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Sensor and data: key elements of human-machine interaction for human-centric smart manufacturing

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Abstract

The proposal of Industry 5.0 has made sustainability, human-centric and resilience the core of digital manufacturing, which also puts forward new requirements for the human-machine interaction (HMI) paradigm in human-centric smart manufacturing (HCSM). In the manufacturing scenario, the process of HMI can be divided into four parts: 1) Sensors and hardware, where the environment information and input signals are collected, 2) Data processing, where the signals are converted into data, 3) Transmission mechanism, where the data is transmitted to the processing centre, and 4) Interaction and collaboration. Among them, sensors and data are expected to become breakthrough points in optimising HMI. This is not only due to the emergence of new research, innovation and technologies but also because they are closely influenced by the new design concepts brought about by Industry 5.0. This paper analyses the latest studies and technologies in the sensor field and their possible applications in HCSM scenarios. Then, opportunities and challenges of data analysis in the HMI in Industry 5.0 are discussed. Finally, based on the design concepts and requirements of Industry 5.0, this paper demonstrates how they will become the key points for future HMI development.

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Keywords: Industry 5.0; Human-machine interaction; Sensor; Human-centric smart manufacturing; Data

1. Introduction

In 2011, at the Hannover Fair, the concept of Industry 4.0 was first proposed when it was regarded as a synonym

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for Cyber-Physical Production Systems (CPPS): that is, to advance the idea of Cyber-Physical Systems (CPS) into manufacturing [1,2]. Over the past ten years or so, Industry 4.0 has arguably met the goal (or at least many aspects) of making the manufacturing process "smart" through the application of approaches and technologies such as the Internet of Things (IoT), Artificial Intelligence (AI) and Digital Transformation (DT) [3]. In the optimisation process of Industry 4.0, the main principle is to reduce human intervention in manufacturing by optimising and popularising automation. Furthermore, the popularisation of automation and digitalisation brought by Industry 4.0 has occurred in manufacturing and penetrated various related areas and peoples' lives [4]. However, its focus remains on improving the productivity of machines, as opposed to the sustainability demands and challenges posed by significant global issues such as climate change, the collapse of biodiversity and COVID-19 [5].

In recent years, with the emergence of Industry 5.0, the demand for sustainability, human-centric and resilience has become a new focus of manufacturing development [6]. Moreover, this demand also brings new opportunities and challenges for developing Human-Machine Interaction (HMI).

Discussion and research on HMI originated in the last century [7]. After years of development, it has become a vast discipline covering data analysis, materials research, human factors, applied psychology, and many other fields [8]. To better study the evolution of HMI, it is necessary to classify the related research. In the authors' previous research, the existing HMI has been divided into four aspects according to the HMI process [9]: (1) sensor & hardware, which represents the acquisition process of raw data; (2) data, which represents the analysis and screening of data; (3) transmission mechanism, which represents the transmission and conversion of data; and (4) interaction & collaboration.

However, there is still debate as to which area(s) will be the key element(s) of HMI in Industry 5.0, partly driven by one goal to have less human involvement in the systems and processes. Although introducing Industry 5.0 is inseparable from the emergence of some new technologies, it is still a value-driven industrial revolution [5]. It brings new design concepts and values and will, we argue, still be human-centric at the core. This shift in philosophy places new demands on workers and challenges existing HMIs.

Over the years, many studies in the HMI field have focused on several significant issues, such as trust, workload (including cognitive), and task allocation [8]. The current paper will demonstrate that sensors and data will be the key element of HMI development in Industry 5.0. This is mainly based on three considerations: First, sensor applications such as wearable devices will become more popular based on human-centric design concepts [10]. Second, human-related data and multi-data fusion analysis will be the main means to achieve human-centric goals [11]. Third, new technologies and materials (such as bionic technology, virtual reality (VR) technology and nanocomposites) will expand the application scenarios of sensors and significantly improve their capabilities.

