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PERSPECTIVE

Human-Centered AI in Smart Farming: Toward Agriculture 5.0

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ABSTRACT This paper delineates the contemporary landscape, challenges, and prospective developments in human-centred artificial intelligence (AI) within the ambit of smart farming, a pivotal element of the emergent Agriculture 5.0, supplanting Agriculture 4.0. Analogous to Industry 4.0, agriculture has witnessed a trend towards comprehensive automation, often marginalizing human involvement. However, this approach has encountered limitations in agricultural contexts for various reasons. While AI's capacity to assume human tasks is acknowledged, the inclusion of human expertise and experiential knowledge (human-in-the-loop) often proves indispensable, corroborated by the Moravec's Paradox: *tasks simple for humans are complex for AI.* Furthermore, social, ethical, and legal imperatives necessitate human oversight of AI, a stance strongly reflected in the European Union's regulatory framework. Consequently, this paper explores the advancements in human-centred AI focusing on their application in agricultural processes. These technological strides aim to enhance crop yields, minimize labor and resource wastage, and optimize the farm-to-consumer supply chain. The potential of AI to augment human decision-making, thereby fostering a sustainable, efficient, and resilient agri-food sector, is a focal point of this discussion - motivated by the current worldwide extreme weather events. Finally, a framework for Agriculture 5.0 is presented, which balances technological prowess with the needs, capabilities, and contexts of human stakeholders. Such an approach, emphasizing accessible, intuitive AI systems that meaningfully complement human activities, is crucial for the successful realization of future Agriculture 5.0.

INDEX TERMS Human-centered AI, smart farming, agriculture 5.0, digital transformation, artificial intelligence.

I. INTRODUCTION

In the summer of 2023, global agriculture faced substantial challenges due to a series of unexpected extreme weather events. Notably, in July 2023, Europe experienced a confluence of extreme weather phenomena. Severe winds, often accompanied by hail, caused widespread damage [1]. These conditions were further exacerbated by significant flooding events [2], [3] associated with catastrophic landslides. The concatenation and the cumulative impact of these events have significantly weakened the agricultural sector: crops and livestock have been severely damaged or destroyed, agricultural infrastructure has been impaired and fields and water sources have been contaminated. This sequence of events highlights

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the increasing vulnerability of agriculture to climate-related extremes and necessitates improved resilience and adaptation strategies in the future. As a result, the improvement of early warning systems and the development of precise weather forecasting methods have sparked global debate [4], [5].

Future projections indicate even an increase in extreme weather conditions on a global scale which will have dramatic effects on global agriculture [6], [7].

In light of such devastating weather events of summer 2023, there has been an intensified discourse on the urgent need to modernize agriculture, making it more resilient to the capricious and often harsh whims of nature. This conversation gains critical relevance against the backdrop of global warming, a phenomenon that is not only altering weather patterns but also escalating their severity and unpredictability. The extreme weather conditions, which have wrought widespread economic havoc at both regional and global scales, serve as a stark reminder of our growing vulnerability [8]. Consequently, steps to modernize agriculture to make it more resilient to such events are ultimately necessary.

The call for modernization encompasses a comprehensive overhaul of agricultural practices, technologies, and policies. It is not merely a question of adapting to change, but of proactively innovating to anticipate and withstand future environmental disturbances [9], [10]. This includes the integration of advanced technologies such as Artificial Intelligence (AI) driven predictive models for weather and crop growth and development, the adoption of sustainable farming practices that enhance biodiversity and soil health, and the implementation of robust infrastructural measures to mitigate the impact of extreme weather events.

Now is the moment to transition from merely discussing smart farming to actively advocating for Agriculture 5.0. This endeavor begins with understanding Industry 5.0, a well-established concept that forms the foundation of our work. Industry 5.0, also known as "human-centered industry", is the next phase in the evolution of manufacturing and production processes [11], [12], [13], [14]. This is in contrast to Industry 4.0, which emerged with the integration of advanced digital and communication technologies into manufacturing and industrial operations and where the primary focus was on total automation, without human intervention [15]. It has already been argued in Industry 4.0 that in all cases of future production management, it is vital that humans have oversight of critical information flows and remain an active participant [16]. Industry 5.0 goes one step further and emphasizes collaboration between humans and advanced technologies [17]. This combination of the "best of both worlds" shall leverage automation, AI, and robotics while empowering human creativity, problem-solving, and adaptability [18]. This aims to create a more inclusive and flexible work environment where humans and machines work together seamlessly, optimizing productivity and efficiency. Industry 5.0 fosters the development of smart factories that use interconnected systems, IoT (Internet of Things) devices based on smart sensors and actuators, and real-time data analytics to enable responsive production operations. Furthermore, Industry 5.0 embraces the concept of mass customization, allowing businesses to cater to individual customer needs at scale.

Alongside this trend towards Industry 5.0, there is also a growing trend towards Agriculture 5.0. The precursor, Agriculture 4.0, already included the use of advanced technologies such as IoT devices, sensors [19], drones [20], robots, numerous artificial intelligence methods and data analysis techniques to collect and evaluate real-time information about animals, crops, plants, soils and the environment as a whole [21], [22]. As a result, these technologies help farmers make data-driven decisions to optimize resource use and apply more precise and sustainable farming and cultivation methods, ultimately leading to a more efficient and technologically advanced agricultural industry. The success of Agriculture 4.0 will be measured by the transition to Agriculture 5.0, which is the next logical step to make the entire agricultural system more sustainable and regenerative and to eliminate the disadvantages of Agriculture 4.0 (e.g. high initial costs, lack of skilled labor, security, dependency, digital divide, energy consumption, lack of network coverage, etc.). This paradigm shift from a purely technology-centric approach embodies the synergy between technology and people. By embracing human-centric AI, we are harnessing the power of technology not only to innovate, but also to complement and enhance human capabilities to ensure that advances are not only groundbreaking, but also ethical and beneficial to society. This synergy is the cornerstone of sustainable and responsible progress, where technology serves as an extension of human will and creativity, leading to more intuitive, effective and inclusive solutions for a digital transformation.

However, this digital transformation in future smart farming requires a human-centered AI approach that incorporates sociological, ethical, and legal issues of Artificial Intelligence [23] - with the goal of augmenting rather than replace human intelligence.

II. HUMAN-CENTERED AI (HCAI)

The term AI to describe one of the oldest fields in computer science has now established itself as a comprehensive umbrella term for a disruptive new generation of information technologies that have penetrated today virtually all areas of life [24].

From the very beginning, the original goal of AI was to develop machines that are capable of performing tasks that require intelligence in humans, such as learning, logical thinking, problem solving, language comprehension, etc. The foundations for AI were laid in the 1940s and 1950s by pioneers such as Alan Turing, who proposed the Turing test as a criterion for intelligence and developed the concept of a universal machine. The term "artificial intelligence" itself was first coined by John McCarthy at the Dartmouth Conference in 1956 and marked the official birth of the discipline.

In the 1950s and 1960s, early AI research focused on problem-solving and symbolic methods and led to the development of the first AI programs. Researchers were overly optimistic about the future, as demonstrated by programs such as the Logic Theorist and the General Problem Solver, which could solve algebra problems and prove theorems. However, in the 1970s and 1980s, the limitations of early AI became apparent, leading to a period known as the "AI winter", in which funding and, unfortunately, interest in large-scale AI research declined. This period led to a re-evaluation and a shift towards more robust and scalable approaches, including the development of simpler machine learning algorithms. The limitations were limited computing power, limited storage space and the associated lack of big data.

