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Review

Mapping the Emergent Trends in Industrial Augmented Reality

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Abstract: Augmented reality (AR) is a rapidly developing technology with the potential to revolutionize various sectors of industry by integrating digital information with the real world. This paper presents an overview of the emergent trends in industrial augmented reality (IAR) over the past five years. The study utilizes a comprehensive literature review analysis of industrial studies (searched on two scientific databases: Scopus and Clarivate Web of Science) to map the evolution of IAR trends from 2018 to 2022. The results revealed ten trending topics of AR application: Industry 4.0, artificial intelligence, smart manufacturing, industrial robots, digital twin, assembly, Internet of Things, visualization, maintenance, and training. Each topic is discussed in detail, providing insight into existing applications and research trends for each application field.

Keywords: augmented reality; Industry 4.0; trends; digitalization

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1. Introduction

Augmented reality (AR) is a rapidly developing technology that has the potential to revolutionize various sectors of industry. In the context of Industry 4.0, AR refers to integrating digital information with the real world using computer-generated sensory input, such as video, sound, graphics, or GPS data. With this technology, users can interact with virtual objects and information in a real-world environment, enhancing their ability to perform tasks and make decisions.

One of the main advantages of AR in Industry 4.0 is its ability to improve efficiency and productivity [1]. For example, in manufacturing, AR can be used to guide workers through complex assembly processes [2], reducing the time and effort to complete tasks [3] and enhancing accuracy [4]. It can be used to provide real-time feedback, allowing workers to identify and fix errors, thus reducing the error rate [5].

In addition to improving efficiency, AR can also increase safety in industrial settings [6]. For instance, it can visually alert workers to dangers such as moving machinery or potentially dangerous items [7]. In order to lower the danger of accidents and injuries, it can also be utilized to provide real-time instructions and guidance for carrying out tasks [8].

The capacity of AR to simplify training and onboarding of new staff is another significant advantage for Industry 4.0. AR can assist new employees in learning complicated tasks quickly and effectively by offering interactive, immersive training sessions [9]. Additionally, it can be utilized to provide experienced personnel with continual training and assistance, enabling them to stay current with emerging methodologies and technology.

Although AR has the potential to impact various industries significantly, it is essential to note that because it is still a relatively new technology, its implementation has some restrictions and challenges [10]. Costs associated with installing AR systems, which can be unaffordable for some enterprises, are a significant barrier. Additionally, as employees get used to AR technology, there can be a learning curve [11] that will immediately impact productivity. AR can generally change how we work and interact with the world. It can enhance productivity, safety, and training in the context of Industry 4.0, making it a valuable tool for any organization trying to maintain competitiveness in an increasingly digital world.

In the context of the emerging Industry 5.0, the next phase of the industrial revolution that focuses on human-centered production [12], our study aims to analyze the impact of AR technology on Industry 4.0. The relevant literature of the last five years was reviewed to investigate the trends of industrial augmented reality (IAR) applications.

This study aims to gain valuable insights concerning the current state of research regarding augmented and mixed reality use in industrial applications whilst revealing the most prominent topics and trends in this field. Furthermore, the presented work is focused on investigating the following research questions:

Q1. What are the most common research topics in IAR?

Q2. What are the trends in using AR for industrial applications?

Q3. What are the main research results?

The review is structured as follows. Section 1 presents the motivation and the research questions, as well as some related studies. Section 2 offers an overview of the research technique used for article identification, outlining the criteria for document searching and selection, the software and data extraction procedure, and the most prominent trends for IAR. Section 3, which focuses on the ten most popular AR topics in Industry 4.0, serves as the main body of our review. Section 4 summarizes several general findings and limitations, and Section 5 formulates the conclusions and provides future directions concerning AR use in industrial environments.

2. Materials and Methods

The documents used in this study were retrieved from Scopus and Clarivate Web of Science (WoS) on January 2023 using the search query "Industrial AND (Augmented OR Mixed) Reality. This search query was chosen in order to ensure that the results would be relevant to the use of AR in industrial applications. The timeframe chosen was from 2018 to 2022. We found 2126 documents from WoS and 1834 documents from Scopus using the selected search keywords. ScientoPy scientometric tool [13] was used for preprocessing data sets and extracting the authors' keywords. After merging and removing duplicate documents from WoS and Scopus, 2695 unique entities were obtained. The following ScientoPy trend indices for the identified top ten topics are given: average growth rate (AGR), average documents per year (ADY), percentage of documents in last years (PDLY), h-index of each topic.

Using ScientoPy, the authors keywords were classified based on the AGR and number of documents in order to determine the top ten applications from published documents (see Figure 1). The most prominent trend topics identified are: (1) Industry 4.0; (2) Internet of Things; (3) Artificial intelligence; (4) smart manufacturing; (5) visualization; (6) human–robot interaction; (7) maintenance; (8) digital twin; (9) training; (10) assembly.

The following ScientoPy trend indices for the identified top ten topics are given [14]:

- Average growth rate (AGR)—the average difference between the number of papers published in one year and the number of papers published the year before;
- Average documents per year (ADY)—the average number of papers published within a timeframe for the selected topic;
- Percentage of documents in last years (PDLY)—the ratio between the ADY and the total number of papers for a certain topic;
- h-Index of each topic—ScientoPy determines the h-index of each topic for different categories, such as authors, countries, institutions, etc.

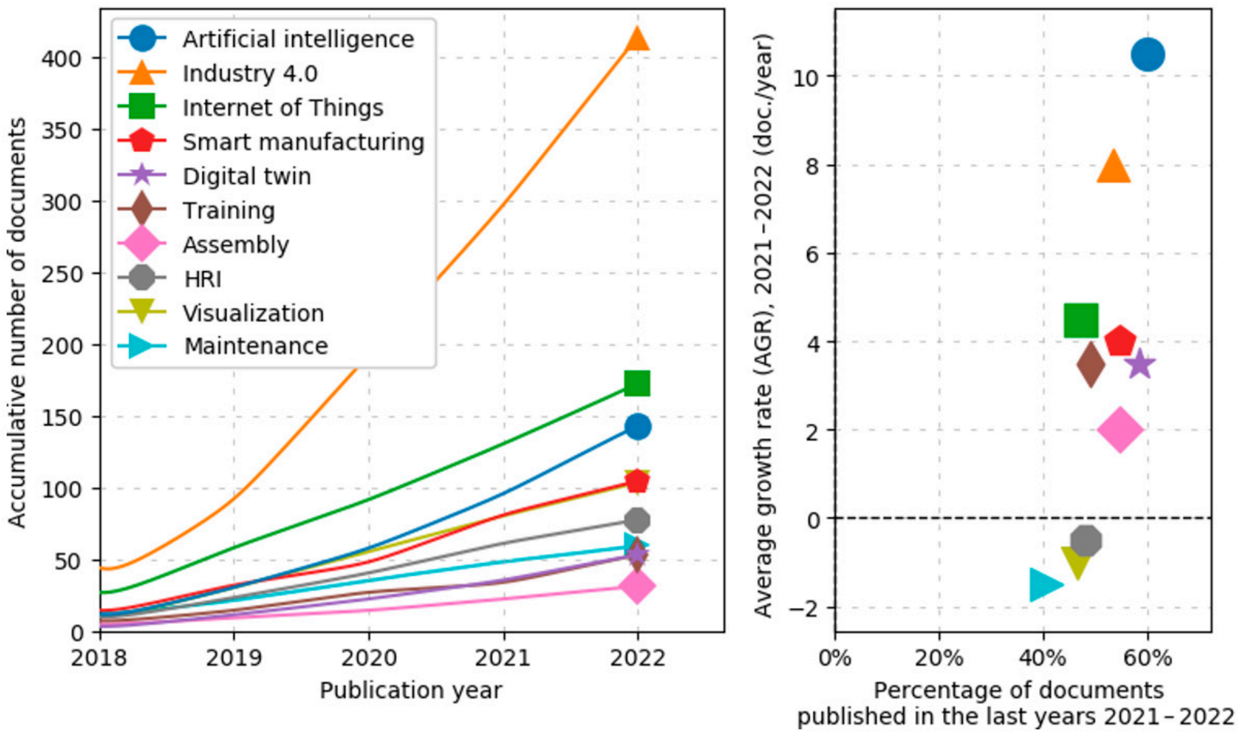

Figure 1. Top trending topics related to industrial augmented reality.

The values of these parameters are reflected in Table 1. The evolution plot (see Figure 1) shows that trending topics have a consistent growth in the specified timeframe. For each trending topic, the AGR between 2021 and 2022 is shown on the Y axis of Figure 1 right diagram, and the PDLY is shown on the X axis. "Industry 4.0" is the trending topic with the most documents, while "artificial intelligence" is the topic with the fastest rate of growth.

Table 1. Trend indices of selected topics.

Pos	Author Keywords	Total	AGR	ADY	PDLY	h-Index
1	Industry 4.0	414	8.0	111.0	53.6	42
2	Internet of Things	172	4.5	40.5	47.1	29
3	Artificial intelligence	143	10.5	43.0	60.1	20
4	Smart manufacturing	104	4.0	28.5	54.8	24
5	Visualization	103	−1.0	24.0	46.6	12
6	Human–robot interaction	77	−0.5	18.5	48.1	15
7	Maintenance	59	−1.5	12.0	40.7	15
8	Digital twin	53	3.5	15.5	58.5	13
9	Training	53	3.5	13.0	49.1	10
10	Assembly	31	2.0	8.5	54.8	11

The identified top ten trending topics are discussed with references to the articles with the highest number of citations and most relevant to the topic. The following exclusion criteria were used in the process of article selection:

1. Publication type: books, book chapters, notes, and editorials were excluded;
2. Publication date: publications outside the 2018–2022 timeframe were excluded;
3. Duplicate publications: duplicate publications are excluded to avoid double-counting;
4. Irrelevant topics: articles that are not relevant to the research question or objectives were excluded.

3. Results

The growing potential of AR applications for Industry 4.0 has resulted in the development of exciting applications that have a more significant impact on various subjects. The top ten trending topics concerning IAR are illustrated in Figure 2.

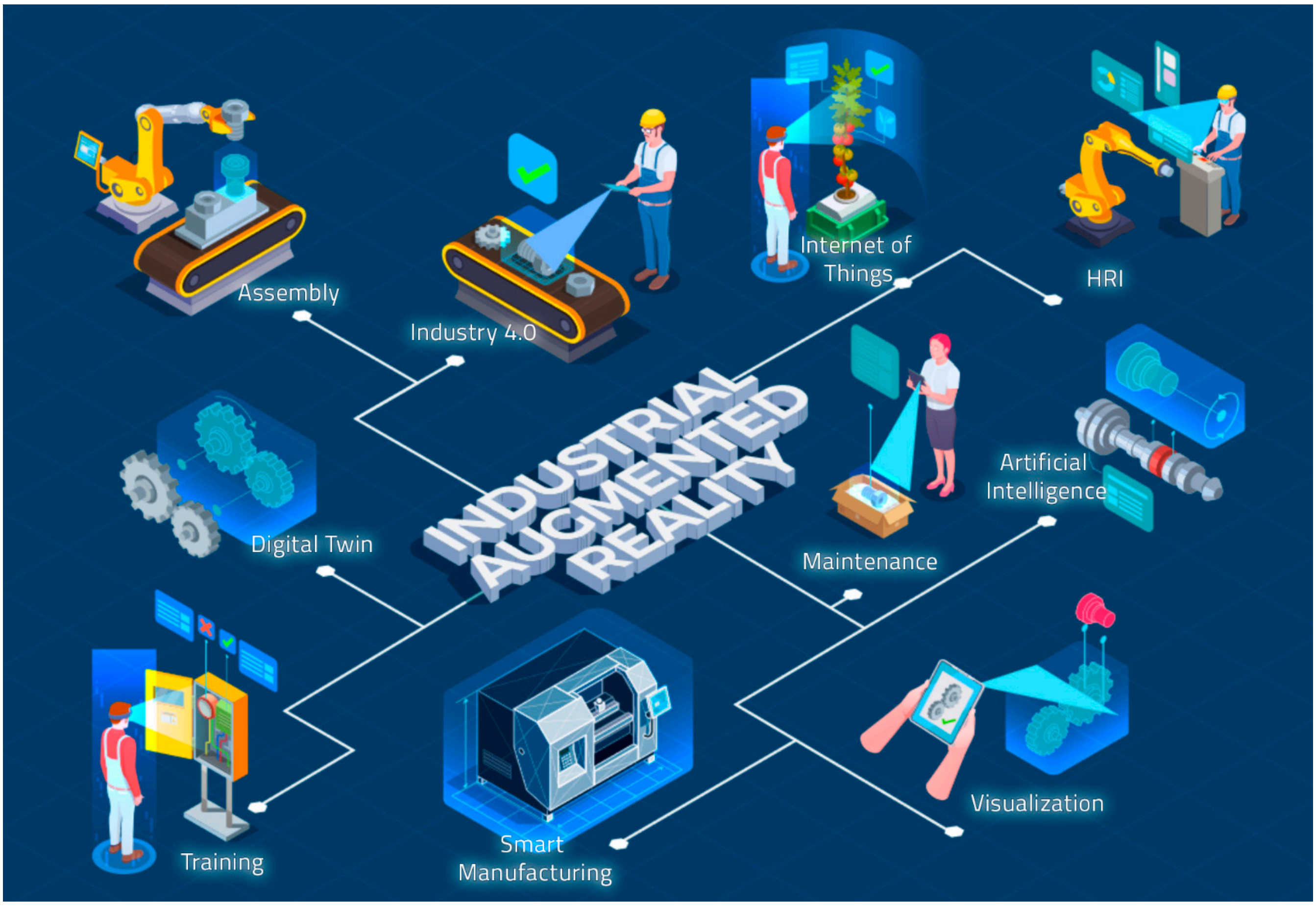

Figure 2. Industrial augmented reality (IAR) trends.

