the characteristics of energy saving, high security, no electromagnetic radiation, and no frequency band, etc., and can play a huge role in 6G. Full applications aim to combine 6G and robotics, AI, big data and other technologies to realise intelligent applications such as smart cities and IoE and provide human beings with personalised and diversified services. The development of all senses focuses on combining 6G with wearable devices and VR, integrating go-you and display, and providing people with a full range of sensory experiences. This will effectively promote the development of remote surgery, skills training and other fields [136]. All digital will further improve the real-time and accuracy of digital twin technology through 6G to realise the deep integration of physical and virtual. Communication security is a hot spot in 6G research. Current research attempts to combine security technologies such as quantum communication [137], blockchain [138], and 6G to ensure data security during data transmission. Many standardisation organisations, such as IEEE and ITUT, have proposed 6G system security architecture and process standards [139].

In HCSM, 6G will be one of the most important enabling technologies. It can bring ultra-low latency and ultra-high-speed data transmission services to smart factories, providing wider coverage and more diversified and customised services [92]. The user experience can thus be improved during the HMI process. The tactile internet is considered an important future application [140]. In industrial settings, telerobotics will act as human avatars. The user's tactile feedback will be transmitted to the robot in real-time through the network, and the robot will be controlled to complete various dangerous tasks. Wireless brain–computer interface, immersive XR, and holographic communication are all inseparable from the superb transmission capabilities of 6G [133,141]. These hardware and technologies form the basis of HMI, and interaction and collaboration behaviours can be completed. The next section will focus on topics that attract researchers' attention in interaction and collaboration.

3.5. Interaction and collaboration

In the research of the HMI field, human–machine function and task allocation, trust and workload allocation are three major issues researchers focus on. Moreover, these issues are expected to continue to receive attention as the degree and scope of automation increase.

3.5.1. human–machine function and task allocation

The distribution of functions and tasks between humans and machines has received continuous attention in human–machine interaction [10]. For example, one of the goals of introducing an automated system is to reduce the workload of humans by using machines to complete or assist with some tasks. However, in different HMI designs, the setting of function allocation is different because researchers have different understandings of the functions that humans and machines are good at. The functions in a smart factory consist of four parts: operation and supervision, management, maintenance services, and cybersecurity [2]. The realisation of these functions is mainly through workers performing corresponding tasks. To achieve operation and supervision functions, workers must utilise HMI to monitor machines and processes, control production parameters, identify and assemble parts, and schedule machines. The tasks involved in the management function include administration, workforce and operation scheduling, and production planning. Maintenance services involve fault detection, repair, quality inspection, and simulation. Tasks involved in network security include data retrieval, authentication, security assessment, and network configuration. As automation increases, some functions and corresponding tasks have been replaced by machines, while some still require human participation. Therefore, in a dynamic production environment, workers should not only focus on the tasks they are currently performing but also understand the functions they want to achieve and the shortcomings of the machine. Humans are generally considered better suited for tasks like creativity and decision-making, while machines are better suited for repetitive tasks [142]. However, this does not mean that all repetitive tasks can be completely separated from operator monitoring. Therefore, the operator can misunderstand what task has been replaced by the machine and what task he should focus on.

A good example is the "irony of automation": Introducing automation equipment into the system changes human behaviour [11]. The goal of introducing automation is to help or even replace humans for some work tasks so that humans can focus more on others — and/or free up resources along the way. Still, these automation devices can also reduce people's concentration in these non-automated tasks and lead to impoverished cognitive processing of information, which impacts cognitive factors such as memory and problem-solving. Studies of driver assistance systems have shown that drivers become less attentive to tasks such as steering, which the system assists, and lose situational awareness [10,143].

The distribution of functions and tasks in HCSM factories will face two major problems. First, the mental load on workers will increase significantly as the professional level of factory equipment increases. The introduction of automation has effectively reduced the physical burden on workers, but the consequence is that a large amount of information is collected. Workers need to process the collected data and information to make correct decisions. Although AI and big data analysis can help people process this data because people are the core and decision-making layer of the factory, the mental load on operators is still heavy. In addition, the growth of non-professional users is also a problem that cannot be ignored. It is unrealistic to expect workers to understand the function of every part of the factory. Workers may not understand the mechanics of the equipment they operate. Good guidance is necessary to assist workers in completing their tasks. Therefore, HMI design in Industry 5.0 should include two considerations: to help professionals reduce their burden and to help non-professionals understand the tasks.