A systematic literature review approach is used in this paper. First, we defined the research question. In the author's previous research [9], the state of the art of HMI in Industry 5.0 has been discussed. This paper focused on two more specific research questions: Q1: Why will the sensor become the key element of HMI in HCSM? Q2: Why will data become the key element of HMI in HCSM? Subsequently, we used ("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") AND ("Nanocomposites" OR "Wearable Sensors" OR "Bionic" OR "VR" OR "Data Security" OR "Big Data" OR "Cloud Computing" OR "Edge Computing" OR "Data Analysis") as keywords to search on Scopus, IEEE Xplore digital library, ScienceDirect, SpringerLink, GoogleScholar, ACM digital library. The selection of keywords was mainly based on our previous research. Then, we set exclusion and selection criteria. There are three main criteria: 1. To ensure the timeliness of the paper, we try to select articles after 2019 because the concept of Industry 5.0 was proposed in 2020. 2. The article must be in English. 3. The article must be able to provide a comprehensive introduction to a certain technology or field. Based on these criteria, we screened out 109 related articles. Some of the articles had duplicate content and were re-screened. Finally, 59 articles were obtained.

The remainder of the paper is structured as follows: Section 2 presents the different areas of HMI in detail. Section 3 offers case examples of technologies for sensors to arguably become one of the key elements of HMI in Industry 5.0. Section 4 outlines why data will be another key element of HMI in Industry 5.0. Section 5 discusses the opportunities and challenges of sensors and data in Industry 5.0. Finally, conclusions are made, and future work is suggested.

2. State-of-the-art of HMI in Industry 5.0

According to the signal's process in the manufacturing scenario, current HMI studies can be divided into four parts. This article will systematically overview and summarise the recent research into these parts.

2.1. Sensor&hardware

Depending on the technology used, sensors can be divided into five categories [12]. Optical-based sensors are used primarily in motion/distance detection, gesture recognition and eye-tracking [13, 14]. Computer vision and VR technology are also optical-based [15].

Speech recognition and sonic detection are the main application scenarios of acoustic-based sensors [12]. Some studies have begun to use acoustic myography for human feature detection, such as muscle acoustic feature detection [16].

Bionic-based sensors generally detect signals through electrodes to acquire data, such as electroencephalography-based brain-computer interface and electromyography-based myoelectric interaction [12]. By changing the electrode material, monitoring frequency, and level amplification, these sensors can be applied in various scenarios, such as bionic eyes, exoskeletons, and human assistive limbs [16, 17].

Tactile and motion-based sensors are widely used in motion detection, pressure detection and other fields [12].

2.2. Data processing

In the late 1990s, the Internet of Things (IoT) was proposed [18]. It creates a network that collects and processes information by integrating Radio Frequency Identification (RFID) and Near Field Communication (NFC) technology, Wireless Sensor Networks (WSN) technology and data storage and analytics technology [19].

However, as the amount of data in IoT continues to increase, dealing with data that contains much noise becomes a problem. Cloud Computing (CC) and Edge Computing (EC) are two data processing methods that are widely used in industrial scenarios [18, 20]. CC implements extensive data analysis by utilising high-performance processors in the cloud to process data. However, limited by the transmission speed, it cannot meet the requirements for timeliness and efficiency in many scenarios [21]. The idea of EC is opposite to that of CC, which focuses more on data analysis at the endpoint to provide real-time response instructions [18].

Machine Learning (ML) is one of the most used methods for analysing manufacturing data, mainly based on these data's multi-dimensional, intrinsic correlation and high complexity characteristics [22]. Deep learning is a branch of ML with shortcomings such as poor interpretability and long computing time [23]. However, it is foreseeable that it will be widely used in future Industry 5.0 scenarios, especially for analysing human-related data. This is because people are mostly resilient (e.g. adaptive, problem solvers, have a range of reasoning capabilities, and so on) and, therefore, can have a higher fault tolerance rate. At the same time, the model based on deep learning also has the advantages of analysing unstructured data, more expansive application fields, and less manual intervention [9].

2.3. Transmission mechanism

How efficiently data can be transmitted has always been one of the focuses of research in smart manufacturing, mainly because industrial scenarios are often complex, and factors such as high temperature and noise will affect the data transmission process. Wired network "Industrial Ethernet" and wireless network WSN are the two main data transmission mechanisms in smart manufacturing. "Industrial Ethernet" has the advantages of strong anti-interference ability and high speed, but it requires a lot of equipment and space [24]. WSN is more portable to deploy, but the environment and network limit the transmission speed and anti-interference ability [25].