As computing power increased and new algorithms were developed in the 1980s and 1990s, statistical machine learning emerged as a dominant force in AI. The concept of neural networks, which had been around since the 1940s but occupied a niche position, gained popularity as researchers recognized its potential. The rapid spread of the World Wide Web on the infrastructure of the Internet and the availability of large amounts of data in the 2000s led to significant advances in AI. Machine learning algorithms improved dramatically with access to big data, leading to breakthroughs in many areas, including natural language processing and computer vision.

The development of deep learning in the 2010s has led to remarkable advances and impressive successes where such systems have matched and even surpassed human performance in tasks such as image recognition, strategic gaming and complex problem solving.

The successes of statistical machine learning became widely visible with the emergence of large language models, which play a crucial role in AI's current surge in popularity. Large language models such as GPT (Generative Pre-trained Transformer) and BERT (Bidirectional Encoder Representations from Transformers) show unprecedented processing power of human language. These models, trained with huge amounts of text data from the Internet, have learned to generate coherent and contextual text, translate languages, answer questions and even create content that is often indistinguishable from that created by humans. Their ability to perform a wide range of language tasks with high accuracy has led to their widespread use in various industries, from customer service chatbots to virtual assistants and advanced research tools.

The success of these models has not only demonstrated the potential of statistical machine learning, but has also contributed significantly to the popularity of AI. They have made AI more accessible and understandable to the general public and demonstrated its potential to support, augment and in some cases automate tasks traditionally performed by humans. This has led to an increase in investment, research and interest in AI across all sectors, which has accelerated the pace of innovation and the range of applications of AI. As these models continue to evolve and improve, they are expected to drive further advances and interest in AI, shaping the future of the technology and its role in society.

AI has thus currently become an integral part of many technologies and services. Throughout its history, the goal of AI has essentially remained the same: to develop machines capable of intelligent behavior. However, the approaches and technologies have changed and evolved, leading to the sophisticated and powerful AI systems we see today. The field is certainly still growing and research will continue to make AI more general and explainable and to bring it in line with human values - this is the starting point for the relatively new Human-Centered AI.

Three factors are particularly important to emphasize here: (i) The most powerful statistical learning methods of today are often so-called "black boxes" that make it difficult, indeed practically impossible, to understand, interpret and explain *why* a certain result was achieved. (ii) These methods lack robustness; even the smallest disturbances in the input data can have dramatic effects on the output and lead to completely different results. This is of importance in practically all critical areas where we suffer from poor data quality, i.e. in the real world we do not have the i.i.d. data (independent, identically distributed data) that we ideally have available under lab conditions. (iii) The issues from (i)+(ii) result in a lack of trust in AI. In vital areas such as agriculture, it is all about trust. It is about user trust in AI in general, and its methods and its results in particular. Explainability is one step in achieving trust, and robustness is the second. Both together - explainability and robustness - promote reliability and trust in the results and ultimately also ensure that humans remain in control [25], [26].

Some developers would probably be relatively indifferent to this and of course could easily be ignored in practice. However, there are ethical, social and, above all, legal requirements worldwide under way that are set by individual countries and entire communities of countries, such as the European Union.

Human-Centered AI (HCAI) is a relatively new approach to provide human control over AI technologies and to align AI with human values, ethical principles, and legal requirements to ensure that AI is reliable, safe and trustworthy [27], [28].

HCAI is rooted in the principle that technology should amplify human potential, HCAI asserts that AI systems should be transparent, intuitive, and adaptable to individual user requirements. This dovetails neatly with the principles of Explainable AI (XAI), which emphasizes the importance of making AI decisions understandable and interpretable to humans. Without this clarity, users may find it challenging to trust or even appropriately utilize AI solutions. From a methodological standpoint, creating truly human-centered AI involves several challenges. Designing these systems requires a deep understanding of human cognition, behavior, and domain-specific expertise. A genuine "human-in-the-loop" approach ensures that AI systems are not developed in isolation but are iteratively refined based on continuous human feedback. This is not just about correcting errors but about aligning the system's operations more closely with human values and needs. Such an approach is crucial to ensure that AI does not supplant human expertise. Instead, the vision is for AI to act as a collaborator, augmenting and enhancing human capabilities. In this light, AI becomes a powerful tool in the hands of domain experts, amplifying their skills and insights, rather than an entity that renders their expertise obsolete.

While this is currently widely discussed, there is to date no single universally accepted framework for HCAI. However, there are general principles and methodologies that form the foundation of what might become a framework for HCAI. Here is an outline based on general principles and considerations:

1) **Human-Centered Design**:
   - Understand and address user needs and contexts.
   - Involve users throughout the development process.
   - Prioritize user experience and intuitive interfaces.
2) **Transparency & Explainability**:
   - AI should provide clarity on its decision-making process.
   - Use Explainable AI (XAI) techniques to make algorithms interpretable.
   - Ensure users can understand and trust AI outputs.
3) **Empowerment & Augmentation**:
   - Design AI to amplify human capabilities.
   - AI should support, not replace, human tasks.
   - Prioritize systems that enhance human creativity.
4) **Ethical Considerations & Fairness**:
   - Prioritize user privacy and data protection.
   - Minimize and address biases in AI models.
   - Ensure AI solutions are equitable.
5) **Adaptability & Flexibility**:
   - AI should adapt to individual user requirements.
   - Offer customization options.
   - Regularly update AI models based on feedback.
6) **Safety & Reliability**:
   - Ensure AI operates safely in all environments.
   - Prioritize robustness against adversarial attacks.
   - Implement fail-safe mechanisms.
7) **Continuous Learning & Iteration**:
   - Implement mechanisms for AI to evolve.
   - Use a "human-in-the-loop" approach.
   - Regularly refine AI systems based on performance.
8) **Collaboration & Interdisciplinary Approach**:
   - Combine insights from AI, cognitive science, and other domains.
   - Promote collaboration between AI experts and domain experts.
   - Promote collaboration between developers and end users.

III. BACK TO THE FUTURE: FROM INDUSTRY 1.0 TO 5.0

In ancient times, goods were primarily crafted by hand for personal use, deeply intertwined with the agrarian lifestyle. By the Middle Ages, basic manufacturing processes began to emerge in small workshops, utilizing rudimentary tools and equipment [29]. This period marked a transition from subsistence farming to commercial production, with individuals who once worked the land starting to receive wages for their labor in these nascent industries. The 20th century heralded a significant shift with the advent of modern technologies, leading to the establishment of the smart manufacturing industry and profoundly altering production processes. In recent decades, "smart factories" [30], [31] have come to the forefront, where the majority of tasks are undertaken by intelligent machines capable of making decisions based on data analytics, communication technologies, and, most notably, the Internet of Things (IoT). This revolution has not only transformed how goods are produced but also redefined the role of the human worker within these advanced industrial settings.

TABLE 1. Evolution of industrial revolutions during the history.

