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Systematic Review

Digital Twin and Computer Vision Combination for Manufacturing and Operations: A Systematic Literature Review

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Abstract

This paper examines the transformative role of the Digital Twin-Computer Vision combination (DT-CV combo) in industrial operations, focusing on its applications, challenges, and future directions. It aims to synthesize the existing literature and explore the practical use cases in operations management (OM). A comprehensive systematic literature review is conducted using PRISMA guidelines to analyze the DT-CV combo across the classification of industrial OM. However, given the breadth and importance of manufacturing and the OM field, the study excludes the literature on the DT-CV combo applied to other domains such as healthcare, smart buildings and cities, and transportation. We found that the DT-CV combo in OM is a relatively young but growing field of research. To date, only 29 articles have examined DT-CV combo solutions from various OM perspectives. Case studies are rare, with most studies relying on experimentation and laboratory testing to investigate DT-CV applications in the OM context. According to the cases and methods reviewed in the literature, the DT-CV combo has applications in different OM areas such as design, prototyping, simulation, real-time production monitoring, defect detection, process optimization, hazard detection and mitigation, safety training, emergency response simulation, optimal resource allocation, condition monitoring, inventory management, and scheduling maintenance. We also identified several benefits of DT-CV combo solutions in OM, including reducing human error, ensuring compliance with quality standards, lowering maintenance costs, mitigating production downtime, eliminating operational bottlenecks, and decreasing workplace accidents, while simultaneously improving the effectiveness of training. In this paper, we classify current applications of the DT-CV combo in OM, highlight gaps in the existing literature, and propose research questions to guide future studies in this domain. By considering the rapid phase of AI technology development and combining it with the current state of the art applications of the DT-CV combo in OM, we suggest novel concepts and future directions. The digital twin-vision language model (DT-VLM) combo as a future direction, emphasizing its potential to bridge physical–digital interfaces in industrial workflows, is one of the future development directions.

Keywords: digital twin; computer vision; operations management; DT-CV combo applications; systematic literature review

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1. Introduction

The field of manufacturing and operations management is going through a transition period due to the increasing supply chain complexities, reciprocal international tariffs, national protectionist policies, a growing shortage of skilled labor, and the emergence of disruptive technologies (e.g., artificial intelligence, additive manufacturing). In light of these developments, manufacturers seek ways to ensure and enhance operational consistency and flexibility alongside efficiency in their production systems [1]. One of the strategies that has emerged as a critical solution for manufacturers is the adoption and deployment of advanced digital technologies in their operations management (OM) [2]. Among the digital technologies used, the digital twin combined with computer vision (DT-CV combo) has emerged as a potent one [1]. The digital twin (DT) provides a real-time virtual replica of a physical system, which in turn enables features such as predictive analytics, performance optimization, and scenario evaluation [3]. When combined with computer vision (CV), an AI-powered tool for automated inspection, defect detection, and event understanding [4,5], manufacturers can achieve unprecedented levels of flexibility, efficiency, and autonomy in production lines [1]. The DT-CV combo has the potential to lay the foundation for the development of intelligent, self-correcting systems that are central to the future of smart and sustainable manufacturing [1,6].

In the 1960s, during the Apollo program, NASA created a physical replica (physical twin) of the space capsule on Earth to match their systems in space, which allowed for simulations, testing, and performance assessment, solution formulation for detected faults. The concept gained momentum after the Apollo 13 mission, where engineers formulated and tested solutions on the ground to fix a life-threatening issue with the capsule's oxygen generator in space [7,8]. This became the foundation for the creation of today's DT. Nowadays, DTs are used across industries, and they transfer real-time data from the physical system to a digital model, enabling tasks like condition monitoring and visualization [9,10]. By integrating the 3D modules, Internet of Things (IoT), and data analytics, DTs enable bidirectional connection between physical assets and their digital counterparts, supporting real-time feedback loops for monitoring, simulation, optimization, and control [10–12].

DT is transforming various industries [13–15]; for instance, in the automotive field [16], DT-driven design and simulation of digital instruments significantly enhance operational efficiency [17]. In agriculture [18], DTs build smart systems that collect real-time data from sensors and process it using machine learning algorithms, improving crop yield and reducing costs [19]. In smart buildings [20–22], DTs integrate data from IoT devices and CAD models, enabling energy efficiency, reduced carbon emissions, enhanced infrastructure management, and improved disaster resilience [22–25]. In the energy and utilities sector [26,27], DTs monitor and control converters, ensuring real-time tracking and fault detection [28]. In airports [29], DTs provide diagnostics and real-time forecasting of aviation electrical equipment, streamlining flight turnaround operations and reducing delays [30,31]. In logistics [32], DT-based distribution management systems enhance real-time transportation efficiency and packaging strategies for temperature control for food [33,34]. As a result of these implementations, the projected market for DTs is expected to grow by nearly USD 32 billion from 2021 to 2026 [10,35].

CV is a field of artificial intelligence that enables computers to interpret visual information from digital images or videos [36]. The global CV market is valued at USD 17.70 billion in 2023 and is expected to grow at a compound annual growth rate of USD 2.50 billion by 2025 [37,38]. It is used in various industries, such as manufacturing, healthcare, agriculture, construction, energy and utilities, logistics, and smart cities, to deliver actionable insights and enable automation. In manufacturing, CV is crucial for defect detection and ensuring consistent production quality [39,40]. In healthcare, it is used in medical imaging, surgical assistance, remote patient monitoring, and telehealth [41,42]. In agriculture, CV is integrated into the digital life cycle of crops, contributing to sustainable farming practices and better resource management [43–45]. In the construction industry, CV is used for structural health monitoring, infrastructure inspection, and site surveillance [46–48]. In energy and utilities, CV is used in real-time shade monitoring for photovoltaic modules, improving power generation efficiency and safety. The meter image capturing system is another example of CV's application in energy consumption monitoring [49,50].

The DT-CV combo has been identified as a promising direction for future research by Wang et al. [51], underscoring its significance. The DT concept traditionally relies on IoT sensors to collect data from the physical world. However, IoT sensors are inherently limited, as they can only measure specific variables and lack the ability to capture rich, contextual information. As Man & Olchawa [52] note, vision is the most data-rich human sense, accounting for approximately 80% of all sensory input. Similarly, computer vision provides high-dimensional, contextual data on shapes, movements, colors, patterns, and conditions. Therefore, the integration of CV into DTs represents a powerful opportunity that merits dedicated research.

DT and CV technologies hold significant potential and applications in manufacturing and operations. However, there is limited literature on the DT-CV combo in industrial operation and production. This paper presents a comprehensive literature review to identify and classify current applications and innovative use cases of the DT-CV combo in OM and to pinpoint the existing gaps. By understanding the current state of the art and exploring future possibilities, this paper aims to contribute to the advancement of the DT-CV combo in production and OM through answering the following research questions.

RQ1: How can the existing literature on DT-CV combo applications in OM be classified? What are the current key industry use cases and applications of the DT-CV combo in the OM field?

RQ2: What are the challenges of integrating the DT-CV combo, and what does the future of industrial operations look like in light of advancements in this technology?

This paper is structured as follows: after the Introduction, in Section 2, a comprehensive literature review on DT and CV technologies, including their individual applications and combined implementations, is presented. In Section 3, the adopted methodology is outlined. In Section 4, the results are presented, including the analysis and classification of the reviewed literature in operations management. In Section 5, we discuss the outcomes and proposed future research directions, and finally, the paper ends with conclusions.

2. Background

2.1. Digital Twins in Manufacturing and Operations

As digitalization reshapes factories through smart technologies and cyber-physical systems, OM is continuing its transition from MRP-based fixed, step-by-step planning to ERP and more flexible, real-time decision-making systems based on data [53,54]. Instead of optimizing individual processes in isolation, OM can now focus on coordinating multiple workflows dynamically [55]. A key enabler of this shift is the DT, a virtual replica of physical systems that supports synchronized monitoring, automation, and maintenance operations [56–58]. DT-based framework used for anomaly detection to enhance operational resilience [59]. Similarly, a digital simulation framework is used to improve process optimization [60]. In production line [61], DT-based models enable multi-physics simulations for multiple scenarios. In smart manufacturing systems [62], the DT model supports adaptive and data-driven decision-making. In control systems [63], DT ensures operational stability under uncertain conditions. Moreover, at the organizational level [64], DTs can enhance coordination across engineering, planning, and shop-floor operations, supporting agility in complex, engineer-to-order environments. DTs also play a critical role in risk mitigation in operations through real-time validation methods that ensure alignment between physical assets and their digital counterparts, thereby improving fault detection and system reliability [65]. From a workforce perspective [66], simulations based on DT models simplify process understanding and reduce reliance on expert knowledge, making worker training more efficient. Additionally, commissioning strategies based on DTs help reduce system validation time and minimize the material waste to support sustainability objectives [67]. DTs are now being positioned as enablers of plant-wide optimization, long-term strategic planning, and real-time decision-making [63]. Recent research on DT as multi-robot collaborative manufacturing (MRCM) emphasizes its potential for flexible, adaptive, and efficient production, but highlights persistent issues of integration complexity, coordination, and scalability [63]. As DT technology matures, opportunities emerge for operations management to evolve into a highly adaptive and intelligent system, capable of optimizing performance across the entire lifecycle of production and operations. To see a summary of the traditional versus new approaches enabled by DT to address different aspects of operations, see Table 1.

Table 1. Summary of traditional and novel approaches enabled by DT for OM practices.

OM Aspect	Conventional Approach	New Approach/Emerging Technologies
Planning & control	MRP-based fixed, step-by-step planning [53]	ERP with flexible, real-time decision-making using data [53]
Process optimization	Optimizing individual processes in isolation [55]	Coordinating multiple workflows dynamically [55]
Maintenance	Manual inspection and scheduled maintenance	DT for synchronized monitoring, automation, anomaly detection, and predictive maintenance [56–59]
Simulation & process design	Limited physical trials, reliance on expert knowledge	DT-based multi-physics simulations, adaptive decision-making, worker training via simulations [60–66]
Operational stability	Rigid control systems with limited adaptability	DT ensuring stability under uncertain conditions [63]
Operational coordination	Separate silos (engineering, planning, shop-floor operations)	DTs enhancing coordination across functions, supporting agility in engineer-to-order environments [64]
Risk management	Reactive fault detection	DT-based real-time validation, improved fault detection, and system reliability [65]
Commissioning & sustainability	Longer system validation, more material waste	DT-based commissioning reduces validation time, minimizes waste, and supports sustainability [67]

2.2. *Computer Vision in Manufacturing and Operations*

CV systems facilitate the automation of inspection processes, reducing dependence on manual labor, enhancing defect detection, and minimizing production errors [68]. In additive manufacturing [69,70], CV enhances real-time monitoring and defect detection of the build job by tracking the printing process layer by layer. In traditional heavy industries such as steel manufacturing [71], CV applications optimize operations by detecting surface defects and ensuring consistent product quality through continuous, automated monitoring. For small and medium-sized enterprises [72,73], CV-based quality control solutions increase defect detection rates and improve production efficiency. In the supply chain [74], CV-driven toolkits enable the digitalization of systems by providing real-time inventory tracking and automated logistics management. In sustainable and circular manufacturing [5], CV is utilized for predictive maintenance, optimizing resource utilization, and reducing waste generation. For safety management [1,75], CV is used to automate personal protective equipment detection for workers and compliance tracking in real-time while supporting defect identification. The deployment of CV in OM reinforces data-driven, intelligent decision-making and fosters agility and sustainability across manufacturing operations. To see a summary of the traditional versus new approaches enabled by CV to address different aspects of operations, see Table 2.

