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Review

Integrating Digital Twin Software Solutions with Collaborative Industrial Systems: A Comprehensive Review for Operational Efficiency

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Abstract

The integration of digital twin software solutions with industrial collaborative robotics applications has gained significant attention due to its potential to enhance operational efficiency in various industries. The authors of this paper provide a comprehensive review of the literature, analyzing the benefits, challenges, and opportunities associated with this unification. The research methodology incorporates both quantitative and qualitative analyses of relevant scholarly articles, case studies, and industry reports. The study identifies research gaps and challenges, including data management, security, scalability, interoperability, and transitioning simulations to digital twins. To address these gaps, the authors explore published frameworks for effectively integrating digital twin software solutions with industrial collaborative robotics applications. An important challenge is to define some tools to develop a digital twin. This paper explores the tools implemented by other researchers to develop a digital twin. The findings of this research contribute to a deeper understanding of the combination of digital twins and collaborative robots, paving the way for improved operational efficiency and informed decision-making.

Keywords: digital twin; collaborative robotics applications; machine learning; system integration; data management

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1. Introduction

In recent years, integrating digital twin software solutions with industrial collaborative robotics applications has gained significant traction and holds immense potential for enhancing operational efficiency [1–4]. The term "digital twin" (DT) refers to a virtual replica or simulation of a physical entity, such as a machine, system, or even an entire manufacturing facility [5]. It encompasses both the physical and digital realms, allowing for real-time synchronization between the virtual and physical components. DT are equipped with the capability to capture and represent data, interactions, and behaviors of their corresponding physical counterparts, enabling a deeper understanding and analysis of real-world systems [6]. The path from DT development to implementation is depicted in Figure 1, illustrating its fundamental principles.

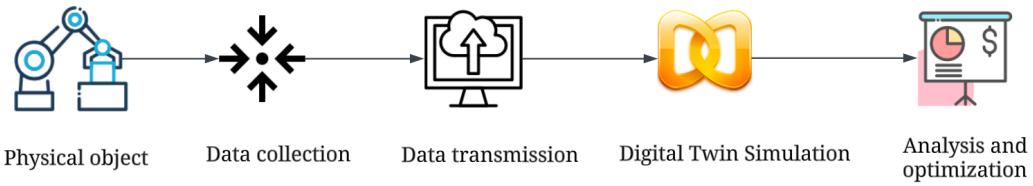


Figure 1. Basic Concept of the Digital Twin Development Lifecycle.

The history of digital twins can be traced back to David Gelernter's book "Mirror Worlds", published in 1993, where the concept of creating virtual replicas of physical entities was anticipated [7]. However, it was in 2002 when Michael Grieves introduced the concept of the digital twin at a manufacturing conference, presenting it as the underlying model for product lifecycle management (PLM) [8]. It was further developed when John Vickers of NASA, together with Michael Grieves, coined the term "digital twin" in a 2010 roadmap report, defining it as a three-part concept comprising the physical object or process, its digital representation, and the communication channel between them known as the digital thread [9,10]. Trauer et al. outlined three fundamental attributes that are integral to the functionality of DT [11]:

- A DT constitutes a virtual, dynamic portrayal of a physical artifact or system.
- Data is exchanged automatically and bidirectionally between the DT and the corresponding physical system.
- The DT encompasses data across all product lifecycle stages and maintains connections to each phase.

The International Council of Systems Engineers (INCOSE) defines a digital twin as a "high-fidelity model" that emulates the actual system [12]. In contrast, the US Department of Defense (DoD) Digital Engineering Strategy defines it as an integrated simulation of an as-built system that mirrors and predicts activities over the life of its physical counterpart [13]. Although there are divergent details on the definition of digital twins, the core concept that Grieves and Vickers presented continues to prevail—at its best, any information that can be gleaned from a physical system should also be acquirable from the digital twin [10]. These definitions and advancements in the field of digital twins have paved the way for industry to understand, evaluate, and apply them.

Digital twins consist of several key components that enable their functionality and effectiveness. These components typically include data analytics and modeling algorithms to replicate the physical system, data acquisition and sensing devices to capture data from the physical system, connectivity infrastructure to transmit data and information between the physical and the virtual systems, and visualization interfaces for operator management and support [14]. The digital twin concept connects a virtual and physical system in real-time. There are different technological aspects that contribute to this. For example, an appropriate selection of sensors, instruments, and controls must be defined for a DT system to acquire and use the correct data for its given objective. In addition, it is important to consider both the sensing accuracy and the data transmission speed and bandwidth, which affects the capabilities of a DT-connected system [15]. By integrating these components, digital twin software solutions empower organizations to monitor and analyze real-time data from physical systems, facilitating informed decision-making and operational optimization.

Data acquisition is a critical component of the DT process. The widely recognized principle in data science applies to DT: "You are only as good as your data". So too are DT, which require accurate data on the state and functionality of the physical system that it represents. While DT can be developed using an existing library of data, the best applications of DT require real-time data, enabling analysis on the impact of the system's current state.

One notable area where integrating digital twin software solutions has become increasingly crucial is in conjunction with industrial collaborative robotics applications [16]. Collaborative robots, also known as cobots, are designed to work alongside human operators, enhancing productivity, safety, and flexibility in various industrial settings [17]. By combining digital twin technology with cobot applications, organizations can achieve a higher level of automation, efficiency, and performance.

Integrating digital twin software solutions and industrial cobot applications offers numerous benefits across different industries [18]. Real-time monitoring of the physical systems through digital twins enables predictive maintenance, identifying potential issues before they escalate into costly failures. Additionally, digital twins promote optimization by simulating and analyzing different scenarios, allowing for data-driven decision-making and performance improvement. Other benefits of digital twins include improved design and development, efficient maintenance and monitoring, predictive analytics, risk reduction, remote operation, data-driven insights, optimized performance, and lifecycle management. They lead to cost savings, support customization, facilitate training, encourage innovation, and contribute to sustainability. Moreover, digital twins enable cross-disciplinary collaboration and real-time decision-making, transforming industries with their holistic and versatile advantages [19].

Before technology enabled the development and application of DT, simulations and analysis were conducted using pre-existing data sources. Physical systems undergo operational verification and validation. Predictive analysis required a large dataset. Prediction only applied to the system as it was when the data was captured. Parameters and constraints were defined by design and not by operation or actual capability.

1.1. Research Gaps and Challenges

Integrating digital twin software solutions with industrial automation systems, where a robotized system (industrial, collaborative, autonomous equipment, etc.) is usually a key part, has highlighted several research gaps and challenges in the field. These gaps primarily focus on data management, security, scalability, and interoperability between different systems [20]. One notable research gap is the optimization of the integration between digital twin software solutions and industrial robotics applications, which entails the development of efficient data exchange protocols, synchronization mechanisms, and real-time interaction algorithms. Additionally, effective data management poses a critical challenge, especially in large-scale systems with real-time data streams. Moreover, the security of digital twins is a significant concern due to their susceptibility to cyber threats. The development of robust security measures, authentication protocols, and encryption techniques is necessary to safeguard digital twin systems and their associated data. Scalability further complicates the implementation of digital twin software solutions in large-scale industrial settings. Lastly, interoperability between diverse systems and platforms represents a crucial challenge in fully harnessing the benefits of digital twin software solutions. Standardization of data formats and communication protocols and developing interoperability frameworks are vital to enable seamless fusion. By addressing these research gaps and challenges, the effective utilization and advancement of digital twin technology in conjunction with industrial systems can be achieved.

1.2. Research Questions

This study focuses on digital twin software solutions and their inclusion in industrial cobot applications. By exploring the integration of digital twin software solutions with industrial cobot applications, it aims to investigate the potential synergies and benefits that arise from combining these technologies. It examines how digital twins can enhance

the capabilities of cobot and contribute to operational efficiency in various industries. The study is driven by several research questions such as:

- What are the key challenges and opportunities associated with utilizing digital twin software solutions in conjunction with industrial collaborative robotics applications?
- How does the integration of digital twins and collaborative robots contribute to improved operational efficiency, productivity, and decision-making processes?
- What are the implications of the integration of digital twin software solutions with industrial cobot applications for different industries, such as manufacturing, energy, healthcare, and transportation?

The findings of this research review will contribute to a deeper understanding of these technologies and their impact on operational efficiency, paving the way for further advancements and practical applications in various industries.

1.3. Structure of the Paper

This paper systematically investigates the ongoing research on the effect of digital twin software solutions with industrial cobot applications and their impact on operational efficiency. This introduction provided an overview of digital twin software solutions, their definition, history, and components, emphasizing their importance in conjunction with industrial cobot applications. In Section 2, the various software applications used for the development and operation of Digital Twins is reviewed. In Section 3, the research methodology details the data collection methods and analytical techniques employed for a comprehensive review of existing literature. Sections 4 and 5 present the quantitative and qualitative sections, respectively, displaying key findings, trends, and insights from the literature, focusing on the benefits, challenges, and opportunities of integrating these technologies. Section 6 discusses the limitations of state-of-the-art research and suggestions for future research directions. Finally, Section 7 concludes the paper by summarizing the key findings.

Unlike other digital twin reviews that focus narrowly on either architecture or domain-specific implementations, this study contributes a hybridized perspective—combining bibliometric trends with multi-industry implementation analysis. It provides a technical mapping between software tools and their domain-specific constraints, offering actionable insights for researchers and practitioners seeking deployment-ready models.

2. Digital Twin Software Solutions

Naturally, since Digital Twins have applicability across multiple industries, related software comes in many flavors. Some applications are designed to enable programmers and operators to tailor their system to their specific needs. Other software comes with a design intent geared towards a particular use case or set of use cases. Given the nature of this review, these applications have been separated between general and manufacturing-specific applications.

2.1. General Applications

Digital twin software solutions find extensive applications across diverse industries, revolutionizing management practices and decision-making processes [21]. By providing valuable insights into the performance and condition of physical assets, these solutions enable predictive maintenance and process optimization, thereby enhancing overall process management.

In industries such as manufacturing, digital twin software solutions have proven invaluable in optimizing production processes. By creating virtual replicas of manufacturing systems, organizations can simulate different operating scenarios, analyze production

data, and identify opportunities for improvement. This enables manufacturers to optimize workflows, reduce downtime, and enhance overall productivity [22]. Furthermore, digital twins facilitate the implementation of predictive maintenance strategies by continuously monitoring the condition of machinery and predicting potential failures [23]. This proactive approach helps organizations minimize unplanned downtime, optimize maintenance schedules, and extend the lifespan of critical assets. Norambuena et al. [24] explored the crossroads of manufacturing processes and education in their multi-user virtual reality (VR) experimentation. They leveraged real-time sensing with a 1:1 capture of all the onboard sensor data of a modern internal combustion engine to simulate the engine in a safe environment. This opportunity enables engineering students to interact safely with an "operating engine", removing the hazards of combustion, exhaust, and highly kinetic components. Some researchers have been using different digital manufacturing tools to explore digital twin functionalities. For example, some researchers use Process Simulate Tecnomatix, Total Integrated Automation (TIA), and PLCSIM, all Siemens Software, to explore connectivity between virtual and physical prototypes in a robotics manufacturing automation system [15]. Other researchers explored, in case studies, the use of the Unity Real-Time Development Platform, for both fully digital scenarios and VR scenarios [19]. Other researchers have been using unspecified versions of NVIDIA IsaacSim and Python programming because of the open-source facility and functionality to create the digital twin scenarios [25,26].