3.5.2. Incorrect use, trust and confusion

Incorrect use, trust and confusion are three topics often discussed together [10]. There are four different kinds of use in HMI: 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") [14,19]. Different initial trust levels in the system will lead to different users' use of the device, and the consequences of incorrect use may further affect users' trust in the system. Incorrect use will not only affect human–machine collaboration, reduce efficiency, and cause safety issues but also lead to loss of workers' trust in machines.

Confusion is mainly produced by system complexity [10]. As the factory develops towards customisation and integration, the system needs multiple modes to meet different needs. The manufacturing environment often involves a dynamic set of systems, and as time changes, its operating mode will also change. Different operating modes often appear to deal with different situations. But this can potentially cause mode confusion on the operator's part. Research on autonomous driving has found that confusion may arise for three reasons. Unexpected situations such as sudden snowfall and overtaking vehicles can cause the car's mode to change before the user has enough reaction time to respond to the new mode. However, users often must respond quickly when the unexpected happens [144]. In addition, the vehicle's functions will change as the environment changes. Certain weather and environments may limit the functionality of some sensors, making it dangerous if the operator's attention is not on driving [15]. This situation is more common in manufacturing environments. Since the factory's equipment status and production conditions are constantly changing, it can be said that most of the time, the functions of the factory are changing [19]. "Irony of automation" is the third reason users pay less attention to mode changes. The introduction of automation will reduce operators' attention to the system, preventing them from detecting changes in the system. In future factories, automated equipment will be used in more complex situations, so multiple operating modes are necessary [11]. Research on modelling and analysis of mode confusion in different manufacturing environments will be one of the most efficient methods of evaluating and improving this problem. An early study found that power plants have high requirements for equipment maintenance, so some equipment will always be in maintenance status. In such an environment, workers can easily become confused about alarms caused by accidents and maintenance [144].

Overall, ensuring that users have sufficient trust in the system is one of the main ways to encourage effective and sustained use and prevent misuse and possible disuse. A bigger problem is that because many technologies and products are developed without user trust, these devices may not have established trust models, and it is very difficult to build models for them. Researchers should not only consider establishing operators' trust in equipment and appropriate evaluation models to accurately assess the degree of trust and prevent the occurrence of excessive trust but also focus on restoring and maintaining trust after an accident. The prevention of confusion should focus on the establishment of an early warning system. This is also inseparable from establishing analytical models for specific environments.

3.5.3. Workload allocation

Several papers within the review were focused on workload and how it can be optimally distributed to achieve tasks at hand better [10,19,145–150]. In general, workload distribution aims to prevent underload and overload so that users are optimally engaged in tasks with enough cognitive resources to perform them effectively. Many studies reviewed often also focus on focus and/or divided attention, as well as attention management, and these will also be discussed below [10].

One purpose of automation is to free up workload (resources) so that people do not have to perform as many repetitive tasks and instead can focus on other tasks where human involvement is more valuable. However, this does not mean that these automated tasks do not require human intervention — and hence workload. When failures or abnormal conditions occur, workers must still participate in these tasks to supervise. Numerous studies have found that workers in automated control environments are less sensitive to alarms [10,19,145]. To this end, a study has used early warning to prepare workers for emergencies in advance [146]. In addition, the researchers proposed six solutions to keep workers focused: avoiding the role of human supervision of automation, reducing the role along an objective dimension (reduce automation tasks and devices), reducing the role along a subjective dimension (add human tasks), support the role from the behaviour paradigm (more training), support the role from the dyadic cognitivism paradigm (align content, structure and functions of computerised systems with human minds), support the role from the triadic ecological paradigm (emphasise the importance of direct perception and informed considerations of adaptation to specific work domains) [147].

Years of research have found that supervising automated processes is not where humans excel. Human errors still occur when people supervise automated equipment that is designed to prevent or at least minimise operational errors. Therefore, it is necessary to reasonably evaluate whether a certain function is suitable for introducing automation. The introduction of automatic flying systems in aircraft sometimes fails to improve safety and, in some cases, causes the pilot to be away from tasks for a long period, and this can keep them out of the loop and lead to errors and potential accidents in some (albeit very few) cases accidents [147]. Research in this field is also called "stay tuned". Other researchers have found that although long-term supervision is difficult for operators to achieve (due to vigilance limitations), requiring operators to perform a short operation over a short period can significantly reduce the occurrence of errors [148].