Ind.rev.	Age	Characteristics
1st	Late 18th (in 1750)	Mechanization, water power, steam power
2nd	Late 19th (in 1850)	Mass production, assembly line, electricity
3rd	Late 20th (in 1970) (in 1970)	Computer & automation (NC, CNC, DNC)
4th	Early 21th (in 2011)	Cyber-Physical Systems (CPS)
5th	Several years ago (in 2021)	Human-centric, resilient, sustainable

In this new era, the manufacturing industry is envisioned as a collaborative synergy between humans and machines, each complementing the other's capabilities in decision-making processes. This collaboration is particularly significant for communities that recognize the foundational role of farming, as it underscores the evolution from manual, agrarian-based work to sophisticated, technology-driven production while still acknowledging the enduring importance of agriculture. Historically, these shifts from a handcraft and farming economy to the modern manufacturing industry we recognize today have often been characterized as revolutions, marking substantial transformations in societal production, work, and lifestyle patterns [32] (Table 1).

The concept of a "revolution" denotes a profound and radical transformation in historical contexts. Within the engineering domain, the term "industrial revolution" is particularly associated with the advent of groundbreaking technologies that have dramatically reshaped economic systems and social structures. The initial shift began approximately 10,000 years ago with the agrarian revolution, marked by the domestication of animals and the cultivation of crops for both sustenance and commerce. Subsequently, a succession of Industrial Revolutions (IR) unfolded, starting in the latter half of the 18th century.

The first Industrial Revolution (IR1) was ignited by the invention of steam power, which catalyzed mechanization in production processes and the utilization of water power. The second Industrial Revolution (IR2), commencing in the late 19th century, was characterized by mass production fueled by electricity and the introduction of assembly lines in factories. This era significantly influenced urbanization as individuals migrated from rural areas to cities in search of employment and new lifestyles. The onset of the third Industrial Revolution (IR3) was signified by the emergence of mainframe computers in the 1960s, personal computers in the 1970s, and the internet in the 1990s. Known as the digital revolution, this period saw the introduction of automation in manufacturing, with technologies such as Numerical Control (NC), Computer Numerical Control (CNC), and Distributed Numerical Control (DNC) becoming prevalent.

The term "Industry 4.0" was first introduced at the Hannover Fair in 2011, marking the beginning of the fourth industrial revolution (IR4). This revolution, primarily driven by the German government's high-tech strategy, introduced the concept of "smart factories" where virtual and physical manufacturing systems (also known as Cyber-Physical Systems or CPS) collaborate globally in an efficient manner. Initially, IR4 focused predominantly on automation, often sidelining the role of human operators. The enormous success in AI fueled the automation.

After the enthusiastic expectations of doing everything automatically, due to the enormous success in AI [33], it was sobering to realise that tasks that are difficult for humans are often easy for AI, but that tasks that are easy for humans are difficult for AI. Moravec's Paradox [34] observes that contrary to traditional assumptions, high-level reasoning requires very little computation, but low-level sensorimotor skills require enormous computational resources. The paradox highlights that tasks humans find complex are easy for machines, and vice versa [35]. In the context of Industry 4.0, this paradox is particularly relevant as it underscores the challenges in automating tasks that require dexterity and perception, skills that humans typically find effortless. This had significant implications for the design and integration of robotics and AI in manufacturing environments, where the goal is to complement human labor with machines that can perform both simple repetitive tasks and complex problem-solving. The appreciation that humans excel at specific tasks and the acknowledgment of social, ethical, and legal imperatives for human involvement led the European Commission in 2021 to introduce "Industry 5.0." This new paradigm re-emphasizes the integration of humans back into the production process, aligning perfectly with the objectives of human-centered AI. Industry 5.0 doesn't just seek to automate but to synergize human intelligence and creativity with technological advancements, thereby fostering a more sustainable, efficient, and ethically responsible industrial landscape, however let us first describe the main concepts of Industry 4.0, as we need this for our journey towards Industry 5.0.

A. CONCEPTS OF INDUSTRY 4.0

In traditional macroeconomics, an industry is a branch of an economy that produces a closely related set of raw materials, goods, or services [36]. However, the paradigm shifted by an advanced digitalization and automation within classical factories, Internet of Things and Services (also called Industrial IoT (IIoT)), and modern Information and Communication Technologies (ICT) to the concept of "smart factories" in Industry 4.0, where costumer demands control smart machines [37]. In this sense, the Industry 4.0 transforms the traditional machine manufacturing to digital manufacturing [38]. The basis of Industry 4.0 presents embedded autonomous systems connected to the wireless internet that caused a convergence of the physical production world with the virtual (also cyber) world. The convergence of these technologies resulted in emerging the CPSs capable of integration network resources, objects and people into smart factories [37]. This integration led to IR4. Although the common definition of IR4 does not exist, many authors defined the concept more or less precisely. In the study, we refers to the definition found in technical report by Fay et al. [39], which say the following: "IR4 refers to the intelligent networking of machines and processes for the industry based on CPSs capable of achieving intelligent control using embedded networked systems." The core concepts include self-organization, adaptation to human needs and corporate social responsibility [40]

Smart factory is category of manufacturing that is distinguished from traditional approaches by computer control and high level of an adaptivity, scalability, reconfigurability, and flexibility [41], allowing the smart factories to survive inside a high dynamic and global market. Mainly, the adaptivity refers to variety of products, scalability to various production parameter settings, reconfiguration to a topology of smart machines within the global network, and flexibility to process organization including corporative strategy, work organization and human-resource management. The goal of the smart factories is to produce smart products (i.e., materials, goods, or services) quickly and in small batches, where many work pieces can be produced cost-effectively in much smaller tasks. Smart products know the details of how they were manufactured and how they are intended to be used [37]. On the other hand, the producing the smart products demands transformation from traditional methods to advanced technologies. Typically, the transformation obeys principle "plug-and-produce" that is the capability of a production system to automatically identify a new or modified component and to integrate it correctly into the running production process without manual efforts and changes.

Modern business bases on global network that incorporate the smart machinery, warehousing systems and production facilities in the shape of CPSs [37]. The goal of CPSs are to merge physical production with the virtual digital world. In line with this, their production facilities are capable of independent controlling the smart machines, exchanging information between human and the other machines, and triggering actions. Indeed, the production facilities of the CPS corresponds to the definition of intelligent agents [42] equipped with multiple sensors, actors, and autonomous systems as decision-making components. According to this definition, the decision making component is capable of exchanging information (i.e., social component of intelligent robots), triggering actions (i.e., the result of decision making), and independent control of its environment (i.e., smart production machine).

Smart factories work in environments that are sensitive to external unpredictable events as well as to internal complexity (i.e., multifunction, autonomy), which usually results in more abnormal events [43]. The response to this issue presents a self-organization that taken inspiration for the production in such factories from the nature.

New systems in distribution and procurement refer to new role that the distribution and procurement have in the smart factories. The distribution of products from the smart manufacturing is delivered to the end user via distribution channels (e.g., direct and indirect), where, a selection for the proper channel depends in individual's preferences. The concept is defined as applying internet technologies for facilitating procurement procedures, like ordering and sourcing tasks [44].

While a characteristic of the Industry 2.0 was mass production (production of the huge number of the same products), the smart factories support mass customization (production of small batched products quickly and efficiently). The mass customization offers the customers the ability (in the sense of services) of selecting among variety of features and accessories to share a final customized assembly combination of a basic product [45].