In the energy sector, digital twin software solutions are utilized to enhance the performance and maintenance of complex infrastructure. For instance, in the field of renewable energy, DT enable operators to monitor and analyze the performance of wind farms, solar installations, and other renewable energy systems [27]. By integrating real-time data from sensors and weather forecasts, operators can optimize energy production, predict maintenance needs, and ensure optimal utilization of resources. Additionally, digital twins facilitate the efficient management of power grids by providing insights into the behavior and demands of the electrical network, enabling operators to optimize power distribution, improve grid stability, and enhance energy efficiency [28].

The healthcare industry also benefits from the application of digital twin software solutions. In the context of personalized medicine, digital twins enable the creation of virtual patient models based on individual health data. Laubenbacher et al. [29] discuss the latest applications of medical digital twins, including the need for personally tailored computational models and the political, technological, medical, and administrative challenges toward improved implementation and better patient outcomes as a result. These include the wealth of bioinformatic unknowns in an individual plus the difficulty of accessing data using sensors, the high computational cost of recording and tracking these datasets in real-time, and the non-deterministic behavior of the human body. They importantly note that there is no broad consensus as to the definition of a DT in the medical field. Use cases for DT in the include managing patient health and testing new therapeutics. Another example: Chakshu et al. [30] explore a digital twin driven by inverse analysis and long short-term memory (LSTM)-based neural networks and apply it to detect aortic abdominal aneurysms using convolutional neural networks (CNN), achieving promising accuracy rates. Frameworks like this can simulate the effects of different treatment options, predict patient responses, and assist medical professionals in making informed decisions. Digital twins also find utility in medical device development, allowing for virtual testing and optimization before physical prototypes are built [31]. This reduces costs, accelerates the development process, and improves the safety and effectiveness of medical devices.

Transportation and logistics industries leverage digital twin software solutions to optimize their operations and improve asset management. Digital twins can be used to create

virtual replicas of vehicles, warehouses, and transportation networks, enabling real-time monitoring, route optimization, and predictive maintenance [32,33]. By harnessing data from sensors, global positioning satellites (GPS) systems, and other sources, organizations can gain insights into vehicle performance, fuel efficiency, and maintenance needs, leading to cost savings and improved effectiveness.

Zhang et al. [34] developed and tested an application framework of the production of a turbofan engine blade using DT-driven smart manufacturing. Their framework is composed of four different layers: the physical layer, the model layer, the information processing layer, and the system layer. These interconnected layers synchronize their respective data to optimize manufacturing parameters. To demonstrate how DT operations are able to address multi-objective optimization problems, the researchers tested their framework with a four-axis CNC machine. The machine was set to transmit data using force sensors, accelerometers, and acoustic sensors during a machining process. Before any milling was completed, the researchers modeled the CNC to replicate it in the virtual space. The digital CNC was virtual commissioning via computer simulation of the production process, followed by a virtual inspection of the digital fan blade. Afterwards, the now virtually tested process is transferred to the physical space, where the physical process data is collected. Their results showed a process time reduction of 26.3% and an increase in machining precision of 23.4%, though the limited sample data does not significantly represent the entire milling process of the CNC. This case study demonstrates the importance of DT for process establishment as well as system health monitoring and fault detection.

Matania et al. [35] created a digital twin to predict the crack propagation of an induced rack in a helicopter gearbox planetary gear. They used fractography after crack propagation to estimate the state of crack propagation over time. They theorized adding four vibration sensors to another planetary gear and fed that data to a DT, which could analyze it in real-time using synchronous averaging and provide alarms and notifications based on a calculated health factor. The team tested this concept against the HUMS datasets that they used as a benchmark. This research represents many other digital twins research cycles. It highlights some insights into DT research, including the difficulty of implementing solutions in real-time, and benchmarking against currently accepted solutions.

2.2. Manufacturing Support Applications

Companies across various industries have successfully implemented digital twin software solutions to improve their production output, reduce costs, and drive innovation, as General Electric (GE) demonstrated in three of their case studies [36]. With their SmartSignal and Asset Performance Management software, they were able to generate digital twins from operational and fleet data and use those twins to perform real-time monitoring, producing an estimated $1.6 billion in savings. Several notable examples of digital twin implementation software include Siemens Process Simulate, FlexSim, and Visual Components.

Digital twin software solutions play a pivotal role in various industries, revolutionizing management practices and decision-making processes. These solutions enable real-time monitoring, analysis, and optimization of physical systems. Table 1 highlights a selection of some digital twin software solutions and their applications across different industries.

Many tools listed in Table 1 overlap in their core simulation capabilities. For clarity, we have consolidated examples and focused commentary on distinguishing features such as their open-source status, integration protocols, and suitability for use in cobot systems. Repetitive commentary has been removed or shifted to highlight comparative advantages (e.g., Gazebo vs. NVIDIA Omniverse in real-time control applications).

Table 1. Examples of digital twin software solutions and their industry applications.

Software Solution	Description	Software Type	Applications	Example Use Case
Siemens Process Simulate	Digital manufacturing software	Commercial	Manufacturing	[37]
FlexSim	Discrete-event simulation	Commercial	Manufacturing, Logistics, Healthcare	[38]
Actin	Universal Robot's simulation/operating software	Commercial; Research	Aerospace, Manufacturing, Healthcare, Research	[39]
CoppeliaSIM	Distributed control architecture-based DT software	Commercial	Robotics Research and Development	[40]
iTwin.js	Digital Twin Tool Library	Open-Source	Infrastructure	[41]
AnyLogic	Multipurpose simulation modeling software	Commercial	Transportation, Logistics, Manufacturing, Healthcare	[42]
RoboDK	Industrial robot simulator and database	Commercial	Industrial Robotics	[43]
Dassault DELMIA	Digital manufacturing software	Commercial	Manufacturing	[44]
Eclipse	Digital Twin/IoT Framework and Library	Open-Source; Research	Software Development, Standards and Regulations	[45]
ABB RobotStudio	ABB industrial robot simulator	Commercial	Industrial Robotics	[46]
Visual Components	Offline robot programming software	Commercial	Robotics Research, Industrial Applications	[47]
Unreal Engine	Physics-based simulator and development platform	Commercial	Gaming, Animation, Architecture, Automotive	[48]
Ansys Twin Builder	Simulation-based Digital Twin software	Commercial	Aerospace, Manufacturing, Robotics Research, Industrial Applications	[46]
Simul8	Digital twin simulation software	Commercial	Logistics, Industrial Applications	[46]
NVIDIA Omniverse	Physical AI-Enabled Application Set	Commercial; Research	Manufacturing, Animation, Artificial Intelligence	[49]
Unity	Real-time Development Platform	Commercial; Research	Gaming, Animation	[50]
Gazebo	Robot Simulator	Open-Source; Research	Robot Development, Design, Education	[51]
Into-CPS	Cyber-Physical System Application	Open-Source	Research and Development	[52]

Siemens Process Simulate is a digital twin software solution recognized for its capabilities in the manufacturing industry [37]. It is a wide-functionality digital twin software solution focused on manufacturing industries [53–55]. It allows organizations to create virtual replicas of production processes, enabling simulation, optimization, and validation of manufacturing operations. Process Simulate provides insights into assembly line layouts,

material flow, and production cycle times, helping manufacturers streamline operations, improve productivity, and reduce costs. An example of using Siemens Process Simulate in industrial cobot applications can be seen in the automotive manufacturing sector. In an assembly line where collaborative robots work alongside human operators, Process Simulate can be utilized to create a digital twin of the production environment. This digital twin can simulate the interaction between cobot and human workers, ensuring optimal safety and proficiency. By analyzing the virtual model, Process Simulate can help identify potential bottlenecks, optimize the layout of work cells, and enhance the overall workflow. This enables organizations to seamlessly merge cobots into the manufacturing process, resulting in improved productivity, reduced errors, and enhanced worker collaboration.

FlexSim is another functional digital twin software solution that finds applications in various industries, including manufacturing, logistics, and healthcare [56,57]. It enables the creation of virtual models that simulate complex systems and processes, allowing for optimization and analysis. FlexSim assists in optimizing facility layouts, scheduling workflows, and improving resource allocation, ultimately leading to increased efficiency and cost savings. Pires et al. [58] leverages FlexSim to develop a digital twin architecture for energy optimization in manufacturing systems. The digital twin in this experiment is capable of enhancing energy management of automated ground vehicles (AGV) in a battery pack assembly line.

Visual Components software is a digital twin software that focuses on simulation and 3D visualization. It is common in the manufacturing industry and in robotics research and development. It enables users to produce dynamic digital replicas of processes, systems, and environments, providing a virtual mirror of real-world situations. Leveraging its drag-and-drop functionality and a library of pre-designed components, Visual Components facilitates the development of digital twin models. Visual Components software can contribute to productivity enhancement, risk mitigation, and innovative practices across various industries, whether for designing manufacturing setups, testing novel strategies, or training personnel within a digital twin environment. Arnarson [59] demonstrates the strengths and capabilities of Visual Components when he implemented it in a stable digital twin of a KUKA KR 30-3 robot, verifying the software's ability to handle the requisite processing power and communication protocols to digitalize the robot.

Companies such as General Electric [60,61] and NVIDIA [62] also provide similar digital twin software tools for manufacturing applications. These examples illustrate the diverse range of digital twin software solutions available and their successful implementations in various industries. The solutions primarily provide the capability to create virtual simulations, enabling engineers and researchers to design, optimize, and validate their robotic processes before implementation. However, implementation of these software packages varies based on the infrastructure of the existing facilities, the proprietary nature of the equipment utilized, the application it is needed for, and other operational factors. These barriers limit a majority of manufacturers to reap the benefits of digital twins. There is a need for a new implementation methodology for DT software resources that will remove the aforementioned obstacles to digital twin implementation and improve the manufacturing value chain across the industry [47]. By harnessing the capabilities of these solutions, companies can increase productivity, reduce costs, and enhance decision-making processes, leading to a competitive advantage in their respective sectors.

3. Methodology

This section provides a detailed overview of the methodology adopted for this research review. It encompasses various phases, such as gathering and assessing pertinent studies,

conducting quantitative and qualitative analyses, identifying research gaps, and exploring potential avenues for further investigation.

3.1. Databases and Keyword Searching

To ensure a comprehensive literature search, this research review will adhere to the Preferred Reporting Items for Systematic Reviews (PRISMA) guidelines [63]. The literature review process was divided into several major phases, as illustrated in Figure 2. The Scopus and Web of Science (WoS) databases were utilized as primary sources, while additional exploration of references and citations were conducted to identify relevant studies. The search strategy encompasses scholarly journals, conference studies, and proceedings, with a restriction on publication years to no earlier than 2017.