To optimise the data transmission process, the Internet of Everything (IoE), as an extension of IoT, has been paid more attention by the industry in recent years. Connecting people, processes, data, and things can optimise and adjust resources throughout the environment [26]. Also, the introduction of 6G has successfully improved the delay and bandwidth issues during transmission in some scenarios [27].

2.4. Interaction and collaboration

Trust, human-machine function/task allocation and workload allocation are three traditional research topics in the HMI field. Depending on the level of trust (and indeed, how it is defined and measured), the HMI process can be divided into four scenarios: use (including initial adoption), misuse (perhaps due to overtrust), disuse (perhaps due to loss of trust) and abuse (e.g. users are able and choose to use the system for purposes other than those intended in particular contexts) [28]. To ensure that system users can handle machine or system trust issues, practical training is required to build trust in the system. Designers also need to design in line with actual needs. With increasing levels of automation, machines do most of the repetitive work in place of humans, while workers' jobs shift to oversight and decision-making [23]. Therefore, proper functionality and optimal task distribution are often key focuses of HMI research. A suitable, manageable, sustainable workload is necessary to ensure work efficiency and quality. Workers' concentration can drop significantly in low-load work scenarios and impair performance [29]. In contrast, overloading can lead to safety problems caused by an inability to keep up with task demands as well as causing fatigue.

With Industry 5.0, some topics have also begun to receive more attention. Interdisciplinary research has proven fruitful. As data becomes one of the production cores, combining computer science, engineering and psychology is already a trend [30]. However, human-centric and sustainability as the core of Industry 5.0 place more ethical and moral requirements for future HMI research.

3. Sensor- a key element for HMI in Industry 5.0

This section discussed four enable technologies that make sensors one of the key elements in Industry 5.0.

3.1. Flexible wearable sensors

Improving user experience is a core pursuit of HMI design. In recent years, flexible wearable devices have upended the uncomfortable experience of traditionally bulky and rigid electronic devices. These flexible sensors can be attached to irregular surfaces such as skin, allowing the monitoring of physiological and environmental indicators [31, 32]. Depending on the power supply mechanism, they can be classified into non-self-powered and self-powered [33, 34]. The application scenarios of self-powered sensors are more comprehensive, but the preparation is more complicated.

Pressure and strain sensors are the most common non-self-powered sensors [33]. The piezoresistive pressure sensor has the advantages of low energy consumption, simple manufacture and high sensitivity [35]. The flexible capacitive pressure sensors (FCPS) have also attracted attention due to their low hysteresis and fast response [36]. The excellent performance of these two sensors is mainly achieved by applying novel materials [37].

Non-self-powered strain sensors are divided into different sensing mechanism types, such as resistive and capacitor. In the design of strain sensors, conductive nanomaterials are one of the critical points, mainly because they reflect resistance changes with high sensitivity and are easy to fabricate [38]. In recent years, strain sensors have been commonly used in medical and speech signal recognition, human motion detection, robot control, and other fields [39].

Self-powered sensors can be divided into triboelectric-type and piezoelectric-type according to the different power supply principles. In 2012, a new energy technology TENG was discovered [40]. It relies on triboelectricity and can extract energy from almost all types of mechanical motion [41, 42]. In recent years, various new materials have also begun to be used as stretchable energy-harvesting electrodes, like knitted conductive fibres/yarns and ionic hydrogel liquid metal [10]. Triboelectric sensors can also be used in human-readable output research [43].

Self-powered piezoelectric sensors are primarily based on the piezoelectric effect. An electric current is generated by polarisation when the dielectric is mechanically deformed (elongated or compressed) in a particular direction. The choice of piezoelectric materials determines the performance of piezoelectric sensors, such as Cellular Polypropylene (PP), ZnO, lead zirconate titanate and PVDF. PP has the advantages of high equivalent piezoelectric coefficient, lightweight and good elasticity, so it has been used in loudspeakers and energy harvesting systems [10].