3.1. Industry 4.0

The fourth industrial revolution is known as "Industry 4.0" and it is defined by the incorporation of advanced technologies, such as artificial intelligence (AI), robotics, Internet of Things (IoT), cybersecurity, and automation to build smart factories and digital production systems. Other components of Industry 4.0 were identified in [15]: big data, cloud computing, and 3D printing. Among these, one of the emerging technologies that has received significant attention in the Industry 4.0 environment is AR. Various fields of industry benefit from the support provided by means of this technology: aerospace [16], textile and apparel sectors [17], meat industry [18], fashion [19], and so on. Real-time user interaction with digital items is made possible by AR, offering a wide range of possible uses in the manufacturing sector, from product design and quality control to maintenance, assembly, human–robot collaboration, and training [20]. With AR systems, the safety of workers could be enhanced [21], while the effort and error rate could be reduced [4].

In the automobile industry, AR assists technicians for fault diagnosis and servicing using machine learning techniques [22]. Moreover, AR applications for medical students, nurses, or doctors can be a major advantage in improving the quality of medical education and training [23]. AR applications for construction can help workers with different tasks, such as design, planning, scheduling, inspection, and other complex work [24].

Several surveys have examined the potential applications of AR in Industry 4.0. In [25], a summary of managerial implementation challenges associated with Industry 4.0 is provided, together with the derived opportunities to prevent these difficulties. The authors classified Industry 4.0 technologies into ten categories, including AR/VR. For this category, they identified the lack of integration for the manufacturing systems (e.g., software integration, information exchange) as an implementation challenge. Strictly focused on the challenges of implementing solutions that use AR in industry, in [26], the authors mentioned several problems related to hardware and software, ergonomics, user acceptance, visual fatigue, security, and so on. Additionally, a framework based on a technology, organization, and environment (TOE) model was proposed to determine the influence of various factors on implementation success. Other challenges related to optical and optoelectronic components, which are indispensable for displaying and processing information in AR-based systems, are presented in [27]. In this paper, the main AR headsets are also reviewed, together with their characteristics.

Despite these limitations and challenges highlighted in the literature, researchers have implemented various frameworks to help integrate all solutions and technologies. Such an approach for industrial process modeling is provided in [28]. The presented framework has some important advantages, such as modularity, flexibility, reusability, and it allows human–robot collaboration, interaction between human workers, task modeling, different automation systems, scenarios, domains, and purposes. In [29], a method for analyzing the integration issues in the context of Industry 4.0. (5 C) is presented, using five integration levels: connection, communication, coordination, cooperation, and collaboration (5 C). AR was considered in this paper as being part of the connection level, since it facilitates the actors' communication with each other, but it also allows communication and cooperation. A middleware architecture enabling the interaction between different technologies without calibration is proposed in [30].

The use of AR in the context of assembly workstations, for example, can help opera-tors execute their tasks, lighten their workload, or simplify cognitive tasks. Moreover, it offers remote work facilities, such as remote support, collaboration [31], or remote control [32]. With the integration of virtual and physical reality, industrial machinery and devices can be operated safely from any location in the world. AR allows the operators to interact with a virtual 3D model of the machine while viewing and operating it in real time [33]. This technology has an important role in the development of smart factories.

3.2. *Artificial Intelligence*

Industry 4.0, AR, and artificial intelligence (AI) are all closely related technologies that are changing the manufacturing sector. By analyzing massive volumes of data, forecasting potential problems, and streamlining production procedures, AI is being utilized to increase efficiency and output. On the other hand, AR could be utilized to improve quality control and eliminate errors.

Artificial Intelligence of Things (AIoT) is the starting point in the development of both interactive systems used in industrial automation and robots for virtual shopping. A multifunctional perception system, with a robot being part of it, was successfully implemented in providing real-time feedback to the user regarding the products [34].

In the past 20 years, new technologies have been used by antenna engineers in order to face the challenges of lightweight, personalized mechanics in industrial design. Emerging technologies provided opportunities, which inspired recently graduated students to provide their own example of a Meta-built virtual industry and university collaboration to foster the application of AI in the area of antenna design [35]. Additionally, over time, in the industrial field, significant changes have occurred in the working environment for plant operators and maintenance technicians. These changes are due to digitalization and Industrial Internet of Things, mostly due to the implementation of artificial intelligence and machine learning [36].

Regarding the medical system, as presented in [37], artificial intelligence is a novel realm of science and technology that is expanding quickly. In terms of disease prediction, communication and treatment strategies have presented many opportunities originating from artificial intelligence systems. Additionally, AI has been utilized to analyze medical images, videos, and signals. In addition to artificial intelligence, in the medical field, extended reality development can be seen as a device suitable for distant trial and error in image processing [38].

In [39], based on a questionnaire survey, the study's purpose was to determine the functional requirements of smart glasses and then conduct a design practice and usability evaluation. The results of the survey highlighted that people believed that smart glasses should be durable, strong, possess face and voice recognition, and be firm when worn. Therefore, the design should first meet all those functions and features.

AR technology was utilized in [40] for converting industrial chemical spraying robots into soap bubbles robots as an interactive game. The potential benefits of augmented reality (AR) for manufacturing are discussed in [41], as well as several factors that prevent the widespread adoption of AR.

The application of deep learning in visual SLAM is discussed in [42] from four aspects according to neural network application models. The nature, advantages, and disadvantages of existing research are summarized and discussed from the perspective of future development trends.

Three-dimensional object detection provides an object's size, position, and direction to obtain information about the surroundings. The research paper [43] discusses the potential applications of 3D object detection and deep learning's role in 3D object detection. The study includes a comprehensive analysis of 3D object detection methods and the existing challenges in the field.

AI includes different algorithms capable of completing various tasks. Considering that AR combines digital and physical environments, it can be concluded that AI and AR are complementary technologies. Together, they provide the user with the ability to understand and use the 3D world in industry, design, or medicine.

3.3. Smart Manufacturing

By using cutting-edge technology such as the Internet of Things (IoT), AI, and data analytics [44], smart manufacturing aims to increase productivity, quality, and efficiency in the manufacturing process [45]. These technologies are integrated in order to automate and optimize various tasks, including supply chain management [46], quality assurance [47], and production planning [48].

In smart manufacturing, AR a technology that is progressively being used. With the aid of devices such as smartphones or headsets, AR can be used to provide workers with information and guidance in real-time while they perform tasks, enabling them to work more accurately and efficiently [49].

An AR headset, for instance, might display detailed instructions for assembling a product [50] and inform the user if a mistake is made [51] or if a tool needs to be replaced. As a result, the manufacturing facility's total productivity can increase [52], and training time and costs can decrease [53].

AR can also help with training and onboarding new employees [54] since it can provide a visual representation of complex tasks and processes [55]. At the same time, managers can know the production status of the production line more quickly through their mobile phones while walking around the factory [56].

In [57], a web-based AR application for smart manufacturing architectures was presented, which gives users real-time access to technical manuals, operating diagrams, maintenance history, training videos, and data analysis, while also being portable to any device.

The state of the art for industrial AR (IAR) applications for shipbuilding and smart manufacturing is reviewed in [58], which also describes the primary use cases for IAR utilization in shipyards as well as pertinent IAR hardware and software solutions. The authors assessed the performance of a system using three IAR devices, two AR software development kits, and several IAR markers at a shipyard workshop. Another AR system for remote assistance is presented in [59] for a repair task, in which the customer is guided by an expert using AR glasses (such as Microsoft HoloLens). In [60], a prototype system consisting of a smartphone and a 3D printer is proposed, allowing users to design customized products. In order to integrate various Industry 4.0 technologies for manufacturing processes, a framework was described in [61], in which a reference architecture covering a broad range of scenarios supports the collaboration between human and robot workers. Additionally, a framework that integrates 5G and tactile internet (TI) for AR maintenance and shop floor rescheduling is proposed in [62].

Through a collection of comparative user studies, [63] offers instructions on how to use AR in manufacturing. The findings were collected from the evaluations of 160 people who undertook the same repair task on an industrial robot's switch cabinet. In both a single-user and collaborative context, the studies compare a variety of AR teaching apps on various display devices (head-mounted display, handheld tablet PC, and projection-based spatial AR) with the standard operating procedures (paper instructions and phone help). The study can provide clear evidence regarding AR strategies that are particularly beneficial in a team environment.

In [64], the concept of "smart factory" and how it is being applied to traditional manufacturing systems is expanded on. The text also discusses the importance of human–robot collaboration (HRC) systems, and a conceptual framework is proposed for efficient human–robot collaboration in a semi-automation process to produce electric motors.

In general, the application of AR in smart manufacturing can result in considerable advantages, such as greater productivity, enhanced quality, and lower training expenses. AR reduced the complexity of manufacturing operations [65] while enhancing the reliability and safety of robotic systems [66]. The future of manufacturing is likely to have increased importance as the adoption of AR technology continues to grow.

3.4. Human–Robot Interaction

There are many initiatives related to the use of extended reality (XR) in industry, one of which is related to robotics and manufacturing. For example, the advantages of AR and potential commercial applications are covered in [67], including a case study with possible applications of AR in business.

Industry 4.0 is a new concept which emerged just a few years ago. The goal of Industry 4.0 is to make society more effective and productive by utilizing industrial robots and AR. AR has received significant attention recently due to its potential to provide distinctive user interfaces that seamlessly combine the natural environment with additional information.

In human–robot collaborative contexts, the literature review presented in [68] attempts to identify AR's key benefits and drawbacks as it is used with industrial robots. The authors' conclusions imply that AR technology is also beneficial in industrial robotics, as in many other fields. The authors infer that users choose AR technologies over conventional methods because they are quicker, more user-friendly, and with the latest technological advances, possibly also cheaper.

Traditional industrial robot programming techniques have drawbacks because they require highly skilled staff and extensive programming time. In a classic approach, users were supposed to use a standard desktop, and potentially a pad-like device, to insert direct commands. AR introduces a paradigm that enhances the human–robot interface and makes it simpler to program robots' trajectories. Using visual cues, factory workers can increase their efficiency and minimize injury risks. The authors of [69] discussed how AR can be used to create an immersive user interface that makes it possible to program robot trajectories naturally. The authors create and present a system based on Unity 3D, ROS, and Vuforia.

The main objective of the study [70] was to present and evaluate the idea of a hybrid programming method that incorporates techniques for designing, programming, and re-configuring robotic cells both offline and online. The digital twin (DT) of a fully synchronized robotic cell created by Tallinn University of Technology's Industrial Virtual and Augmented Laboratory provides the foundation for this method's testing. Using an online programming technique, researchers could program robotic cells and alter their predetermined path by using their virtual avatar via telepresence. Additionally, this study found that AR shortens the time required for designing and reprogramming robotic cells, allowing for the reduction of the robotic cell's downtime on the manufacturing floor.

In [71], the authors present a fresh approach for the intuitive and organic interaction with various kinds of robots. They designed and created an expanded render client architecture that uses the HoloLens' ability to recognize gestures and display three-dimensional content in AR. Researchers propose a new natural interaction and information representation method by fusing the HoloLens' capabilities with the simulation program VEROSIM.