Periodic proactive engagement maintains operator engagement and response times better than reactive handling when an incident occurs. For the system, sometimes the operator can be made more involved in the system by increasing the operator's workload, although this seems counter-intuitive. One study found that autonomous driving systems can attract the driver's attention by showing a lack of ability or even deliberately making wrong judgements [149]. A major focus in future operator training should be creating immersive applications that can motivate operators to operate correctly. Some VR operation training equipment is designed based on increased engagement. During training, workers build a better understanding and trust in the system and develop their interest in work. To ensure that computerised systems are consistent with human thinking, it is necessary to explore workers' mental models and follow the user-centred cognitive interface design concept in the design of HMI. The part of the system displayed to the user must meet the four key points: the process is understandable, the results are understandable, consistent with user goals, and meets user reliability expectations [150].

Finally, external environmental context and task considerations should not be ignored in the design of HMI. The operators always perceive the external environment, which directly affects their behaviour. While considering people's psychological state, constructing a suitable external environment and setting appropriately challenging tasks can improve operators' feelings and ability to cope with the workload.

In HCSM, research needs to focus more on how to make worker and machine work partners (and to optimise this) rather than being studied separately as two individuals. The changes brought about by the development of AI to HMI may be inflammatory. These AI-based interactive systems can improve people's communication experience in a humanised way and stimulate recognised creativity and thinking ability in more creative tasks like an assistant, improving workers' comfort and satisfaction. This may be one of the best ways to solve these HMI problems.

In a manufacturing environment, sensors are the first hardware devices to interact when humans and machines interact. They collect signals and information, convert them into data, and pass them to the data centre for analysis. Various sensors based on different mechanisms and with different performances build the foundation for big data analysis. The application of CC and EC in different scenarios allows factories to solve the problem of insufficient data processing and/or transmission capabilities to a certain extent, thereby helping factories realise IoT/IoE. Machine learning and deep learning algorithms have become important means for factory data analysis. In the future, with the popularisation of 6G, WSNs and networks in factories will have stronger anti-interference capabilities and data transmission capabilities, improving the factory's data analysis and collection capabilities and data security. Finally, as the concept of human-centric gradually becomes popular, more and more products and equipment will consider human factors during production and design, which will play an important role in the construction of HMI analysis in these scenarios in the future. In Industry 5.0, machines and humans should cooperate and coexist, trust each other, allocate tasks reasonably, and achieve the goal of improving human well-being.

4. Towards human-centric smart manufacturing: Challenges and opportunities

The previous section reviewed some important research and enabling technologies in the field of HMI, thereby providing some basic understanding for analysing how they will realise the Industry 5.0 vision. This section will focus on the challenges faced when realising the vision of Industry 5.0 and the opportunities that Industry 5.0 brings to future manufacturing.

4.1. Challenges

4.1.1. Non-deployed technology and costs

Applying new technologies to HMI in real manufacturing scenarios can be challenging. Although some developing technologies such as ChatGPT and AI-based voice recognition assistants have been widely used in people's daily lives, technologies such as brain–computer interface and 6G are still mainly based on laboratory research. The development and application of these technologies mainly have three constraints. To design a suitable HMI product/system, factors such as material selection, ergonomic design, equipment performance, etc., must be considered in terms of hardware. At the theoretical level, it is also necessary to consider how humans and machines collaborate, how work is distributed, how to ensure workers' trust in machines, and how to evaluate and monitor these indicators quantitatively. The complexity brought to HMI system design involving multiple disciplines and fields is a major restriction for HMI technology to be applied in actual scenarios [10].

In addition, cost is also a major factor restricting the development of these technologies. Big companies with high-profit margins, such as Intel, Nvidia, Tesla, etc., are the main drivers of HMI research in manufacturing [16]. However, those companies with low-profit margins need more incentives and strength to invest in this area, even if these studies can bring huge benefits to the company in the long run. Manufacturers with low-profit margins often find implementing measures and equipment with long payback periods difficult because their capital pools are not generous. Therefore, Industry 5.0 should focus on how to reduce the cost of HMI technology and deployment.