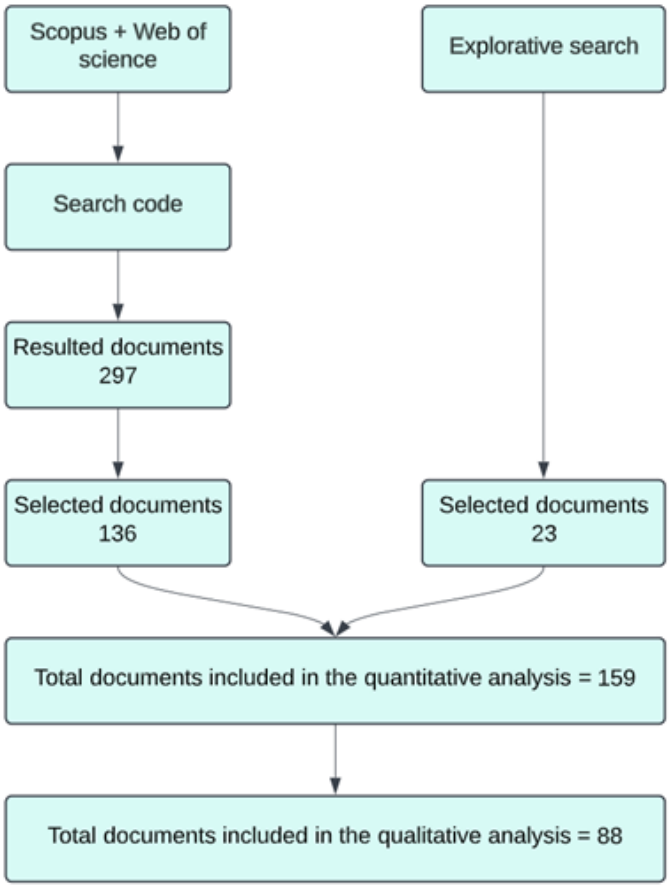


Figure 2. Flowchart of the systematic literature review used in this study.

3.2. Collection and Evaluation of Literature

To ensure the inclusion of unique studies, a meticulous process of removing duplicates was employed, comparing the results obtained from different databases. An exploratory search was conducted to gather a broad range of literature related to the research topic. This paper presents a comprehensive literature review identifying research gaps, exploring frameworks to develop digital twins. This paper presents a wide understanding of the integration of digital twins using collaborative robots. Subsequently, a screening process based on title and abstract relevance was carried out to identify studies suitable for quantitative analysis. The remaining studies were qualitatively analyzed, considering factors such as scholarly impact, recency, and credibility, to refine the selection further.

3.3. Analytical Approach

To gain insights into publishing patterns and the significance of terms in the field, bibliometric analysis was employed. This analysis provides a quantitative understanding of publication trends and identifies key authors, institutions, and journals. Additionally, a keyword co-occurrence analysis, utilizing a distance-oriented method, was conducted to establish bibliometric networks and visualize the relationships between different research concepts [64]. The initial launch version of VOSviewer was used to conduct trials to determine the optimal number of keywords for co-occurrence analysis and enhance the clustering outcomes [65]. To ensure a comprehensive analysis, qualitative methods were also employed to identify significant publications, critical knowledge areas, and vital research contributions. The chosen methodology aims to ensure a thorough and systematic approach to gathering relevant literature and employ a combination of quantitative and qualitative analyses [66]. By utilizing bibliometric analysis and qualitative methods, including publication patterns studies, keyword co-occurrence analysis, and citation analysis, this comprehensive methodology provides valuable insights and lays the foundation for further investigation in the field.

4. Quantitative Analysis

Summarizing the publication trends in the field of digital twin software solutions with industrial cobot applications can provide valuable insights into the technological advancements documented in the literature. Figure 3 illustrates the patterns observed in the cited sources, highlighting the progression of research in this area. From the comprehensive literature search conducted, a total of 159 articles were selected for quantitative evaluation. It is clear from the figure that digital twin research has gained popularity as a tool for tracking conditions, notifying asset managers of necessary repairs, and facilitating real-time data transfer to virtual models since 2018.

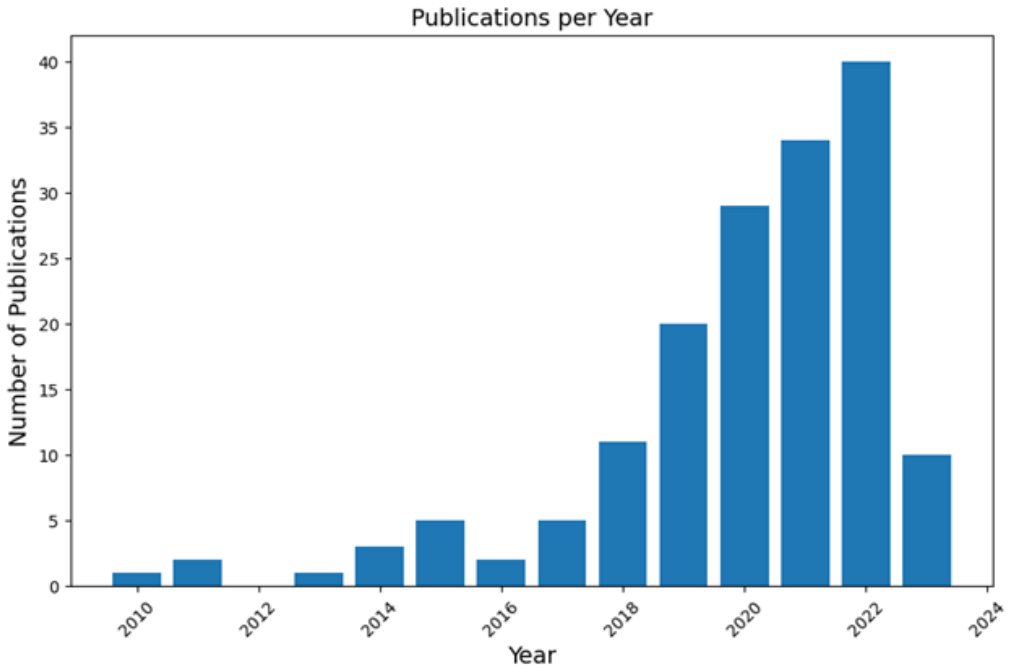


Figure 3. Number of digital twin-related publications per year based on keyword co-occurrence: 'digital twin', 'collaborative robotics', and 'operational efficiency'.

Density Visualization of Keyword Co-Occurrence Analysis

Co-occurrence analysis of keywords was employed to examine the relationships and patterns within the collected data from the literature review [67], providing insights into

the concepts and structure conveyed by these keywords. The analysis involves representing keywords as nodes and visualizing their co-occurrence, highlighting the density and frequency of specific keyword combinations. This approach enhances our understanding of the interconnections and prevalence of certain concepts, enabling a comprehensive exploration of the literature and identifying key themes and relationships within the research field. Figure 4 illustrates a density visualization technique employed to gain a holistic view of the knowledge structure based on keyword co-occurrence analysis. This approach utilizes variables such as node-to-node distance and weight (representing the number of co-occurrences) to determine the density of each node, providing a snapshot of the entire structure and highlighting significant points within the scholarly work [65]. The intensity of the colors in the visualization is based on factors such as the proximity of research works, the distance between nodes, and their level of interconnectedness. The study's findings reveal that concepts like the Internet of Things, machine learning, and industry 4.0 exhibit substantial correlation and significance, as indicated by their positioning in the middle of the map, consistent with the literature review. However, automation, information management, deep learning, and security have received comparatively less attention and development.

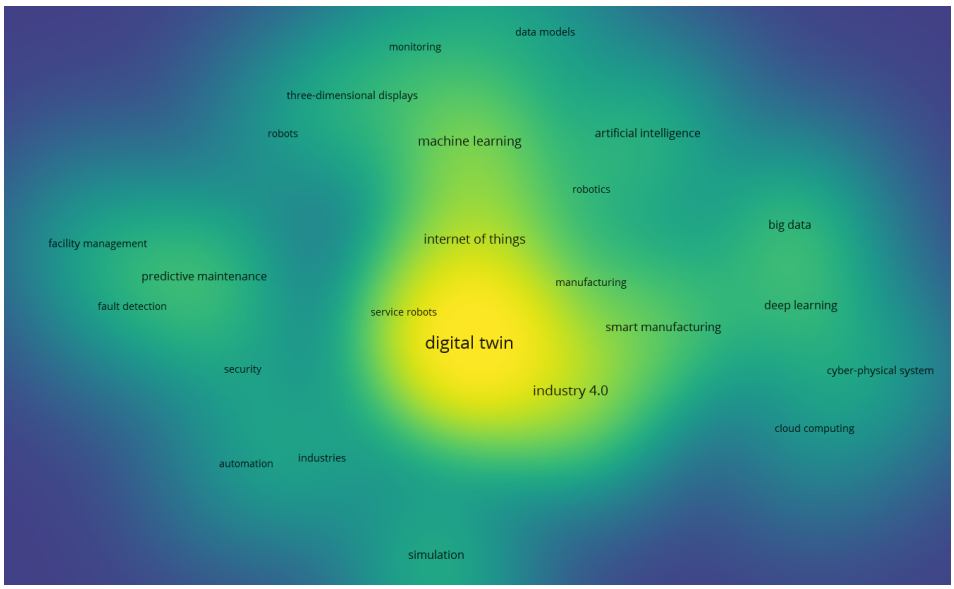


Figure 4. Cloud density visualization of the co-occurrence of keywords used in the literature search.

Table 2 shows the highest cited research publications in the Industrial Digital Twin space At the time of this publication (excluding reviews and survey-based publications). This search was conducted in Scopus using "Industrial Digital Twins" as the search keywords. These papers share similar foundations, such as the complete definitions of a DT, the development of a framework for creating and using a DT, and a case study which reflects the exploration of the framework and approach that was expressed. Moreover, each of these publications highlight the need for more detailed and scrutinized experimentation in the DT domain, evaluating more use cases through experimentation.

Table 2. Top 5 Cited Industrial Digital Twins Research on Scopus.

Title	Goals	Methods	Findings	No. of Citations	Reference
Digital twin-driven product design, manufacturing and service with big data	Developed a novel approach to product design, manufacturing, and service utilizing digital twins	Integrated digital data processing in the traditional product development lifecycle	Qualitatively assessed framework performance in three conceptual case studies as successful	2266	[68]
Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing	Produced an original concept of a digital twin shop-floor (DTS)	Four key components are explored: physical shop-floor, virtual shop-floor, shop-floor service system, and shop-floor digital twin data	Provided an insight into conceptual DTS operation and a framework for further research	1130	[69]
Digital twin-based smart production management and control framework for the complex product assembly shop-floor	Proposed a system of digital twin-based intelligent production management approach for assembly of complex product	Presented a detailed implementation of the proposed approach for a satellite assembly shop-floor scenario	Successfully illustrated the pragmatic application of the proposed framework in a conceptual satellite assembly shop floor	601	[70]
An application framework of digital twin and its case study	Created an application framework of DT for product lifecycle management	A DT case study of a welding production line is built and studied using total-elements information perception technology, data storage, data processing, data mapping, and parametric virtual modeling	The proposed system can show 19 types of key data of the production line in real time, limit simulation delay below 1 s, and update a 4 million piece model at more than 50 times per second	493	[71]
Digital Twin as a Service (DTaaS) in Industry 4.0: An Architecture Reference Model	Designed a holistic reference architecture model for DT-enabled applications	Case study using DTaaS on the virtualization of wetlands to improve maintenance scheduling	Findings indicate that there is a significant relationship between DT capabilities as a service and mass individualization	462	[72]

5. Qualitative Analysis

In this section, a qualitative analysis will be conducted to explore the factors that could enhance management in the context of digital twin software solutions and their use with

industrial cobot applications. This analysis is made based on the quantitative studies above, excluding certain clusters, as they pertain to specific applications outside the scope of digital twin software solutions and industrial cobot applications. Through this qualitative analysis, the authors aim to gain valuable insights into the utilization of digital twin software solutions and other advanced technologies in the context of industrial cobot applications and develop a comprehensive framework for enhanced operating performance.