Industrial robot manipulators are becoming more versatile, which means that the teaching pendant or keyboard may not meet the need for delicate manipulation. Intuitive manipulation and a friendly human–robot interface are, thus, demanded. In [72], a novel manipulation system using the AR technique implemented on a tablet PC was proposed. Experiments are performed to demonstrate their effectiveness, along with a questionnaire conducted to evaluate user response.

In [73], the authors discuss how industrial robots are being programmed in order to meet the increasing demand for flexible and low-cost production. They present an affordance-based approach for process programming that uses low-level feature detection and a consecutive evaluation. The results of their experiments show promising results for both speed and accuracy.

The growing use of industrial robots in contemporary manufacturing surroundings and how effectively they undertake pre-programmed duties are covered in [74]. Researchers examine how robots can handle unexpected situations. As introducing humans into the production loop usually results in unnecessary downtime and calls for human intervention, this study's objective is to suggest a technique for creating adaptive industrial robots that use machine learning and machine vision techniques. In [75], the authors propose a virtual and AR paradigm on mobile and mixed reality devices for human–robot interaction. By fusing information from actual robots with the vision and skills of human operators, researchers hope to develop cutting-edge applications. The paper presents an overview of the implementation and describes an architecture divided into three functional sections.

Human–robot and robot–robot collaborations are also important for Industry 4.0 as they can lead to improved efficiency, productivity, safety, quality, interaction, and innovation. By collaborating, robots can perform tasks that are hazardous or repetitive for humans, while humans can focus on tasks that require creativity and decision-making skills. Collaborating robots can help to reduce the risk of accidents in dangerous environments, perform quality control checks on products, and open up new opportunities for innovation. Ultimately, human–robot and robot–robot collaboration can lead to a more effective and efficient working environment.

Regarding human–robot collaboration and robot–robot collaboration, [76] discusses the importance of autonomous robotic systems in Industry 4.0 and how they should be designed to allow for a closer collaboration between operators and automated technologies. A user-centered design approach may be used to address the challenges of future human–robot collaboration (HRC). AR and virtual reality (VR) technologies are mentioned as necessary tools for the operator to have a central position in the design, control, and assessment of current industrial collaborative scenarios.

The industrial human–robot collaboration aims to achieve a higher productivity by combining human intelligence and robotic capability. Communication is essential to this collaboration, and brain–computer interface (BCI) technology can be used to establish a direct and efficient communication channel between humans and robots. However, BCI is limited in its ability to control robots with a high degree of freedom. A closed-loop BCI with contextual visual feedback by an AR headset is proposed in [77].

In [78], a set of safety indicators is determined, and an assessment model is established based on the latest safety-related ISO standards and manufacturing conditions. A dynamic modified SSM (speed and separation monitoring) method was presented to ensure the safety of human–robot collaboration while maintaining productivity as high as possible. The real-time risk status of the working robot can be known, and the risk field around the robot is visualized in an augmented reality environment to ensure safe human–robot collaboration. This system is experimentally validated on a human–robot collaboration cell using an industrial robot with six degrees of freedom.

Industrial HRC in manufacturing allows industrial robots and humans to complete production tasks jointly at a closer distance. An intuitive interaction channel between humans and robots is needed to enhance the efficiency and security of collaboration. In this context, an AR-based approach is introduced in [79] into the industrial HRC to develop an intuitive human and robot interaction. The intuitive interaction uses an AR head-mounted display (HMD) to offer an augmented information feedback channel and to enhance the human worker's in situ perception capabilities of the manufacturing environment. The system also has a user interface to interactively operate the robot. A visual trajectory is displayed to present the planned path of the robot and can be edited by the intuitive user interfaces, and the 3D robot model is built to simulate the movement of a real robot as a preview to improve the robot's operation efficiency.

In [80], the growing popularity of robots, specifically collaborative robots, is discussed. These robots are not user-friendly for working within a collaborative setting and require a high level of engineering and computational capabilities for the program. Industry 4.0, or the fourth industrial revolution, has endorsed the use of mixed reality technology to improve human–robot interaction. A marker-based algorithm is proposed, which is a user-friendly and facile way to program a collaborative robot.

An extensive review discusses the increasing use of robots in various industries and how effective human–robot collaboration can be. It examines various approaches to human–robot interaction and how easy it is to program robots using various techniques [81].

3.5. Digital Twin

Digital twins have numerous interpretations in the literature; however, the one presented in [82] seems the most comprehensive and states that a DT is a "self-adapting, self-regulating, self-monitoring, and self-diagnosing system-of-systems" that has three main properties: (1) bidirectional communication between the real and virtual entities, (2) accuracy, number of enabling technologies, and rate of synchronization should be tailored to specific use cases, and (3) the implementation of DTs should bring operational and business value to the physical object. Even though the concept of the digital twin (DT) was first introduced in 2002 [83], it was only after 2015 that DTs received various definitions which helped to increase their significance among several industrial sectors. For example, researchers pointed out the significant contribution that DTs could have within Industry 4.0 and the Industrial IoT framework [84,85]. In [86], a DT model of an industrial robot (FANUC) is proposed. The authors obtained an error range of -0.3 to 0.3° at a latency of approximately 40 ms in simulating the robot's trajectory. Multi-robot teleoperation tasks with human-in-the-loop control were investigated in [87]. Their novel approach, based on AR and DT, was tested by two experimental studies that demonstrated the system's efficiency, which enabled real-time motion control and robot monitoring. The combination of AR and DT can be used for predictive maintenance [88], to increase the efficiency and reliability of the processes, to provide operator training and in situ guidance for maintenance processes [89], and enhance worker performance whilst also reducing risks [90,91].

The works presented in [33,92] aimed to improve current DTs with multi-user experience, allowing workers to operate and reprogram equipment from remote places in a more natural way. The authors suggested expanding the proposed approach to other use cases, such as smart cities and healthcare. Industrial processes can further benefit from integrating a real-time locating system (RTLS) combined with a DT, which can reduce operational waste and facilitate the performance of Lean 4.0 [93]. Furthermore, there is a need for a human-like vision system that can ensure real-time analysis of video streams [94].

Education should also keep up with the progress of technology. ARNO, a cost-effective mixed reality-based DT (MRDT) platform which can be used for robotics education, is presented in [95]. The acceptance of new technology needs to also be addressed in order to understand which factors can motivate users to adopt such tools or methods. An extended technology acceptance model (TAM) for MRDT adoption is proposed in [96]. The authors conclude that the main factors that can be used to predict MDRT adoption in the architecture, engineering, construction, and operations (AECO) industry are perceived ease of use, subjective norm, perceived enjoyment, perceived usefulness, satisfaction, attitude, and behavioral intention.

The use of collaborative robots in industrial plants raises new safety and ergonomics concerns, as pointed out in [97]. A mixed reality solution combined with DT could represent a viable solution to obtain the necessary safety ergonomics.

Conventional interfaces for control and maintenance are not well suited for DTs in Industry 4.0. A gamified solution based on Unity3D, robot operating system (ROS), and the MQTT protocol for connectivity is proposed in [98]. The modular framework enables online connectivity and intuitive interactions, whilst machine learning algorithms allow the control and simulation of the production line. The user interface (UI) for DTs should integrate at least three functions: monitoring, controlling, and diagnosing the state of DTs. A detailed analysis of the critical components of such a platform is presented in [99]. Furthermore, a literature review concluded that researchers should focus more on UI and the involvement of users in the development of new MRDT tools, not only on the technology [100].

The quality of service for virtual reality digital twins can be efficiently enhanced by implementing a blockchain-based distributed resource allocation scheme, as demonstrated in [101]. Aheleroff et al. [102] also suggested that the use of blockchain and AI could be beneficial for using DTs for mass personalization.

Several limitations hinder the rapid adoption of DTs in industry, such as the complexity of effective communication, data accumulation [103], the lack of standardized development methodologies [82], the convergence of physical and cyber worlds [104], rendering delays [91], computing intensity, and security-sensitive features [101].

3.6. Assembly

Assembly is a critical component of many industrial processes, and a growing body of research explores how AR can be used to enhance assembly operations. By using AR, workers can access real-time instructions and guidance as well as 3D models and animations that can help them understand complex assembly procedures. This can increase efficiency, accuracy, and safety in the assembly process.

Several studies targeted this area of research. For example, in [105], the authors develop and evaluate an algorithm for dynamic gesture recognition and prediction in augmented reality-assisted assembly training (ARAAT). They proved to increase recognition accuracy while reducing the computational cost. In [106], a new remote collaboration platform using head pointers designed to enhance assembly performance is described, which reduces errors and improves user experiences, and can be implemented in a low-cost head-tracking system. In [107], the acceptance of AR in assembly scenarios using a model-based approach is examined. The proprietary acceptance measurement model synthesizes previous models and is simplified for industrial assembly.

In [108], three main contributions were presented: identifying potential barriers to AR adoption in manufacturing environments, proposing an AR training methodology to overcome these challenges, and evaluating the approach in a real-world use case. A methodology for human–robot collaboration in an industrial assembly is outlined in [109], utilizing a collaborative robot (Cobot) and spatial augmented reality (SAR) assistant system. The Cobot performs difficult/dangerous tasks while SAR provides worker assistance and information.

A coupling AR-supported assembly task instructions with image-based state tracking to assist operators in product assembly is proposed in [110]. The developed system includes a visualization platform, a state tracker using deep neural networks, and a server for data exchange. The framework is applied and validated in an industrial use case.

Efficiency in modern manufacturing requires standardized ontologies. The authors of [111] propose modelling an AR-based work instruction framework in an ontology based on ISA-95. The suggested data exchange model is validated in an agriculture machinery use case. In [112], an automated approach for generating AR assembly assistance from CAD models is proposed. The assembly information is transferred to a HoloLens 2 with two user interfaces, eliminating manual effort.

In [113], it is discussed how gamification, using game design elements in nongame contexts, can be an effective training solution for assembly workers. The authors found that traditional training methods are unsuitable for future trends, while augmented reality training methods may offer some advantages. The study [114] focuses on using AR to assemble printed circuit boards (PCBs) manually. It presents an AR system architecture and requirements based on existing research. The study highlights that an effective AR-based assembly can be achieved without a high cost and emphasizes the importance of carefully assessing each assembly configuration for proper system configuration. The authors of [115] found that AR can be a faster solution for complex assemblies, but there are limitations to the technology. Their future studies focus on ways to reduce errors and overall usage time. A new projection-based augmented reality system for aiding operators during electronic component assembly was introduced in [116]. It includes descriptions of the hardware and software solutions and the usability test results.

The authors of [117] examined how smart factories can be connected to the IoT network and present ways to enhance efficiency by reducing employee workload. They compare different types of assembly instructions and find that non-paper instructions can significantly reduce learning time. The impact of the fourth industrial revolution on production processes and the adoption of digital technologies in industrial settings were discussed in [118]. They present a research study proposing a hardware/software architecture to assist operators in manual assembly processes during the training phase.

In [119], the authors discuss the challenges in the collaboration between human operators and industrial robots for assembly operations, focusing on safety and simplified interaction. A case study is presented involving perception technologies for the robot in conjunction with wearable devices used by the operator. A complete system is coordinated under a common integration platform, and it is validated in a case study of the white goods industry.

The challenges that companies are facing with regard to the process of assembly are discussed in [120]. The high dynamics of globalized markets and the increasing competition are resulting in major challenges for production companies. Collaborative assembly, which is a form of automation in which humans and robots interact simultaneously, has the potential to provide flexibility and relieve people of non-ergonomic tasks.

3.7. Internet of Things

The Internet of Things (IoT) concept involves the inclusion of physical devices for communication and connection to information systems. It has evolved into large-scale environments and various business sectors, leading to the emergence of the Industrial Inter-net of Things (IIoT). The approaches found in the literature can include one or more concepts, such as augmented reality (AR), artificial intelligence (AI), fog computing, mixed reality, and the need for human-centric methods. A synthetic analysis of how sensors may be used to track items in real time and how productivity can be increased as a result of the information gathered, based on a combination of AR and the IoT, is presented in [121]. A similar study proposed a framework that uses AR and IoT data visualization to support key performance indicator (KPI)-based process supervision in smart factory environments [122]. The design and implementation of an innovative form of a human–machine interface

(HMI) to control and monitor mechatronic systems in IoT networks using AR concepts is presented in [123].

AR can be used in the IIoT to analyze and interact with a real system through virtual production, offering greater flexibility in the product lifecycle. Going further, the use of AI is motivated by unstructured data from various sources, enabling the transformation of data into relevant information. The convergence of IoT, AR, and AI can make systems increasingly autonomous and problem-solving [124].