As a result, the products produced by mass customization are more flexible, while the customers have possibility to adapt their products according to them personal needs. This means that the customers have the leverage to affect the production in smart factories directly, while the results of such production is whole personalized. As a result, the concept of mass personalization has emerged that allows smart factories to mass produce personalized products in dynamic quantities, where the cost of production is comparable to the mass production [46].

The aim of Corporate Social Responsibility (CSR) is to promote sustainable development. The CSR is focused on three main issues of the modern business: the environment, the society, and the economy. It needs to understand challenges of the modern business and to indicate the risks that the proposed solutions have for society. The CSD practices have the positive impact on society, and, thus, they improve the competitiveness and sustainability for companies [47]. Being social responsible means more productivity, since an improvement in conditions for workers also optimize their effectiveness [48].

The concepts of Industry 4.0 define theoretical foundations, on which this is built. However, the concrete implementation depends on the way how they are conveyed in practice. In order to discover how the general concepts are implemented in practice, a short survey was made in this study that indicates, in which directions this vibrant domain has promoted (Table 2).

TABLE 2. Industry 4.0 concepts and their implementations in practice.

Industry 4.0 concepts	Implementations	References
Smart factory	Conceptual framework	[49]
CPS	CPPS	[50]
Self-organization	SOMS, SOMN	[46]
Distribution/procurement	Procurement 4.0	[51]
Product/services	PSS	[52]
Adaptation to user needs	DT	[53]
CSR	CSR practices	[54]

Industry 4.0 suffers from a lack of a general framework of smart factory systems guiding the academic research and industrial implementation. Many specific frameworks have been developed in special domains, including one by Zheng et al. [49]. This framework is represented as a 2D layered structure connecting the physical world with the virtual ones. It assumes that the physical world consists of five layers, representing the following production processes: smart design, smart monitoring, smart machining, smart control, and smart scheduling. The virtual world comprises the four layers, representing digital data generated by the production processes and include sensors and actuators, data collection, data analysis, and decision making.

Typically, Cyber-Physical Production Systems (CPPSs) represents a materialization of the general concept of CPS in the smart manufacturing environment [55]. CPPSs comprise of smart machines, warehousing systems, and production facilities depending on their role inside the smart factory. For instance, the facilities of the CPPS in the textile smart manufacturing is distinguished in the CPPS in automobile smart manufacturing. Irrespective of the differences between them, the CPPS in one application domain may also communicate with the CPPS from an other application domain.

The concept of self-organization is taken from nature and has inspired designers of smart factories by constructing the so-called Self-Organized Manufacturing Systems (SOMS) to deal with the abnormal events automatically and spontaneously without any external control [56]. Recently, agile system modeling and control architecture demands that the traditional centralized and hierarchical control in SOMS is replaced by the decentralized control in Self-Organizing Manufacturing Networks (SOMN) capable of joining multiple SOMS into a whole. Consequently, more decentralized paradigms can be applied in SOMN, as for instance: Multi-Agent Systems (MAS) [42], Holonic Manufacturing Systems (HMS), or Bionic Manufacturing Systems (BMS).

Procurement 4.0 represents one of several proposed solutions for the new distribution/procurement system development in Industry 4.0. It transforms supply chains to smarter systems, which uses digital technologies for purchasing and selling in order to save time and money [51]. Suppliers in smart factories are typically connected with the ordering companies by some kind of Electronic Data Interchange (EDI) systems. In this case, the smart factory production system is capable to automatically generate an order to be transmitted to the specific supplier, when this discovers that a certain material is needed.

The concept of new product/service system development demands changes in a smart factory production in the sense of so-called Product-Service Systems (PSS). The PSS integrates smart products and customer services, and thus, allows a basic product to be redesigned using customization by costumers [57]. In this manner, the customer is integrated into the PPS development on the one hand, while the PPS operations require skilled workers for controlling them on the other [58]. The readers are invited to look the survey of Annarelli et al. [52] for obtaining more information about the subject.

The concept of adaptation to user needs leads normally to a concept of mass personalization. In paper of Aheleroff et al. [53], the authors have proposed a Digital Twin (DT) technology for solving the problem in smart factories. The factories supporting the mass pesonalization are also known under the name Mass Personalized Manufacturing (MPM). The advantages of the DT is that this technology is capable to suitable fill the gap between thy physical and virtual world, and to provide insights for meeting mass personalization during the product development and later during the whole product life cycle.

The implementations of Corporate Social Responsibility (CSR) have evolved also in generations from CSR 1.0 to CSR 4.0, where the focus of practitioners has changed from generation to generation [54]. While the practitioners in CSR 1.0 perceived the CSR as a philanthropic activity (making goods that help others or society as whole), their focus in CSR 2.0 was to promote these activities through better marketing and sharing values serving a healthy society. Recently, the focus of CSR 4.0 is "a social good" that benefits the largest number of people, like: clean air, clean water, healthcare and literacy.

CSR 4.0 encompasses many studies (also CSR practices), in which an influence of introducing the concept in the companies has on their economy, society, and ecology. Based on the CSR practices, Govindan [54] developed a theoretical CSR framework being of general nature that connects the practical results with the theory of social goods.

In early day of Industry 4.0, the concept was referred only to manufacturing initiative. Nowadays, the initiative moved to almost all domains of human activities. As a result, the Industry 4.0 is present today in smart transportation and logistics, smart buildings, oil and gases, smart healthcare, smart cities, and smart agriculture. These concepts are only a blueprint for how the Industry 4.0 should be designed. The implementation of these concept in practice requires key enabling technologies that are discussed in the next subsection.

B. KEY ENABLING TECHNOLOGIES OF INDUSTRY 4.0

Industry 4.0 transforms production in the sense of joining the isolated cells together as a fully integrated, automated and optimized production flow [59]. It enables the greater efficiency on the one hand, affects relationships among suppliers, producers, and customers as well as the relationships between man and machines on the other. Indeed, the goal of Industry 4.0 is building smart machines that can predict and make intelligent/smart decisions using modern information and communication technologies [13]. In line with this, the key enabling technologies (also pillars) of Industry 4.0 serve as the implementation aid that include [60]:

- big data and analytics,
- autonomous robots,
- simulation,
- horizontal and vertical integration,
- IIoT,
- cybersecurity,
- cloud computing,
- additive manufacturing (robotics, 3D-printing),
- augmented reality.

In the landscape of Industry 4.0, data generation is an integral part of the production process. This data is collected and stored in intricate collections known as big data [61]. Within numerous organizations, these datasets become the backbone of decision-making processes, shaping and driving company strategies. Given the voluminous nature of big data, sophisticated analytical tools are essential for processing and extracting meaningful insights. These tools are adept at uncovering customer preferences, discerning correlations across disparate data sets, and revealing underlying trends. Moreover, these analytical capabilities extend to predictive error detection, allowing companies to preemptively address potential issues, thereby mitigating risks and preventing damage. This proactive approach not only enhances operational efficiency in production and marketing but also refines customer engagement strategies. By leveraging these insights, companies can gain a competitive edge, optimizing their operations and aligning more closely with customer needs and market dynamics. In essence, big data analytics serves as a pivotal enabler in Industry 4.0, transforming raw data into strategic assets that drive innovation, efficiency, and market responsiveness. Another important aspects is in robotics. In modern companies, robots have replaced humans by dealing with simple, but repetitive, tedious, and dangerous. Nowadays, the coinage "cobotics" is used to join words "collaborative" and "robotics", with which the characteristics of these are indicated. The cobots are even able to learn from human beings to perform various complex and challenging tasks [62]. Introducing autonomous robots in manufacturing process results in better employee safety and satisfaction, increased productivity, and higher profitability for company. Some robots support also mobility. However, the mobility is a challenging aspect in manufacturing that needs incorporation of intelligent navigation solutions.