5.1. Automation in Industrial Collaborative Robotics Applications

Automation in industrial collaborative robotics applications refers to the process of enabling collaborative robotic systems to perform tasks and operations autonomously, with minimal human intervention. It involves blending advanced technologies, such as digital twin software solutions, to streamline operations and enhance productivity in industrial settings. By harnessing the potential of advanced technologies, a Digital Twin-enabled framework can be created to automate processes, optimize performance, and enable proactive decision-making in industrial cobot applications. For example, Schou et al. developed task-level programming software that defines robot skills using kinesthetic teaching [73]. Their results indicated that personnel new to operating robots were quicker to adapt to their software solution in a manufacturing setting. A digital twin framework can benefit from similar programming software in preparing industrial operators for digital twin use. Programming software skills are important to create a digital twin in an industrial automation application.

One of the goals of automation is to reduce the reliance on manual labor and repetitive tasks, allowing collaborative robots to handle routine operations independently [74]. Malik and Brem studied a case where the manual labor of assembling a battery pack was reduced by 50% using a digital twin of a human-robot collaboration cell [16]. This digital twin optimized the manufacturer's cell layout and collision avoidance, verified that their production rate could be maintained with reduced manual labor, and enabled more flexibility in their volume production.

To achieve successful automation in industrial cobot applications, several factors come into play. The design and implementation of digital twin software solutions tailored specifically for collaborative robots are crucial in enabling data transfer in the system, as demonstrated by Pires et al. [75]. The available data types from the different sensors and other data acquisition sources on the robot did not natively match the data derived in the virtual environment, so a software solution, a custom Java application in this case, alleviates this constraint by handling and transforming the data for recognition at each end of the system. This is a likely scenario for industry, given the complex variety of data sources in each facility. These solutions should possess the necessary functionalities and capabilities to effectively monitor, analyze, and simulate collaborative robotic systems.

Digital twin software solutions provide a digital representation of the physical robotic system, allowing for precise monitoring and control [76]. Through seamless data exchange between the digital twin and the physical robot, collaborative robotic systems can adapt to changing conditions, optimize their actions, and improve overall performance [77]. Effective communication and synchronization mechanisms are essential for seamless data exchange between the digital twin and the physical robot. This is the difference between a digital snapshot of the system at a point in time versus a live, dynamic model that always represents the system in real time. Lu et al. indicated that the change of industrial network systems from legacy fieldbus to ethernet-based networks is indicative of the enhanced performance enabled by real-time data transmission [78]. This ensures real-time monitoring, coordination, and control, enabling the digital twin to accurately reflect the state of the physical system and facilitate optimal decision-making for automation. However, the In-

dustrial Internet-of-Things (IIoT) trend may be a challenge to ethernet-based networks, trading improved infrastructure costs for latency due to wireless transmission [55].

Moreover, integrating artificial intelligence (AI) and machine learning (ML) algorithms into digital twin software solutions enhances automation capabilities. Alexopoulos, Nikolakis, and Chryssolouris demonstrated this by developing and testing a machine vision system using a DT [79]. The DT model expedited the algorithm's training, reducing the start-up cost that is typical for manually trained machine learning algorithms. These algorithms enable decision-making and adaptive control, allowing collaborative robotic systems to autonomously respond to changing conditions, optimize their actions, and continuously improve their performance.

Automation in industrial cobot applications enables organizations to optimize processes, minimize downtime, and allocate human resources to more complex and value-added tasks. However, challenges exist in achieving automation, such as data quality, algorithm complexity, computational requirements, and the need for domain expertise. Overcoming these challenges requires careful consideration, planning, and the adoption of best practices in the design, implementation, and utilization of digital twin software solutions.

5.2. Design and Implementation of Digital Twin Software Solutions for Collaborative Robots

During the implementation phase, the digital twin software solutions are developed and configured to synchronize with the physical robots in real time [80]. It is crucial to ensure compatibility and integration between the digital twin software and the collaborative robot's hardware and software components [81]. This involves developing interfaces and protocols that facilitate seamless communication and data exchange. Additionally, the software solutions should possess advanced functionalities for real-time monitoring, analysis, and simulation, including data acquisition, processing, visualization, and modeling.

Scalability and flexibility are also essential considerations, allowing the software to adapt to changes in the collaborative robotic system without compromising its functionality and performance [82]. Collaborative efforts among robotics experts, software developers, and domain specialists are crucial to ensuring successful design and implementation, as this multidisciplinary approach ensures the software solutions are tailored to meet the collaborative robotic system's specific requirements and objectives.

5.2.1. Communication and Synchronization Mechanisms

Communication and synchronization mechanisms are essential components in the design and implementation of digital twin software solutions for collaborative robots [81]. These mechanisms facilitate seamless data exchange and real-time coordination between the digital twin and the physical robot, enabling effective automation and optimization.

In cobot applications, communication between the digital twin and the physical robot involves the exchange of sensor data, control signals, and feedback information [83]. This communication allows the digital twin to continuously monitor the physical robot's state and behavior while also providing instructions and guidance based on the digital twin's analysis and simulation.

Various protocols and interfaces are utilized to establish effective communication. These protocols ensure standardized data transmission and enable interoperability between different software and hardware components. Examples of commonly used protocols in cobot applications include OPC UA (Unified Architecture), MQTT (Message Queuing Telemetry Transport), and ROS (Robot Operating System) [84].

The synchronization process involves updating the digital twin with real-time data received from the physical robot and feeding back the analysis and simulation results to the physical system. This two-way flow of information enables the digital twin to provide

insights, recommendations, and instructions to the physical robot, contributing to improved decision-making and adaptive control.

Effective communication and synchronization mechanisms require careful consideration of factors such as latency, reliability, and bandwidth [85–89]. Low-latency communication is crucial for real-time monitoring and control, ensuring that the digital twin responds promptly to changes in the physical robot's state [90]. Reliable communication ensures that data transmission is accurate and error-free, avoiding any discrepancies between the digital twin and the physical system [91]. Sufficient bandwidth is necessary to handle the exchange of large amounts of data generated by sensors and actuators in the collaborative robotic system [92].

5.2.2. Integration of Artificial Intelligence and Machine Learning Algorithms

The integration of artificial intelligence (AI) and machine learning (ML) algorithms is a key aspect in harnessing the full potential of digital twin software solutions for collaborative robots. By incorporating AI and ML capabilities, organizations can enhance decision-making, adaptive control, and overall performance in collaborative robotic systems [93]. AI and ML algorithms enable collaborative robots to learn from data, adapt to changing conditions, and make intelligent decisions. These algorithms can analyze large datasets generated by the digital twin and the physical robot, extracting patterns, identifying anomalies, and deriving insights that can optimize robot behavior and performance [42,94].

One area where AI and ML algorithms are particularly impactful is in predictive analysis and maintenance [95]. By analyzing historical data and real-time sensor information, these algorithms can predict potential faults or failures in the robotic system, allowing for proactive maintenance and minimizing unplanned downtime. This predictive capability improves the overall reliability and efficiency of collaborative robots.

The coalescence of AI and ML algorithms also enables advanced capabilities such as computer vision, natural language processing, and speech recognition in collaborative robotic systems [96]. These capabilities enhance human-robot interaction, allowing for intuitive and efficient communication between humans and robots. Collaborative robots can understand and interpret commands, recognize objects or obstacles in their environment, and perform complex tasks with higher accuracy and precision.

To successfully integrate AI and ML algorithms, organizations need to consider the availability and quality of data, the selection and training of appropriate algorithms, and the computational resources required for running these algorithms. Data pre-processing, feature engineering, and model training are important steps in preparing the data for AI and ML algorithms. Organizations should also ensure that the algorithms are continually updated and refined as new data becomes available, enabling the collaborative robot to improve its performance over time.

5.2.3. Challenges and Considerations

While automation in industrial cobot applications brings numerous benefits, there are also several challenges and considerations that need to be addressed. These challenges may arise from technical, operational, and organizational perspectives and require careful planning and implementation.

One key challenge is the complexity of system integration [97]. Integrating digital twin software solutions with collaborative robots involves connecting various components, such as sensors, actuators, control systems, and the digital twin itself. Ensuring seamless communication and synchronization between these components can be a technical challenge that requires expertise in system integration and compatibility.

Another challenge is the availability and quality of data [98]. Digital twins rely on accurate and up-to-date data from both the physical system and the virtual model. However, acquiring and maintaining high-quality data can be a challenge, especially in dynamic industrial environments. Organizations need to establish robust data collection mechanisms, ensure data integrity, and address issues such as data gaps or inconsistencies.

Furthermore, scalability is an important consideration when implementing digital twin software solutions for collaborative robots [99]. As industrial operations scale up, the digital twin needs to handle increasing amounts of data and provide real-time analysis and the decision-making process. Organizations should consider the scalability of the digital twin architecture, including the computational resources and storage capacity required to support larger robotic systems.

Data privacy and security also pose significant challenges. Digital twin software solutions rely on sensitive data from the physical system, such as production processes, equipment specifications, or operational data [20]. Protecting this data from unauthorized access or malicious attacks is crucial. While digital twin software can feature rigorous cybersecurity measures, infrastructure security is only as good as its weakest link. Organizations need to implement robust security measures, such as encryption, access controls, and data anonymization techniques, to ensure data privacy and protect against cyber threats.

Moreover, the inclusion of AI and ML algorithms introduces additional challenges. Training and fine-tuning these algorithms require large amounts of labeled data and computational resources. Organizations need to consider the availability of suitable training datasets and the computational infrastructure needed to support the training process. Additionally, the interpretability and explainability of AI and ML algorithms should be considered to ensure transparency and trust in the decision-making process of collaborative robots.

Organizational readiness and change management are also important considerations. Integrating digital twin software solutions with collaborative robots may require organizational restructuring, skill development, and change in work processes. To facilitate a smooth transition, organizations need to foster a culture of collaboration, provide training and support for employees, and ensure effective communication and buy-in from stakeholders.

5.3. Interoperability and Architectural Design

Interoperability and architectural design play a pivotal role in ensuring seamless data exchange, integration of architectural design, and efficient information management for successful implementation. Interoperability is the ability of different systems, platforms, and technologies to seamlessly exchange data and work together harmoniously. Achieving interoperability is essential for harnessing the full potential of digital twin software solutions in collaborative robotic systems [100]. It enables efficient and accurate transfer of information between the physical system and its digital twin, facilitating real-time monitoring, analysis, and optimization. To achieve interoperability, interfaces and protocols that enable seamless communication between the digital twin and the physical system must be developed. Standardized data formats, communication protocols, and integration frameworks are crucial for effective interoperability. By ensuring compatibility and integration with the collaborative robot's hardware and software components, data exchange and integration can be streamlined, enabling seamless coordination between the digital twin and the physical robot. Table 3 shows some protocols for integration.

Table 3. Commonly used protocols in integrating digital twin software solutions with industrial collaborative robotics applications.

Protocol	Description	Example Use Case
OPC UA (Unified Architecture)	A standard protocol for secure and reliable communication between devices, systems, and applications.	[101]
MQTT (Message Queuing Telemetry Transport)	A lightweight publish-subscribe messaging protocol for efficient data exchange.	[102]
ROS (Robot Operating System)	A flexible framework for writing robot software, providing libraries and tools for communication and control.	[103]
DDS (Data Distribution Service)	A data-centric publish-subscribe communication protocol for real-time and scalable systems.	[104]
CoAP (Constrained Application Protocol)	A protocol designed for resource-constrained devices, suitable for IoT and low-power applications.	[105]

Another crucial aspect is architectural design. A well-designed architecture ensures the proper integration and functioning of the digital twin software within an industrial automation system [106,107]. It involves identifying and arranging components, interfaces, and data flows to enable effective communication and collaboration between the physical system and its digital twin. The optimized architectural design supports the seamless exchange of information, enhances data integrity, and improves overall system performance. The Figure 5 below illustrates a step-by-step workflow for the integration of digital twin software solutions in the case of industrial cobot applications. The workflow begins with system analysis and requirements gathering, followed by the identification of components and interfaces. An optimized architectural design is developed to facilitate seamless incorporation and effective communication between the physical system and its digital twin. Interfaces are then developed and integrated to enable data exchange between the collaborative robot and the digital twin software solution. Real-time synchronization is established, allowing for continuous data exchange, monitoring, and analysis. The synchronized digital twin software solution provides valuable insights and analysis to support data-driven decision-making in the collaborative robotic system. The integration process involves continuous improvement and optimization based on system performance and emerging technologies. This workflow enables organizations to unlock the full potential of digital twin technology in the realm of industrial cobot applications. This research is a literature review, and a case study is out of this paper's scope.