A context and augmented reality extension (CARX) for business process model and notation (BPMN) which facilitates the integration of process automation, IIoT context, and AR devices in smart factories was presented in [125]. The feasibility and applicability of BPMN-CARX are demonstrated through an Industry 4.0 case study.

Fog computing has been identified as a promising approach to overcome the limitations of cloud-only implementations for industrial applications, such as latency, network traffic reduction, and reliability. Two case studies presented in [126] demonstrated its applicability for IIoT applications, showing that the use of fog computing concepts can in-crease system availability, achieve low latency for sensor data analysis, and optimize bandwidth utilization, leading to reliable applications. Rahimi et al. [127] proposed an SDN-based virtual Fog-RAN architecture for IIoT networks. The findings were positive, as their solution was found to maximize the achievable sum-rate, minimize network power consumption, and provide better savings in terms of radio and baseband resources utilized.

Seitz et al. [128] proposed using emojis in combination with AR and fog computing to create novel interactions that could make analysis simpler and facilitate preventive maintenance. Their proof-of-concept implementation with customers from the industry is based on five requirements (5 Ds): device detection, device identification, data gathering, data interpretation, and device characteristics visualization. According to the authors, such a strategy can result in production economies that are more resource-efficient and sustainable.

IIoT is developing quickly, creating a demand for ongoing reskilling and a shortage of trained people. The quantitative behavioral model learning emerging digital skills (LEDS), based on the ambidextrous learning theory and the validated unified theory of acceptance and use of technology (UTAUT), was proposed in [129] in an effort to better understand the factors that affect the capacity to learn a new technology. The primary elements that influence the behavioral intention to learn are social influence, personal in-novation, anxiety, long-term consequence, and job relevance, according to a systematic survey of 685 professionals from 95 different organizations.

A study on the usage of Internet of Things (IoT) applications in the construction industry in Malaysia found that social media, email, and websites are the most commonly used applications, while sensor technology for flood monitoring, waste management, scan markers, and smart watches for health monitoring have the lowest usage [130]. The study suggests that the under-utilization of IoT applications in the industry is due to a lack of implementation and encouragement among industry players, as well as the high cost of IoT products. The majority of respondents were aware of IoT applications, but their usage rates remain low. Further research is recommended to explore the feasibility of implementing IoT in building projects.

Hyperconnectivity, edge computing, distributed ledger technologies (DLTs), artificial intelligence (AI), including machine learning (ML) and neural networks (NNs), robotic devices, drones, autonomous vehicles, augmented and virtual reality (AR/VR), and digital assistants will all be part of the next generation of the Internet of Things (IoT) and the Industrial Internet of Things (IIoT). New goods, services, and experiences will result from this integration, which will be advantageous to businesses, customers, and industries. By fusing social capabilities with intelligent objects and addressing the smooth interactions between autonomous systems and people, a human-centered approach will enable the best use of the upcoming IoT/IIoT technologies and applications [131].

3.8. Visualization

Visualization technologies are essential for an efficient IAR system [132] because al-lowing operators to intuitively understand the augmented data collocated in the real environment and can provide a realistic view of Industrial Internet of Things data [122,133], digital twins [134], on-site product inspection [135], industrial assembly [136], and industrial robotic tasks [137,138]. Additionally, visualization can help with training [139,140] maintenance tasks [133,141,142], providing workers with enhanced AR instructions. The majority of research conducted in past five years on the use of AR-based methods in industrial applications used see-through head-mounted displays (STHMDs), mobile AR (MAR) systems based on handheld devices such as smartphones or tablet and showing the augmented scene on a monitor or using a projector [143]. The authors of [135] presented a survey of the current state of augmented reality smart glasses (ARSG), with a focus on their use in the manufacturing industry from a technological maturity perspective. Results of the survey showed that the general technological readiness level (TRL) of ARSG is 9, but the individual parts needed to be improved because they are still at a lower TRL. Manufacturing engineers and technicians need to know how to integrate ARSG, and a is the diversity in hardware specifications.

The study presented in [139] compares the benefits and drawbacks of using the Microsoft HoloLens compared to a big screen tactile display for an encapsulation assembly task. A prototype for testing was made using digital twins of the workplace, animations, films, and interactive components. The feedback was positive, suggesting that the prototype based on HoloLens device could potentially replace current training methods. In [144], a STHMD-based AR system was developed to assist with the wiring of control cabinets. HoloLens was chosen as the most advanced technology for the maintenance operation, and other AR glasses were excluded due to various reasons, such as lack of software support, lack of mobility, lack of ambient scanning sensors, and lack of 3D hologram displays. The tests conducted by two experts in the industry showed that the use of AR glasses could significantly reduce the time it takes for the operator to complete the task compared to the traditional screen-based method which involves looking at a touch screen and interpreting 3D graphics.

The study published in [139] investigated the feasibility of hands-on training using a Microsoft HoloLens AR system. Regardless of gender, age, education level, or role, it was discovered that the AR system was effective, and that user satisfaction was acceptable. Handheld tablet-based AR systems and traditional electronic document-based maintenance instructions were compared in [145]. According to the findings, the AR tablet system had shorter consultation times and the system usability scale (SUS) score for the AR tablet was over 72. In [143], three visualization AR-based methods were investigated (mobile AR, monitor-based AR, and optical STHMD), by having participants perform a Lego assembly task in each setup. The results showed that participants preferred the monitor-based AR, followed closely by optical STHMD, while mobile AR was the least preferred.

3.9. Maintenance

Maintenance is the process of carrying out tasks and actions intended to keep a system running. Because the maintenance activities are usually complex, the maintenance operator must be supported by an expert or must search the specific documentation manual to be able to accomplish the required maintenance activities. AR technology can be used to enhance the existing maintenance methods and make them more effective and time-saving [145]. AR technologies allow remote maintenance experts to communicate the information they need to a maintenance technician using an intuitive system [146]. In [147], an AR-based framework for real-time remote maintenance and repair operations is presented. The tests conducted in a lab-based machine shop and in a real-life industrial scenario confirm the successful development of a zero-time content authoring AR tool and the minimization of the mean time to repair (MTTR). Another remote AR system was recently implemented in [141]. The proposed low-cost device, called “DAR”, consists of a helmet and a smartphone which transmit information about the surrounding environment and collocate the AR content. A new image enhancement algorithm is proposed which improves the accessibility of specialists to complex remote maintenance operations. The test conducted using the proposed system on real and synthesized images indicates that it can improve AR for remote maintenance tasks. With the use of AR, 5G networking, and edge computing, remote assistive maintenance may process information in real-time and increase the effectiveness of communications between local operators and remote experts. In the context of the COVID-19 pandemic, AR remote assistance can help ensure the safety and efficiency of employees, reduce the risk of mistakes, and decrease downtime [148].

Multimodal AR systems can be used to perform maintenance tasks without needing to refer to written instructions or diagrams. In [149], an augmented reality voice assistant (AREVA) designed to provide natural and hands-free assistance for the maintenance of a universal robot gripper is presented. The AREVA system, which combines a voice assistant and AR visualization to make the maintenance process simpler to understand for non-expert operators, was well-received by the subjects. In [145], the advantages of AR maintenance instructions are compared with electronic document-based complex instructions in an industrial setting. The main results show that the consultation time on the AR tablet is 34% faster than on the PDF tablet, and AR reduces errors. In [150], an example of how AR technology can be used for oil pump maintenance is presented. The experiment conducted with four groups of test participants shows the effectiveness and applicability of AR technology for industrial equipment maintenance. The authors of [151] discuss how having access to machine data may enhance the use of augmented reality for maintenance. The added value of direct machine data access from an AR maintenance application has been confirmed by a qualitative assessment with technicians. In [152], a maintenance augmented reality system (MARMA) that uses a smartphone camera to detect and track an asset of interest is proposed. AR technologies are then used to generate detailed instructions for maintenance operators in a natural and understandable way. MARMA was tested in an A/C compressor of the automotive industry and results showed that the 3D visualization of maintenance instructions improved the user experience. In [153], a new AR system called MANTRA is presented, which uses an RGB-D sensor and an IRT camera to automatically align virtual information and temperature on any 3D object in real-time. The MANTRA system was validated in a real-use case, demonstrating the effectiveness of the system compared to traditional methods.

An adaptive augmented reality human–machine interface (AR-HMI) provides suitable sets of maintenance information and guidance to an operator during maintenance to enhance efficiency and safety [154]. In [155], a method for providing an intelligent and adaptable maintenance service assisted by AR technologies is proposed. The approach was validated on an industrial case study, ensuing less time for mold inspection and a reduction in energy.

Intelligent maintenance control combined with AR technologies enables users to track and assess the status of modern manufacturing equipment in real time and reduce the risk of unexpected production stops [156]. The main drawback of using AR for maintenance is related to the complexity of the AR systems which may require specialized training and expertise to be used efficiently.

3.10. Training

Nowadays, classic training has many limitations, and in this area, AR can make a difference in day-to-day life at work or school. There are many methods to introduce this technology at the workplace or school, in a way that employees and students would appreciate.

The augmented reality for teaching, innovation and design (ARTID) tool is used for the representation of mechanical components in engineering. It allows several teaching materials for the representation of surfaces in the Dihedral system to be developed. The students gave very satisfactory feedback in using these complementary contents within an

Industrial Design II course [157]. Additionally, in the educational field, augmented reality and virtual reality were used in a training workshop to help students understand how robot systems work. The study used questionnaire and quizzes to evaluate the contribution of the workshop in training integrative thinking skill and understanding the robot system [158].

Deep learning for object detection integrated into the augmented reality application was designed for an oscilloscope, power supply, multimeter, and wave generator, making a framework for a better learning experience for electrical engineering students. The study shows that the average precision of the detection model is satisfactory, and the framework can be useful in industry and educational training [159].

Over time, industrial augmented reality (iAR) has gathered important advantages in transmitting technical information in the fields of maintenance, assembly, and training. The review, based on papers from 1997 to 2019, classifies the visual assets based on what is displayed, on how it conveys information, and why is used [160].

A method of industrial operation training is based on panoramic images. Panoramic augmented reality has been formed by two technologies: training knowledge dynamic guidance technology and the knowledge point mapping technology. The technology of panoramic augmented reality can improve the training effect, compared with traditional training [161].

In order to increase operator engagement and competence, a new approach is related to the training of operators in industrial production processes using VR, AR, and game-based learning [162].

Statistical process control tools were used in research in order to evaluate the effectiveness of virtual and augmented reality-based pedagogical resources. SPC tools are suitable for analyzing data generated by human–computer interactions in virtual learning environments, although the application of SPC is normally used in business processes quality control [163].

The manufacturing sector is the main theme of the research paper where it is argued that augmented reality can be used to provide more effective instructions and guidance than traditional methods. After applying specific examples, it is concluded that AR has the potential to improve worker productivity and support new employees to acquire new learning skills quicker [164]. Additionally, in the aviation field, the current training of pre-flight safety is inefficient and of low quality and cannot meet the current trend of urgently introducing aircraft inspection personnel. Augmented reality is a powerful industrial training technology that directly links instructions on how to perform the service tasks to the aircraft components that require processing. AR training technology pursues high-precision process guidance [165].

A review based on 64 research papers on augmented reality training system (ARTS) shows the trends in the training methods that use augmented reality in each field. Additionally, different training strategies used by the prevailing ARTS are investigated and recommendations for the implementation and evaluation of future ARTSs are provided [166].

Considering the financial aspect in developing an AR training system, the research in [167] proposes a low-cost ARTS that would be more effective than using computer-aided design. The system was designed based on a long-term case study conducted in a boiler manufacturing plant.

The "beWare of the Robot" is a virtual reality training system that simulates the cooperation between industrial robotic manipulators and humans in real-time [168]. The system is designed to help users learn how to work with industrial robotic systems. Researchers describe the system's setup and configuration, as well as user tracking and navigation issues. Safety issues, such as contacts and collisions, are mainly tackled through "emergencies", which are warning signals in terms of visual stimuli and sound alarms.

AR is a complex technology that can be used to support trainees to understand better and faster different types of information or to acquire new skills easier. Starting with the educational sector, schools, and universities, and up to the industrial sector, AR is extremely useful both for the educator or trainer, as well as for the student or employee.

4. Discussion

The main aim of this study was to identify the main emergent trends in using augmented and mixed reality technologies in industrial applications. The bibliometric study, which was focused on the past five years of research, allowed us to identify the top ten most popular topics. The contribution of the research study includes an overview of the IAR sector, the synthetic analysis of each topic, and the identification of the current challenges and future directions.