Table 2. Summary of traditional and novel approaches enabled by CV for OM practices.

OM Aspect	Traditional Approach	New Approach/Emerging Technologies
Inspection & quality control	Manual inspection, human-dependent, lower efficiency	CV automating QC inspection, defect detection, quality monitoring, potential for higher efficiency [68,72,73]
Process design in additive manufacturing	Limited monitoring of print jobs	CV for real-time defect detection during 3D printing [69,70]
Quality assurance in heavy industry (e.g., steel)	Manual surface defect checks	CV for automated defect detection and consistent quality control [71]
Supply chain management	Manual inventory tracking and logistics management	CV-driven toolkits for real-time inventory tracking, automated logistics [74]
Sustainable manufacturing	Higher waste, reactive maintenance	CV and DT for predictive maintenance, resource optimization, waste reduction [5]
Workforce safety	Manual compliance tracking, reliance on supervisors	CV automating PPE detection, compliance tracking, and safety monitoring [1,75]

2.3. Digital Twin with Computer Vision in Manufacturing and Operations

DT can enhance tool design and machining process optimization by enabling the simulation of machining operations, as demonstrated in the work of Pivkin et al. [76]. By integrating CV, DT-driven analytics can forecast tool wear and refine cutting parameters, thereby improving overall process efficiency. In aerospace manufacturing, CV-enhanced DT models, as examined by Li et al. [6], enhance machining feature extraction, thus reducing errors in the production of complex parts. For fused filament fabrication, Moretti et al. [77] create DT-driven optical imaging systems that use CV to improve defect detection. In Wire Arc Additive Manufacturing, a data-driven DT framework utilizes CV for real-time defect prediction and process modifications, thereby improving quality in metal deposition processes, as identified by Mohammad Mahdi et al. [78]. In robotics and automation, the DT-CV combo, as explored by Humphries et al. [79], replaces laser-based safety mechanisms, enabling human-adaptive speed control in collaborative robots (cobots) and enhancing workplace safety. In autonomous pick-and-place operations, DT-enabled robots with CV, as discussed by Jakhotiya et al. [80], eliminate the need for manual item placement, enhancing efficiency and precision in industrial workflows. In soft robotic grippers, the DT framework, as examined by Xiang et al. [81], regulates gripper operations using CV for real-time position estimation and pressure mapping, enhancing precision and adaptability. For automotive welding, Ji et al. [73] replace manual ultrasonic inspections with a DT-CV combo. In the assembly line, Cristofoletti et al. [82] use the DT-CV combo framework to automate defect detection and corrections to improve production efficiency. In robotic assembly, the YOLOv8-based DT-CV combo architecture, as discussed by Touhid et al. [83], enhances real-time synchronization, improving event tracking and operational efficiency. In micro learning factories, DT-driven robotic arms with CV tools, as presented by Sow et al. [84], provide real-time industrial training, simulating shop-floor scenarios for skill development.

In industrial operations, Siemens, in collaboration with NVIDIA, employs a DT-CV combo for predictive maintenance in collaborative robotics through its "Industrial Copilot for Operations" platform [85]. For production, BMW Group adopts the 3DEXPERIENCE platform [86], which integrates the DT-CV combo for quality control. In digital manufacturing and the aerospace industry, Addepto's [82] process monitoring solutions improve operations, increase efficiency, and reduce costs. In the supply chain domain, NavVis collaborates with Amazon Web Services to automate the creation of DTs for indoor environments, leveraging CV-driven object detection for enhanced logistics management [87]. Konecranes [88] integrates advanced DT technology into its Smart Factory application, enhancing maintenance and production efficiency through real-time 3D modeling. Similarly, Detectium's [89] DT amalgamates real-time sensor data, three-dimensional modeling, and CV for the detection of fire, smoke, and hazards in industrial settings.

Despite their transformative potential, the DT-CV combo faces several challenges, including sensor data interoperability, latency in system response, cybersecurity vulnerabilities, and the need for adaptable frameworks capable of serving diverse industrial contexts. However, as evidenced by Siemens' Product Lifecycle Management innovations [90], Detectium's safety monitoring system [89], and BMW's virtual twin modeling [86], the DT-CV combo continues to enhance precision, operational efficiency, and proactive decision-making. By addressing these challenges, industries can fully harness the capabilities of the DT-CV combo to establish robust, data-driven workflows that seamlessly bridge physical and digital operations.

3. Materials and Methods

This study adopts a systematic literature review methodology, aligned with established standards for systematic reviews in engineering and operations management, to rigorously address the research questions. The methodology is designed to ensure transparency, reproducibility, and methodological rigor. A comprehensive search was conducted across five major academic databases—Google Scholar, IEEE Xplore, ScienceDirect, SpringerLink, and ResearchGate—focusing on publications from January 2020 to June 2025 to capture recent advancements in the integration of Digital Twin (DT) and Computer Vision (CV) technologies in the context of operations management and manufacturing. Our selection of these five databases was strategic, designed to ensure both comprehensive breadth and disciplinary depth. Google Scholar provided a broad, interdisciplinary starting point to capture a wide range of the literature, including the gray literature and citations. IEEE Xplore was essential for its focused, high-quality content in engineering and computer science, while ScienceDirect and SpringerLink ensured coverage of core, high-impact journals from two leading scientific publishers. Finally, ResearchGate was used as a supplementary tool to access emerging research and preprints directly from authors, ensuring our review was up-to-date.

The search strategy employed a synthesis of keywords derived from the research questions, including: "digital twin," "computer vision," "industrial operations," "production," "manufacturing," "quality control," "predictive maintenance," "logistics," "defect detection," and "safety monitoring." Boolean operators were applied to optimize search results, using the primary query: ("digital twin" AND "computer vision") AND ("manufacturing" OR "operations").

We established clear inclusion and exclusion criteria to ensure the relevance and quality of the reviewed literature. The inclusion criteria comprised research articles, peer-reviewed journal papers, conference proceedings, and case studies that focused on the integration of Digital Twin (DT) and Computer Vision (CV) in the context of industrial operations and management.

The exclusion criteria ruled out publications that examined only DT or only CV without their integration. Additionally, studies applying the DT-CV combo in non-industrial domains—such as transportation, healthcare, smart cities and buildings, construction and real estate, defense and security, or agriculture and precision farming—were excluded from consideration. This focus on the industrial domain is driven by the substantial potential of the DT-CV combination to transform manufacturing and operations management—a sector that represents a major share of the global economy and has significant ripple effects on other industries and overall economic performance. It also aligns closely with the emerging Industry 5.0 research agenda [91]. Therefore, this study focuses on the field of OM, intending to help fill the identified literature gap in this area.

The PRISMA framework (Figure 1) was used for the screening procedure. The initial search identified 132 articles. After removing 35 duplicates, the abstracts of 97 articles were reviewed. Based on abstract screening, 67 articles were excluded due to irrelevance. A comprehensive review of 30 articles was then conducted to assess their eligibility, resulting in the final selection of 29 articles (one article's DOI was unavailable) that met all criteria and were included in the analysis.

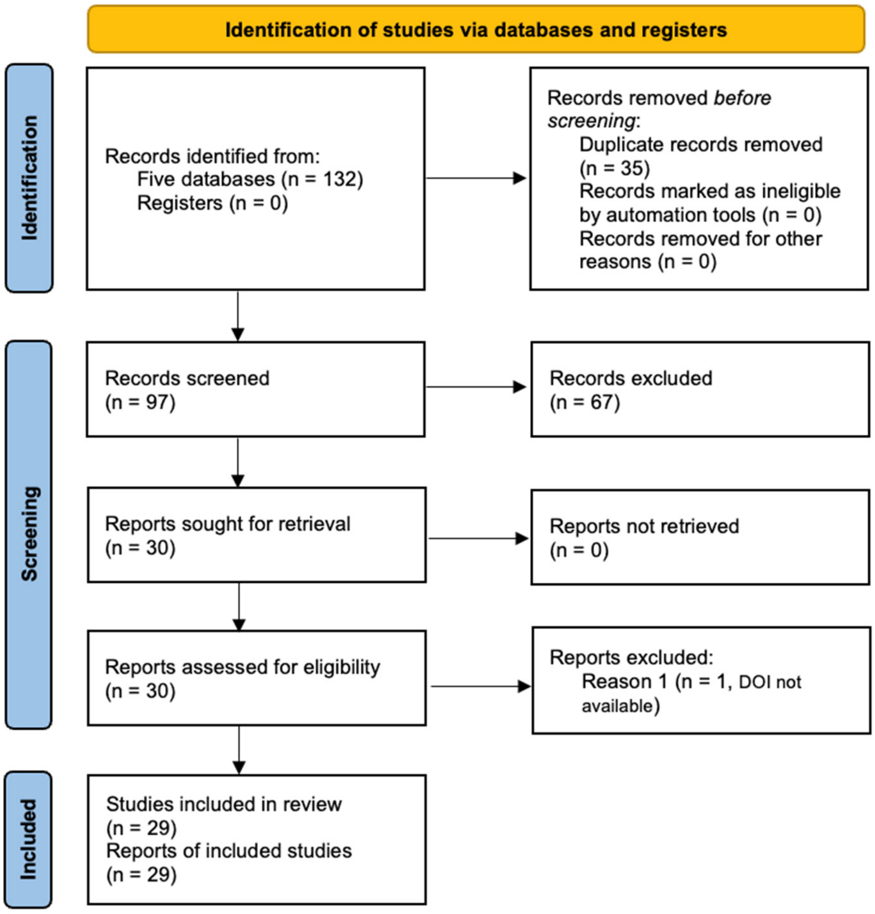

Figure 1. PRISMA flow diagram.

A comprehensive analysis, supported by coding in an Excel spreadsheet, was conducted to classify applications into domains such as product and process design, manufacturing and quality assurance, location selection and layout design, human resources and worker safety, supply chain, inventory and logistics management, scheduling and operational efficiency, and maintenance. We began by analyzing the abstracts of the 29 selected articles for an initial classification. Next, two authors independently reviewed the full texts and compared their respective summaries. The findings were then consolidated into an Excel file using a coding framework that considered multiple criteria, including research method, field of study, proposed solution, and identified limitations.