3.2. Nanocomposites

Applying new materials is a good way to improve flexible wearable sensors' performance and detection range [10]. Among these materials, novel functional nanocomposites have recently received much attention [44, 45, 46]. This article will introduce four common novel functional nanocomposites.

Carbon-based nanocomposites are a series of materials already widely used in industry. One-dimensional Carbon Nanotubes (CNTs) are flexible materials used to manufacture strain sensors, which have the characteristics of high durability and multi-dimensional sensing, so they are used in fields such as robot hand control and gesture detection [10, 43]. Graphene has good mechanical and electrical properties and has played a considerable role in making skin-like sensors that detect human movement [47].

Metal Nanowires (NWs) such as silver (Ag) and gold (Au) NWs and Nanoparticle (NP) composites are also very suitable for wearable strain sensors due to their high electrical conductivity [39]. Sensors made of these materials are fast in response, highly sensitive and have excellent elongation.

Liquid composites have begun to attract attention in recent years, and liquid metals and ionic liquid composites are representatives of them [48]. Because of their stickiness, these materials tend to bring hysteresis to the sensor. However, the advantage of this class of materials is that they allow infinite deformation and maintain normal functioning.

Bio-hybrid composites consist mainly of hydrogels (biological components) and one or more nano-reinforcements that provide them with excellent biocompatibility and flexibility [44, 45, 49]. But the hydrophobic nature of the inorganic nano-reinforcements and the intrinsic brittleness of hydrogels make them hard to process. Due to their properties, these materials are widely used in skin-wearable devices.

3.3. VR-based sensors

Virtual Reality (VR) technology presents the virtual world to people in three dimensions and provides an interactive experience that spans multiple senses [12, 15]. This process is achieved through a variety of wearable HMI devices. However, most VR-based devices on the market are bulky (often headsets), which can markedly reduce user experience in actual use and cannot meet long-term use needs. New materials like nanowires open up new opportunities for VR-based sensors and devices. Compared with traditional Head-mounted Projection Displays (HMPD), heterogeneous semiconductor nanowire displays have the advantages of small size and muscular flexibility [50]. Ultra-thin contact lenses made of this material also have the potential to be applied directly to the human eye [51], which may solve the impact of VR devices on vision. Electronic skins based on new materials also provide opportunities for haptic feedback systems in VR, especially in medical and training areas. One study [52] revealed that in robot-assisted surgery's teleoperation, tissue damage caused by no-force feedback could be up to three times that of a force feedback system.

3.4. Future of human-machine interface: bioinspired sensor

The bionic sensor is an emerging technology with adaptive, low power consumption and ultra-sensitivity, and has been widely used in military, robotic, medical, industrial and other fields [12]. According to bionic inspiration, the bionic strategies of these sensors can be divided into bionic materials, bionic structures, and functional bionic [53].

Bionic materials refer to materials inspired by natural materials and, therefore, have unique sensing properties. This biomimetic strategy requires researchers to fully understand biological materials' intrinsic composition and mechanism, making it challenging to implement.

Bionic structures are more straightforward than bionic materials, which mainly start from the structure of organisms and nature and design similar functional systems and components to achieve imitation of functions. Super-wetting bionic materials are a prime example. By studying natural super-wettable materials, scientists have developed superhydrophobic materials that are waterproof and self-cleaning [54].

The primary goal of functional bionic is to imitate biological senses through structural design and engineering techniques. It requires a deep understanding of the sensing mechanisms of organisms, so it focuses more on the detection capabilities of the sensor (sight, smell, hearing, taste, touch, etc.) rather than focusing more on improving system performance or giving new capabilities to the system as in the first two [53]. This strategy is widely used in artificial prosthetics.

4. Data and data-driven in Industry 5.0

According to the different objects, the data collected in the industry can be divided into three categories: human-related, production-related, and environment-related. In Industry 4.0, factories tend to focus more on data related to improving production efficiency and quality, which are production- and environment-related data. Environment-related data is used in safety detection and multi-sensor information fusion to ensure production runs normally. Therefore, the sensors deployed in practice are mainly designed to collect these data.

Industry 5.0 will focus on human-related data, changing the sensor deployment strategy. Some sensors that will gain prominence in Industry 5.0 have been described earlier. This chapter will further explore how they will enable Industry 5.0 with the data they generate.