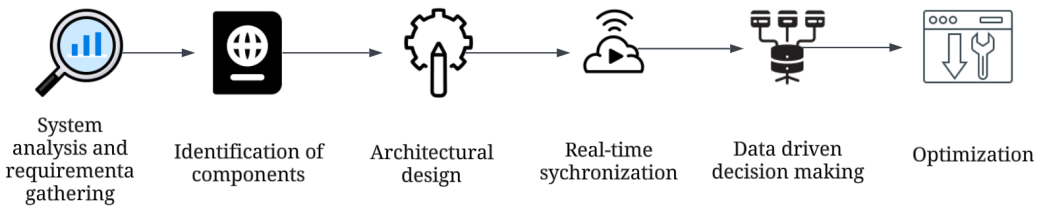


Figure 5. Workflow for the Integration of Digital Twin Software Solutions with Industrial Robotics Application.

5.4. Machine Learning in Industrial Collaborative Robotics Applications

Artificial Intelligence (AI) and Machine Learning (ML) algorithms are pivotal in modern digital twin implementations. This section explains how AI/ML methods have been applied in real-world cobot systems using digital twins and proposes architectural concepts for closed-loop optimization. ML algorithms from Tables 4 and 5 support predictive diagnostics, anomaly detection, and motion optimization in industrial settings.

5.4.1. Conventional Approaches to Machine Learning Techniques in Industrial Collaborative Robotics Applications

In the context of industrial collaborative robotics applications, conventional approaches to machine learning techniques encompass several key steps, including data preparation, model development, and algorithm selection [108]. These steps play a crucial role in harnessing the potential of machine learning algorithms to enhance the performance and decision-making capabilities of collaborative robotic systems supported by digital twin software solutions. Data preparation is an essential first step in the conventional approach to machine learning. It involves collecting relevant data from various sources, including sensors, historical records, and real-time monitoring systems [109]. The data must be cleaned, pre-processed, and transformed to ensure its quality, integrity, and compatibility with the machine learning algorithms. This process may include tasks such as data normalization, feature engineering, and outlier detection to optimize the data for model development. Once the data is prepared, the next step is model development [110]. In this stage, machine learning models are trained using the prepared data to learn patterns, make predictions, or perform specific tasks. The choice of model depends on the nature of the problem and the desired outcome. Commonly used conventional machine learning algorithms for industrial cobot applications are included in Table 4.

Additional approaches such as reinforcement learning have shown promise in enabling robotic agents to optimize pick-and-place strategies over time. GAN-based models have also been explored for synthetic dataset augmentation when real-world datasets are limited. These techniques offer flexible training pipelines and can operate effectively in high-dimensional parameter spaces common in robotic control.

Table 4. Conventional machine learning algorithms for industrial collaborative robotics applications.

Algorithm	Description	Example Use Case
Support Vector Machines (SVM)	A powerful algorithm for classification and regression tasks, known for its ability to handle complex data sets.	[111]
Random Forest	An ensemble learning algorithm that combines multiple decision trees to make predictions or classifications.	[112]
Naive Bayes	A probabilistic algorithm often used for text classification and other tasks involving discrete data.	[113]
k-Nearest Neighbors (k-NN)	Classifies new data points based on their k nearest neighbors, commonly used for pattern recognition.	[114]
Neural Networks	Interconnected nodes that mimic biological neural networks, used for classification, regression, and pattern recognition tasks.	[115]

5.4.2. Deep Learning in Industrial Collaborative Robotics Applications

Deep learning is frequently regarded as a black-box estimator due to its highly complex and non-linear internal representations, which hinder interpretability. Although it excels in capturing intricate patterns in high-dimensional data, the decision-making process remains largely inscrutable, limiting its trustworthiness and applicability in domains requiring transparency or accountability. In the context of this review, deep learning techniques offer advanced capabilities for augmenting the decision-making capabilities of collaborative robotic systems supported by digital twin software solutions [116].

Deep learning's use in DT spans multiple modalities—from vision-based CNNs used in visual inspection and part recognition, to recurrent neural networks (RNNs) for time-series-based maintenance predictions. However, model interpretability remains limited, and real-time applicability is constrained by computational demands. Emerging research is exploring hybrid models combining symbolic AI with neural backends for greater control and transparency.

Deep learning models excel at automatically learning and discovering intricate patterns and relationships in large data sets, enabling them to make accurate predictions, classifications, and decisions. They have the potential to revolutionize various aspects of industrial cobot applications, including perception, control, and decision-making.

One of the key advantages of deep learning is its ability to handle unstructured data, such as images, audio, and text [117]. This makes it particularly relevant for applications in industrial cobot applications, where sensor data, visual inputs, and textual information are critical for effective system operation. Deep learning models can learn from vast amounts of data, allowing them to perform complex tasks such as object recognition, gesture detection, and natural language processing. However, it is not without its drawbacks. The downsides of using deep learning include its dependency on large amounts of labeled data for training, the computational resources required, susceptibility to overfitting, lack of interpretability leading to "black box" models, vulnerability to adversarial attacks, inefficiency in learning from small datasets, limitations in transfer learning, and ethical concerns related to privacy, bias, and fairness. Despite its remarkable success in various fields, these downsides highlight the need for caution and careful consideration when applying deep learning techniques to real-world problems.

The integration of deep learning with digital twin software solutions opens up new opportunities for enhancing the capabilities of collaborative robotic systems [118]. By leveraging the power of deep learning algorithms, these systems can benefit from real-time analysis, predictive maintenance, and intelligent decision-making. Deep learning models can analyze sensor data streams, identify anomalies, predict equipment failures, and optimize robotic systems' operation. Table 5 shows the commonly used deep learning methods in this domain.

Table 5. Deep learning techniques are commonly employed in industrial collaborative robotics applications.

Technique	Description	Example Use Case
Convolutional Neural Networks (CNN)	Well-suited for image and video processing tasks, CNNs excel at object recognition and segmentation.	[119]
Recurrent Neural Networks (RNN)	Effective for sequential data processing, RNNs capture temporal dependencies and handle time-series data.	[120]

Table 5. *Cont.*

Technique	Description	Example Use Case
Generative Adversarial Networks (GAN)	GANs consist of two neural networks competing against each other, enabling tasks such as image generation and anomaly detection.	[121]
Reinforcement Learning	RL focuses on training agents to make decisions and take actions based on feedback from the environment. It can be utilized for robotic control and optimization tasks.	[122]

Long Short-Term Memory (LSTM) networks are a type of RNN that enables the consideration of older data patterns in the progression of a time-series analysis. LSTM networks have been used in robotic digital twins to model and forecast time-series data such as sensor readings, actuator states, and environmental conditions [123]. They are particularly powerful in capturing temporal dependencies in industrial equipment operation, enabling predictive maintenance and anomaly detection. By anticipating downtime and minimizing unexpected failures, LSTM-based models integrated into digital twins can significantly reduce maintenance costs and production halts, enhancing throughput and reliability.

Reinforcement Learning has also been used within digital twin environments for training industrial robots in simulation before real-world deployment [124]. RL-based DT is useful for adaptive path planning and motion control, optimized pick-and-place operations, and collaborative robot behavior adaptation under dynamic and variable conditions. Digital twins can serve as high-fidelity, physics-based simulators where RL agents can learn policies without the risk or cost of physical experimentation. Such learning accelerates deployment, reduces trial-and-error on physical systems, and enables rapid reconfiguration of production cells, leading to increased flexibility and productivity.

6. Knowledge Gaps and Future Trends

In this paper, several knowledge gaps and future trends emerge that require attention and further exploration. These gaps and trends play a crucial role in advancing the effectiveness of cobot applications and addressing issues related to fault detection and prediction. The following areas present opportunities for future research and development:

- *Innovative Techniques for Efficiency Improvement*: To enhance efficiency in cobot applications, innovative techniques such as data management, predictive analysis, and real-time monitoring can be explored. These techniques enable proactive fault detection, performance optimization, and timely decision-making. Further research is needed to develop advanced algorithms and methodologies that can handle complex data sets and extract valuable insights for improved operational efficiency.
- *Context Awareness and Data Types*: In the context of digital twin-enabled systems, dissonant or even incompatible data types captured by a diverse suite of sensors limit the ability to include context awareness in forecasts. Considering the autonomous characteristics inherent in Digital Twins and their capacity to parse pertinent data for practical utilization, future research should focus on integrating diverse data sources and exploring advanced techniques to incorporate context awareness, such as contextual sensing, adaption, resource discovery, and augmentation [125]. This will enhance the accuracy and reliability of predictions, enabling more effective fault detection and smart management in industrial cobot applications.

- *System-Level Integration*: It can be said that the value of a Digital Twin is positively correlated with the level at which it is implemented. The workflow and infrastructure that exist in manufacturing are typically arranged in five levels: station, cell, shop, factory, and enterprise. A "station" refers to a location where a single manufacturing or assembly process is carried out. A "cell" represents a collection of stations that collectively perform a set of processes within a subsystem. A "shop" encompasses a cluster of cells responsible for the manufacturing or assembly of a subsystem. A "factory" comprises a grouping of shops that handle the manufacturing or assembly of an entire system. An "enterprise" is constituted by a collection of factories that contribute a diverse array of complete systems to the market. It is easy to see how quickly the accomplished tasks of humans and machines scale up, which is why operation efficiency is critical. One of the biggest considerations for operational efficiency is knowledge management. Considerations should be made for which level of the manufacturing scheme a digital twin will be implemented. Incorporating components that operate at the system level is crucial for accurate predictions in context-aware smart management and fault detection in industrial cobot applications. Future research should explore the integration of various subsystems, sensors, and data sources to create a holistic view of the collaborative robotic system. This will enable a comprehensive understanding of system behavior and facilitate proactive maintenance, optimization, and decision-making.
- *Deep Learning Applications and Challenges*: Deep learning techniques offer significant analytical capabilities for processing large data sets and detecting complex problems within collaborative robotic systems. However, to broaden their application, challenges such as high computing complexity and lengthy training times need to be addressed. Further research should focus on developing efficient deep learning algorithms, hardware accelerators, and distributed computing techniques to overcome these challenges and unlock the full potential of deep learning in industrial cobot applications. Furthermore, the dilemma of "black box" AI and ML models can be addressed with Explainable AI (XAI), a subset of AI and ML that supports human trustworthiness and compliance by explaining the reasoning that draws. The inclusion of XAI in Industrial DT applications would authenticate the reasoning for operators in the field. This is particularly useful for risk reduction, ethical consideration, and real-time decision making, when collaborating with operators.
- *Reduced Human Involvement in Data Pre-processing and Interpretation*: Further research is needed to explore deep learning applications in the context of cobot applications with the aim of reducing the need for human involvement in data pre-processing and interpretation. Automation of these tasks through advanced algorithms and methodologies will streamline the analysis process, accelerate decision-making, and enable real-time responses in industrial collaborative robotic systems.