According to definition of Leong et al. [62], a simulation approximately imitates the operations of a process or system. In Industry 4.0, it essentially reduces unnecessary waste in time and resources, and increases efficiency in manufacturing. It role in the design stage of product evolution is very important, because all changes to product can be eliminated virtually on computer, before the product comes into the real production [63]. This means that the simulation represents the strong modelling and evaluation tool for analyzing complex systems. It serves also for establishing the proof of concepts, before the real system is built. Moreover, different system designs can be simulated in order to determine the most optimized one. Furthermore, the simulation model can be used for prediction of system performance. Finally, the simulation optimization helps designers to find the optimal design of the physical system based on simulation model in digital computer.

Systems in Industry 4.0 can be integrated in two ways, i.e., horizontally and vertically. The horizontal integration refers to a connection network between CPSs laying on the same level of manufacturing. It allows to connect multiple production facilities across the whole enterprise as well as the production facilities in the other organization. The horizontal integration can capture the entire supply chains, more precisely, the upstream supply and logistic chains as demand by production process, and the downstream chain along delivery of product to market. The vertical integration refers to a connection network that connects organization structures at different levels of the enterprise hierarchy usually using the different communication protocols. Typically, the organization structures within enterprises consist of the following departments: production, research and development, quality assurance, information technology, sales and marketing, and human resources. The vertical integration is connected with tactical and strategical decision making, and enables the cross-company universal data integration.

IoT refers to an ecosystem of devices, machines and systems that are connected to the Internet, equipped with sensors and actuators, capable to function separately and to communicate with each other [64]. Industrial IoT (IIoT) represents a robust version of the traditional IoT that is embedded in an industrial environment. The goal of IIoT is to enhance manufacturing processes by using smart sensors and actuators. Connected together in the same network, they form the whole system for collecting, exchanging and analyzing data. In line with this, the IIoT systems typical consists of three components: (1) intelligent device for storing, collecting and communicating data, (2) networking infrastructure, and (3) data collection and analytical system for analyzing business information. The main challenge of IIoT is suffering for a lack of standardized communication protocols that can relieve different producers of IIoT devices to be connected in the same network easily and secure [65].

With the expansion of the internet, especially increasing the number of computer systems and communication devices, has resulted in increasing malicious activities of attackers on these networks, like unauthorized access, network attacks, data corruptions, damage, etc. As a consequence, the cybersecurity has emerged, which purpose is safeguarding of data by maintaining the performance of systems [62]. The main challenge of the cybersecurity is how to ensure data integrity in conditions of increasing data density, information and operational technology fusion. Thus, the users of IIoT are affected with these problems either directly or indirectly, where the indirect affect refers to the malicious attacks, like system crashes, data leaks, data corruptions, and denial of services by the systems, that represent treats in the sense of immense financial losses by companies. In general, the cyber defence of the IIoT is divided into four levels: (1) perception,(2) networking, (3) service, and (4) application layers. In order to ensure a complete security, the cybersecurity needs to offer the solutions for each of these layers.

Cloud computing enable accessing data using the internet from anywhere. This means that the traditional computing based on local computer systems connected into local networks are replaced with internet computing, where computational resources, like databases, data storage, processors, servers, and even software are accessible virtual through internet. The data are easily accessed by users on remote servers by moving these resources on the Internet, while the various software solutions allow them to manipulate and process data securely. The goal of the cloud computing is to help remotely located people to work together. In this way, the companies get access to virtually infinite processing and storage capabilities cost-effectively by using the pay-per-use payment model, where costs for ICT depends on resource usage.

Additive manufacturing is a part of mass production and mass personalization concepts of Industry 4.0. This process is focused on joining more parts together in forming the product and fundamentally change the traditional production process. Usually, it is used in mass customization, where only small batches are produced at once. Normally, this kind of production requires a complex but lightweight design [62]. The growth of the production lies also in increasing of personalization of products as well as reducing time for delivering them to customers. As opposed to traditional mass production, the additive manufacturing exploits an advanced technology for manufacturing accurate and complex smart products quickly and efficiently.

Augmented reality enhances the user's interactive experience of the real-world environment with visual objects generated by computer based on acquired information from environment [62]. In Industry 4.0, it is most often used in the sense of Human Robot Collaboration (HRC), where the communication between human and robot is enhanced using innovative interfaces. This technology can be successfully applied for maintenance, repair, and assembly tasks in manufacturing. However, these tasks request a set of virtual assets capable of acquiring data, on which basis they can give aids, indication or suggestion to the user on the graphical assets, and thus guides user's decision making process substantially. The augmented reality usually guides tasks that are dangerous in nature, but can also be applied for product quality control.

C. HUMAN-OUT-OF-THE-LOOP IN INDUSTRY 4.0

Interestingly, Industry 4.0 is founded on manufacturing environment consisting of: smart products, intelligence, Machine to Machine (M2M) communication, and connection network. The focus of this industry is devoted to intelligent robots, autonomous systems, problem solving without human involvement, and communication between machines. The smart machines become more independent in deciding what to do in a specific situation without any human intervention. Also tasks, that are delegated to them, are more and more complex.

The factors in Industry 4.0 are designated with a set of adjectives, as follows: smart, flexible, adaptive, autonomous, unmanned, and sensor-based without a human in a production loop. It almost appears that the Industry 4.0 has forgotten the presence of humans. Indeed, this system can be observed as machine-centric, and, therefore, the concept could be considered as "human-out-of-loop" [66].

D. CONCEPTS OF INDUSTRY 5.0

The Industry 5.0 paradigm, proposed in 2021 sets new relations between industry and society. It is not just a continuation of Industry 4.0 and not an alternative to it, because it complements and extends features of the Industry 4.0 by placing the industry into the future society (i.e., Society 5.0). In line with this, three concepts of Industry 5.0 are formulated as follows [11]:

- human-centric,
- resilient,
- sustainable.

Human-centric industry means that human needs and interests represent a hearth of the production process [67]. In Industry 5.0, the production process needs to be adapted to the needs of workers in the sense of guiding and training them. The basis of the industry becomes the human-centered technologies that do not determine social development as is the case with technologies appearing in Industry 4.0. The human-centric technologies of Industry 5.0 tries to develop workers' abilities, and take care of their safer and creates a more satisfying production environment. Workers' fundamental rights, like privacy, anatomy, and human dignity, are preserved by these new technologies.

Industry 5.0 is characterized by: (1) robustness in industrial production, (2) smooth recovering after disruptions, and (3) providing the critical infrastructure in crisis times.

Industry 5.0 offers a solution for a Sustainable industry considering that natural resources on the planet Earth are limited by be re-usable, re-purposely, and recycling in order to reduce waste and environmental impact.

E. KEY TECHNIQUES OF INDUSTRY 5.0

Key enabling technologies of Industry 5.0 [67] include:

- individualised man-machine interaction,
- bio-inspired technologies and smart materials,
- digital twins and simulation,
- data transmission, storage, and analysis technologies,
- Artificial Intelligence,
- technologies for energy efficiency, renewables, storage and autonomy.