Finally, we examined the challenges and emerging trends associated with DT-CV integration. To provide empirical context, we complemented the systematic literature review with industrial case studies from companies such as Siemens, BMW, Amazon, and NVIDIA, alongside academic research contributions.

4. Results

4.1. Application of DT-CV Combo in Industrial Operations and Management

In Industry 4.0, manufacturers embrace cutting-edge technologies to enhance efficiency, reduce waste, and support data-driven decision-making. According to Heizer and Render in their book on Operations Management [92], manufacturing company operations can be classified into key areas such as product and process design, manufacturing and quality assurance, location selection and layout design, human resources and worker safety, supply chain, inventory and logistics management, scheduling and operational efficiency, and maintenance. An emerging trend within this domain is the integration of the DT-CV combo, which enables advanced capabilities such as virtual prototyping [6], defect detection [93], hazard identification [79], supply chain optimization [94], real-time production monitoring [77], and predictive maintenance [95]. The growing research interest in this integration is reflected in the increasing number of academic publications, as illustrated in Figure 2. Furthermore, Figure 3 illustrates the distribution of research papers across operations management classes, highlighting the key focus areas where the DT-CV combo is applied within industrial operations and manufacturing.

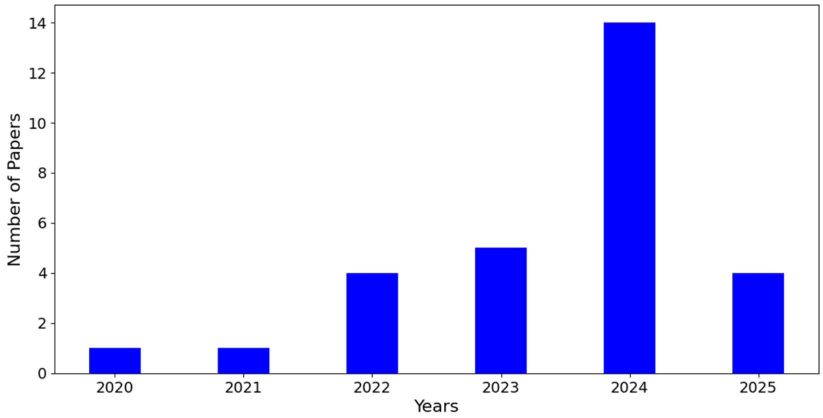

Figure 2. DT-CV combo integration research trend in operations management.

Figure 3. Classification of DT-CV combo research paper by key operations management areas.

In Sections 4.1.1–4.1.6 we analyze the literature and classify DT-CV combo studies across the main OM activities to address the first part of RQ1. This is followed by a summary in Section 4.2. Then, using Figure 3, Section 4.2 addresses the second part of RQ1, which concerns the current industrial applications and use cases of the DT-CV combo in the context of OM.

4.1.1. Product and Process Design

In operations management, product design is concerned with developing high-quality products that deliver customer value, while process design focuses on ensuring efficient and cost-effective production [92]. The integration of the DT-CV combo enhances these functions by enabling virtual process validation and facilitating early detection and elimination of product defects. For instance, Çapunaman et al. [96] use vision-based sensing in 3D printing to achieve high geometric accuracy and to assist in material selection. They also utilize adaptive toolpath strategies and real-time DTs for production, which enhance manufacturing precision and reduce material waste. In a preliminary conceptual study, Pivkin et al. [76] discussed the idea of using a DT-CV combo for the design and manufacturing of machining tools. Stürmer et al. [97] highlight that automated simulation generation utilizing CV significantly reduces human error in hydraulic system modeling by improving accuracy in parameter extraction, system identification, and real-time validation. Similarly, Li et al. [6] developed a feature-level digital twin process model (FL-DTPM). FL-DTPM is a digital replica of a process that tracks and analyzes it at the level of individual features. The FL-DTPM model improves machining process planning by facilitating accurate feature extraction and incorporating on-site data, quality metrics, and process training for enhanced aerospace manufacturing. Moreover, Oyekan et al. [98] propose the design and prototyping of an automation cell that integrates the DT-CV combo, a 6-DoF industrial robot, and an end-effector grinder for the automatic reconditioning of turbofan engine fan blades. According to Oyekan et al. [94], the use of their system based on the DT-CV combo allowed for automated, real-time tracking and control of the grinding process in a robotic work cell. Material removal was executed, monitored, and adjusted in a closed-loop manner. Moreover, the iterative search algorithm embedded in the digital twin allowed safe, rapid exploration of grinding parameters (e.g., cutting depth), reducing reliance on costly physical trials. The system could pre-test hypotheses digitally before deployment.

As the cases illustrated, the use of the DT-CV combo for product and process design accelerates development stages, reduces redesign costs, and ensures both functional and aesthetic precision—transforming traditional processes into agile, data-driven systems.

4.1.2. Manufacturing and Quality Assurance

Manufacturing ensures efficient production of products consistent with the company's mission, and quality assurance maintains product standards and minimizes defects in operations, while paying attention to design, procurement, production, and service opportunities [92]. Xiang et al. [81] illustrate that DT-CV combo frameworks improve robotic gripper control for accurate assembly tasks, whereas automated defect detection enhances manufacturing efficiency and quality assurance. Automated defect detection systems, as defined by Moretti et al. [77], integrate CV to detect anomalies, such as fractures in 3D-printed layers, while DT simulations facilitate real-time modifications in fused filament manufacturing, which contributes to reliability and minimizes material waste. Furthermore, in robotic assembly and inspection systems, Cannabrava et al. [99] developed a DT-CV combo, enabling vision-driven robots to perform tasks such as automobile welding inspections with enhanced precision and efficiency. Doroszuk et al. [100] developed a calibrated DT of a laboratory ball mill for copper ore milling by combining CV with discrete element method and smoothed particle hydrodynamics (DEM-SPH) simulations. DEM is a numerical technique that models the motion and interaction of discrete particles (e.g., grains, powders, rocks) to study bulk material behavior, while SPH is a mesh-free computational method that represents fluids (and sometimes solids) as particles and computes their dynamics using smoothing functions. By integrating these methods, the approach optimizes grinding operations by accurately simulating particle–fluid interactions in suspension, thereby enhancing both the accuracy and efficiency of the milling process in a controlled laboratory setting.

Döbrich et al. [101] investigate the DT approach to improve the quality of composite production, leveraging an Azure Kinect camera to monitor fiber orientations and simulate potential deviations. This method minimizes waste while ensuring component reliability. Weckx et al. [102] developed a cloud-based DT for an adaptive clamping mechanism in composite machining. The DT-CV combo monitors and enhances the quality of drilled holes. This approach decreases bending during drilling, reduces delamination, and maintains the proper functioning of the clamping mechanism by analyzing data collected and processed on the Microsoft Azure cloud platform. Yousif et al. [1] explore the improvement of manufacturing efficiency through utilizing the DT-CV combo in an assembly line that autonomously validates product assembly using advanced object recognition algorithms. Moreover, the integration of these technologies reduces human error, accelerates inspection cycles, and ensures compliance with high-quality standards—transforming quality control into a streamlined, scalable process.

4.1.3. Human Resources and Worker Safety

Human resources and worker safety provide a good quality of work life with well-designed, safe, healthy, and hazard-free jobs and work environment [92]. Aiken et al. [103] explore the DT-CV combo with mixed reality training to improve hazard detection accuracy in the oil and gas sector. This strategic digitalization enhances safety, situational awareness, and preparedness, substantially advancing operational readiness in industrial environments. Similarly, a vision-based human–robot collaborative system developed by Yi et al. [104] utilizes federated CV systems trained on synthetic DT data. The method standardizes inspections across automobile assembly lines, ensuring safe operation and reducing discrepancies among various manufacturing facilities. Humphries et al. [79] analyze the advancement of safety in the manufacturing environment through an integration of DT simulations and CV. The proposed methodology actively regulates robot velocity to reduce collision hazards, significantly enhancing safety and operational efficacy in robotic systems. Similarly, Cristofoletti et al. [93] propose a technical framework that integrates the DT-CV combo to facilitate remote control of robotic operations in hazardous environments. This system reduces human risk by performing dangerous tasks autonomously, leveraging advanced sensor integration for enhanced situational awareness. Inherent risks in a production environment can be mitigated by this system, as it reduces the safety risk of exposing human operators to hazardous situations. Additionally, the risk of equipment damage and operational errors is minimized by training the robot in a virtual environment before deployment. These advancements not only reduce workplace accidents but also enhance training effectiveness and ensure compliance with safety regulations, thereby fostering a safer and more resilient industrial ecosystem.

4.1.4. Supply Chain, Inventory, and Logistics Management

Supply chain, inventory, and logistics management ensure the effective transport of materials, inventory monitoring, and supplier coordination to enable and enhance production processes. It focuses on timely delivery, cost minimization, and seamless workflow integration to improve overall operational efficiency and customer satisfaction [92]. The DT-CV combo developed by Arbabian et al. [105] optimizes route planning in semiconductor and electronic manufacturing, guaranteeing punctual deliveries. These systems continuously evaluate container conditions to decrease risks and reduce disruptions, utilizing CV to improve operational efficiency and reliability. Similarly, Rivera et al. and Liu et al. [94,106] demonstrate how the DT-CV combo can improve retail inventory monitoring by automating real-time 3D product localization and dynamic DT updates, to enhance operational precision and efficiency. For example, in robotic bin picking, robots utilize simulated environments from DTs to perform accurate warehouse operations, increasing logistics efficiency. Collectively, these advances demonstrate that the DT-CV combo not only can eliminate operational bottlenecks but also can enhance adaptability and scalability, positioning logistics management as a fundamental element of next-generation industrial operation and production systems.

4.1.5. Scheduling and Operational Efficiency

Scheduling and operational efficiency involve the optimal utilization of resources, processes, and technology to enhance overall performance, ensure timely customer delivery, and high throughput [92]. Jakhotiya et al. [80] demonstrate the effectiveness of the DT-CV combo in enhancing collaborative robot (cobot) efficiency during pick-and-place operations, utilizing the Tecnomatix Process Simulator. This CV-guided automation method significantly reduces errors, improves precision, and enhances efficiency in collaborative industrial operations. Cheng et al. [107] propose a DT-driven framework for human–machine collaborative assembly, leveraging lightweight YOLO models to improve the precision of gear reducer assembly. This method enhances both accuracy and operational efficiency, rendering it a significant asset in complex manufacturing processes. Alsakka et al. [108] present lean manufacturing improvements through dynamic scheduling enabled by a DT-CV combo framework. Moreover, Legaz et al. [109] developed a DT-CV combo to enhance the reverse engineering of maritime systems. The DT-CV combo automation framework enables the autonomous operation of maritime vessels by improving the accuracy and efficacy of component modeling and simulation, while reducing the need for manual intervention in system design and operational processes. Ward et al. [110] introduce a novel Industry 4.0 system that uses real-time DTs, integrating commercially available cameras with programmable logic controllers to improve the monitoring and optimization of manufacturing processes. Ullah et al. [111] developed a DT framework using Wi-Fi fingerprinting and deep learning for real-time asset tracking in flexible manufacturing. The system enhances the management of autonomous guided vehicles (AGVs) using CV, achieving high obstacle avoidance and reduced energy consumption. Additionally, Urgo et al. [95] proposed a method utilizing artificial intelligence for supervising manufacturing systems, leveraging convolutional neural networks (CNNs) trained on synthetic data derived from a digital factory twin. This method, integrated with computer vision, facilitates real-time monitoring of factories, greatly improving predictive analytics and decision-making for intricate industrial systems. These applications streamline workflows, shorten cycle times, and optimize resource allocation, enabling industries to achieve greater productivity and competitiveness in dynamic markets.