Sustainability has been discussed since the age of Industry 4.0. But it has now turned into an urgent need. The realisation of sustainability cannot be achieved without applying new technologies. In recent years, incidents and events such as the COVID-19 pandemic and the Russia-Ukraine war have exposed the fragility of existing international supply systems. Global warming is also making sustainability an urgent need in industry. Countries have passed bills to stop using highly polluting gasoline cars in the next two decades [8,9,19]. To implement the concept of sustainability in HMI in the industry, factories must adopt greener equipment and sensors from the technical level and improve workers' understanding of this concept. Improving the explainability of the system will not only prevent the emergence of unnecessary processes but also encourage workers to implement appropriate behaviours to improve the sustainability of the factory [130,131].

4.1.2. The application of human-centric concept: from efficiency and profit to human-centric

Although Industry 5.0 have proposed the human-centric concept, it is difficult to expect enterprises to focus more on human than their profit-pursuing nature. As discussed in previous sections, improving factory output through people's well-being is a long-term goal. Most small and medium-sized enterprises lack the corresponding funds and sometimes the motivation to undertake related investment and industrial upgrading. An important point of contradiction is that low-end manufacturers are where people's well-being is neglected the most. Still, they lack the corresponding funds to improve the system in this area because their demand for innovation is relatively low. Therefore, implementing Industry 5.0 not only depends on enterprises but also needs help from the government and policy.

In addition, for factories, the human-centric concept should be implemented at the beginning of design to fully understand and meet human needs. In a human-centred factory, everything should be about serving people. Devices and systems based on AI should continuously enhance their collaboration and empathy capabilities based on real-time data and help workers maintain a good physical and mental state at all times.

A comprehensive HCSM factory should include human-centric process planning, workshop scheduling, processing and assembly [151].

Human-centric process planning requires factories to consider workers' needs when coordinating production processes. Some researchers have explored the differences in decision models under different design philosophies (e.g. [152,153]). Human-centric workshop scheduling focuses on putting the interests of operators and consumers in the first place in production in the workshop. AI can help factories complete intelligent workshop scheduling, thereby assisting operators and improving efficiency [154]. Human-centric processing focuses on recognised safety and health. Remote operations and more human-friendly smart assistants are technologies already used in some smart factories [7,26,32,64]. Human-centric assembly is mainly based on the following considerations. First, humans still dominate the assembly process. Second, assembly work is repetitive. Therefore, this part mainly aims to use automated equipment to replace repetitive tasks and fully stimulate the operator's cognition and flexible innovation capabilities.

Besides, research in the HMI field in the industry has yet to focus on human-related data. Human-related data is expected to be central in HCSM, as it is one of the indispensable data to help HMI devices understand people. Collecting and analysing these data allows the machine to provide humanised and personalised assistance to the operator. This makes the IoE that the industry has always imagined cannot be well implemented. More effort must be put into human-related data in deploying and applying sensors, which also puts forward new requirements for developing technology and research [9].

4.1.3. Training of employees

Training employees is also a big challenge that needs to be optimised to reap HCSM's rewards fully. These training efforts should train workers to understand the equipment and teach them how to use it as a supporting feature of their work lives [10].

In some previous sub-sections, we explored the growth of non-professional users and the emergence of professional users as the core of manufacturing. It needs to be clear that with the increase in integration and complexity of manufacturing systems, even professional users need help understanding the entire system. In today's fast-paced technological iteration, operators in manufacturing scenarios have both the attributes of professional users and the attributes of non-professional users. Therefore, a major difficulty in worker training is that different workers have different knowledge backgrounds, and it is difficult to achieve the desired effect only by centralised training [155].

Therefore, personalised training based on big data and AI is necessary. This personalised training should focus on helping workers understand the system rather than on subtle technical difficulties. At its core, HCSM is about helping workers unleash their creativity and flexibility while safeguarding their well-being. Training that sticks to the HCSM core can help workers better understand factory systems and make the best decisions.

4.1.4. Data and personnel security

Security is also a major issue that factories will pay attention to. Security can be divided into two issues: data security and personnel security. Data security not only depends on confidentiality technology but also on workers' awareness of protection. In the HMI process, how to transmit this concept to workers will be a more permanent and effective way to improve. The safety of workers is inseparable from the addition of humanised design, such as the empathy ability of the interactive system. These designs improve worker comfort and give them a greater awareness of hazards.