7. Conclusions

In conclusion, integrating digital twin software solutions with industrial collaborative robotics applications has the potential to enhance operational efficiency, productivity, and decision-making processes across various industries. This comprehensive review has explored the concept of digital twins, their historical development, components, and significance in the context of industrial collaborative robotics applications. Through qualitative analysis, key factors that can enhance automation, interoperability, architectural design, and the utilization of machine learning and deep learning techniques have been identified. These factors pave the way for the development of comprehensive frameworks that reduce reliance on human intervention, improve efficiency, and enable real-time monitoring, pre-

dictive maintenance, and optimized operation of collaborative robotic systems. The review has also shed light on knowledge gaps and future trends in this field. While this review is extensive, it is limited in a few areas. The databases used for literature searching are limited to Scoptus and WoS. Other avenues may reveal additional insights for published research in the Industrial DT domain. This research also limits the publication years of literature referenced to 2017. This was meant to focus on the state of the art in this research space but allow some fundamental publications that laid a foundation for it as well. Because they are mutually exclusive, improving one area weakens the other, and thus this paper may not present the strongest argument for state of the art nor fundamental research, but rather focuses on striking a balance between the two. Lastly, there is inherent bias in the subjectivity in qualitative analysis. This section was included to provide additional insights into Industrial DT application based on the wide, but not all-encompassing, experience of the authors in this domain. Further research is needed to address challenges related to data management, context awareness, system-level integration, and the application of deep learning techniques. Overcoming these challenges will contribute to the effective implementation and utilization of digital twin software solutions in industrial collaborative robotics applications, leading to streamlined operations, improved collaboration, and enhanced performance across the various industrial domains. Moreover, those applications could have a broader impact on the other areas of automotive system usage, such as civil engineering, healthcare, smart workplace planning, and more.

***Disclaimer:** No approval or endorsement of any commercial product by NIST is intended or implied. Certain commercial software systems are identified in this paper to facilitate understanding. Such identification does not imply that these software systems are necessarily the best available for the purpose.

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References

1. Hosamo, H.H.; Nielsen, H.K.; Alnmr, A.N.; Svennevig, P.R.; Svidt, K. A review of the Digital Twin technology for fault detection in buildings. *Front. Built Environ.* **2022**, *8*, 1013196. [CrossRef]
2. Hosamo, H.H.; Imran, A.; Cardenas-Cartagena, J.; Svennevig, P.R.; Svidt, K.; Nielsen, H.K. A Review of the Digital Twin Technology in the AEC-FM Industry. *Adv. Civ. Eng.* **2022**, *2022*, 2185170.

3. Sharma, A.; Kosasih, E.; Zhang, J.; Brintrup, A.; Calinescu, A. Digital Twins: State of the art theory and practice, challenges, and open research questions. *J. Ind. Inf. Integr.* **2022**, *30*, 100383. [CrossRef]
4. Khan, S.; Farnsworth, M.; McWilliam, R.; Erkoyuncu, J. On the requirements of digital twin-driven autonomous maintenance. *Annu. Rev. Control* **2020**, *50*, 13–28. [CrossRef]
5. Al-Ali, A.R.; Gupta, R.; Zaman Batool, T.; Landolsi, T.; Aloul, F.; Al Nabulsi, A. Digital Twin Conceptual Model within the Context of Internet of Things. *Future Internet* **2020**, *12*, 163. [CrossRef]
6. Schluse, M.; Priggemeyer, M.; Atorf, L.; Rossmann, J. Experimentable Digital Twins—Streamlining Simulation-Based Systems Engineering for Industry 4.0. *IEEE Trans. Ind. Inform.* **2018**, *14*, 1722–1731. [CrossRef]
7. Gelernter, D. *Mirror Worlds: Or the Day Software Puts the Universe in a Shoebox...How It Will Happen and What It Will Mean*; Oxford University Press: Oxford, UK, 1991.
8. Grieves, M. Digital twin: Manufacturing excellence through virtual factory replication. *White Pap.* **2014**, *1*, 1–7.
9. Rajamurugu, N.; Karthik, M. Introduction, History, and Concept of Digital Twin. In *Digital Twin Technology: Fundamentals and Applications*; Wiley: Hoboken, NJ, USA, 2022; pp. 19–32.
10. Grieves, M.; Vickers, J. Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems. In *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches*; Springer: Cham, Switzerland, 2017; pp. 85–113.
11. Trauer, J.; Schweigert-Recksiek, S.; Engel, C.; Spreitzer, K.; Zimmermann, M. What is a digital twin?—Definitions and insights from an industrial case study in technical product development. *Des. Soc. DESIGN Conf.* **2020**, *1*, 757–766. [CrossRef]
12. Madni, A.M.; Madni, C.C.; Lucero, S.D. Leveraging digital twin technology in model-based systems engineering. *Systems* **2019**, *7*, 7. [CrossRef]
13. Popa, L.; Berdich, A.; Groza, B. CarTwin—Development of a digital twin for a real-world in-vehicle CAN network. *Appl. Sci.* **2022**, *13*, 445. [CrossRef]
14. Hosamo, H.H.; Svennevig, P.R.; Svidt, K.; Han, D.; Nielsen, H.K. A Digital Twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics. *Energy Build.* **2022**, *261*, 111988. [CrossRef]
15. Guerra-Zubiaga, D.; dos Santos, M.C.; Voicu, R.C.; Richards, G.; Gosnell, S.; Barbosa, G.F. A digital twin approach to support a multi-task industrial robot operation using design of experiments. *J. Braz. Soc. Mech. Sci. Eng.* **2024**, *46*, 516. [CrossRef]
16. Malik, A.A.; Brem, A. Digital twins for collaborative robots: A case study in human-robot interaction. *Robot. Comput.-Integr. Manuf.* **2021**, *68*, 102092. [CrossRef]
17. Matheson, E.; Minto, R.; Zampieri, E.G.; Faccio, M.; Rosati, G. Human–robot collaboration in manufacturing applications: A review. *Robotics* **2019**, *8*, 100. [CrossRef]
18. Avila, E.A.; Chapa, D.P.; Arenas, I.D.; Hurtado, C.V. A Digital Twin implementation for Mobile and collaborative robot scenarios for teaching robotics based on Robot Operating System. In Proceedings of the 2022 IEEE Global Engineering Education Conference (EDUCON), Tunis, Tunisia, 28–31 March 2022; pp. 559–564.
19. Guerra-Zubiaga, D.; Kuts, V.; Mahmood, K.; Bondar, A.; Nasajpour-Esfahani, N.; Otto, T. An approach to develop a digital twin for industry 4.0 systems: Manufacturing automation case studies. *Int. J. Comput. Integr. Manuf.* **2021**, *34*, 933–949. [CrossRef]
20. Holmes, D.; Papathanasaki, M.; Maglaras, L.; Ferrag, M.A.; Nepal, S.; Janicke, H. Digital twins and cyber security–solution or challenge? In Proceedings of the 2021 6th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM), Preveza, Greece, 24–26 September 2021; pp. 1–8.
21. Lim, K.Y.H.; Zheng, P.; Chen, C.H. A state-of-the-art survey of Digital Twin: Techniques, engineering product lifecycle management and business innovation perspectives. *J. Intell. Manuf.* **2020**, *31*, 1313–1337. [CrossRef]
22. Qi, Q.; Tao, F.; Hu, T.; Anwer, N.; Liu, A.; Wei, Y.; Wang, L.; Nee, A.Y. Enabling technologies and tools for digital twin. *J. Manuf. Syst.* **2021**, *58*, 3–21. [CrossRef]
23. Van Dinter, R.; Tekinerdogan, B.; Catal, C. Predictive maintenance using digital twins: A systematic literature review. *Inf. Softw. Technol.* **2022**, *151*, 107008. [CrossRef]
24. Norambuena, N.; Ortega, J.; Muñoz-La Rivera, F.; Covarrubias, M.; Valín Rivera, J.L.; Ramírez, E.; Ketterer, C.I.G. Integrating Digital Twins of Engineering Labs into Multi-User Virtual Reality Environments. *Appl. Sci.* **2025**, *15*, 3819. [CrossRef]
25. Nambiar, S.; Jonsson, M.; Tarkian, M. Automation in Unstructured Production Environments Using Isaac Sim: A Flexible Framework for Dynamic Robot Adaptability. *Procedia CIRP* **2024**, *130*, 837–846. [CrossRef]
26. Zhou, Z.; Song, J.; Xie, X.; Shu, Z.; Ma, L.; Liu, D.; Yin, J.; See, S. Towards building AI-CPS with NVIDIA Isaac Sim: An industrial benchmark and case study for robotics manipulation. In Proceedings of the 46th International Conference on Software Engineering: Software Engineering in Practice, Lisbon, Portugal, 14–20 April 2024; pp. 263–274.
27. Yu, W.; Patros, P.; Young, B.; Klinac, E.; Walmsley, T.G. Energy digital twin technology for industrial energy management: Classification, challenges and future. *Renew. Sustain. Energy Rev.* **2022**, *161*, 112407. [CrossRef]
28. Onile, A.E.; Machlev, R.; Petlenkov, E.; Levron, Y.; Belikov, J. Uses of the digital twins concept for energy services, intelligent recommendation systems, and demand side management: A review. *Energy Rep.* **2021**, *7*, 997–1015. [CrossRef]