4.1. From efficiency-driven to resilience, sustainability and workers' wellbeing-driven

The change in the focus of data research has led to changes in the sensors used and the data collected. The development of Industry 4.0 over the years has made most smart factories already have a complete multi-sensor system to track and detect the production process in real-time [55]. The data collected by these sensors often need to meet industrial-grade requirements such as low latency, accuracy, and interpretability [9]. Some of the abovementioned sensors are not widely used in Industry 4.0 because they cannot meet these industrial needs. Industry 5.0 will provide better opportunities for these sensors and related data.

In Industry 5.0, factories will inherit the previous collection and utilisation of production and environment-related data. However, more attention will be paid to considering resilience and sustainability in these designs. To improve the factory's resilience, the plant must enhance the immunity of the infrastructure to interference, which requires more analysis of environment-related data in the automatic control system [27]. Analysing environment-related data does not require as much accuracy and response as industrial data, so big data and neural network algorithms are well suited to analyse this data [56]. This data is also one of the key points for implementing digital twins [57]. Production-related data can be used to optimise production, reduce energy consumption and improve recycling. Conventional sensors such as temperature, acoustic waves, and displacement sensors will be the workhorses for collecting this data.

Human-related data needs more application areas within industries, although the following considerations mainly limit it. First, the collection of this data often requires care of worker privacy, as well as security. This is also why wearable sensors, although widely used in the medical, military, industrial exoskeleton and other fields, have not been commonly used in industry [41, 44]. In addition, because these data are collected from "flexible" people, the relevant sensors do not have high requirements for interpretability and accuracy but pay more attention to biophilia, simple interaction, strong control and other needs. Due to the security problems caused by data transmission and storage, CC is difficult to be applied to analyse this type of data in the short term [20]. Combining EC and machine learning may be suitable for analysing human-related data [18]. Wearable sensors and bioinspired sensors will be the workhorses for collecting this type of data, but when deployed, they must change the thinking of industrial design to serve people [58].

4.2. Data processing in Industry 5.0

Industry 5.0 places sustainability, resilience and human-centric at the heart of factory development, which places new demands on data processing. Focusing on worker well-being and increasing worker creativity will be the new goal of data processing.

Data collection in Industry 5.0 will focus more on human-related data. Social media through big data analysis to accurately push users is one example of human-related data analysis [20], but there are still differences between industrial scenarios and this scenario. The number of users in industrial systems is smaller but more professional, and the equipment is more customised, so the data collected is more professional [9]. Since wearable devices are expected to be used in large numbers in Industry 5.0, wireless transmission will be the main way to input and output these data to ensure the device’s convenience [25]. Data processing and storage will still be dominated by existing equipment and algorithms.

Collecting and analysing environment-related data is also one of the important ways to improve worker well-being. The influence of the environment on the psychological state of people is enormous. Most smart factories have deployed sensors but have yet to focus their research on providing a comfortable working environment for workers. Combining environment-related data and human-related data can better achieve this goal.

We believe that the current data analysis system in the industry must make the following three changes if it wants to adapt to the new goals and value orientation of Industry 5.0:1. Deploy a secure and private data analysis system. 2. Use more intelligent and adaptive data analysis algorithms. 3. Improve the interpretable performance of the system

Data security is a major issue in industrial data analysis. In recent years, some researchers have tried integrating blockchain technology into the industrial cloud computing system to solve the data security problem, but this research has yet to be applied [59]. As sensitive and private data related to people is incorporated into the data analysis system, data security must be paid more attention. The multi-verification system is a security system currently adopted by some factories, but it will affect the system response speed, and the cost is high [18, 20]. Industry 5.0 currently expects to ensure the security of data transmission through new technologies such as 6G and quantum communication [56, 59]. Due to the black-box effect of some machine learning algorithms, their use in industry has been limited. Voice assistants based on machine learning, big data analysis and text recognition assistants have proven their potential to interact with people [12, 16, 22]. Therefore, in Industry 5.0, a continuously optimised intelligent data analysis system is an indispensable tool to make equipment a worker's assistant. In order to ensure that workers make accurate judgments in the factory, a data analysis system with good empathy and interpretability is necessary. We cannot expect workers to have a deep understanding of everything designed in the factory. A good data analysis system must have good interpretability to ensure that workers can understand the results it gives.