Individualised man-machine interaction supports humans by working technologies, and, thus, combines human innovation and machine capabilities. Thereby, computational models are applied to mimic human thought processes for solving complex problems [68], and merges AI, ML, pattern recognition and data mining with a cognitive science. The cognitive science integrates more distinct interdisciplinary domains, like visual recognition, language processing, psychology, philosophy, and anthropology, capable of augmenting human reasoning and thinking abilities similar to the human brain [69].

Bio-inspired technologies refer to bio-inspired sensors embedded into smart materials. The smart materials (also intelligent and responsive materials) present synthetic material that can mimics the biological items encountered in our daily lives [70]. Characteristics of these materials are [71]: sustainability, biodegradability, conformability, biorecognition, self-repair and stimuli response qualities. In line with this, they are sensitive on the external stimuli, like stress, moisture, electric or magnetic fields, light, temperature, etc.

Human Digital Twins (HDT) realizes a human-centric paradigm in smart manufacturing systems of Industry 5.0 [72]. Indeed, the human-system integration is achieved by coupling human characteristics to system design. As a result, HDT visualizes the real state of manufacturing system as 3D simulation with real-time implementation [73]. The following phases of industrial production in smart factories are the favorite candidates for the HDT simulations: In product research and development, the visual models of products are verified through simulations. Simulation of equipment operations and parameter adjustment are usually applied in smart manufacturing. In maintenance, the tasks of the HDT are, for instance: to determine the proper time for maintenance, to discover the potential fault points in industrial production and, consequently, to reduce costs in industrial manufacturing.

A cyber-security/safe of data transmission between interoperability systems serves as the common denominator of data transmission, storage, and analysis technologies. In Industry 5.0, data have arisen using networking sensors in the sense of IOT. These sensors demand the so-called edge servers that need to be deployed closer to data sources due to the better performances. Typically, the edge servers are building blocks of the edge computing. The network sensors produce a lot of data demanding a big data management. On the other hand, the big data are analyzed using ML methods, while the data processing is conducted in clouds. This means that the ICT in Industry 5.0 captures the whole spectrum of various ICT devices, i.e., from the simple IOT sensors to the complex cloud IT infrastructures. From the security point of view, all computer systems and networks must be protected by cyber-security in order to prevent unauthorized information disclosure, or damage of hardware, software, or data.

The Industrial AI represents a special case of Narrowed AI that is capable to solve specific problems arisen in automating specific, and, typically, repetitive tasks. This is in contrast with the General AI that tries to create machines capable of thinking and reasoning like human [74]. In general, the purpose of the Industry 5.0 AI is to detect, for example, causalities in complex, dynamic systems, leading to actionable intelligence.

Technologies for energy efficiency, renewables, storage and autonomy support the sustainable paradigm of Industry 5.0. In line with this, techniques are promoted by this that lessen the hazardous impacts on nature. Indeed, the revolutions preceding the fifth revolution never put working on a sustainable environment as their goal. Industry 5.0, on the other hand, encourages building such smart factories that produce minimal waste. Another suitable solution for improving sustainability represents circular manufacturing supporting the use of renewable energy sources. Sustainable storage refers to data storage with minimum effects on the environment and does not contribute to the depletion of natural resources. Autonomy in Industry 5.0 affects enhancing decision-making by human due to more agile and more efficient processing that is supported with information from sensors and software. This results in increasingly efficient and sustainable use of resources.

Finally, the emergence of 6G, anticipated to support Industry 5.0, will also influence smart agriculture. The integration of 6G and IoT will enable the deployment of AI at the network's edges and facilitate the utilization of digital twins, IoT, and robotic systems along this pathway [14], [75].

F. HUMAN-INTO-THE-LOOP IN INDUSTRY 5.0

While Industry 4.0 emphasizes an efficient use of industrial automation, Industry 5.0 is focused on key values of human resources. This means that worker's well-being and human values are put at the centre of the manufacturing/production processes [66]. The last world crises have exposed limitations of our planet that stimulate searching for sustainable and resilient manufacturing production. Although the majority of the key enabling technologies in Industry 4.0 remains also the key enabling technologies of Industry 5.0, the new view on the role of workers into production have brought updating the key enabling technologies of Industry 4.0, like edge computing, digital twins [76], cobots and IIoT, and new applications, including smart health, cloud manufacturing, and supply chain management.

In Industry 5.0, the AI community has started to develop in a direction of "weak AI", where specific tasks needs to be understandable and manageable by humans. Consequently, the existing concept "(hu)man-out-of-the-loop" in Industry 4.0 has been replaced by the concept "(hu)man-back-into-the-loop" in Industry 5.0 that supports a transparent human-machine cooperation [77]. Collaboration between humans and machines is crucial when it comes to overcoming challenges arising from device malfunctions or overcoming ethical dilemmas in decision-making processes.

The human-in-the-loop (HITL) [78] approach makes use of valuable domain knowledge, expertise and contextual understanding which sometimes a human expert can bring in. This approach not only enhances the accuracy and reliability of AI systems but also fosters transparency and explainability. This valuable knowledge integration, aka knowledge injection [79] allows for the correction of biases and errors that automated systems may overlook, ensuring that AI outputs are more aligned with ethical standards and societal values. Moreover, HITL facilitates the continuous learning and improvement of AI models through dynamic interaction with human insights, leading to more nuanced and contextually appropriate AI solutions. Consequently, the HITL approach significantly contributes to the development of trustworthy and human-centered AI, promoting a synergy between human intelligence and artificial capabilities.

IV. FROM AGRICULTURE 4.0 TO AGRICULTURE 5.0

The three previous industrial revolutions have profoundly changed agriculture - from animal-assisted agriculture to mechanised agriculture to the recent precision agriculture [80]. In Agriculture 4.0 [81], inspired by Industry 4.0, the focus has mainly been on automation through the Internet of Things, robotics, artificial intelligence, Big Data analytics and blockchain technologies, and above all the paradigm of precision agriculture, which, similar to precision medicine, is expected to contribute to a huge improvement in quality [82]. While the precision agriculture paradigm is showing good success, the initial successes in automation have given way to the disillusionment that it will not work to autonomize everything - see the current limitations of robotics, even in such comparably simple tasks of autonomous driving.

V. EXISTING APPROACHES AND FRAMEWORKS OF AGRICULTURE 4.0

In the context of Agriculture 4.0, which encompasses the integration of advanced digital technologies into farming practices, several conceptual and operational frameworks have been developed. These frameworks are designed to guide the adoption and implementation of technologies like the Internet of Things, AI, robotics, and big data analytics, facilitating a transition towards more efficient, sustainable, and productive agricultural systems. Whilst there is no universal list of Agriculture 4.0 frameworks due to the diversity in agricultural practices, technological applications, and regional needs and requirements, below are some example issues of such frameworks:

- Precision Agriculture Frameworks: These focus on the precise and controlled use of agricultural resources, optimizing inputs like water, fertilizer, and pesticides through technologies such as GPS-guided equipment, soil sampling, and drone or satellite imagery. The goal is to enhance crop yields and sustainability while minimizing environmental impacts.