Augmented and mixed reality technologies are slowly but steadily gaining traction in our society. The development of immersive experiences that seamlessly merge the real and virtual worlds has several advantages, such as increased worker productivity, enhanced education and training sessions, and reduced risk of accidents or errors on the job. The industry sector can fully benefit from the progress of modern technologies, such as IoT, AI, and digital twins. One major challenge is how these advanced tools can be combined in order to overcome each other's limitations. So far, the most common approaches have included a combination of IoT with AI and an AR/VR/XR-based user interface. Deep learning algorithms that collect real-time data from a factory are the stepping stone for predictive maintenance and the development of digital twins. Moreover, DTs rely on the synergy between most of the topics presented in this study and represent a leap forward for the industry sector. However, their rapid adoption is hindered by many limitations, such as computing power, the convergence of the physical and digital world, security issues, and so on.

Current XR devices represent a significant limitation because of their high price, limited field of view, reduced battery autonomy, and weak computing performance, especially in the case of untethered headsets. However, major tech companies are investing heavily in AR/XR technology, and there are ongoing efforts to optimize production and lower the price of producing AR/XR headsets. We may anticipate more cutting-edge and valuable applications for AR/XR glasses as the technology develops, which may boost consumer demand and make them more widely available.

5. Conclusions

This paper aimed to identify the main trends regarding industrial augmented reality through a comprehensive literature review between 2018 and 2022. The analysis revealed ten major topics which were addressed separately. Industry 4.0 was found to be the most popular, with more than 400 papers, followed by the Internet of Things with around 170 references, and artificial intelligence taking third place with 143 studies. Many papers include several high interest topics, for example, the combination of Industry 4.0 with Augmented Reality and IoT can offer information based on real-time data from sensors using a mixed reality headset, such as HoloLens 2. There is an increased interest in applying AR technologies for work training, collaborative assistance and maintenance, as well as to provide data visualization and analytics.

AR technology can provide effective support in industrial processes and improve performance indicators, leading to shorter production times, less training effort, a reduction of errors, and ultimately reduced production costs [144]. Industrial AR has specific constraints compared to other application areas that can lead to application barriers. AR technology has imperfections and limitations, particularly lacking reliability and software support, work safety fulfillment, and overlay accuracy [136]. Therefore, while AR technology can provide benefits in industrial applications, there are still challenges that need to be addressed by AR devices before successful implementation in industrial applications.

The contribution of the research study includes an overview of the IAR sector, the synthetic analysis of each topic, and the identification of the current challenges which will allow the development of future studies.

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References

1. Choi, S.; Park, J.-S. Development of Augmented Reality System for Productivity Enhancement in Offshore Plant Construction. *J. Mar. Sci. Eng.* **2021**, *9*, 209. [CrossRef]
2. Dalle Mura, M.; Dini, G. Augmented Reality in Assembly Systems: State of the Art and Future Perspectives. In Proceedings of the Smart Technologies for Precision Assembly, Cham, Switzerland, 14–15 December 2020; pp. 3–22.
3. Smith, E.; Semple, G.; Evans, D.; McRae, K.; Blackwell, P. Augmented Instructions: Analysis of Performance and Efficiency of Assembly Tasks. Virtual, Augmented and Mixed Reality. Industrial and Everyday Life Applications. In Proceedings of the 12th International Conference, VAMR 2020, Held as Part of the 22nd HCI International Conference, HCII 2020, Copenhagen, Denmark, 19–24 July 2020; pp. 166–177.
4. Vidal-Balea, A.; Blanco-Novoa, O.; Fraga-Lamas, P.; Vilar-Montesinos, M.; Fernández-Caramés, T.M. Creating Collaborative Augmented Reality Experiences for Industry 4.0 Training and Assistance Applications: Performance Evaluation in the Shipyard of the Future. *Appl. Sci.* **2020**, *10*, 9073. [CrossRef]
5. Osman, S.; Phon, D.; Omar, N.; Mohd Rameli, M.R.; Ahmad, N.; Gusman, T. Using Augmented Reality Application to Reduce Time Completion and Error Rate in PC Assembly. *JOIV Int. J. Inform. Vis.* **2020**, *4*, 166. [CrossRef]
6. Tatic, D. An augmented reality system for improving health and safety in the electro-energetics industry. *Facta Univ.-Ser. Electron. Energetics* **2018**, *31*, 585–598. [CrossRef]
7. Wu, S.; Hou, L.; Zhang, G.; Chen, H. Real-time mixed reality-based visual warning for construction workforce safety. *Autom. Constr.* **2022**, *139*, 104252. [CrossRef]
8. Tatić, D.; Tešić, B. The application of augmented reality technologies for the improvement of occupational safety in an industrial environment. *Comput. Ind.* **2017**, *85*, 1–10. [CrossRef]
9. Sorko, S.R.; Brunnhofer, M. Potentials of Augmented Reality in Training. *Procedia Manuf.* **2019**, *31*, 85–90. [CrossRef]
10. Villagran-Vizcarra, D.C.; Luviano-Cruz, D.; Pérez-Domínguez, L.A.; Méndez-González, L.C.; Garcia-Luna, F. Applications Analyses, Challenges and Development of Augmented Reality in Education, Industry, Marketing, Medicine, and Entertainment. *Appl. Sci.* **2023**, *13*, 2766. [CrossRef]
11. Tortorella, G.; Fogliatto, F.; Anzanello, M.; Vassolo, R.; Antony, J.; Otto, K.; Kagioglou, M. Learning Curve Applications in Industry 4.0: A scoping review. *Prod. Plan. Control* **2022**, 1–13. [CrossRef]
12. Nahavandi, S. Industry 5.0—A Human-Centric Solution. *Sustainability* **2019**, *11*, 4371. [CrossRef]
13. Ruiz-Rosero, J.; Ramírez-González, G.; Viveros-Delgado, J. Software survey: ScientoPy, a scientometric tool for topics trend analysis in scientific publications. *Scientometrics* **2019**, *121*, 1165–1188. [CrossRef]
14. Munoz-Ausecha, C.; Ruiz-Rosero, J.; Ramirez-Gonzalez, G. RFID applications and security review. *Computation* **2021**, *9*, 69.
15. Calış Duman, M.; Akdemir, B. A study to determine the effects of industry 4.0 technology components on organizational performance. *Technol. Forecast. Soc. Chang.* **2021**, *167*, 120615. [CrossRef]
16. Carou, D. Aerospace Transformation through Industry 4.0 Technologies. In *Aerospace and Digitalization: A Transformation Through Key Industry 4.0 Technologies*; Carou, D., Ed.; Springer International Publishing: Cham, Switzerland, 2021; pp. 17–46.
17. Dal Forno, A.J.; Bataglini, W.V.; Steffens, F.; Ulson de Souza, A.A. Industry 4.0 in textile and apparel sector: A systematic literature review. *Res. J. Text. Appar.* **2023**, *27*, 95–117. [CrossRef]
18. Echegaray, N.; Hassoun, A.; Jagtap, S.; Tetteh-Caesar, M.; Kumar, M.; Tomasevic, I.; Goksen, G.; Lorenzo, J.M. Meat 4.0: Principles and Applications of Industry 4.0 Technologies in the Meat Industry. *Appl. Sci.* **2022**, *12*, 6986. [CrossRef]
19. Watson, A.; Alexander, B.; Salavati, L. The impact of experiential augmented reality applications on fashion purchase intention. *Int. J. Retail Distrib. Manag.* **2018**, *48*, 433–451. [CrossRef]
20. Reljic, V.; Milenkovic, I.; Dudić, S.; Šulc, J.; Bajci, B. Augmented Reality Applications in Industry 4.0 Environment. *Appl. Sci.* **2021**, *11*, 5592. [CrossRef]
21. Damiani, L.; Revetria, R.; Morra, E. Safety in Industry 4.0: The Multi-Purpose Applications of Augmented Reality in Digital Factories. *Adv. Sci. Technol. Eng. Syst. J.* **2020**, *5*, 248–253. [CrossRef]
22. Lin, Y.C.; Kan, H.C.; Lu, J.M.; Yao, C.M.; Liao, Y.C.; Chung, C.H.; Shih, K.C.; Tsai, M.C. Integration of intelligent diagnosis system and augmented reality for electric motors. *IOP Conf. Ser. Mater. Sci. Eng.* **2021**, *1113*, 012023. [CrossRef]

23. Dhar, P.; Rocks, T.; Samarasinghe, R.M.; Stephenson, G.; Smith, C. Augmented reality in medical education: Students' experiences and learning outcomes. *Med. Educ. Online* **2021**, *26*, 1953953. [CrossRef]
24. Nassereddine, H.; Hanna, A.; Veeramani, D.; Lotfallah, W. Augmented Reality in the Construction Industry: Use-Cases, Benefits, Obstacles, and Future Trends. *Front. Built Environ.* **2022**, *8*, 1–17. [CrossRef]
25. Bajic, B.; Rikalovic, A.; Suzic, N.; Piuri, V. Industry 4.0 Implementation Challenges and Opportunities: A Managerial Perspective. *IEEE Syst. J.* **2021**, *15*, 546–559. [CrossRef]
26. Masood, T.; Egger, J. Augmented reality in support of Industry 4.0—Implementation challenges and success factors. *Robot. Comput.-Integr. Manuf.* **2019**, *58*, 181–195. [CrossRef]
27. Masood, T.; Egger, J. Augmented Reality: Focusing on Photonics in Industry 4.0. *IEEE J. Sel. Top. Quantum Electron.* **2021**, *27*, 1–11. [CrossRef]
28. Ottogalli, K.; Rosquete, D.; Amundarain, A.; Aguinaga, I.; Borro, D. Flexible Framework to Model Industry 4.0 Processes for Virtual Simulators. *Appl. Sci.* **2019**, *9*, 4983. [CrossRef]
29. Sanchez, M.; Exposito, E.; Aguilar, J. Industry 4.0: Survey from a system integration perspective. *Int. J. Comput. Integr. Manuf.* **2020**, *33*, 1017–1041. [CrossRef]
30. Simões, B.; De Amicis, R.; Barandiaran, I.; Posada, J. X-Reality System Architecture for Industry 4.0 Processes. *Multimodal Technol. Interact.* **2018**, *2*, 72. [CrossRef]
31. Jakl, A.; Schöffer, L.; Husinsky, M.; Wagner, M. Augmented Reality for Industry 4.0: Architecture and User Experience. In Proceedings of the 11th Forum Media Technology, St. Pölten, Austria, 28–29 November 2018.
32. Zakoldaev, D.A.; Gurjanov, A.V.; Shukalov, A.V.; Zharinov, I.O. Implementation of H2M technology and augmented reality for operation of cyber-physical production of the Industry 4.0. *J. Phys. Conf. Ser.* **2019**, *1353*, 012142. [CrossRef]
33. Geng, R.; Li, M.; Hu, Z.; Han, Z.; Zheng, R. Digital Twin in smart manufacturing: Remote control and virtual machining using VR and AR technologies. *Struct. Multidiscip. Optim.* **2022**, *65*, 321. [CrossRef]
34. Sun, Z.; Zhu, M.; Zhang, Z.; Chen, Z.; Shi, Q.; Shan, X.; Yeow, R.C.-H.; Lee, C. Artificial Intelligence of Things (AIoT) Enabled Virtual Shop Applications Using Self-Powered Sensor Enhanced Soft Robotic Manipulator. *Adv. Sci.* **2021**, *8*, 2100230. [CrossRef]
35. Dou, W.; Tian, Y.; Ye, G.; Zhu, J. Antenna Artificial Intelligence: The Relentless Pursuit of Intelligent Antenna Design [Industry Activities]. *IEEE Antennas Propag. Mag.* **2022**, *64*, 128–130. [CrossRef]
36. Wittenberg, C. Challenges for the human-machine interaction in times of digitization, CPS & IIoT, and artificial intelligence in production systems. *IFAC-Pap.* **2022**, *55*, 114–119. [CrossRef]
37. Olaniyan, O.T.; Adetunji, C.O.; Dare, A.; Adeyomoye, O.; Adeniyi, M.J.; Enoch, A. Chapter 12-Cognitive therapy for brain diseases using artificial intelligence models. In *Artificial Intelligence for Neurological Disorders*; Abraham, A., Dash, S., Pani, S.K., García-Hernández, L., Eds.; Academic Press: Cambridge, MA, USA, 2023; pp. 185–207.
38. Vijayakumar, P.; Dilliraj, E. A Comparative Review on Image Analysis with Machine Learning for Extended Reality (XR) Applications. In Ubiquitous Intelligent Systems, Proceedings of the International Conference on Ubiquitous Computing and Intelligent Information Systems, Singapore, 16–17 April 2021; pp. 307–328.
39. Sun, H.; Kim, K. Design of Glasses Products Based on Artificial Intelligence. In Cyber Security Intelligence and Analytics, Proceedings of the 2020 International Conference on Cyber Security Intelligence and Analytics (CSIA 2020), Haikou, China, 28–29 February 2020; pp. 1051–1058.
40. Lashin, M.; Malibari, A. Using Fuzzy Logic Control System as an Artificial Intelligence Tool to Design Soap Bubbles Robot as a Type of Interactive Games. *Inf. Sci. Lett.* **2022**, *11*, 15–19. [CrossRef]
41. Durchon, H.; Preda, M.; Zaharia, T.; Grall, Y. Challenges in Applying Deep Learning to Augmented Reality for Manufacturing. In Proceedings of the 27th International Conference on 3D Web Technology, Evry-Courcouronnes, France; 2022; p. 13.
42. Li, S.; Zhang, D.; Xian, Y.; Li, B.; Zhang, T.; Zhong, C. Overview of deep learning application on visual SLAM. *Displays* **2022**, *74*, 102298. [CrossRef]
43. Saif, A.F.M.; Mahayuddin, Z.R. Vision based 3D Object Detection using Deep Learning: Methods with Challenges and Applications towards Future Directions. *Int. J. Adv. Comput. Sci. Appl.* **2022**, *13*, 203–214. [CrossRef]
44. Chau, M.Q.; Nguyen, X.P.; Huynh, T.T.; Chu, V.D.; Le, T.H.; Nguyen, T.P.; Nguyen, D.T. Prospects of application of IoT-based advanced technologies in remanufacturing process towards sustainable development and energy-efficient use. *Energy Sources Part A Recovery Util. Environ. Eff.* **2021**, 1–25. [CrossRef]
45. Jasmine, S.G.; Anbarasi, L.J.; Narendra, M.; Raj, B.E. Augmented and virtual reality and its applications. In *Multimedia and Sensory Input for Augmented, Mixed, and Virtual Reality*; IGI Global: Hershey, PA, USA, 2021; pp. 68–85.
46. Aslan, E. How supply chain management will change in the industry 4.0 era? In *Handbook of Research on Sustainable Supply Chain Management for the Global Economy*; IGI Global: Hershey, PA, USA, 2020; pp. 154–173.
47. Koreng, R.; Kroemker, H. Augmented Reality Interface: Guidelines for the Design of Contrast Ratios. In Proceedings of the ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Anaheim, CA, USA, 18–21 August 2019.
48. Bellalouna, F. Digitization of industrial engineering processes using the augmented reality technology: Industrial case studies. *Procedia CIRP* **2021**, *100*, 554–559. [CrossRef]