4.1.6. Maintenance

Maintenance ensures high utilization of facilities and equipment by employing strategies and monitoring techniques to anticipate failures before they occur or by enabling prompt repairs when needed [92]. Zhang [112] utilizes 3D imaging and DTs technology to improve the monitoring and dependability of Gas-Insulated Switchgear (GIS) high-voltage power bushings. This DT-CV combo enables precise failure prediction even under electromagnetic interference, significantly enhancing the system's operational reliability. Pila [113] reduced downtime by using machine learning-powered predictive maintenance, enhancing system reliability through real-time diagnostics and providing collaborative visualization systems powered by the DT-CV combo. Kovári [114] developed a DT for a car service station by combining CV, simulation modeling, and artificial intelligence to optimize workflows, reduce inefficiencies, and improve maintenance efficiency. The DT-CV combo integration ensures uninterrupted operations and long-term cost efficiency by extending equipment lifespan, reducing maintenance costs, and preventing production halts.

4.2. Summary of DT-CV Combo Research and Real-World Industrial Applications

Table 3 presents a summary of research articles published on the applications of the DT-CV combo in the field of operations management. There are 17 journal articles, 11 conference papers, and one book chapter related to the DT-CV combo as of June 2025. The Journal of Intelligent Manufacturing, and the Machines Journal have two articles on this topic each. Among the 29 publications, nine are in manufacturing and industrial engineering outlets, six in electrical, electronic, and communications engineering, four in computer science, and three in mechatronics, robotics, and control engineering. In addition, three papers were published in general engineering publication outlets, while the remaining four appeared in education, energy, materials, and mechanical engineering outlets.

Table 3. The DT-CV combo role in operations and manufacturing, based on the literature review.

Classification	Scope	Outlet	Applications
Product and Process Design	1. DT-CV combo for optimized 3D printing material selection [6]	J. Intell. Manuf.	Material Optimization
	2. Digital Cyber-Physical System for Tool Design & Machining Process [76]	E3S Web Conf.	Virtual Prototyping & Simulation
	3. Digitization of Engineering Diagrams for Hydraulic System Model Creation [96]	Constr. Robot. J.	3D printing optimization
	4. Feature-Level Digital Twin Process Model (FL-DTPM) for Aerospace Manufacturing Optimization [97]	IEEE International Conference on Machine Learning and Applications	Automated Design Validation
	5. The design prototype utilizes a DT-CV combo, a 6-DoF industrial robot, and an end-effector grinder for optimizing the grinding process [98]	Sensors	Real-time monitoring & performance analysis
Manufacturing & Quality Assurance	1. A Novel Object Recognition Approach with DT-CV combo for Autonomous Robot Correction [1]	J. Intell. Manuf.	Minimizes human interaction and reduces disruption of manufacturing operations.
	2. Vision-Guided Micro adjustments framework for fused filament Fabrication [77]	Addit. Manuf.	Defect Detection, Quality Controls
	3. DT-CV combo for Adaptive Quality Control of Industrial Robot Grippers [81]	29th International Conference on Automation and Computing	Robot Performance Analytics
	4. Quality Inspection for Automotive Welding with DT-CV combo [99]	12th Conference on Learning Factories	Quality inspection
	5. DT-CV combo for Process Synchronization in Grinding Mill Operations [100]	Minerals	Energy Consumption Monitoring

Table 3. *Cont.*

Classification	Scope	Outlet	Applications
Manufacturing & Quality Assurance	6. Digitalization of the composite production Process chain [101]	Front. Mater.	Optimization of the manufacturing of Composite Material.
	7. A Cloud-Based DT-CV combo Model for Monitoring the Machining of Composite Parts in Manufacturing [102]	IET Collab. Intell. Manuf.	Visual Anomaly Detection
Human resources and worker safety	1. A DT-CV combo Approach for Managing Human Safety on the Factory Floor [79]	Technol. Sustain.	Hazard monitoring
	2. DT-CV combo Framework for Route Planning to Train Robots to Interact with Objects [93]	International Conference on Intelligent Metaverse Technologies & Applications	Anomaly detection
	3. DT-CV combo Framework with Adaptive Architectures for Employee Training in the Oil and Gas Industry [103]	IEEE Access	Mixed reality safety training
	4. A Novel DT-Based Approach for Developing a Human–robot Collaborative Assembly System [104]	Procedia CIRP	Robotic safety enhancement, Emergency Response Simulation
Supply chain, inventory, and logistics management	1. AI-driven multi-modal approach with DT for real-time in-store product recognition and reconstruction [94]	IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops	Package Integrity Verification, Warehouse/Retail automation
	2. A DT-CV-Based Human–machine Collaboration Model with Indoor Tracking for Electronics Manufacturing [105]	19th International Microsystems, Packaging, Assembly and Circuits Technology Conference	Route Optimization, Smart Inventory Tracking
	3. A Bin Picker Using Mono and Stereo Vision with DT-CV for Classifying and Arranging Cylinders by Color and Size [106]	2022 IEEE Global Engineering Education Conference	Robotic Bin Picking, Autonomous Robots Coordination
Scheduling and operational efficiency	1. A Cobot Optimizing Pick-and-Place Operations with DT-CV combo in Tecnomatix Process Simulate [80]	Int. J. Interact. Des. Manuf.	Enhance Cobot Efficiency, Resource Optimization, Process Automation
	2. A DT-CV-Enabled Model for Advanced Real-Time Monitoring in Manufacturing Systems [95]	CIRP Annals—Manufacturing Technology	Historical Failure Analysis, Downtime Reduction
	3. The Human–machine Collaborative Method Using DT-CV combo for Assembly Operations in the Automotive Industry [107]	2024 International Conference on Networking, Sensing and Control	Human–machine Collaboration Analytics, PPE Compliance Monitoring
	4. A DT-CV combo Framework for Analyzing Multidimensional Data, Integrating Operational and Visual Streams for Real-Time Tracking and Decision-Making in Industry [108]	Machines	Workflow Visualization and Optimization,
	5. A DT-CV combo Framework for Reverse Engineering in Maritime Systems [109]	38th ECMS International Conference on Modelling and Simulation	Recreation of the model/system
	6. A design model for real-time vision-based multi-object tracking in production processes [110]	Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.	Dynamic Demand-Response Scheduling

Table 3. *Cont.*

Classification	Scope	Outlet	Applications
Scheduling and operational efficiency	7. A DT- CV combo framework integrating real-time asset tracking for smart flexible manufacturing systems [111]	Machines	AI-Driven Resource Allocation
Maintenance	1. A DV-CV combo Method for High-Precision Gas Composition Detection in High-Voltage Equipment Using 3D Imaging for Insulation Monitoring [112]	8th International Conference on Image, Vision and Computing	Insulation Monitoring, Gas linkage
	2. Enhancing Industrial Operations with DT by Integrating Image Processing for Real-Time Monitoring [113]	Int. J. Comput. Eng. Technol.	Automated Repair Planning
	3. A DT-CV combo Simulation Model for the Predictive Maintenance of Car Service Stations [114]	The Future of Industry Book	Condition-Based Simulations

As Table 3 indicates, research on the DT-CV combo applications in the field of OM is scarce. More specifically, OM sub-domains such as maintenance and supply chain, inventory, and logistics management warrant further investigation. Furthermore, of the 29 articles reviewed, only three were published in high-impact, leading outlets such as the Journal of Intelligent Manufacturing and Additive Manufacturing. This suggests a clear need for both higher-quality research in this field and greater focus from its leading publication outlets.

The DT-CV combo is starting to be used in real-world industrial applications. The DT-CV adoption drivers of cost reduction (lowering the redesign costs and need for fewer physical prototypes), shorter time-to-market (faster development cycles), and improved operational agility (DT-CV combo enables real-time monitoring and iterative optimization) can give a competitive edge to the early adopters as they can be more nimble to meet the customer need in a time and cost sensitive market. Figure 4 shows companies adopting this combo in their operational functions. For example, Siemens [90], GE Vernova [115], Dassault Systèmes, and Konecranes use the DT-CV combo in areas including product and process design, manufacturing, and quality assurance [88]. Konecranes uses the DT-CV combo in their "Smart Factory," which helps companies in their daily production and maintenance operations. From a production point of view, important information on machine downtimes and their duration is obtained and then used to address the causes of production disruptions [88]. Other companies like NVIDIA and Addepto (now part of Grape Up) support process design and improvement, real-time production monitoring, and defect detection [82,85] through systems enabled by the DT-CV combo. For instance, NVIDIA's Isaac Sim—built on the Omniverse platform—allows companies like Amazon to generate photorealistic synthetic images for training CV models used in warehouse and factory robotic operations [116].

For supply chain and logistics management, Amazon and Vimaan use the DT-CV combo for inventory and transportation optimization [87,117]. In Vimaan's solution, "well beyond a means of reading warehouse barcode data, Vimaan CV captures and analyzes images of inventory and surrounding environments. Vimaan sensors capture and interpret visual data, providing warehouse teams with actionable insights to help increase inventory accuracy and improve operational efficiencies" [87,117].