5. Discussion

Sensors and data will be key elements in Industry 5.0 because they meet human-centric, sustainable and resilient needs. They will bring new opportunities to the industry, but we are also concerned about the challenges faced during deployment and implementation.

Cost is an important issue when factories deploy new sensors and data analysis systems. Large-scale, high-value-added manufacturers often have more incentives to complete equipment updates and iterations. This is because they tend to be more sensitive to the development of new technologies, and because their profit margins are relatively high, they can invest in equipment with a high return cycle. However, small basic manufacturers cannot deploy new equipment on time due to funding limitations and being out of touch with the development of the latest technology. To this end, corresponding equipment should be gradually updated to reduce cost pressure on manufacturers. Iteration and updating of sensor equipment is a long-term goal. The main goals in the early stage should focus on improving sustainability, reducing energy consumption, improving resilience through bionic technology, and gradually introducing equipment to collect environment-related and human-related data. Sensors based on nanocomposites are also a good choice for improving performance and saving energy. The collection of human-related data should be combined with worker training. VR-based sensor equipment will play a huge role in this process.

We believe that for manufacturers, changing from an efficiency-centred to a people-centred concept is another issue that manufacturers should pay attention to. Human-centric process planning, workshop scheduling, processing and assembly are the four elements that HCSM factories need to consider [60]. Human-centric process planning requires factories to consider workers' needs when coordinating production processes [61, 62]. Human-centric workshop scheduling focuses on putting the interests of operators and consumers in the first place in production in the workshop. Artificial intelligence has been proven to have a significant improvement in this aspect [63]. However, many factories do not pay enough attention to workers' interests. 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. 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.

Data security issues will be a major issue smart factories face in Industry 5.0. We have introduced some of the methods currently used in the industry to solve data security problems. However, due to factors such as equipment, cost, transmission speed requirements, and immature technology, this problem has still not been completely solved. The introduction of human-related data will put forward new requirements for data security because these data are closely related to human privacy. The data leakage problem caused by cloud computing has made data security issues more important. In addition to improving security through more secure encryption and equipment, increasing worker awareness of data security is also important. For this purpose, proper training of workers is required to build workers' understanding of the factory system. To help workers establish data security awareness, a more humane and empathetic HMI interactive system is necessary. Likewise, such systems are key to ensuring workers' safety and making the right decisions in different scenarios.

Since human-related data will become an important part of HCSM factories, privacy and ethics should also be considered. The goal of HCSM factories is to use data analysis to better help workers, not to control workers. To this end, relevant laws, regulations and systems still need to be improved. In recent years, people have gradually realised the information cocoon caused by social platforms using big data analysis to locate users. In future smart factories, the user data collected will be more comprehensive than that on social platforms. How to ensure the correct use of these data will be a big problem. Fully considering the rights and interests of people involved in the data collected when designing is a key to solving the problem. Due to their natural attributes, wearable sensors must consider how not to infringe on human privacy in the design. The same design concept should be implemented throughout the manufacturing system.

6. Conclusion

The realisation of human-centric smart manufacturing is inseparable from developing sensor technology and enhancing data analysis capabilities. Wearable sensors will enhance worker well-being and safety. New materials such as nanomaterials make wearable devices less bulky and free them from the limitations of external power sources. VR-based sensors are already being used in industry for worker training, remote control, robotics and other fields. Compared with traditional sensors, bionic sensors have breakthroughs in function and performance with good biophilic. Applying the bionic concept to wearable sensors will solve many safety and health problems. Data will be one of the cores of Industry 5.0. Like in Industry 4.0, improving efficiency and quality is still important, but there will be more weight on resilience and sustainability. Human-related data, as data that have not yet been valued properly, will become the breakthrough point to help factories improve the well-being of workers in the future together with new sensor technology.

Although Industry 5.0 is a value-driven industrial revolution, integrating and developing new technologies will still play an essential role. Future work will focus on transforming system design concepts in Industry 5.0 and integrating and applying technologies.

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