29. Laubenbacher, R.; Mehrad, B.; Shmulevich, I.; Trayanova, N. Digital twins in medicine. *Nat. Comput. Sci.* **2024**, *4*, 184–191. [CrossRef]
30. Chakshu, N.K.; Sazonov, I.; Nithiarasu, P. Towards enabling a cardiovascular digital twin for human systemic circulation using inverse analysis. *Biomech. Model. Mechanobiol.* **2021**, *20*, 449–465. [CrossRef]
31. Ahmadi-Assalemi, G.; Al-Khateeb, H.; Maple, C.; Epiphaniou, G.; Alhaboby, Z.A.; Alkaabi, S.; Alhaboby, D. Digital twins for precision healthcare. In *Cyber Defence in the Age of AI, Smart Societies and Augmented Humanity*; Springer: Cham, Switzerland, 2020; pp. 133–158.
32. Qian, C.; Liu, X.; Ripley, C.; Qian, M.; Liang, F.; Yu, W. Digital twin—Cyber replica of physical things: Architecture, applications and future research directions. *Future Internet* **2022**, *14*, 64. [CrossRef]
33. Schwarz, C.; Wang, Z. The role of digital twins in connected and automated vehicles. *IEEE Intell. Transp. Syst. Mag.* **2022**, *14*, 41–51. [CrossRef]
34. Zhang, X.; Zhu, W. Application framework of digital twin-driven product smart manufacturing system: A case study of aeroengine blade manufacturing. *Int. J. Adv. Robot. Syst.* **2019**, *16*, 1729881419880663. [CrossRef]
35. Matania, O.; Bechhoefer, E.; Bortman, J. Digital twin of a gear root crack prognosis. *Sensors* **2023**, *23*, 9883. [CrossRef]
36. Zorchenko, N.; Tyupina, T.; Parshutin, M. Technologies used by General Electric to create digital twins for energy industry. *Power Technol. Eng.* **2024**, *58*, 521–526. [CrossRef]
37. Xia, K.; Sacco, C.; Kirkpatrick, M.; Saidy, C.; Nguyen, L.; Kircaliali, A.; Harik, R. A digital twin to train deep reinforcement learning agent for smart manufacturing plants: Environment, interfaces and intelligence. *J. Manuf. Syst.* **2021**, *58*, 210–230. [CrossRef]
38. Agalianos, K.; Ponis, S.; Aretoulaki, E.; Plakas, G.; Efthymiou, O. Discrete event simulation and digital twins: Review and challenges for logistics. *Procedia Manuf.* **2020**, *51*, 1636–1641. [CrossRef]
39. Saavedra Sueldo, C.; Perez Colo, I.; De Paula, M.; Villar, S.A.; Acosta, G.G. ROS-based architecture for fast digital twin development of smart manufacturing robotized systems. *Ann. Oper. Res.* **2023**, *322*, 75–99. [CrossRef]
40. Magrin, C.E.; Del Conte, G.; Todt, E. Creating a digital twin as an open source learning tool for mobile robotics. In Proceedings of the 2021 Latin American Robotics Symposium (LARS), 2021 Brazilian Symposium on Robotics (SBR), and 2021 Workshop on Robotics in Education (WRE), Natal, Brazil, 11–15 October 2021; pp. 13–18.
41. Pedraza López, A. Evaluación de Implementación Utilizando iTwin. js Para la Integración de Gemelos Digitales en el Puerto de Buenaventura. Master's Thesis, Universidad de Los Andes, Bogota, Colombia, 2022.
42. Bécue, A.; Maia, E.; Feeken, L.; Borchers, P.; Praça, I. A new concept of digital twin supporting optimization and resilience of factories of the future. *Appl. Sci.* **2020**, *10*, 4482. [CrossRef]
43. Nava-Téllez, I.A.; Elias-Espinosa, M.C.; Escamilla, E.B.; Saavedra, A.H. Digital twins and virtual reality as means for teaching industrial robotics: A case study. In Proceedings of the 2023 11th International Conference on Information and Education Technology (ICIET), Fujisawa, Japan, 18–20 March 2023; pp. 29–33.
44. Jin, X.; Dong, H.; Yao, X. Research on the integrated application of digital twin technology in the field of automobile welding. In Proceedings of the International Conference on Advanced Manufacturing Technology and Manufacturing Systems (ICAMTMS 2022), Shijiazhuang, China, 30 August 2022; Volume 12309, pp. 38–42.
45. Kherbache, M.; Maimour, M.; Rondeau, E. Digital twin network for the IIoT using eclipse ditto and hono. *IFAC-PapersOnLine* **2022**, *55*, 37–42. [CrossRef]
46. Martins, A.; Costelha, H.; Neves, C. Supporting the design, commissioning and supervision of smart factory components through their digital twin. In Proceedings of the 2020 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), Ponta Delgada, Portugal, 15–17 April 2020; pp. 114–119.
47. Arnarson, H.; Solvang, B.; Shu, B. The application of open access middleware for cooperation among heterogeneous manufacturing systems. In Proceedings of the 2020 3rd International Symposium on Small-Scale Intelligent Manufacturing Systems (SIMS), Gjovik, Norway, 10–12 June 2020; pp. 1–6.
48. Sørensen, J.V.; Ma, Z.; Jørgensen, B.N. Potentials of game engines for wind power digital twin development: An investigation of the Unreal Engine. *Energy Inform.* **2022**, *5*, 39. [CrossRef]
49. Lin, X.; Kundu, L.; Dick, C.; Obiodu, E.; Mostak, T.; Flaxman, M. 6G digital twin networks: From theory to practice. *IEEE Commun. Mag.* **2023**, *61*, 72–78. [CrossRef]
50. Wang, Z.; Han, K.; Tiwari, P. Digital twin simulation of connected and automated vehicles with the unity game engine. In Proceedings of the 2021 IEEE 1st International Conference on Digital Twins and Parallel Intelligence (DTPI), Beijing, China, 15 July–15 August 2021; pp. 1–4.
51. Mattila, J.; Ala-Laurinaho, R.; Autiosalo, J.; Salminen, P.; Tammi, K. Using digital twin documents to control a smart factory: Simulation approach with ROS, gazebo, and Twinbase. *Machines* **2022**, *10*, 225. [CrossRef]

52. Tøttrup, M.F.; Hu, E.C.; Kramer, B.A.; Macedo, H.D.; Esterle, L. Using INTO-CPS Tools in the Development of a Digital Twin for the F1TENTH Race Car. In Proceedings of the International Conference on Software Engineering and Formal Methods, Berlin, Germany, 26–29 September 2022; Springer: Cham, Switzerland, 2022; pp. 200–209.
53. Al-Geddawy, T. A digital twin creation method for an opensource low-cost changeable learning factory. *Procedia Manuf.* **2020**, *51*, 1799–1805. [CrossRef]
54. Ngo, D.; Guerra-Zubiaga, D.A.; González-Badillo, G.; Vatankhah Barenji, R. Towards a digital twin for cloud manufacturing: Case study. In Proceedings of the ASME International Mechanical Engineering Congress and Exposition, Pittsburgh, PA, USA, 9–15 November 2018; American Society of Mechanical Engineers: New York, NY, USA, 2018; Volume 52019, p. V002T02A072.
55. Perry, L.; Guerra-Zubiaga, D.A.; Richards, G.; Abidoye, C.; Hantouli, F. Optimizing a manufacturing pick-and-place operation on a robotic arm using a digital twin. In Proceedings of the ASME International Mechanical Engineering Congress and Exposition, New Orleans, LO, USA, 29 October–2 November 2023; American Society of Mechanical Engineers: New York, NY, USA, 2023; Volume 87608, p. V003T03A077.
56. Zhang, Q.; Zhang, X.; Xu, W.; Liu, A.; Zhou, Z.; Pham, D.T. Modeling of digital twin workshop based on perception data. In Proceedings of the Intelligent Robotics and Applications: 10th International Conference, ICIRA 2017, Wuhan, China, 16–18 August 2017; Proceedings, Part III 10; Springer: Cham, Switzerland, 2017; pp. 3–14.
57. Leng, J.; Wang, D.; Shen, W.; Li, X.; Liu, Q.; Chen, X. Digital twins-based smart manufacturing system design in Industry 4.0: A review. *J. Manuf. Syst.* **2021**, *60*, 119–137. [CrossRef]
58. Pires, F.; Ahmad, B.; Moreira, A.P.; Leitão, P. Digital twin based what-if simulation for energy management. In Proceedings of the 2021 4th IEEE International Conference on Industrial Cyber-Physical Systems (ICPS), Victoria, BC, Canada, 10–12 May 2021; pp. 309–314.
59. Arnarson, H. Digital Twin Simulation with Visual Components. Master's Thesis, UiT Norges Arktiske Universitet, Tromsø, Norway, 2019.
60. Keith, D.; Suparna Pal, R.M.K.Y. Contextual Digital Twin Runtime Environment. U.S. Patent 11 119 799, 7 November 2017.
61. GE Vernova Is the Pioneer of Digital Twin Technology. Available online: https://www.gevernova.com/software/innovation/digital-twin-technology (accessed on 29 May 2025).
62. Omniverse Digital Twins. Available online: https://docs.omniverse.nvidia.com/digital-twins/latest/index.html (accessed on 29 May 2025).
63. Gong, X.; Sui, L.; Morton, J.; Brennan, M.A.; Brennan, C.S. Investigation of nutritional and functional effects of rice bran protein hydrolysates by using Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines: A review. *Trends Food Sci. Technol.* **2021**, *110*, 798–811. [CrossRef]
64. Van Eck, N.J.; Waltman, L. Visualizing bibliometric networks. In *Measuring Scholarly Impact: Methods and Practice*; Springer: Cham, Switzerland, 2014; pp. 285–320.
65. Van Eck, N.; Waltman, L. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* **2009**, *84*, 523–538. [CrossRef] [PubMed]
66. Wallin, J.A. Bibliometric methods: Pitfalls and possibilities. *Basic Clin. Pharmacol. Toxicol.* **2005**, *97*, 261–275. [CrossRef]
67. Radhakrishnan, S.; Erbis, S.; Isaacs, J.A.; Kamarthi, S. Novel keyword co-occurrence network-based methods to foster systematic reviews of scientific literature. *PLoS ONE* **2017**, *12*, e0172778.
68. 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]
69. Tao, F.; Zhang, M. Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing. *IEEE Access* **2017**, *5*, 20418–20427.
70. Zhuang, C.; Liu, J.; Xiong, H. Digital twin-based smart production management and control framework for the complex product assembly shop-floor. *Int. J. Adv. Manuf. Technol.* **2018**, *96*, 1149–1163. [CrossRef]
71. Zheng, Y.; Yang, S.; Cheng, H. An application framework of digital twin and its case study. *J. Ambient Intell. Humaniz. Comput.* **2019**, *10*, 1141–1153. [CrossRef]
72. Aheleroff, S.; Xu, X.; Zhong, R.Y.; Lu, Y. Digital Twin as a Service (DTaaS) in Industry 4.0: An Architecture Reference Model. *Adv. Eng. Inform.* **2021**, *47*. [CrossRef]
73. Schou, C.; Andersen, R.S.; Chrysostomou, D.; Bøgh, S.; Madsen, O. Skill-based instruction of collaborative robots in industrial settings. *Robot. Comput.-Integr. Manuf.* **2018**, *53*, 72–80. [CrossRef]
74. Javaid, M.; Haleem, A.; Singh, R.P.; Suman, R. Substantial capabilities of robotics in enhancing industry 4.0 implementation. *Cogn. Robot.* **2021**, *1*, 58–75. [CrossRef]
75. Pires, F.; Cachada, A.; Barbosa, J.; Moreira, A.P.; Leitão, P. Digital twin in industry 4.0: Technologies, applications and challenges. In Proceedings of the 2019 IEEE 17th International Conference on Industrial Informatics (INDIN), Helsinki, Finland, 22–25 July 2019; Volume 1, pp. 721–726.