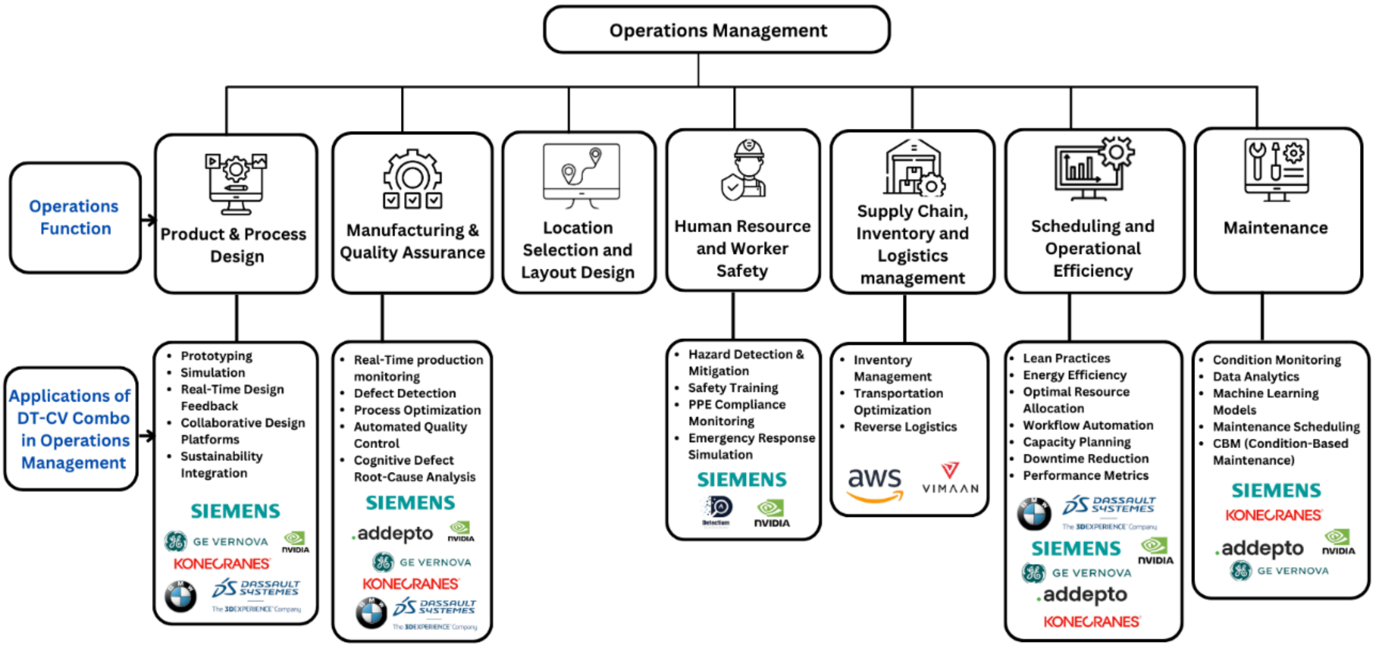

Figure 4. DT-CV combo adoption by companies across operational functions.

Similarly, companies like Siemens and Detectium use this combo to improve worker safety. Detectium uses environmental digital twins combined with computer vision to rapidly and accurately detect fire and hazardous conditions leading to a potential fire and present that in a digital twin in real-time for improved situational awareness during the response [89].

BMW and Dassault Systèmes companies use it for scheduling, operational efficiency, and maintenance [86]. For instance, BMW utilizes Dassault Systèmes' 3DEXPERIENCE platform to enable engineering team collaboration across all departments and to accelerate product development [86].

After reviewing the literature, we show that the current deployments are still limited and the existing literature does not offer detailed case studies of large and successful deployments (e.g., Amazon warehouses) of the DT-CV combo for operations management. Moreover, these deployments by the aforementioned companies are being performed in countries with advanced digital industrial infrastructure, including the US (AWS, NVIDIA, GE Vernova, Grape Up, and Vimaan), Germany (Siemens and BMW), France (Dassault Systèmes), and Finland (Konecranes and Detectium). This also calls for further investigation of a potential correlation between the company location and its tendency to adopt the DT-CV combo technology in its operations. This may also result from outlets favoring the publication of research work in this context, predominantly from these regions.

4.3. Overcoming Barriers to DT-CV Combo Implementation in Industry

In Section 4.3.1, we investigate the challenges of implementation and integration of the DT-CV combo in industrial operations to answer the first part of RQ2. Then, in Section 4.3.2, we review the emerging technological advancements related to the DT-CV combo to shed light on the future of industrial operations and answer the second part of RQ2.

Several factors inhibit the adoption of the DT-CV combo in industry. These include the high initial costs of technology development and implementation, resistance from management and employees due to significant strategic adjustments, and gaps in the skills required to integrate, operate, and maintain DT-CV-enabled systems.

4.3.1. Implementation Barriers

Despite the DT-CV combo's potential to revolutionize industrial operation and production, deployments encounter significant technical and operational limitations. For instance, high reliance on precise sensor data [77,105] and delays in processing real-time vision [80] limit responsiveness in applications such as robotic assembly [81] and hazard monitoring [103]. Challenges in achieving interoperability restrict scalability across different systems, as reviewed in logistics management [106] and federated quality control [104]. Additionally, the dependency on structured visual inputs reduces adaptability in unstructured settings like composite production [101]. Furthermore, synchronizing real-time sensor data across old and new technologies proves complex [82], with resource constraints and high computational costs making adoption difficult, particularly for small and medium-sized enterprises (SMEs) [74,102]. These factors demonstrate the necessity for advancements in the DT-CV combo to better support a range of industrial operations, particularly in resource-limited environments.

4.3.2. Emerging Trends in Industry

The DT-CV combo is gaining traction through various technological advancements. Standardization initiatives by Siemens [90,118] are advancing industrial AI through its Industrial Copilot for Operations (ICO) platform. The ICO is a platform designed to enhance AI-driven processes within manufacturing environments, increasing efficiency and reducing downtime. This platform is part of an evolving ecosystem integrated with the Industrial Edge, which employs AI to manage models within production environments. The approach supports DT creation and employs CV to improve real-time decision-making and predictive maintenance. In addition, Addepto and GE Vernova [82,115] identify the DT-CV combo as a crucial enabler of real-time simulation and enhanced control of manufacturing processes. The DT-CV combo in this case facilitates accurate production line monitoring, predictive maintenance, and enhanced quality control via data-driven insights. AWS-NavVis and Vimaan [87,117] DT-CV combo in warehouse operations significantly improves inventory management and operational efficiency. This system obtains and analyzes visual data, facilitating real-time, precise updates for the warehouse's DT. This DT-CV combo integration supports automated inventory tracking, quality control, and safety improvements by delivering actionable insights that result in more accurate inventory management, reduced discrepancies, optimized space utilization, and enhanced overall warehouse productivity.

4.4. Identified Gaps in the Literature

Reviewing the existing literature enables us to pinpoint the gap in the literature and point out a number of research questions based on those existing gaps.

4.4.1. Case Studies

The main finding concerns the lack of real-world case studies. Only one article [103] out of 29 employs an actual case in developing its solution. Most publications focus on design experimentation based on general problem statements and validate their approaches in laboratory settings, which is expected in the early stages of a new technological shift. Furthermore, none of the papers investigates flagship deployments by companies. Data on such deployments is only beginning to emerge through video demonstrations on platforms like YouTube or via company websites [82,87,90,115–118].

Therefore, there is an urgent need to study and scientifically analyze flagship deployments of DT-CV combo solutions. One example is Amazon's deployment of NVIDIA's Omniverse platform to integrate Proteus autonomous robots across its fulfillment centers [116].

The following important research questions emerged based on our literature review:

- What are the strategic financial costs and potential savings associated with deploying DT-CV combo solutions in manufacturing and operations?
- Which industries or operational areas offer the most immediate opportunities ("low-hanging fruit") for achieving cost competitiveness relative to conventional approaches?
- What are the long-term sustainability implications of adopting DT-CV combinations in operations management?

4.4.2. Context and Method

In the context of OM, although the number of studies on DT-CV combinations has shown steady growth over the last five years (Figure 2), the overall volume of research remains limited. There is still substantial room for further work, particularly in the specific OM activities of maintenance operations, supply chain, inventory and logistics management, as well as human resources and worker safety. Furthermore, it is important to initiate studies on the concept of an "Internet of Digital Twins," where DTs from different supply chains can intertwine and interact to form a global DT. Such integration, leveraging CV and vision-language models (VLM), has the potential to affect efficiency, resilience, and overall effectiveness of operations.

Moreover, there is a need for quantitative comparisons between DT-CV combo-enabled solutions and traditional methods, an area currently lacking in the literature. Such an analysis would provide a clearer understanding of the actual efficiency gains and cost savings that can be achieved in OM.

The following important research questions emerged based on our literature review:

- What are the real-world use cases of DT-CV combo solutions for industrial maintenance operations?
- How can worker safety benefit from DT-CV combo adoption while simultaneously improving efficiency and ensuring that both employers and employees maintain trust in the computer vision aspects of these solutions?
- How can logistics operations and supply chains—occurring outside factory boundaries and embedded in the physical world—deploy DT-CV solutions to strengthen resilience and mitigate challenges such as the bullwhip effect or supplier shocks during exogenous disruptions (e.g., pandemics, natural disasters)?
- In the context of the Internet of Digital Twins, how do DT-CV and DT-VLM combos impact operational efficiency, resilience, and sustainability in manufacturing networks?
- How do DT-CV combo-enabled solutions quantitatively impact cost and efficiency in OM?

4.4.3. Ethical and Regulatory Aspects

There is a growing need for research on the ethical and regulatory frameworks related to the creation, operation, and maintenance of DT 3D models, as well as the integration of real-world data using CV to complement and update these DTs. In a human-centric field such as OM, it is crucial to address the challenges of CV deployment while ensuring worker privacy, protecting manufacturers' intellectual property rights (IPR), and developing frameworks for data sharing and federated learning.

The following important research questions emerged based on our literature review:

- How can worker privacy be ensured when deploying DT-CV combo-based solutions in an operational setting? And what are the different regulatory/ethical frameworks governing such deployment in different countries?

- What governance models can effectively balance the need for collaborative data sharing and federated learning with the protection of manufacturers' intellectual property rights (IPR)?
- How can regulatory frameworks ensure compliance while enabling innovation in DT-CV combo applications in OM?

5. Discussion

In this section, we discuss the DT-CV combo for actionable outputs in operations safety and the DT-CV combo integration with VLMs for manufacturing and quality assurance. Moreover, we elaborate on the dynamic remodeling of the factory for operational accuracy and efficiency. Ultimately, we discuss the future research direction.

5.1. The DT-CV Combo for Actionable Outputs in Operations Safety

The data embedded in the DT allows for simulation of system behavior, but the accuracy of this simulation is highly dependent on the details embedded in the digital twin regarding the simulated situation and the sensor data feed [3]. Systems relying on the DT-CV combo have access to visual data that can be used for the detection of various environmental elements and situations [108,110]. This, in turn, can allow for the real-time recalling of the simulation outcomes that were simulated before and saved to be used as a similar incident occurs. In this case, the reaction to an incident can be highly coordinated as the similarity of the DT simulation and the real-world event would allow for a significantly higher level of preparedness.

For instance, in the case of fire safety in a factory or warehouse, the DT-CV combo enables fire detection, localization, and integration with autonomous response and extinguishment platforms [89,119]. These platforms can utilize real-time CV data to precisely place the fire within the virtual model of the DT, retrieve a pre-existing fire propagation simulation from system memory, and deploy interventions accordingly. This may involve dispatching a fire suppression drone or assisting in evacuation efforts.