49. Uva, A.E.; Gattullo, M.; Manghisi, V.M.; Spagnulo, D.; Cascella, G.L.; Fiorentino, M. Evaluating the effectiveness of spatial augmented reality in smart manufacturing: A solution for manual working stations. *Int. J. Adv. Manuf. Technol.* **2018**, *94*, 509–521. [CrossRef]
50. Alves, J.; Marques, B.; Oliveira, M.; Araújo, T.; Dias, P.; Santos, B.S. Comparing Spatial and Mobile Augmented Reality for Guiding Assembling Procedures with Task Validation. In Proceedings of the 2019 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), Gondomar, Portugal, 24–26 April 2019; pp. 1–6.
51. Ivaschenko, A.; Sitnikov, P.; Katirkin, G. Accented Visualization in Digital Industry Applications. In Recent Research in Control Engineering and Decision Making, Proceedings of the International Conference on Information Technologies 2019 (ICIT-2019), Saratov, Russia, 7–8 February 2019; pp. 366–378.
52. Kocisko, M.; Teliskova, M.; Baron, P.; Zajac, J. An integrated working environment using advanced augmented reality techniques. In Proceedings of the 2017 4th International Conference on Industrial Engineering and Applications (ICIEA), Nagoya, Japan, 21–23 April 2017; pp. 279–283.
53. Lotsaris, K.; Gkournelos, C.; Fousekis, N.; Kousi, N.; Makris, S. AR based robot programming using teaching by demonstration techniques. *Procedia CIRP* **2021**, *97*, 459–463. [CrossRef]
54. Semm, A.; Erfurth, C.; Uslu, S. Potentials of Augmented Reality–Insights into Industrial Practice. Innovations for Community Services. In Proceedings of the 19th International Conference, I4CS 2019, Wolfsburg, Germany, 24–26 June 2019; pp. 103–122.
55. Jost, J.; Kirks, T.; Mättig, B. Multi-agent systems for decentralized control and adaptive interaction between humans and machines for industrial environments. In Proceedings of the 2017 7th IEEE International Conference on System Engineering and Technology (ICSET), Shah Alam, Malaysia, 2–3 October 2017; pp. 95–100.
56. Chan, T.C.; Chang, C.C.; Lin, H.H. Augmented Reality intelligent interactive machine tool monitoring system. In Proceedings of the 2021 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS), Hualien, Taiwan, China, 16–19 November 2021; pp. 1–2.
57. Deac, G.C.; Popa, C.L.; Ghinea, M.; Cotet, C.E. Using Augmented Reality in Smart Manufacturing. In Proceedings of the 28th DAAAM International Symposium, Zadar, Croatia, 8–11 November 2017; pp. 0727–0732.
58. Oscar, B.-N.; FernáNdez-CaraméS, T.M.; Fraga-Lamas, P.; Vilar-Montesinos, M.A. A Practical Evaluation of Commercial Industrial Augmented Reality Systems in an Industry 4.0 Shipyard. *IEEE Access* **2018**, *6*, 8201–8218. [CrossRef]
59. Zenisek, J.; Wild, N.; Wolfartsberger, J. Investigating the Potential of Smart Manufacturing Technologies. *Procedia Comput. Sci.* **2021**, *180*, 507–516. [CrossRef]
60. Zhang, Y.; Kwok, T.-H. Design and Interaction Interface using Augmented Reality for Smart Manufacturing. *Procedia Manuf.* **2018**, *26*, 1278–1286. [CrossRef]
61. Traganos, K.; Grefen, P.; Vanderfeesten, I.; Erasmus, J.; Boultadakis, G.; Bouklis, P. The HORSE framework: A reference architecture for cyber-physical systems in hybrid smart manufacturing. *J. Manuf. Syst.* **2021**, *61*, 461–494. [CrossRef]
62. Mourtzis, D.; Angelopoulos, J.; Panopoulos, N. Smart Manufacturing and Tactile Internet Based on 5G in Industry 4.0: Challenges, Applications and New Trends. *Electronics* **2021**, *10*, 3175. [CrossRef]
63. Aschenbrenner, D.; Leutert, F.; Çençen, A.; Verlinden, J.; Schilling, K.; Latoschik, M.; Lukosch, S. Comparing human factors for augmented reality supported single-user and collaborative repair operations of industrial robots. *Front. Robot. AI* **2019**, *6*, 37. [CrossRef] [PubMed]
64. Lee, H.; Liau, Y.Y.; Kim, S.; Ryu, K. A Framework for Process Model Based Human-Robot Collaboration System Using Augmented Reality. In Proceedings of the FIP International Conference on Advances in Production Management Systems, Seoul, Korea, 26–30 August 2018; 2018; pp. 482–489.
65. Maheswari, M.; Brintha, N.C. Smart Manufacturing Technologies in Industry-4. In 0. In Proceedings of the 2021 Sixth International Conference on Image Information Processing (ICIIP), Pradesh, India, 26–28 November 2021; pp. 146–151.
66. Leong, W.Y.; Chuah, J.H.; Tee, B.T. *The Nine Pillars of Technologies for Industry 4.0*; The Institution of Engineering and Technology: London, UK, 2020.
67. Chu, J.; Kabir, A.; Rose, W.; Wang, D.; Yao, M.; Gupta, S.K. Augmented Reality Applications in Industrial Robots. In *Manufacturing in the Era of 4th Industrial Revolution: A World Scientific Reference Volume 3: Augmented, Virtual and Mixed Reality Applications in Advanced Manufacturing*; World Scientific: Singapore, 2020; pp. 213–237.
68. De Pace, F.; Manuri, F.; Sanna, A.; Fornaro, C. A systematic review of Augmented Reality interfaces for collaborative industrial robots. *Comput. Ind. Eng.* **2020**, *149*, 106806. [CrossRef]
69. Gallo, J.C.; Cárdenas, P.F. Designing an interface for trajectory programming in industrial robots using augmented reality. In Proceedings of the Advances in Automation and Robotics Research: Proceedings of the 2nd Latin American Congress on Automation and Robotics, Cali, Colombia, 30 October–1 November 2019; Springer International Publishing: Cham, Switzerland, 2020; pp. 142–148.
70. Kuts, V.; Sarkans, M.; Otto, T.; Tähemaa, T.; Bondarenko, Y. Digital Twin: Concept of Hybrid Programming for Industrial Robots—Use Case. In Proceedings of the ASME International Mechanical Engineering Congress and Exposition, Salt Lake City, UT, USA, 11–14 November 2019; p. 02.
71. Alfrink, M. Enhanced interaction with industrial robots through extended reality relying on simulation-based digital twins. In Proceedings of the ISC'2019, Lisbon, Portugal, 5–7 June 2019; p. 90.