- Smart Farming Frameworks: Such frameworks leverage IoT and AI to create interconnected farms. Examples include the use of sensor networks for real-time monitoring of crop and soil conditions, automated irrigation systems, and AI-based decision support systems for predicting crop health issues.
- Sustainable Agriculture Frameworks: These frameworks emphasize sustainability and environmental protection, integrating technologies for resource conservation, renewable energy use, and reduction of greenhouse gases. They support practices that are not only technologically advanced but also environmentally sound and economically viable.
- Data-Driven Agriculture Frameworks: Centered on big data analytics, these frameworks guide the collection, analysis, and application of data from various sources (e.g., satellite imagery, weather stations, on-farm sensors) to inform decision-making processes, enhance productivity, and reduce risks.
- Digital Extension Services Frameworks: Aimed at improving knowledge transfer, these frameworks leverage digital platforms (e.g., mobile apps, online platforms) to provide farmers with timely information, advisory services, and training on best practices in Agriculture 4.0.
- Blockchain for Agriculture Frameworks: These involve the use of blockchain technology for improving supply chain transparency, traceability, and efficiency, ensuring food safety and reducing fraud by securely recording transactions and product movements from farm to consumer.
- Regulatory and Policy Frameworks: These frameworks focus on creating conducive regulatory environments that support the deployment of Agriculture 4.0 technologies, addressing issues such as data privacy, drone regulations, and intellectual property rights.

While specific frameworks may vary in name and focus, common across all is the aim to integrate cutting-edge technology into agriculture in a way that is sustainable, efficient, and beneficial for all stakeholders involved, from farmers to consumers. The effective implementation of these frameworks requires collaboration between technologists, agriculturists, policymakers, and communities to ensure that the benefits of Agriculture 4.0 are fully realized:

- Precision Agriculture approaches
- Smart Pest Management Frameworks
- Sustainable Agriculture/Farming Frameworks
- Digital Supply Chain Frameworks
- Farm Data Privacy Frameworks

In the following sections, we will briefly outline approaches and frameworks of the essential areas of smart agriculture where Industry 4.0 left massive traces. The main goal is to present the existing frameworks, but in some studied areas, there still needs to be more frameworks developed, or even frameworks do not exist, i.e., precision agriculture [83]. Hence, we present established approaches and leading technologies regarding hardware, algorithms & methods on which applications are built.

A. PRECISION AGRICULTURE FRAMEWORKS

Precision agriculture (PA) employs various information technologies to collect data from various sources (i.e., water, soil, plants) to support decisions related to crop production [80], [83]. PA appeared in the early 80s and is defined by its capacity to optimize resource usage, minimize unwarranted financial outlays and environmental pollution, and reap advantages across economic, social, and environmental domains. This field employs a spectrum of hardware tools and software solutions, processing data garnered by these tools to furnish essential information for decision-making processes [83], [84], [85]. Several goals that correspond with PA are the following:

- reducing the use of fertilizers and pesticides,
- optimizing the water and nutrient use,
- optimization of the workforce.

Although most farmers in the past and even today are managing and profiling the whole field based on the average conditions, PA is intended to address and profile the smaller parts of the area and hence have a better overview of conditions found in different parts of the field. According to the paper [83], five activities are usually associated with precision agriculture:

- seeding,
- fertilization,
- irrigation,
- disease, pests, and weeds control, and
- harvest.

The recent review paper [83] identified ten hardware technologies widely applied and utilized in precision agriculture. These hardware technologies are the following: GPS, smartphones & cameras, nanosensors, remote sensors, sensors in general, unmanned aerial systems, unmanned aerial vehicles, unmanned ground vehicles, variable rate technology, and wireless sensor networks (WSN). On the contrary, the following techniques that fall under the software umbrella plays a very important role in precision farming, i.e. geographic information systems, multispectral images, soil mapping, variable rate applications, variable rate fertilization, variable rate irrigation, yield maps, yield monitors [83].

Practical ramifications of precision agriculture have been manifested in numerous applications developed on pure theoretical and functional levels. Although a lot of research presents only prototypes, several industries also apply precision agriculture approaches in the real world. Some examples of practical utilization of precision agriculture include machine vision to agriculture, mainly for crop farming [86] or pest detection using machine vision [87]. Remote sensing techniques are another critical pillar widely used in precision agriculture [88]. On the other hand, using simlutation techniques for crop prediction is another vital cornerstone of PA [89] or nitrogen status estimation [90].

Finally, according to the literature search, there needs to be more frameworks or guidelines in precision agriculture that would guide users/farmers on which combination of hardware and software can be implemented for specific crops in the context of precision agriculture. Since the authors of the paper came to the same conclusion [83], we are convinced that a human-centric approach developed within the Industry 5.0 may definitely help in this aspect.

B. SMART PEST MANAGEMENT APPROACHES AND FRAMEWORKS

In addition to weather conditions, crop yields in agriculture worldwide are also significantly affected by various pests such as insects and rodents. These pests pose a significant threat to agricultural productivity, leading to considerable economic losses and raising concerns about food security. The destruction caused by various pests often necessitates the use of chemicals such as herbicides and pesticides, which pose a threat to the environment and human health and can have lasting effects on the soil [91], [92].

The swift and reliable monitoring of insect pests is critical in population prediction and the implementation of control measures. Traditionally, pest monitoring and identification relied heavily on specialized experts in the field, demanding labor-intensive efforts and involving numerous individuals. However, the emergence of deep learning (DL) techniques combined with intelligent sensors and cameras has opened up the potential for monitoring, profiling, and managing pest populations [87], [93]. These advancements serve as the foundation for smart pest monitoring (SPM) [94] – many strategies within SPM hinge on integrating image processing with classification methodologies.

SPM can also be conceptualized as a versatile framework. While the authors of paper [94] introduced a unified pipeline for monitoring insect pests, it could serve as a broader framework encompassing various types of pests in SPM. Some adjustments would be necessary to customize data collection approaches for different pests, such as rodents, while other steps can be practically very similar.

The outlined pipeline (framework) comprises three distinct steps or tiers. The initial phase involves automated data collection, integrating diverse nodes for monitoring insects and employing techniques to store this data digitally. This stage also incorporates specialized equipment, such as various types of traps [95]. Following the data collection phase, the subsequent stage engages intelligent data processing methods. Within this stage, we encompass all the essential data preprocessing techniques required to refine, sanitize, and tailor the data to serve as input for artificial intelligence methods and algorithms. This data processing phase also encompasses image processing algorithms. Once the second stage concludes, the final step is designated for decision-making [96], post-processing visualization [97], and the assessment of methods. This step also incorporates explainable AI approaches [98].

In the context of modern agriculture, particularly precision agriculture augmented by AI, the pursuit of sustainability is paramount, as underscored by the European Commission's "Green Deal Industrial Plan for the Net-Zero Age." This plan not only advocates for climate neutrality but also integrates agriculture as a key sector for innovation and sustainability. PA in this context promises optimized resource use and enhanced productivity through data-driven decisions. However, it introduces complexities such as high costs, data management issues, and a significant skill gap, all of which can alienate smaller farms and necessitate substantial investment in training. Moreover, an over-reliance on AI systems can lead to vulnerabilities in farm operations, and the environmental impact of the technology's lifecycle remains a concern. As the European Commission's initiatives suggest, the future of agriculture will increasingly depend on balancing advanced technological practices with sustainable development. Precision agriculture, while offering transformative potential, must navigate these challenges to truly align with the principles of sustainability and climate neutrality [99].