In the case of an autonomous drone response, the system leverages fire localization data from the DT based on CV data to calculate optimal paths for drones [89,120]. Using the DT's 3D model, it is possible to determine the most efficient routes for both firefighting teams and drones. A drone equipped with a water tank can then be dispatched from a central location within the factory or warehouse, responding to the fire based on predictions extracted from prior fire propagation simulations.

Utilizing the DT-CV combo as an infrastructure enables the real-time navigation of firefighting teams and emergency responders. This is achieved by integrating location-based data within DT to enable dynamic routing and navigation assistance for optimizing the deployment of resources during fire emergencies.

5.2. Integration with Vision Language Models for Manufacturing and Quality Assurance

The integration of VLMs, such as multimodal AI systems that combine vision perception and natural language processing (e.g., GPT-4V) [121], with DT can have significant implications for industrial operations and manufacturing. This convergence improves interpretability, allows contextual reasoning, and supports interactive decision-making, effectively connecting raw visual data with actionable insights. At the same time, adaptive VLMs that incorporate operator feedback foster a new aspect of human–machine collaboration, enabling workers to interact with DTs via natural language inquiries, which improves efficiency and usability. The DT-VLM combo represents a paradigm shift toward contextually aware, self-explanatory industrial systems. While computational efficiency and domain adaptation remain challenges, industry leaders such as Siemens [90], which is leveraging Industrial Copilot to drive DT platforms, and NVIDIA, which is developing multimodal AI tools [85], are at the forefront of this transformation.

An example of this implementation can be used for the automation of safety monitoring and compliance verification at a factory, where the non-compliant actions can be detected and compared with the specific location of activity in the digital twin in near real-time, and the corrective actions can be sent to the relevant managers and employees in natural language to be implemented for corrective interventions. Manufacturing companies that hold ISO certifications (such as ISO 9001:2015 for Quality Management Systems [122] or ISO 14001:2015 for Environmental Management Systems [123]) typically need to undergo regular audits to maintain compliance [124]. The frequency of these inspections depends on the specific ISO standard and the certification body's requirements. For instance, Annual Surveillance Audits (most ISO-certified companies undergo yearly audits by an accredited certification body to ensure ongoing compliance) or Recertification Audits (every three years, a more in-depth recertification audit is required to renew the certification) or more frequent Internal Audits (companies must also perform regular internal audits to monitor compliance and identify areas for improvement) [125] can take advantage of the DT-VLM combo where the ISO certified digital twin can be compared with the situation on the ground using the VLM. When the discrepancies are detected, then corrective actions and reports can be generated and sent to the respective stakeholders for decision-making and implementation.

5.3. Dynamic Remodeling (Online Semantic 3D Mapping) of Factory DT for Operational Accuracy and Efficiency

One of the main limitations of a digital twin is the manual work required for the creation and adjustments of a digital twin's 3D model to have an accurate geometrical and material type accuracy, while also keeping the segmentation of the objects and spaces [126]. Online semantic 3D mapping is a real-time pipeline that reconstructs and incrementally updates a 3D map while segmenting objects/areas (semantics) and detecting changes in dynamic scenes. This is widely used in robotics and aligns exactly with "CV-driven dynamic remodeling" of a DT [127]. A DT-CV combo system can use the CV for the detection and tracking of the 3D model segments to enable online semantic 3D mapping of the space and its equipment and objects. This is very important in applications such as fire detection and localization in a warehouse (e.g., hay warehouse), manufacturing operations, and in a factory where autonomous collaborative robots and humans are operating side by side.

Online semantic 3D mapping (also known as. semantic SLAM with change detection) can allow for the anonymization of individuals for enhanced privacy and data security in the DT environment and to present the personnel and machinery in the digital twin in real-time. This would allow for a closer collaboration possibility as the autonomous systems can rely on a holistic view of the factory and plan their routes and movements based on the data from their sensors as well as the data receive from the digital twin database that would allow for complementary data points for instance pinpointing a collision or a blocked path beyond the detection zones of the autonomous platforms [45,119].

5.4. Future Research Directions and Limitations

Future research should focus on developing scalable architectures, improving VLM training pipelines, and ensuring ethical AI governance to fully realize the synergy's potential in manufacturing and industrial operations. Moreover, additional research is necessary to standardize the communication protocols through DTs in manufacturing and operations for autonomous platforms (e.g., drones, robots) as well as protocols to assemble digital twins in an internet of digital twins' configuration for global supply chains, where the systems and platforms integrated in one DT-VLM combo can also serve other ones throughout the entire supply chain. In a DT-CV-VLM architecture, an open question concerns how tasks should be distributed between the CV and VLM components, as well as whether critical manufacturing operations should run locally or in the cloud. Furthermore, current VLM systems are large and general-purpose, highlighting the need to develop smaller, specialized models that can operate at the edge. When designing such specialized VLM systems for production and operations, it is also essential to consider training data requirements—an issue that remains equally important for existing CV models.

Another direction for future research is to explore the detailed positive and negative responses of different industries to the adoption of the DT-CV combo, and to compare the drivers and inhibitors across various industrial domains. In the same direction, conducting detailed case studies of companies using the DT-CV combo for their operational activities, as well as performing cost analyses of these deployments compared to traditional OM activities, is necessary.

In this work, we performed a literature review using secondary data to shed light on the current trends and trajectories of the DT-CV combo and to illustrate a path forward for this line of scientific inquiry. As with any literature review, the limitations include the time window of the study, which restricts the review to articles published between 2020 and June 2025, and the potential algorithmic bias in article selection. We mitigated this by using multiple academic search engines and diverse keywords. However, literature reviews also have inherent limitations: they rely on the availability and quality of published studies, which may introduce publication bias; they often lack primary empirical validation; and their findings can be influenced by the authors' interpretation and synthesis choices. Additionally, literature reviews may not capture the most recent developments if those have not yet been published or indexed.

6. Conclusions

The DT-CV combo can transform industrial operations and production by utilizing virtual replicas of physical systems and providing real-time monitoring, predictive maintenance, worker safety, and improved decision-making capabilities. In this systematic literature review, we explored the applications, challenges, and future directions of the DT-CV combo, demonstrating its significant contributions across OM functions. We used seven OM functions for our DT-CV combo literature classification, product and process design, manufacturing and quality assurance, location selection and layout design, human resource and worker safety, supply chain, inventory and logistics management, scheduling and operational efficiency, and maintenance. Furthermore, we explored the industrial use cases of the DT-CV combo; for example, Siemens' Industrial Copilot and NVIDIA's geospatial visualization tools are utilized for industrial operations and production.

Despite the potential benefits of the DT-CV combo, several challenges remain, including computational complexity, data interoperability barriers, and CV framework integration. Moreover, we found that academic research on the OM aspects of real-world deployments of the DT-CV combo by companies is scarce and warrants further exploration. In the future, the DT-VLM combo can be a transformative step toward smart, autonomous manufacturing. By leveraging real-time data, locally deployed Small Language Models (SLMs), AI-driven insights, and automated visual inspection, manufacturers can achieve higher efficiency, reduced downtime, and improved adaptability in an increasingly competitive industrial climate. Moreover, within the realm of OM, the DT-VLM combo may facilitate natural language interactions, enhance contextual perception and reasoning, and bridge the gap between physical and digital operational interfaces.

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References

1. Yousif, I.; Burns, L.; El Kalach, F.; Harik, R. Leveraging computer vision towards high-efficiency autonomous industrial facilities. *J. Intell. Manuf.* **2024**, *36*, 2983–3008. [CrossRef]
2. Albukhitan, S. Developing digital transformation strategy for manufacturing. *Procedia Comput. Sci.* **2020**, *170*, 664–671. [CrossRef]
3. Rasheed, A.; San, O.; Kvamsdal, T. Digital twin: Values, challenges and enablers from a modeling perspective. *IEEE Access* **2020**, *8*, 21980–22012. [CrossRef]
4. Qamar, R.; Zardari, B.A. Application of computer vision in manufacturing. In *Machine Vision and Industrial Robotics in Manufacturing*; CRC Press: Boca Raton, FL, USA, 2025; pp. 36–56.
5. Omri, S.; Mehta, D.; Neuhüttler, J. Leveraging computer vision for sustainable manufacturing: Potentials, challenges and future perspectives. *Adv. Emerg. Technol.* **2023**, *115*, 115. [CrossRef]
6. Li, J.; Zhou, G.; Zhang, C.; Hu, J.; Chang, F.; Matta, A. Defining a feature-level digital twin process model by extracting machining features from MBD models for intelligent process planning. *J. Intell. Manuf.* **2025**, *36*, 3227–3248. [CrossRef]
7. NASA. Why Does the World (and NASA) Need Digital Twins? 2025. Available online: https://science.nasa.gov/biological-physical/why-does-the-world-and-nasa-need-digital-twins/ (accessed on 27 August 2025).
8. Attaran, M.; Celik, B.G. Digital Twin: Benefits, use cases, challenges, and opportunities. *Decis. Anal. J.* **2023**, *6*, 100165. [CrossRef]
9. Botín-Sanabria, D.M.; Mihaita, A.S.; Peimbert-García, R.E.; Ramírez-Moreno, M.A.; Ramírez-Mendoza, R.A.; Lozoya-Santos, J.D.J. Digital twin technology challenges and applications: A comprehensive review. *Remote Sens.* **2022**, *14*, 1335. [CrossRef]
10. Liu, M.; Fang, S.; Dong, H.; Xu, C. Review of digital twin about concepts, technologies, and industrial applications. *J. Manuf. Syst.* **2021**, *58*, 346–361. [CrossRef]
11. Mihai, S.; Yaqoob, M.; Hung, D.V.; Davis, W.; Towakel, P.; Raza, M.; Karamanoglu, M.; Barn, B.; Shetve, D.; Prasad, R.V.; et al. Digital twins: A survey on enabling technologies, challenges, trends and future prospects. *IEEE Commun. Surv. Tutor.* **2022**, *24*, 2255–2291. [CrossRef]
12. Liu, L.; Zhang, X.; Wan, X.; Zhou, S.; Gao, Z. Digital twin-driven surface roughness prediction and process parameter adaptive optimization. *Adv. Eng. Inform.* **2022**, *51*, 101470. [CrossRef]
13. Zhang, K.; Zhou, H.-Y.; Baptista-Hon, D.T.; Gao, Y.; Liu, X.; Oermann, E.; Xu, S.; Jin, S.; Zhang, J.; Sun, Z.; et al. Concepts and applications of digital twins in healthcare and medicine. *Patterns* **2024**, *5*, 101028. [CrossRef] [PubMed]
14. Vallée, A. Envisioning the future of personalized medicine: Role and realities of digital twins. *J. Med. Internet Res.* **2024**, *26*, e50204. [CrossRef]
15. Asciak, L.; Kyeremeh, J.; Luo, X.; Kazakidi, A.; Connolly, P.; Picard, F.; O'nEill, K.; Tsaftaris, S.A.; Stewart, G.D.; Shu, W. Digital twin assisted surgery, concept, opportunities, and challenges. *NPJ Digit. Med.* **2025**, *8*, 32. [CrossRef] [PubMed]
16. Deng, S.; Ling, L.; Zhang, C.Z.; Li, C.; Zeng, T.; Zhang, K.; Guo, G. A systematic review on the current research of digital twin in automotive application. *Internet Things Cyber-Phys. Syst.* **2023**, *3*, 180–191. [CrossRef]
17. Yang, Z.; Zhao, X. Design and simulation of automotive digital instruments based on digital twin technology. In Proceedings of the 2024 4th International Symposium on Computer Technology and Information Science (ISCTIS), Xi'an, China, 12–14 July 2024; IEEE: New York, NY, USA, 2024; pp. 800–803.
18. Kim, S.; Heo, S. An agricultural digital twin for mandarins demonstrates the potential for individualized agriculture. *Nat. Commun.* **2024**, *15*, 1561. [CrossRef]