72. Su, Y.; Liao, C.; Ko, C.; Cheng, S.; Young, K.-Y. An AR-based manipulation system for industrial robots. In Proceedings of the 2017 11th Asian Control Conference (ASCC), Gold Coast, QLD, Australia, 17–20 December 2017; pp. 1282–1285.
73. Heimann, O.; Krüger, J. Affordance based approach to automatic program generation for industrial robots in manufacturing. *Procedia CIRP* **2018**, *76*, 133–137. [CrossRef]
74. Kuts, V.; Otto, T.; Tähemaa, T.; Bukhari, K.; Pataraia, T. Adaptive industrial robots using machine vision. In Proceedings of the ASME International Mechanical Engineering Congress and Exposition, Pittsburgh, PA, USA, 9–15 November 2018; p. V002T002A093.
75. Guhl, J.; Tung, S.; Kruger, J. Concept and architecture for programming industrial robots using augmented reality with mobile devices like microsoft HoloLens. In Proceedings of the 2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), Limassol, Cyprus, 13–15 September 2017; pp. 1–4.
76. Pizzagalli, S.L.; Kuts, V.; Otto, T. User-centered design for Human-Robot Collaboration systems. *IOP Conf. Ser. Mater. Sci. Eng.* **2021**, *1140*, 012011. [CrossRef]
77. Ji, Z.; Liu, Q.; Xu, W.; Yao, B.; Liu, J.; Zhou, Z. A closed-loop brain-computer interface with augmented reality feedback for industrial human-robot collaboration. *Int. J. Adv. Manuf. Technol.* **2023**, *124*, 3083–3098. [CrossRef]
78. Liu, Z.; Wang, X.; Cai, Y.; Xu, W.; Liu, Q.; Zhou, Z.; Pham, D.T. Dynamic risk assessment and active response strategy for industrial human-robot collaboration. *Comput. Ind. Eng.* **2020**, *141*, 106302. [CrossRef]
79. Wang, X.; Wang, L. Augmented Reality Enabled Human–Robot Collaboration. In *Advanced Human-Robot Collaboration in Manufacturing*; Springer International Publishing: Cham, Switzerland, 2021; pp. 395–411.
80. Gallala, A.; Hichri, B.; Plapper, P. Human-Robot Interaction using Mixed Reality. Proceedings of 2021 International Conference on Electrical, Computer and Energy Technologies (ICECET), Cape Town, South Africa, 9–10 December 2021; pp. 1–6.
81. Villani, V.; Pini, F.; Leali, F.; Secchi, C.; Fantuzzi, C. Survey on Human-Robot Interaction for Robot Programming in Industrial Applications. *IFAC-Pap.* **2018**, *51*, 66–71. [CrossRef]
82. Mihai, S.; Yaqoob, M.; Hung, D.V.; Davis, W.; Towakel, P.; Raza, M.; Karamanoglu, M.; Barn, B.; Shetve, D.; Prasad, R.V. Digital twins: A survey on enabling technologies, challenges, trends and future prospects. *IEEE Commun. Surv. Tutor.* **2022**, *24*, 2255–2291. [CrossRef]
83. Grieves, M.; Vickers, J. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary Perspectives on Complex Systems*; Springer International Publishing: Cham, Switzerland, 2017; pp. 85–113.
84. Ríos, J.; Hernandez-Matias, J.; Oliva, M.; Mas, F. Product Avatar as Digital Counterpart of a Physical Individual Product: Literature Review and Implications in an Aircraft. In Proceedings of the 22nd ISPE Inc. International Conference on Concurrent Engineering (CE2015), Delft, The Netherlands, 20–23 July 2015.
85. Tao, F.; Cheng, J.; Qi, Q.; Zhang, M.; Zhang, H.; Sui, F. Digital twin-driven product design, manufacturing and service with big data. *Int. J. Adv. Manuf. Technol.* **2018**, *94*, 3563–3576. [CrossRef]
86. Garg, G.; Kuts, V.; Anbarjafari, G. Digital twin for fanuc robots: Industrial robot programming and simulation using virtual reality. *Sustainability* **2021**, *13*, 10336. [CrossRef]
87. Li, C.; Zheng, P.; Li, S.; Pang, Y.; Lee, C.K. AR-assisted digital twin-enabled robot collaborative manufacturing system with human-in-the-loop. *Robot. Comput.-Integr. Manuf.* **2022**, *76*, 102321. [CrossRef]
88. Rabah, S.; Assila, A.; Khouri, E.; Maier, F.; Ababsa, F.; Maier, P.; Mérienne, F. Towards improving the future of manufacturing through digital twin and augmented reality technologies. *Procedia Manuf.* **2018**, *17*, 460–467. [CrossRef]
89. Büchner, A.; Micheli, G.; Gottwald, J.; Rudolph, L.; Pantförder, D.; Klinker, G.; Vogel-Heuser, B. Human-centered Augmented Reality Guidance for Industrial Maintenance with Digital Twins: A Use-Case Driven Pilot Study. In Proceedings of the 2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), Singapore, 17–21 October 2022; pp. 74–76.
90. Caiza, G.; Sanz, R. Digital Twin for Monitoring an Industrial Process Using Augmented Reality. In Proceedings of the 2022 17th Iberian Conference on Information Systems and Technologies (CISTI), Madrid, Spain, 22–25 June 2022; pp. 1–5.
91. Vidal-Balea, A.; Blanco-Novoa, O.; Fraga-Lamas, P.; Vilar-Montesinos, M.; Fernández-Caramés, T.M. A.; Blanco-Novoa, O.; Fraga-Lamas, P.; Vilar-Montesinos, M.; Fernández-Caramés, T.M. A collaborative industrial augmented reality digital twin: Developing the future of shipyard 4.0. In *Science and Technologies for Smart Cities: 7th EAI International Conference, SmartCity360°, Virtual Event, 2–4 December 2021, Proceedings*; Springer International Publishing: Cham, Switzerlan, 2022; pp. 104–120.
92. Kuts, V.; Otto, T.; Bondarenko, Y.; Yu, F. Digital twin: Collaborative virtual reality environment for multi-purpose industrial applications. In Proceedings of the ASME International Mechanical Engineering Congress and Exposition, Virtual, 16–19 November 2020; p. V02BT02A010.
93. Tuan-anh, T.; Ruppert, T.; Eigner, G.; Abonyi, J. Real-Time Locating System and Digital Twin in Lean 4. In 0. In Proceedings of the 2021 IEEE 15th International Symposium on Applied Computational Intelligence and Informatics (SACI), Timisoara, Romania, 19–21 May 2021; pp. 000369–000374.
94. Deac, G.C.; Deac, C.N.; Popa, C.L.; Ghinea, M.; Cotet, C.E. Machine vision in manufacturing processes and the digital twin of manufacturing architectures. In Proceedings of the 28th DAAAM International Symposium, Zadar, Croatia, 8–11 November 2017; pp. 0733–0736.

95. Orsolits, H.; Rauh, S.F.; Estrada, J.G. Using mixed reality based digital twins for robotics education. In Proceedings of the 2022 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), Singapore, 17–21 October 2022; pp. 56–59.
96. Sepasgozar, S.M.E.; Ghobadi, M.; Shirowzhan, S.; Edwards, D.J.; Delzendeh, E. Metrics development and modelling the mixed reality and digital twin adoption in the context of Industry 4.0. *Eng. Constr. Archit. Manag.* **2021**, *28*, 1355–1376. [CrossRef]
97. Weistroffer, V.; Keith, F.; Bisiaux, A.; Andriot, C.; Lasnier, A. Using physics-based digital twins and extended reality for the safety and ergonomics evaluation of cobotic workstations. *Front. Virtual Real.* **2022**, *3*, 781830. [CrossRef]
98. Kuts, V.; Bondarenko, Y.; Gavriljuk, M.; Paryshev, A.; Jegorov, S.; Pizzagall, S.; Otto, T. Digital Twin: Universal User Interface for Online Management of the Manufacturing System. In Proceedings of the ASME International Mechanical Engineering Congress and Exposition, Virtual Conference, 1–5 November 2021; p. V02BT02A003.
99. Leskovský, R.; Kučera, E.; Haffner, O.; Rosinová, D. Proposal of digital twin platform based on 3d rendering and iiot principles using virtual/augmented reality. In Proceedings of the 2020 Cybernetics & Informatics (K&I), Velké Karlovice, Czech Republic, 29 June–1 February 2020; pp. 1–8.
100. Künz, A.; Rosmann, S.; Loria, E.; Pirker, J. The potential of augmented reality for digital twins: A literature review. In Proceedings of the 2022 IEEE Conference on Virtual Reality and 3D User Interfaces (VR), Christchurch, New Zealand, 12–16 March 2022; pp. 389–398.
101. Song, J.; Kang, Y.; Song, Q.; Guo, L.; Jamalipour, A. Distributed Resource Optimization With Blockchain Security for Immersive Digital Twin in IIoT. *IEEE Trans. Ind. Inform.* **2022**, 1–10. [CrossRef]
102. Aheleroff, S.; Zhong, R.Y.; Xu, X. A digital twin reference for mass personalization in industry 4.0. *Procedia Cirp* **2020**, *93*, 228–233. [CrossRef]
103. Stein, C.; Behr, J. Industrial Use Cases: 3D Connectivity for Digital Twins: Decoupling 3D data utilization from delivery and file formats on an infrastructure level. In Proceedings of the 27th International Conference on 3D Web Technology, Evry-Courcouronnes, France, 2–4 November 2022; pp. 1–2.
104. Li, K.; Cui, Y.; Li, W.; Lv, T.; Yuan, X.; Li, S.; Ni, W.; Simsek, M.; Dressler, F. When internet of things meets metaverse: Convergence of physical and cyber worlds. *arXiv* **2022**, arXiv:2208.13501. [CrossRef]
105. Dong, J.; Xia, Z.; Zhao, Q. Augmented Reality Assisted Assembly Training Oriented Dynamic Gesture Recognition and Prediction. *Appl. Sci.* **2021**, *11*, 9789. [CrossRef]
106. Wang, Z.; Zhang, S.; Bai, X. A mixed reality platform for assembly assistance based on gaze interaction in industry. *Int. J. Adv. Manuf. Technol.* **2021**, *116*, 3193–3205. [CrossRef]
107. Schuster, F.; Engelmann, B.; Sponholz, U.; Schmitt, J. Human acceptance evaluation of AR-assisted assembly scenarios. *J. Manuf. Syst.* **2021**, *61*, 660–672. [CrossRef]
108. Lavric, T.; Bricard, E.; Preda, M.; Zaharia, T. Exploring Low-Cost Visual Assets for Conveying Assembly Instructions in AR. In Proceedings of the 2021 International Conference on INnovations in Intelligent SysTems and Applications (INISTA), Biarritz, France, 25–27 August 2021; pp. 1–6.
109. Schmitt, J.; Hillenbrand, A.; Kranz, P.; Kaupp, T. Assisted Human-Robot-Interaction for Industrial Assembly: Application of Spatial Augmented Reality (SAR) for Collaborative Assembly Tasks. In Proceedings of the Companion of the 2021 ACM/IEEE International Conference on Human-Robot Interaction, Boulder, CO, USA, 8–11 March 2021; pp. 52–56.
110. Zogopoulos, V.; Birem, M.; De Geest, R.; Hofman, R.; Jorissen, L.; Vanherle, B.; Gors, D. Image-based state tracking in Augmented Reality supported assembly operations. *Procedia CIRP* **2021**, *104*, 1113–1118. [CrossRef]
111. Gors, D.; Birem, M.; Geest, R.D.; Domken, C.; Zogopoulos, V.; Kauffmann, S.; Witters, M. An adaptable framework to provide AR-based work instructions and assembly state tracking using an ISA-95 ontology. *Procedia CIRP* **2021**, *104*, 714–719. [CrossRef]
112. Neb, A.; Brandt, D.; Rauhöft, G.; Awad, R.; Scholz, J.; Bauernhansl, T. A novel approach to generate augmented reality assembly assistance automatically from CAD models. *Procedia CIRP* **2021**, *104*, 68–73. [CrossRef]
113. Uletika, N.S.; Hartono, B.; Wijayanto, T. Gamification in Assembly Training: A Systematic Review. In Proceedings of the 2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, 14–17 December 2020; pp. 1073–1077.
114. Bauer, R.D.; Agati, S.S.; Hounsell, M.d.S.; Silva, A.T.d. Manual PCB assembly using Augmented Reality towards Total Quality. In Proceedings of the 2020 22nd Symposium on Virtual and Augmented Reality (SVR), Porto de Galinhas, Brazil, 7–10 November 2020; pp. 189–198.
115. de Souza Cardoso, L.F.; Mariano, F.C.M.Q.; Zorzal, E.R. Mobile augmented reality to support fuselage assembly. *Comput. Ind. Eng.* **2020**, *148*, 106712. [CrossRef]
116. Ojer, M.; Alvarez, H.; Serrano, I.; Saiz, F.A.; Barandiaran, I.; Aguinaga, D.; Querejeta, L.; Alejandro, D. Projection-Based Augmented Reality Assistance for Manual Electronic Component Assembly Processes. *Appl. Sci.* **2020**, *10*, 796. [CrossRef]
117. Horejsi, P.; Novikov, K.; Michal, Š. A Smart Factory in a Smart City: Virtual and Augmented Reality in a Smart Assembly Line. *IEEE Access* **2020**, *8*, 94330–94340. [CrossRef]
118. Pilati, F.; Faccio, M.; Gamberi, M.; Regattieri, A. Learning manual assembly through real-time motion capture for operator training with augmented reality. *Procedia Manuf.* **2020**, *45*, 189–195. [CrossRef]