In recent years, blockchain technology has also been applied to data encryption in the IoT field due to its confidentiality. Blockchain has the characteristics of traceability, anti-tampering, and decentralisation, so it has received much attention in ensuring information security in industrial IoT [91,92]. However, this technology still faces three major problems [151]:

- The blockchain model relies on the IoT architecture, and its ability to deal with problems alone is weak, and its ability to deal with physical attacks is weak.
- The current technology is immature, and there still needs to be more research on how to evaluate the security and privacy of the network.
- How to promote the integration of people and systems and how to protect the privacy and security of people still needs to be solved.

In addition to ensuring physical safety, factories should also ensure workers' psychological safety and privacy. The manufacturing industry has relatively mature processes and measures to protect workers' health and life safety. Considering psychological conditions and privacy protection will receive more attention in Industry 5.0. Since human-related data will become an important part of HCSM data, these data are closely related to workers' psychological state and privacy. Due to their natural attributes, technologies such as brain–computer interface and myoelectric-based myoelectric interaction must consider how not to infringe on human privacy when designing. The goal of Industry 5.0 is to enable humans and machines to work closely together rather than manipulating workers through HMIs. Therefore, how to protect workers' mental health without abusing these data and models will be a problem that needs to be addressed in future research.

4.1.5. Real-world HMI implementation

To ensure that HMI systems can be deployed in the real world, some principles and factors must be considered during the design process of HMI systems. As research continues to deepen, people have established different design principles for HMI systems [156]. The frameworks of Shneiderman [157], Wickens, Lee, Liu, and Becker [158] et al. believe that user experience, needs, and capabilities should be the core of the design. The principles summarised by Shneiderman include system consistency (using consistent instructions), providing feedback on input (sending status information when the system has a request), designing a closed loop of dialogue (task completion prompts), providing simple error prompts (avoiding multiple clicks), and reducing cognitive memory load (avoiding complex menus). Wickens et al. are more concerned with human cognitive abilities and limitations and therefore regard perception (clear interactive interface), attention (reducing the difficulty of obtaining information), memory (simplifying the steps to obtain important information), mental models (ensuring that icons and logic are easy to understand), and situational awareness (the ability to predict the future and remind of key past events) as general HMI design principles [158]. Cuevas [159] proposed a four-factor criterion: ethnographic/anthropomorphic traits, cognitive factors, predictive modelling, and empirical testing. This criterion states that HMI systems must be evaluated from these four perspectives to meet practical application requirements.

During the design process, we believe an HMI system must be verified to meet the requirements from the perspectives of adaptability, accessibility, usability and functionality. Adaptability is the ability of the HMI system to adapt to changes in the environment, tasks and personnel. A good HMI system should be customised according to user needs and the external environment to ensure user experience. Accessibility refers to whether the HMI system is easy to use. In particular, when users have special needs or physical disabilities, the HMI system should ensure they can still access it. Usability refers to the efficiency and ease of use of the HMI. A good HMI system should be easy to understand and reduce the user's learning cost and error probability. Functionality means that when designing the HMI, the system should ensure the required functions are available to prevent functional deficiencies.

4.2. Opportunities

Although implementing Industry 5.0 faces many challenges, it will also bring new opportunities to the HMI system in the manufacturing scenario. Next, three emerging technologies will be introduced. They are expected to drive the development of HMI in Industry 5.0.

4.2.1. Digital twins and industrial metaverse

Digital twin (DT) is a technology that digitises physical devices and processes to enable remote manipulation, prediction, optimisation, simulation, and control of manufacturing processes [160]. It is a discipline that is still developing. Early DT models included three dimensions: physical, virtual, and connected. In this model, models in the virtual space are mapped to the physical world through data transmission [161]. Fei Tao et al. proposed a five-dimensional model that includes virtual models, physical entities, connections, digital twin data, and services [162]. The theory of DT includes four parts: modelling and simulation, data fusion, interaction and collaboration, and services. According to the five-dimensional model theory, DT modelling includes physical modelling (extracting physical features), virtual modelling (building virtual models), connection modelling (building connections between models), data modelling (storing and processing data), and service modelling (identifying and analysing services). Data fusion involves data preprocessing, mining, and optimisation. It helps to build and connect models. Interaction and collaboration include physical–physical, physical–virtual, and virtual–virtual interactions. Physical–physical interaction allows multiple devices to work together. Physical–virtual interaction can connect remote models and entities to achieve manipulation. Virtual–virtual interaction can share data within the network to achieve remote collaboration. Services include business encapsulation, service optimisation and matching, quality assessment, etc., which can help DT provide the best service to customers. DT is used in product design, production process monitoring and health management [160].