VI. FRAMEWORK OF AGRICULTURE 5.0

Our framework in Figure 1 is based on a combination of human-centered AI and Industry 5.0. The central goals are at the bottom of Figure 1: a stable climate, healthy plants and soils, environmentally friendly cultivation systems, sustainable plant products and satisfied customers. To achieve this goal, we need three major areas in Level 1: (i) crop monitoring (crop identification, water, nutrient and plant health monitoring), (ii) crop management (tillage control, water and nutrient supply, weed, pest and disease control) and (iii) food technology (quality assessment and control, supply chain management).

Technically, this is enabled at Level 2 through the use of digital twins - also to measure changing resources over time, enable resilience to disturbances and ensure the passability of fields.

At level 3, this requires a digital hardware infrastructure, such as Internet-of-Things platforms, robotic platforms and cyber-physical architectures with cloud computing and the necessary cyber security.

At the next level 4, this enables a collaborative digital ecosystem for the entire agricultural supply chain (from farm to fork) with collaborative, transparent decision-making.

Level 5 is the area of privacy, safety, security and ensures occupational safety (accident prevention), eco-efficiency, cost efficiency, simulation and training and new engaging forms of education and instruction.

Finally, at level 6, at the top of our system is a human-centered AI that ensures robustness and explainability and thus enables the necessary trustworthiness (in social, ethical and legal terms) with the aim of complementing and

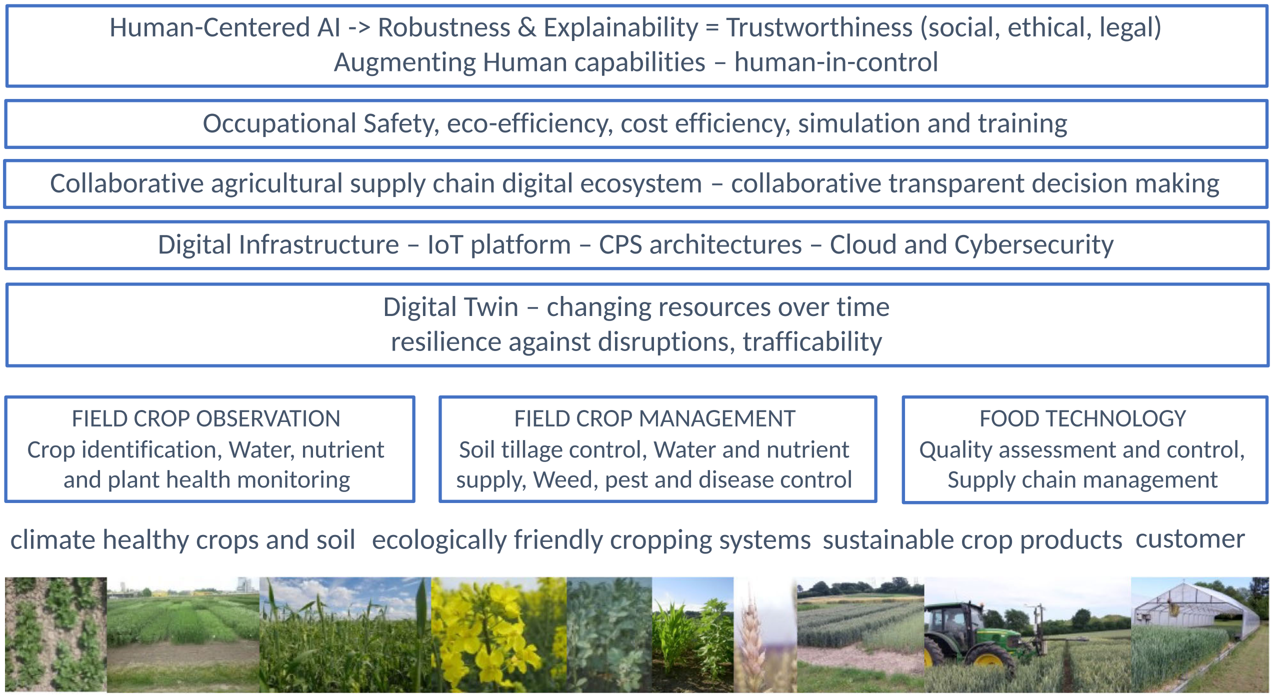

FIGURE 1. **The framework: Human-centered AI + industry 5.0 = agriculture 5.0.**

not replacing human capabilities and thus also taking away the fears of new technologies.

Sustainable land management requires the protection and promotion of natural soil fertility. Various concepts are discussed for this purpose, such as organic farming, conservation tillage and regenerative agriculture. The aim of all these approaches is to cultivate the soil in such a way that plant growth and health are promoted without or with reduced use of synthetic chemical substances such as mineral fertilisers and pesticides. The EU's Green Deal calls for and promotes such forms of cultivation. AI can support the selection of suitable crop rotations. At field level, sensors can be used to determine the condition of crops in terms of nutrient supply and health. Mixed crops of different plant species in order to increase biodiversity in the field pose a challenge here. Important unresolved tasks are the differentiation of the species in the crop in order to be able to determine their proportions quantitatively, as well as the separate determination of biomass, nutrient supply and health status of the mixture components. Increasingly, soil microorganisms - both naturally occurring and artificially inoculated - are being propagated to support plant populations in terms of growth and health. Sensor applications that can determine and quantify the effectiveness of such treatments on nutrient uptake and plant health, combined with forecast models are helpful for testing the effectiveness of such treatments.

VII. CONCLUSION

Our Agriculture 5.0 framework marries the principles of Human-Centered AI with the ideals of Industry 5.0 to propel forward the cause of sustainable farming practices. It is dedicated to fostering climate resilience, enhancing the health of plants and soil, fostering ''One Health'' [100]. The framework employs environmentally friendly approaches, and is ensuring consumer contentment. This model encompasses exhaustive surveillance of field crops (including plant identification, and monitoring of water, nutrients, and health), strategic management practices (covering soil, water, nutrient management, and pest mitigation), alongside innovations in food technology (spanning quality assurance and supply chain optimization). At the heart of this framework lie digital twins, pivotal for efficient resource utilization and fortifying resilience, all built upon a solid digital foundation that includes IoT, robotics, and cyber-physical systems, buttressed by cloud technology and rigorous cybersecurity protocols.

This architecture fosters a synergistic digital ecosystem that enhances decision-making, safety, eco-efficiency, and training. At its core lies a robust, explainable, and trustworthy human-centered AI, designed to augment human capabilities and maintain human oversight. With a focus on sustainable land management, our approach promotes natural soil fertility and practices such as organic farming and conservation tillage, aligning with initiatives like the EU's Green Deal. AI plays a pivotal role in optimizing crop rotation and deploying field-level sensors for precise crop condition monitoring.

However, challenges persist, including species differentiation in mixed cropping systems and separate evaluations of biomass, nutrient supply, and health. We are also investigating the potential of soil microorganisms and sensor-driven probabilistic models to boost plant health and nutrient absorption. Our framework is not just a technological leap but a step towards a more sustainable, efficient, and human-centric agricultural future.

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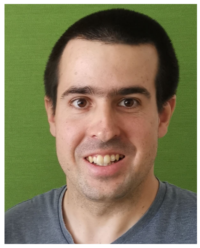

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