76. Melesse, T.Y.; Di Pasquale, V.; Riemma, S. Digital Twin models in industrial operations: State-of-the-art and future research directions. *IET Collab. Intell. Manuf.* **2021**, *3*, 37–47. [CrossRef]
77. Wang, B.; Zhou, H.; Yang, G.; Li, X.; Yang, H. Human digital twin (HDT) driven human-cyber-physical systems: Key technologies and applications. *Chin. J. Mech. Eng.* **2022**, *35*, 11. [CrossRef]
78. Lu, Y.; Liu, C.; Kevin, I.; Wang, K.; Huang, H.; Xu, X. Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robot. Comput.-Integr. Manuf.* **2020**, *61*, 101837. [CrossRef]
79. Alexopoulos, K.; Nikolakis, N.; Chryssolouris, G. Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. *Int. J. Comput. Integr. Manuf.* **2020**, *33*, 429–439.
80. Liang, C.J.; McGee, W.; Menassa, C.C.; Kamat, V.R. Real-time state synchronization between physical construction robots and process-level digital twins. *Constr. Robot.* **2022**, *6*, 57–73. [CrossRef]
81. Douthwaite, J.A.; Lesage, B.; Gleirscher, M.; Calinescu, R.; Aitken, J.M.; Alexander, R.; Law, J. A modular digital twinning framework for safety assurance of collaborative robotics. *Front. Robot. AI* **2021**, *8*, 758099. [CrossRef] [PubMed]
82. Javaid, M.; Haleem, A.; Singh, R.P.; Suman, R. Enabling flexible manufacturing system (FMS) through the applications of industry 4.0 technologies. *Internet Things Cyber-Phys. Syst.* **2022**, *2*, 49–62. [CrossRef]
83. Ramasubramanian, A.K.; Mathew, R.; Kelly, M.; Hargaden, V.; Papakostas, N. Digital twin for human–robot collaboration in manufacturing: Review and outlook. *Appl. Sci.* **2022**, *12*, 4811. [CrossRef]
84. Profanter, S.; Tekat, A.; Dorofeev, K.; Rickert, M.; Knoll, A. OPC UA versus ROS, DDS, and MQTT: Performance evaluation of industry 4.0 protocols. In Proceedings of the 2019 IEEE International Conference on Industrial Technology (ICIT), Melbourne, VIC, Australia, 13–15 February 2019; pp. 955–962.
85. Proos, D.P.; Carlsson, N. Performance comparison of messaging protocols and serialization formats for digital twins in IoV. In Proceedings of the 2020 IFIP Networking Conference (Networking), Paris, France, 22–26 June 2020; pp. 10–18.
86. Duong, T.Q.; Van Huynh, D.; Khosravirad, S.R.; Sharma, V.; Dobre, O.A.; Shin, H. From digital twin to metaverse: The role of 6G ultra-reliable and low-latency communications with multi-tier computing. *IEEE Wirel. Commun.* **2023**, *30*, 140–146. [CrossRef]
87. Gonga, A.; Landsiedel, O.; Johansson, M. MobiSense: Power-efficient micro-mobility in wireless sensor networks. In Proceedings of the 2011 International Conference on Distributed Computing in Sensor Systems and Workshops (DCOSS), Barcelona, Spain, 27–29 June 2011; pp. 1–8.
88. Scott, K.; Refaei, T.; Trivedi, N.; Trinh, J.; Macker, J.P. Robust communications for disconnected, intermittent, low-bandwidth (DIL) environments. In Proceedings of the 2011—MILCOM 2011 Military Communications Conference, Baltimore, MD, USA, 7–10 November 2011; pp. 1009–1014.
89. Soret, B.; Mogensen, P.; Pedersen, K.I.; Aguayo-Torres, M.C. Fundamental tradeoffs among reliability, latency and throughput in cellular networks. In Proceedings of the 2014 IEEE Globecom Workshops (GC Wkshps), Austin, TX, USA, 8–12 December 2014; pp. 1391–1396.
90. Laaki, H.; Miche, Y.; Tammi, K. Prototyping a digital twin for real time remote control over mobile networks: Application of remote surgery. *IEEE Access* **2019**, *7*, 20325–20336. [CrossRef]
91. Mykoniatis, K.; Harris, G.A. A digital twin emulator of a modular production system using a data-driven hybrid modeling and simulation approach. *J. Intell. Manuf.* **2021**, *32*, 1899–1911. [CrossRef]
92. Calandra, D.; Pratticò, F.G.; Cannavò, A.; Casetti, C.; Lamberti, F. Digital twin-and extended reality-based telepresence for collaborative robot programming in the 6G perspective. *Digit. Commun. Netw.* **2024**, *10*, 315–327. [CrossRef]
93. Alam, A. Should robots replace teachers? Mobilisation of AI and learning analytics in education. In Proceedings of the 2021 International Conference on Advances in Computing, Communication, and Control (ICAC3), Mumbai, India, 3–4 December 2021; pp. 1–12.
94. Lăzăroiu, G.; Andronie, M.; Iatagan, M.; Geamănu, M.; Ștefănescu, R.; Dijmărescu, I. Deep learning-assisted smart process planning, robotic wireless sensor networks, and geospatial big data management algorithms in the internet of manufacturing things. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 277. [CrossRef]
95. Zonta, T.; Da Costa, C.A.; da Rosa Righi, R.; de Lima, M.J.; Da Trindade, E.S.; Li, G.P. Predictive maintenance in the Industry 4.0: A systematic literature review. *Comput. Ind. Eng.* **2020**, *150*, 106889. [CrossRef]
96. Wu, X.; Xiao, L.; Sun, Y.; Zhang, J.; Ma, T.; He, L. A survey of human-in-the-loop for machine learning. *Future Gener. Comput. Syst.* **2022**, *135*, 364–381. [CrossRef]
97. Fuller, A.; Fan, Z.; Day, C.; Barlow, C. Digital twin: Enabling technologies, challenges and open research. *IEEE Access* **2020**, *8*, 108952–108971. [CrossRef]
98. Hu, W.; Wang, C.; Liu, F.; Peng, X.; Sun, P.; Tan, J. A grasps-generation-and-selection convolutional neural network for a digital twin of intelligent robotic grasping. *Robot. Comput.-Integr. Manuf.* **2022**, *77*, 102371. [CrossRef]
99. Qamsane, Y.; Moyne, J.; Toothman, M.; Kovalenko, I.; Balta, E.C.; Faris, J.; Tilbury, D.M.; Barton, K. A methodology to develop and implement digital twin solutions for manufacturing systems. *IEEE Access* **2021**, *9*, 44247–44265. [CrossRef]

100. Kamble, S.S.; Gunasekaran, A.; Parekh, H.; Mani, V.; Belhadi, A.; Sharma, R. Digital twin for sustainable manufacturing supply chains: Current trends, future perspectives, and an implementation framework. *Technol. Forecast. Soc. Chang.* **2022**, *176*, 121448. [CrossRef]
101. Jhunjhunwala, P.; Atmojo, U.D.; Vyatkin, V. Applying skill-based engineering using OPC-UA in production system with a digital twin. In Proceedings of the 2021 IEEE 30th International Symposium on Industrial Electronics (ISIE), Kyoto, Japan, 20–23 June 2021; pp. 1–6.
102. Hunkeler, U.; Truong, H.L.; Stanford-Clark, A. MQTT-S—A publish/subscribe protocol for Wireless Sensor Networks. In Proceedings of the 2008 3rd International Conference on Communication Systems Software and Middleware and Workshops (COMSWARE'08), Bangalore, India, 6–10 January 2008; pp. 791–798.
103. Mafioletti, D.R.; de Mello, R.C.; Ruffini, M.; Frascolla, V.; Martinello, M.; Ribeiro, M.R. Programmable data planes as the next frontier for networked robotics security: A ROS use case. In Proceedings of the 2021 17th International Conference on Network and Service Management (CNSM), Izmir, Turkey, 25–29 October 2021; pp. 160–165.
104. Yun, S.; Park, J.H.; Kim, H.S.; Kim, W.T. Importance-aware sdn control mechanism for real-time data distribution services. In Proceedings of the 2018 International Conference on Information and Communication Technology Convergence (ICTC), Jeju, Republic of Korea, 17–19 October 2018; pp. 1113–1118.
105. Layer, C.A.; Protocol, C.L.L. for the Internet of Things (IoT) and CoAP-IPSEC Security with DTLS. In *Digital Twin Technologies and Smart Cities*; Springer: Cham, Switzerland, 2019; p. 151.
106. Jin, T.; Sun, Z.; Li, L.; Zhang, Q.; Zhu, M.; Zhang, Z.; Yuan, G.; Chen, T.; Tian, Y.; Hou, X.; et al. Triboelectric nanogenerator sensors for soft robotics aiming at digital twin applications. *Nat. Commun.* **2020**, *11*, 5381. [CrossRef]
107. Szpytko, J.; Salgado Duarte, Y. A digital twins concept model for integrated maintenance: A case study for crane operation. *J. Intell. Manuf.* **2021**, *32*, 1863–1881. [CrossRef]
108. Angelopoulos, A.; Michailidis, E.T.; Nomikos, N.; Trakadas, P.; Hatziefremidis, A.; Voliotis, S.; Zahariadis, T. Tackling faults in the industry 4.0 era—A survey of machine-learning solutions and key aspects. *Sensors* **2019**, *20*, 109. [CrossRef] [PubMed]
109. Lopes, D.; Coelho, L.; Silva, M.F. Development of a collaborative robotic platform for autonomous auscultation. *Appl. Sci.* **2023**, *13*, 1604. [CrossRef]
110. Lee, H.; Kim, S.D.; Al Amin, M.A.U. Control framework for collaborative robot using imitation learning-based teleoperation from human digital twin to robot digital twin. *Mechatronics* **2022**, *85*, 102833. [CrossRef]
111. Wang, Q.; Jiao, W.; Wang, P.; Zhang, Y. Digital twin for human-robot interactive welding and welder behavior analysis. *IEEE/CAA J. Autom. Sin.* **2020**, *8*, 334–343. [CrossRef]
112. Huang, Z.; Shen, Y.; Li, J.; Fey, M.; Brecher, C. A survey on AI-driven digital twins in industry 4.0: Smart manufacturing and advanced robotics. *Sensors* **2021**, *21*, 6340. [CrossRef] [PubMed]
113. Tellaeche, A.; Kildal, J.; Maurtua, I. A flexible system for gesture based human-robot interaction. *Procedia CIRP* **2018**, *72*, 57–62. [CrossRef]
114. Chen, J.H.; Song, K.T. Collision-free motion planning for human-robot collaborative safety under cartesian constraint. In Proceedings of the 2018 IEEE International Conference on Robotics and Automation (ICRA), Brisbane, QLD, Australia, 21–25 May 2018; pp. 4348–4354.
115. Czubenko, M.; Kowalczuk, Z. A simple neural network for collision detection of collaborative robots. *Sensors* **2021**, *21*, 4235. [CrossRef]
116. Heo, Y.J.; Kim, D.; Lee, W.; Kim, H.; Park, J.; Chung, W.K. Collision detection for industrial collaborative robots: A deep learning approach. *IEEE Robot. Autom. Lett.* **2019**, *4*, 740–746. [CrossRef]
117. Yu, Y.; Li, M.; Liu, L.; Li, Y.; Wang, J. Clinical big data and deep learning: Applications, challenges, and future outlooks. *Big Data Min. Anal.* **2019**, *2*, 288–305. [CrossRef]
118. Lee, J.; Azamfar, M.; Singh, J.; Siahpour, S. Integration of digital twin and deep learning in cyber-physical systems: Towards smart manufacturing. *IET Collab. Intell. Manuf.* **2020**, *2*, 34–36. [CrossRef]
119. Wang, T.; Li, J.; Deng, Y.; Wang, C.; Snoussi, H.; Tao, F. Digital twin for human-machine interaction with convolutional neural network. *Int. J. Comput. Integr. Manuf.* **2021**, *34*, 888–897. [CrossRef]
120. Shi, Y.; Shen, W.; Wang, L.; Longo, F.; Nicoletti, L.; Padovano, A. A cognitive digital twins framework for human-robot collaboration. *Procedia Comput. Sci.* **2022**, *200*, 1867–1874. [CrossRef]
121. Tuli, T.B.; Kohl, L.; Chala, S.A.; Manns, M.; Ansari, F. Knowledge-based digital twin for predicting interactions in human-robot collaboration. In Proceedings of the 2021 26th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), Vasteras, Sweden, 7–10 September 2021; pp. 1–8.
122. 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]
123. Lee, J.; Davari, H.; Singh, J.; Pandhare, V. Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. *Manuf. Lett.* **2018**, *18*, 20–23. [CrossRef]

124. Hu, J.; Xiao, H.; Ye, Z.; Luo, N.; Zhou, M. Research and Prospects of Digital Twin-Based Fault Diagnosis of Electric Machines. *Sensors* **2025**, *25*. [CrossRef]
125. Hribernik, K.; Cabri, G.; Mandreoli, F.; Mentzas, G. Autonomous, context-aware, adaptive Digital Twins—State of the art and roadmap. *Comput. Ind.* **2021**, *133*, 103508. [CrossRef]

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