The Industrial Metaverse has continued to develop in the manufacturing industry in recent years. It is a concept very similar to Digital twins. Digital twins start from the virtualised design and development of complex products, while the industrial metaverse originated from the game industry and gradually developed into the industrial world. Digital twins are first oriented towards technology, while the Industrial Metaverse focuses more on people [163]. The Industrial Metaverse aims to merge the physical and digital worlds. It builds an online virtual factory parallel to the real factory so that all relevant researchers can work together in the same scenario [164]. In this virtual factory, users can simulate real work scenarios to train, design, test and operate real-world equipment [165]. The Industrial Metaverse focuses on building a complete 3D environment, allowing workers to use and analyse data from the spatial dimension to solve previously unsolvable problems. In the industrial virtual world, when technical experts join an invitation link to a remote factory, they can use wearable devices to see the manufacturing scene visually.

The Industrial Metaverse can bring many benefits to manufacturers. First, it can be optimised and designed through simulation, reducing actual production costs and trial and error costs [166]. In addition, it can also improve the production efficiency of manufacturing companies, allow employees to become familiar with operations through virtual training, and reduce failures in actual operations. The industrial metaverse can promote company innovation. Rapid design, testing, and development of new products through virtual environments can help companies form competitive advantages [167]. The Industrial Metaverse can also help companies become more sustainable. It can maximise resource utilisation while meeting individual needs through intelligent, planned production, procurement, quality and inventory management [163,166,167].

4.2.2. Worker safety, health monitoring and ergonomics design

Sensors and monitoring systems in Industry 5.0 will focus not only on processes but also on the status of workers. Research on worker fatigue in manufacturing environments is not new [168–170]. However, because people's definition of fatigue is relatively subjective, and related analysis requires collecting some data that may involve privacy, large-scale applications of this model have not yet been seen in actual production. With the collection and research of human-related data, future smart factories will have personalised safety and health detection systems for each worker to ensure the well-being of workers [171]. The expected goal is that in the future, big data analytics can be used to create personalised profiles based on workers' different indicators, thereby improving worker well-being from an ergonomic, medical and psychological perspective. Since every worker's situation differs, using universal data to meet their needs is unrealistic. Only a personalised, customised system can meet the needs of each worker.

Ergonomics will also be a big focus in Industry 5.0. Monitoring systems can only provide us with early warnings and indications, while ergonomics will improve conditions that may arise for workers [172]. In the future, in Industry 5.0, a large number of ergonomic equipment will be designed using human-centric methodology [173]. These devices can reduce the cognitive load on workers, reduce the probability of errors, and increase productivity. In addition to this, these devices prevent the occurrence of many occupational diseases and health problems. These devices will also serve as a monitoring system to safeguard workers' well-being.

4.2.3. Brain-Computer Interface (BCI)

Brain–computer interface technology will be an extremely important key technology that will promote social development in the future. This system can connect the human brain and the external environment, allowing users to control devices through brain signals [174]. Researchers have always favoured this field. The system can be classified as passive or active depending on how the brain is used. Passive BCI analyses the brain's unconscious signals and emotions, while active BCI involves the user's voluntary brain movements. Passive BCI can be used in fault and fatigue detection. For example, an early warning is given when a person is exhausted [175]. Active BCI can help users complete interactions with devices.

BCI has broad application prospects. However, most current research on BCI still focuses on the medical aspect [174]. It replaces the central nervous system and controls prosthetic limbs [176]. BCIs are used in some clinical settings to assess and diagnose patients for various diseases [177]. In the industrial field, BCI can effectively promote human–machine collaboration and help humans and robots understand each other's intentions. One study used eye blinks as a signal input to complete loading and unloading work through BCI-controlled robots [1]. In the future, as the number of psychological states and input signals that BCI can classify increases, it can be used to control robots to complete more complex tasks. This can significantly reduce the physiological load on workers and prevent possible accidents. The deployment and development of BCI will greatly promote realising the Industry 5.0 vision.