19. Kim, H.J.; Lee, M.H.; Yoe, H. Research on the design and application of digital twin-based smart agricultural systems. In Proceedings of the 2023 Congress in Computer Science, Computer Engineering & Applied Computing (CSCE), Las Vegas, NV, USA, 24–27 July 2023; IEEE: New York, NY, USA, 2023.
20. Chernyshev, D.; Dolhopolov, S.; Honcharenko, T.; Haman, H.; Ivanova, T.; Zinchenko, M. Integration of building information modeling and artificial intelligence systems to create a digital twin of the construction site. In Proceedings of the 2022 IEEE 17th International Conference on Computer Sciences and Information Technologies (CSIT), Lviv, Ukraine, 10–12 November 2022; IEEE: New York, NY, USA, 2022.
21. Nie, X. Design of building construction quality supervision system based on digital twin. In Proceedings of the 2023 International Conference on Telecommunications, Electronics and Informatics (ICTEI), Lisbon, Portugal, 11–13 September 2023; IEEE: New York, NY, USA, 2023.
22. Xiong, T.; Cheng, Q.; Yang, C.; Yang, X.; Lin, S. Application of digital twin technology in intelligent building energy efficiency management system. In Proceedings of the 2021 International Conference on E-Commerce and E-Management (ICECEM), Dalian, China, 24–26 September 2021; IEEE: New York, NY, USA, 2021.
23. Khan, M.S.; Chinnaiyan, R.; Balachandar, S.; Ibrahim, S.J.A.; Chakravarthy, N.K.; Kalaiarasan, C.; Divya, R. Centralized and reliable digital twin models for smart city's buildings protection during disaster. In Proceedings of the 2022 International Conference on Computational Modelling, Simulation and Optimization (ICCMSO), Pathum Thani, Thailand, 23–25 December 2022; IEEE: New York, NY, USA, 2022.
24. Liu, Z.; Li, M.; Ji, W. Development and application of a digital twin model for Net zero energy building operation and maintenance utilizing BIM-IoT integration. *Energy Build.* **2024**, *328*, 115170. [CrossRef]
25. Khajavi, S.H.; Hossein Motlagh, N.; Jaribion, A.; Werner, L.C.; Holmström, J. Digital twin: Vision, benefits, boundaries, and creation for buildings. *IEEE Access* **2019**, *7*, 147406–147419. [CrossRef]
26. Zhao, X. A novel digital-twin approach based on transformer for photovoltaic power prediction. *Sci. Rep.* **2024**, *14*, 26661. [CrossRef]
27. Deakin, M.; Vanin, M.; Fan, Z.; Van Hertem, D. Smart energy network digital twins: Findings from a UK-based demonstrator project. *arXiv* **2023**, arXiv:2311.11997. [CrossRef]
28. Lei, Z.; Zhou, H.; Dai, X.; Hu, W.; Liu, G.P. Digital twin based monitoring and control for DC-DC converters. *Nat. Commun.* **2023**, *14*, 5604. [CrossRef]
29. Liu, J.; Yang, H.; Niu, H.; Guan, M.; Chen, W.; Wang, Q.; Zheng, D.; He, P. Digital Twin Civil Aviation Research Airport for Aircraft Security and Environment Protection. In Proceedings of the 2022 IEEE 4th International Conference on Civil Aviation Safety and Information Technology (ICCASIT), Dali, China, 12–14 October 2022; IEEE: New York, NY, USA, 2022.
30. Starostin, I.E.; Khalyutin, S.P.; Druzhinin, A.A.; Gavrilenkov, S.I. Development of an Information System of Digital Twins of Aviation Electrical Equipment as a Software Module of the Local Load Control Center. In Proceedings of the 2023 XX Technical Scientific Conference on Aviation Dedicated to the Memory of N.E. Zhukovsky (TSCZh), Moscow, Russia, 13–14 April 2023; IEEE: New York, NY, USA, 2023.
31. Conde, J.; Munoz-Arcentales, A.; Romero, M.; Rojo, J.; Salvachúa, J.; Huecas, G.; Alonso, Á. Applying digital twins for the management of information in turnaround event operations in commercial airports. *Adv. Eng. Inform.* **2022**, *54*, 101723. [CrossRef]
32. Kong, Q.; Zhou, H.; Du, Y.; Liu, N. Design of logistics distribution scheduling system based on computer digital twin. In Proceedings of the 2023 IEEE 3rd International Conference on Data Science and Computer Application (ICDSCA), Dalian, China, 27–29 October 2023; IEEE: New York, NY, USA, 2023; pp. 1161–1165.
33. Hu, B.; Guo, H.; Tao, X.; Zhang, Y. Construction of digital twin system for cold chain logistics stereo warehouse. *IEEE Access* **2023**, *11*, 73850–73862. [CrossRef]
34. Liu, Y.; Pan, S.; Ballot, E. Unveiling the potential of digital twins in logistics and supply chain management: Services, capabilities, and research opportunities. *Digit. Eng.* **2024**, *3*, 100025. [CrossRef]
35. Grand View Research. Digital Twin Market Size & Trends. Grand View Research Report. 2023. Available online: https://www.grandviewresearch.com/horizon/outlook/digital-twin-market-size/global (accessed on 15 April 2025).
36. Szeliski, R. *Computer Vision: Algorithms and Applications*, 2nd ed.; Springer: Cham, Switzerland, 2022.
37. GlobalData. Computer Vision Market Size, Share, Trends and Analysis by Region, Industry Vertical and Segment Forecasts to 2026. GlobalData Report. 2023. Available online: https://www.globaldata.com/store/report/computer-vision-market-analysis/ (accessed on 15 April 2025).
38. Kaushal, S.; Tammineni, D.K.; Rana, P.; Sharma, M.; Kandi, S.; Chen, H.H. Computer vision and deep learning-based approaches for detection of food nutrients/nutrition: New insights and advances. *Trends Food Sci. Technol.* **2024**, *146*, 104408. [CrossRef]
39. Almazán-Lázaro, J.A.; López-Alba, E.; Díaz-Garrido, F.A. Applied computer vision for composite material manufacturing by optimizing the impregnation velocity: An experimental approach. *J. Manuf. Process.* **2022**, *74*, 52–62. [CrossRef]
40. Mezher, A.M.; Marble, A.E. Computer vision defect detection on unseen backgrounds for manufacturing inspection. *Expert. Syst. Appl.* **2024**, *243*, 122749. [CrossRef]

41. Kabir, M.M.; Rahman, A.; Hasan, M.N.; Mridha, M.F. Computer vision algorithms in healthcare: Recent advancements and future challenges. *Comput. Biol. Med.* **2025**, *185*, 109531. [CrossRef]
42. Javaid, M.; Haleem, A.; Singh, R.P.; Suman, R. Computer vision to enhance healthcare domain: An overview of features, implementation, and opportunities. *Sens. Int.* **2024**, *5*, 100234. [CrossRef]
43. Ghazal, S.; Munir, A.; Qureshi, W.S. Computer vision in smart agriculture and precision farming: Techniques and applications. *Artif. Intell. Agric.* **2024**, *13*, 64–83. [CrossRef]
44. Lin, S.; Qi, X. Development of intelligent agricultural automation based on computer vision. In Proceedings of the 2023 International Conference on Integrated Intelligence and Communication Systems (ICIICS), Kalaburagi, India, 24–25 November 2023; IEEE: New York, NY, USA, 2023. [CrossRef]
45. Carbon Robotics. Laserweeding Technology. 2025. Available online: https://carbonrobotics.com/laserweeding-technology (accessed on 27 August 2025).
46. Hou, X.; Li, C.; Fang, Q. Computer vision-based safety risk computing and visualization on construction sites. *Autom. Constr.* **2023**, *156*, 105129. [CrossRef]
47. Jayaram, M.A. Computer vision applications in construction material and structural health monitoring: A scoping review. *Mater. Today Proc.* **2023**, *74*, 52–62. [CrossRef]
48. Li, J.; Miao, Q.; Zou, Z.; Gao, H.; Zhang, L.; Li, Z.; Wang, N. A review of computer vision-based monitoring approaches for construction workers' work-related behaviors. *IEEE Access* **2024**, *12*, 7134–7155. [CrossRef]
49. Bajaj, S.; Yemula, P.K. Computer vision based energy monitoring system using Meter Image Capturing System (MICAPS). In Proceedings of the 2020 First International Conference on Power, Control and Computing Technologies (ICPC2T), Raipur, India, 3–5 January 2020; IEEE: New York, NY, USA, 2020.
50. Liu, X.; Xia, H.; Li, K.; Lu, Y.; Lv, S.; Zhao, Q.; Song, W.; Wang, L. The real-time shadow detection of the PV module by computer vision based on histogram matching and gamma transformation method. *Sci. Rep.* **2024**, *14*, 21781. [CrossRef]
51. Wang, G.; Zhang, C.; Liu, S.; Zhao, Y.; Zhang, Y.; Wang, L. Multi-robot collaborative manufacturing driven by digital twins: Advancements, challenges, and future directions. *J. Manuf. Syst.* **2025**, *82*, 333–361. [CrossRef]
52. Man, D.; Olchawa, R. The possibilities of using BCI technology in biomedical engineering. In Proceedings of the International Scientific Conference BCI 2018 Opole, Opole, Poland, 13–14 March 2018; Springer: Berlin/Heidelberg, Germany, 2018; pp. 30–37.
53. Stark, A.; Ferm, K.; Hanson, R.; Johansson, M.; Khajavi, S.; Medbo, L.; Holmström, J. Hybrid digital manufacturing: Capturing the value of digitalization. *J. Oper. Manag.* **2023**, *69*, 890–910. [CrossRef]
54. Lu, Q.; Zhu, D.; Wang, M.; Li, M. Digital twin-driven thermal error prediction for CNC machine tool spindle. *Lubricants* **2023**, *11*, 219. [CrossRef]
55. Kaur, N. Intelligent manufacturing in Industry 4.0. In *Intelligent Manufacturing: Exploring AI, Blockchain, and Smart Technologies in Industry 4.0*; CRC Press: Boca Raton, FL, USA, 2025; pp. 5–25.
56. Soori, M.; Arezoo, B.; Dastres, R. Digital twin for smart manufacturing: A review. *Sustain. Manuf. Serv. Econ.* **2023**, *2*, 100017. [CrossRef]
57. Vetrivel, S.; Sowmiya, K.C.; Sabareeshwari, V. Digital Twins: Revolutionizing Business in the Age of AI. In *Harnessing AI and Digital Twin Technologies in Businesses*; IGI Global: Hershey, PA, USA, 2024; pp. 111–131.
58. Yazdi, M. Digital twins and virtual prototyping for industrial systems. In *Advances in Computational Mathematics for Industrial System Reliability and Maintainability*; Springer: Cham, Switzerland, 2024; pp. 155–168.
59. Sahal, R.; Alsamhi, S.H.; Breslin, J.G.; Brown, K.N.; Ali, M.I. Digital twins collaboration for automatic erratic operational data detection in Industry 4.0. *Appl. Sci.* **2021**, *11*, 3186. [CrossRef]
60. Onaji, I.; Tiwari, D.; Soulatiantork, P.; Song, B.; Tiwari, A. Digital twin in manufacturing: Conceptual framework and case studies. *Int. J. Comput. Integr. Manuf.* **2022**, *35*, 831–858. [CrossRef]
61. Leng, J.; Chen, Z.; Sha, W.; Lin, Z.; Lin, J.; Liu, Q. Digital twins-based flexible operating of open architecture production line for individualized manufacturing. *Adv. Eng. Inform.* **2022**, *53*, 101676. [CrossRef]
62. Zhang, C.; Xu, W.; Liu, J.; Liu, Z.; Zhou, D.; Pham, D.T. Digital twin-enabled reconfigurable modeling for smart manufacturing systems. *Int. J. Comput. Integr. Manuf.* **2021**, *34*, 709–733. [CrossRef]
63. Jiang, Y.; Ding, Y.; Zhang, Y.; Wang, Y.; Wang, J. Industrial applications of digital twins. *Philos. Trans. A Math. Phys. Eng. Sci.* **2021**, *379*, 20200360. [CrossRef] [PubMed]
64. Vinci-Carlavan, G.; Rossit, D.; Toncovich, A. A digital twin for operations management in manufacturing engineering-to-order environments. *J. Manuf. Syst.* **2024**, *42*, 100679. [CrossRef]
65. Lugaresi, G.; Gangemi, S.; Gazzoni, G.; Matta, A. Online validation of digital twins for manufacturing systems. *Comput. Ind.* **2023**, *150*, 103942. [CrossRef]
66. Friederich, J.; Francis, D.P.; Lazarova-Molnar, S.; Mohamed, N. A framework for data-driven digital twins for smart manufacturing. *Comput. Ind.* **2022**, *136*, 103586. [CrossRef]