119. Papanastasiou, S.; Kousi, N.; Karagiannis, P.; Gkournelos, C.; Papavasileiou, A.; Dimoulas, K.; Baris, K.; Koukas, S.; Michalos, G.; Makris, S. Towards seamless human robot collaboration: Integrating multimodal interaction. *Int. J. Adv. Manuf. Technol.* **2019**, *105*, 3881–3897. [CrossRef]
120. Blankemeyer, S.; Recker, T.; Stuke, T.; Brokmann, J.; Geese, M.; Reiniger, M.; Pischke, D.; Oubari, A.; Raatz, A. A Method to Distinguish Potential Workplaces for Human-Robot Collaboration. *Procedia CIRP* **2018**, *76*, 171–176. [CrossRef]
121. Sureshkumar, S.; Agash, C.; Ramya, S.; Kaviyaraj, R.; Elanchezhiyan, S. Augmented Reality with Internet of Things. In Proceedings of the 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), Coimbatore, India, 25–27 March 2021; pp. 1426–1430.
122. Vasilis, S.; Nikos, N.; Kosmas, A. An Augmented Reality Framework for Visualization of Internet of Things Data for Process Supervision in Factory Shop-Floor. *Procedia CIRP* **2022**, *107*, 1162–1167. [CrossRef]
123. Stark, E.; Kučera, E.; Haffner, O.; Drahoš, P.; Leskovský, R. Using augmented reality and internet of things for control and monitoring of mechatronic devices. *Electronics* **2020**, *9*, 1272. [CrossRef]
124. Gomes, P.; Magaia, N.; Neves, N. Industrial and artificial Internet of Things with augmented reality. In *Convergence of Artificial Intelligence and the Internet of Things*; Springer International Publishing: Cham, Switzerlan, 2020; pp. 323–346.
125. Grambow, G.; Hieber, D.; Oberhauser, R.; Pogolski, C. A context and augmented reality bpmn and bpms extension for industrial internet of things processes. In *Business Process Management Workshops, Proceedings of the BPM 2021 International Workshops, Rome, Italy, 6–10 September 2021*; Revised Selected Papers; Springer International Publishing: Cham, Switzerlan, 2022; pp. 379–390.
126. Seitz, A.; Buchinger, D.; Bruegge, B. The conjunction of fog computing and the industrial internet of things-an applied approach. In Proceedings of the 2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), Athens, Greece, 19–23 March 2018; pp. 812–817.
127. Rahimi, P.; Chrysostomou, C.; Pervaiz, H.; Vassiliou, V.; Ni, Q. Joint radio resource allocation and beamforming optimization for industrial internet of things in software-defined networking-based virtual fog-radio access network 5G-and-beyond wireless environments. *IEEE Trans. Ind. Inform.* **2021**, *18*, 4198–4209. [CrossRef]
128. Seitz, A.; Henze, D.; Nickles, J.; Sauer, M.; Bruegge, B. Augmenting the industrial internet of things with emojis. In Proceedings of the 2018 Third International Conference on Fog and Mobile Edge Computing (FMEC), Barcelona, Spain, 23–26 April 2018; pp. 240–245.
129. Kar, S.; Kar, A.K.; Gupta, M.P. Industrial internet of things and emerging digital technologies–modeling professionals' learning behavior. *IEEE Access* **2021**, *9*, 30017–30034. [CrossRef]
130. Mahmud, S.H.; Assan, L.; Islam, R. Potentials of internet of things (IoT) in Malaysian construction industry. *Ann. Emerg. Technol. Comput. (AETiC)* **2018**, *2*, 44–52. [CrossRef]
131. Vermesan, O.; EisenHauer, M.; Serrano, M.; Guillemin, P.; Sundmaeker, H.; Tragos, E.Z.; Valiño, J.; Copigneaux, B.; Presser, M.; Aagaard, A. The next generation internet of things–hyperconnectivity and embedded intelligence at the edge. In *Next Generation Internet of Things–Distributed Intelligence at the Edge and Human-Machine Interactions*; River Publishers: Gistrup, Denmark, 2022; pp. 19–102.
132. Yang, W.; Zhang, Y. Visualization Error Analysis for Augmented Reality Stereo Video See-Through Head-Mounted Displays in Industry 4.0 Applications. In Proceedings of the International Manufacturing Science and Engineering Conference, West Lafayette, ID, USA, June 27–1 July 2022; p. V002T006A016.
133. Husinsky, M.; Schlager, A.; Jalaeefar, A.; Klimpfinger, S.; Schumach, M. Situated Visualization of IIoT Data on the Hololens 2. In Proceedings of the 2022 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW), Christchurch, New Zealand, 12–16 March 2022; pp. 472–476.
134. Körppen, T.; Thim, C. Visualisierung des digitalen Zwillings mit AR. *Fabriksoftware* **2020**, *254*, 19–22. [CrossRef]
135. Moteki, A.; Yamaguchi, N.; Karasudani, A.; Kobayashi, Y.; Yoshitake, T.; Kato, J.; Aoyagi, T. Manufacturing defects visualization via robust edge-based registration. In Proceedings of the 2018 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct), Munich, Germany, 16–20 October 2018; pp. 172–173.
136. Danielsson, O.; Holm, M.; Syberfeldt, A. Augmented reality smart glasses in industrial assembly: Current status and future challenges. *J. Ind. Inf. Integr.* **2020**, *20*, 100175. [CrossRef]
137. Avalle, G.; De Pace, F.; Fornaro, C.; Manuri, F.; Sanna, A. An augmented reality system to support fault visualization in industrial robotic tasks. *Ieee Access* **2019**, *7*, 132343–132359. [CrossRef]
138. Juhás, M.; Juhásová, B.; Važan, P. Implementation of Heterogeneous Multirobotic Cell Control Using Visualization Techniques. In Proceedings of the 2022 Cybernetics & Informatics (K&I), Visegrád, Hungary, 11–14 September 2022; pp. 1–6.
139. Xue, H.; Sharma, P.; Wild, F. User satisfaction in augmented reality-based training using microsoft HoloLens. *Computers* **2019**, *8*, 9. [CrossRef]
140. Pusch, A.; Noël, F. Augmented reality for operator training on industrial workplaces–Comparing the Microsoft hololens vs. small and big screen tactile devices. In *Product Lifecycle Management in the Digital Twin Era, Proceedings of the 16th IFIP WG 5.1 International Conference, PLM 2019, Moscow, Russia, 8–12 July 2019*; Revised Selected Papers 16; Springer: Cham, Switzerland.
141. Naumov, I.; Sinakin, M.; Semenishchev, E.; Gapon, N. Mobile smartphone-based augmented reality for industry remote monitoring and maintenance. In Proceedings of the Unconventional Optical Imaging III, Strasbourg, France, 3–7 April 2022; pp. 342–350.

142. Verde, S.; Marcon, M.; Milani, S.; Tubaro, S. Advanced assistive maintenance based on augmented reality and 5G networking. *Sensors* **2020**, *20*, 7157. [CrossRef]
143. Alves, J.B.; Marques, B.; Ferreira, C.; Dias, P.; Santos, B.S. Comparing augmented reality visualization methods for assembly procedures. *Virtual Real.* **2022**, *26*, 235–248. [CrossRef]
144. Szajna, A.; Stryjski, R.; Woźniak, W.; Chamier-Gliszczyński, N.; Kostrzewski, M. Assessment of augmented reality in manual wiring production process with use of mobile AR glasses. *Sensors* **2020**, *20*, 4755. [CrossRef]
145. Havard, V.; Baudry, D.; Jeanne, B.; Louis, A.; Savatier, X. A use case study comparing augmented reality (AR) and electronic document-based maintenance instructions considering tasks complexity and operator competency level. *Virtual Real.* **2021**, *25*, 999–1014. [CrossRef]
146. Breitkreuz, D.; Müller, M.; Stegelmeyer, D.; Mishra, R. Augmented Reality Remote Maintenance in Industry: A Systematic Literature Review. In *Extended Reality, Proceedings of the First International Conference, XR Salento 2022, Lecce, Italy, 6–8 July 2022, Proceedings, Part II*; Springer International Publishing: Cham, Switzerland, 2022; pp. 287–305.
147. Mourtzis, D.; Siatras, V.; Angelopoulos, J. Real-time remote maintenance support based on augmented reality (AR). *Appl. Sci.* **2020**, *10*, 1855. [CrossRef]
148. Naumov, I.; Sinakin, M.; Sinakina, O.; Voronin, V. Using augmented reality devices for remote maintenance and repair of industrial equipment as new challenges in the COVID-19 pandemic. In Proceedings of the Digital Optical Technologies 2021, Online, 21–25 June 2021; pp. 9–15.
149. Serras, M.; García-Sardiña, L.; Sim, B.; Ávarez, H.; Arambarri, J. AREVA: Augmented Reality Voice Assistant for Industrial Maintenance. *Proces. Del Leng. Nat.* **2020**, *65*, 135–138.
150. Koteleva, N.; Buslaev, G.; Valnev, V.; Kunshin, A. Augmented reality system and maintenance of oil pumps. *Int. J. Eng.* **2020**, *33*, 1620–1628.
151. Lorenz, M.; Shandilya, S.; Knopp, S.; Klimant, P. Industrial augmented reality: Connecting machine-, NC-and sensor-data to an AR maintenance support system. In Proceedings of the 2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW), Lisbon, Portugal, 27 March–3 April 2021; pp. 595–596.
152. Konstantinidis, F.K.; Kansizoglou, I.; Santavas, N.; Mouroutsos, S.G.; Gasteratos, A. Marma: A mobile augmented reality maintenance assistant for fast-track repair procedures in the context of industry 4.0. *Machines* **2020**, *8*, 88. [CrossRef]
153. Ortega, M.; Ivorra, E.; Juan, A.; Venegas, P.; Martínez, J.; Alcañiz, M. Mantra: An effective system based on augmented reality and infrared thermography for industrial maintenance. *Appl. Sci.* **2021**, *11*, 385. [CrossRef]
154. Siew, C.; Nee, A.; Ong, S. Improving maintenance efficiency with an adaptive AR-assisted maintenance system. In Proceedings of the 2019 4th International Conference on Robotics, Control and Automation, Shenzhen, China, 19-21 July 2019; pp. 74–78.
155. Angelopoulos, J.; Mourtzis, D. An intelligent product service system for adaptive maintenance of Engineered-to-Order manufacturing equipment assisted by augmented reality. *Appl. Sci.* **2022**, *12*, 5349. [CrossRef]
156. Kostoláni, M.; Murín, J.; Kozák, Š. Intelligent predictive maintenance control using augmented reality. In Proceedings of the 2019 22nd International Conference on Process Control (PC19), Strbske Pleso, Slovakia, 11–14 June 2019; pp. 131–135.
157. Parras-Burgos, D.; Melgarejo-Torralba, M.; Cañavate, F.J.F.; Fernández-Pacheco, D.G. Graphic Interpretation of Surfaces with the Support of Augmented Reality as a Training Complement in Engineering Studies. In Advances in Design Engineering II, Proceedings of the International conference on The Digital Transformation in the Graphic Engineering, Málaga, Spain, 29 June–1 July 2022; pp. 318–326.
158. Verner, I.; Cuperman, D.; Perez-Villalobos, H.; Polishuk, A.; Gamer, S. Augmented and Virtual Reality Experiences for Learning Robotics and Training Integrative Thinking Skills. *Robotics* **2022**, *11*, 90. [CrossRef]
159. Estrada, J.; Paheding, S.; Yang, X.; Niyaz, Q. Deep-Learning-Incorporated Augmented Reality Application for Engineering Lab Training. *Appl. Sci.* **2022**, *12*, 5159. [CrossRef]
160. Gattullo, M.; Evangelista, A.; Uva, A.E.; Fiorentino, M.; Gabbard, J.L. What, How, and Why are Visual Assets Used in Industrial Augmented Reality? A Systematic Review and Classification in Maintenance, Assembly, and Training (From 1997 to 2019). *IEEE Trans. Vis. Comput. Graph.* **2022**, *28*, 1443–1456. [CrossRef] [PubMed]
161. Chen, M.; Wei, H.; Hu, H.; Liu, R.; Geng, J. Industrial Operation Training Technology Based on Panoramic Image and Augmented Reality. In Proceedings of the 2022 5th World Conference on Mechanical Engineering and Intelligent Manufacturing (WCMEIM), Ma'anshan, China, 18–20 November 2022; pp. 1216–1220.
162. Santos, J.E.; Nunes, M.; Pires, M.; Rocha, J.; Sousa, N.; Adão, T.; Magalhães, L.G.; Jesus, C.; Sousa, R.; Lima, R.; et al. Generic XR game-based approach for industrial training. In Proceedings of the 2022 International Conference on Graphics and Interaction (ICGI), Aveiro, Portugal, 3–4 November 2022; pp. 1–8.
163. de Jesus, C.; Marcorin, A.; Lima, R.; Sousa, R.; Souza, I.; Oliveira, E. SPC-Based Model for Evaluation of Training Processes in Industrial Context. *J. Ind. Eng. Manag.* **2022**, *15*, 538–551. [CrossRef]
164. Hsu, H.H.; Chuang, C.Y. Application of Augmented Reality for Equipment Maintenance and Employee Training in Manufacturing Plant. In Proceedings of the 2022 IEEE 4th Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS), Tainan, Taiwan, 27–29 May 2022; pp. 136–139.
165. Ye, W.; He, N.; Wang, J. Research on Augmented Reality Technology in the Training of Pre-flight Safety Inspect Process. In Proceedings of the 2022 IEEE Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC), Dalian, China, 14–16 April 2022; pp. 68–71.

166. Butaslac, I.M.; Fujimoto, Y.; Sawabe, T.; Kanbara, M.; Kato, H. Systematic Review of Augmented Reality Training Systems. *IEEE Trans Vis Comput Graph* **2022**, 1–20. [CrossRef]
167. Lavric, T.; Bricard, E.; Preda, M.; Zaharia, T. A low-cost AR training system for manual assembly operations. *Comput. Sci. Inf. Syst.* **2022**, *19*, 1047–1073. [CrossRef]
168. Matsas, E.; Vosniakos, G.-C. Design of a virtual reality training system for human–robot collaboration in manufacturing tasks. *Int. J. Interact. Des. Manuf. (IJIDeM)* **2017**, *11*, 139–153. [CrossRef]