4.2.4. MES systems in Industry 5.0

The concept of the manufacturing execution system (MES) emerged in the 1990s. It builds a top-down system for managing workshops and enterprise resource planning to establish detailed operating plans for enterprises [178]. Through this system, enterprises can manage workshops in real time. In the past three decades, the industry has established 11 functions of MES systems: resource allocation and status management, job scheduling, product unit scheduling, document control, data collection and acquisition, labour management, quality management, process management, maintenance management, product tracking and performance analysis [179]. In the field of MES, there are currently some different solutions on the market. POMSNet Aquila, ABB MES, Siemens Opcenter, GE Digital's Proficy MES, 3DS's DELMIAworks and PLEX's MES/MOM are some of the popular MES solutions and software on the market [180]. These solutions and software have their characteristics in terms of functions and applicable scenarios. Many companies use a combination of different software to meet actual needs. However, the intelligence level of these existing commercial MES systems is not very high and cannot meet the requirements of enterprises for predictive capabilities [180].

There are three frontiers in the research of MES: combining AI and MES systems, DT and augmented reality [180]. By combining AI, MES systems can handle tasks in the system more efficiently, ensure the safety of the working environment, and meet productivity and quality goals [181]. DT can connect the intelligent layer of MES with the physical world to achieve real-time monitoring and management of the workshop [182]. Augmented reality can promote the collaboration and integration of people and MES systems. In Industry 5.0, people will still play an important role in the factory. In the MES system, augmented reality can visualise data to assist operators in better managing the MES system [183,184].

The development of MES systems will promote the realisation of Industry 5.0. It is an effective measure for smart factories to achieve sustainability and elasticity goals. MES systems combined with augmented reality will make the interaction between operators and systems more humane in the future, thereby making the relationship between people and systems closer. This system can ensure production and is an important guarantee for employee well-being. By incorporating employee well-being into production workflow management, factories can become people-centric.

5. Conclusions

This paper gives a systematic review of the development of HMI in the future HCSM and Industry 5.0 and the constraints that may be encountered by analysing and summarising the existing research and technology in the HMI field. According to the signal transfer process in the HMI, this article classifies and summarises these related studies in four parts: sensor, data processing, data transmission mechanism, interaction and collaboration. In the sensor field, the equipment involved in HMI is summarised from the perspectives of optical, acoustic, bionic, tactile and motion. The review on data processing mainly focuses on IoT and IoE, CC, EC, machine learning and deep learning. The data transmission mechanism discusses WSN and 5G/6G. In the interaction and collaboration part, this article focuses on three main issues in HMI field research: 1. human–machine function and task allocation, 2. incorrect use, trust and confusion, and 3. workload allocation.

Reviewing the current HMI Research in the field, this paper explores the challenges and opportunities that HMI may encounter in Industry 5.0. There are four challenges facing the realisation of the Industry 5.0 vision. The development maturity and deployment costs of technologies limit their practical application. The human-centric concept has not been placed in an important position in the design of products and processes. This has resulted in many equipment and links in the factory being naturally incapable of building HMI analysis models. Workers' current knowledge and skill levels cannot cope with the new equipment and processes of Industry 5.0. Security issues brought about by the personalisation of HMI analysis and increased data collected about people are also important challenges facing Industry 5.0.

Many new opportunities will emerge in Industry 5.0. This paper explores three opportunities related to manufacturing. The industrial metaverse will bring a new online operating model to manufacturers, enhance collaboration and innovation, and enable factories to make more informed data-driven decisions. Ergonomics, human factors and many more intelligent safety and health monitoring systems will bring people and machines closer together and ensure the well-being of people in HMI. Brain–computer interface (BCI) will connect people and machines, with a promise of making future machines truly like part of the human body, serving as human assistants to help people complete manufacturing tasks.

CRediT authorship contribution statement

Jialu Yang: Writing – original draft, Methodology, Investigation, Conceptualization. **Ying Liu:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Phillip L. Morgan:** Writing – review & editing, Supervision, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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