67. Leng, J.; Zhou, M.; Xiao, Y.; Zhang, H.; Liu, Q.; Shen, W.; Su, Q.; Li, L. Digital twins-based remote semi-physical commissioning of flow-type smart manufacturing systems. *J. Clean. Prod.* **2021**, *306*, 127278. [CrossRef] [PubMed]
68. Balakrishna, K.; Tiwari, V.; Deshpande, A.V.; Patil, S.R.; Garg, A.K.; Geetha, B.T. Computer vision for automated quality inspection in manufacturing. In Proceedings of the 2024 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI), Chennai, India, 9–10 May 2024; IEEE: New York, NY, USA, 2024.
69. Yu, H.Z.; Li, W.; Li, D.; Wang, L.J.; Wang, Y. Enhancing additive manufacturing with computer vision: A comprehensive review. *Int. J. Adv. Manuf. Technol.* **2024**, *132*, 5211–5229. [CrossRef]
70. Nascimento, R.; Martins, I.; Dutra, T.A.; Moreira, L. Computer vision based quality control for additive manufacturing parts. *Int. J. Adv. Manuf. Technol.* **2023**, *124*, 3241–3256. [CrossRef]
71. O'Donovan, C.; Giannetti, C.; Pleydell-Pearce, C.J. Revolutionising the sustainability of steel manufacturing using computer vision. *Procedia Comput. Sci.* **2024**, *232*, 1729–1738. [CrossRef]
72. Akhtar, S.; Martha, F. Quality Control in Retail and Manufacturing: Computer Vision Innovations for SME Operations. ResGate Preprint. 2024. Available online: https://www.researchgate.net/publication/386397839_Quality_Control_in_Retail_and_Manufacturing_Computer_Vision_Innovations_for_SME_Operations (accessed on 28 April 2025).
73. Ji, J.; Pannakkong, W.; Buddhakulsomsiri, J. A computer vision-based system for metal sheet pick counting. *Comput. Mater. Contin.* **2023**, *75*, 3643–3656. [CrossRef]
74. Deshpande, A.M.; Telikicherla, A.K.; Jakkali, V.; Wickelhaus, D.A.; Kumar, M.; Anand, S. Computer vision toolkit for non-invasive monitoring of factory floor artifacts. *Procedia Manuf.* **2020**, *48*, 1020–1028. [CrossRef]
75. Yousif, I.; Samaha, J.; Ryu, J.; Harik, R. Safety 4.0: Harnessing computer vision for advanced industrial protection. *Manuf. Lett.* **2024**, *41*, 1342–1356. [CrossRef]
76. Pivkin, P.; Nazarenko, E.; Grechishnikov, V.; Kuznetsov, V.; Uvarova, L.; Ershov, A.; Yazev, A.; Nadykto, A.; Onyusheva, I.; Markovich, D.; et al. Digital cyber-physical system for designing and manufacturing of conical end mill. *E3S Web Conf.* **2024**, *592*, 05024. [CrossRef]
77. Moretti, M.; Rossi, A.; Senin, N. In-process monitoring of part geometry in fused filament fabrication using computer vision and digital twins. *Addit. Manuf.* **2021**, *37*, 101609. [CrossRef]
78. Mahdi, M.M.; Sadeqi Bajestani, M.; Noh, S.D.; Kim, D.B. Digital twin-based architecture for wire arc additive manufacturing using OPC UA. *Robot. Comput. Integr. Manuf.* **2025**, *94*, 102944. [CrossRef]
79. Humphries, J.; Van de Ven, P.; Amer, N.; Nandeshwar, N.; Ryan, A. Managing safety of the human on the factory floor: A computer vision fusion approach. *Technol Sustain.* **2024**, *3*, 309–331. [CrossRef]
80. Jakhotiya, Y.; Rahul, M.R.; Chiddarwar, S.S. Integrating digital twin and computer vision system for efficient pick-and-place operation using Tecnomatix Process Simulate. *Int. J. Interact. Des. Manuf.* **2024**, *18*, 7429–7443. [CrossRef]
81. Xiang, T.; Li, B.; Zhang, Q.; Leach, M.; Lim, E.G. A novel approach to grasping control of soft robotic grippers based on digital twin. In Proceedings of the 29th International Conference on Automation and Computing (ICAC), Sunderland, UK, 28–30 August 2024.
82. Haponik, A. Digital Twin—Computer Vision Use Case. Addepto Blog. 2024. Available online: https://addepto.com/blog/digital-twin-computer-vision-use-case/ (accessed on 27 August 2025).
83. Touhid, M.T.B.; Zhu, E.; Ehteshamfara, M.V.; Yang, S. Evaluation of digital twin synchronization in robotic assembly using YOLOv8. *Int. J. Adv. Manuf. Technol.* **2024**, *134*, 871–885. [CrossRef]
84. Sow, M.C.; Assila, A.; Garcia, D.; Martinez, S.; Zghal, M.; Baudry, D. Towards the development of a digital twin for micro learning factory: A proof of concept. In *Extended Reality: International Conference, XR Salento 2023, Lecce, Italy, 6–9 September 2023, Proceedings, Part I*; Lecture Notes in Computer Science; Springer: Cham, Switzerland, 2023; Volume 14218, pp. 284–298.
85. Busch, R. Explore Digital Twins Accelerated by NVIDIA Omniverse. NVIDIA. 2024. Available online: https://www.nvidia.com/en-us/learn/learning-path/digital-twins/ (accessed on 27 August 2025).
86. Hohenstein, J. BMW to Work Globally on Vehicle Virtual Twins with Data-Driven Approach. Metrology and Quality News. 2024. Available online: https://metrology.news/bmw-to-work-globally-on-vehicle-virtual-twins-with-data-driven-approach/ (accessed on 27 August 2025).
87. Sauerwein, D.; Winterholer, M.; Boehmer, S.; Perez Hallerbach, I. Using Computer Vision to Enable Digital Building Twins with NavVis and AWS. AWS Partner Network Blog. 2023. Available online: https://aws.amazon.com/blogs/apn/using-computer-vision-to-enable-digital-building-twins-with-navvis-and-aws/ (accessed on 27 August 2025).
88. Akkila, J. Production and Maintenance Operations in Real Time on the 3D Digital Twin Platform. Process Genius/Konecranes. 2021. Available online: https://processgenius.eu/konecranes/ (accessed on 27 August 2025).
89. Detectium. Leveraging Digital Twins and Artificial Intelligence. Detectium.io. 2023. Available online: https://next.detectium.io/ (accessed on 27 August 2025).
90. Koerte, P. Siemens Unveils Breakthrough Innovations in Industrial AI and Digital Twin Technology. Siemens Press Release. 2025. Available online: https://press.siemens.com/global/en/pressrelease/siemens-unveils-breakthrough-innovations-industrial-ai-and-digital-twin-technology-ces (accessed on 27 August 2025).

91. Akundi, A.; Euresti, D.; Luna, S.; Ankobiah, W.; Lopes, A.; Edinbarough, I. State of Industry 5.0—Analysis and identification of current research trends. *Appl. Syst. Innov.* **2022**, *5*, 27. [CrossRef]
92. Heizer, J.; Render, B. *Operations Management*, 7th ed.; Pearson Prentice Hall: Saddle River, NJ, USA, 2003; p. 29.
93. Cristofoletti, M.; Emrith, K.; Elsaddik, A.; Karray, F. Towards a computer vision-based approach for digital twin implementation. In Proceedings of the 2023 International Conference on Intelligent Metaverse Technologies & Applications (iMETA), Tartu, Estonia, 18–20 September 2023; IEEE: New York, NY, USA, 2023.
94. Liu, J.; Huang, I.; Anand, A.; Chang, P.-H.; Huang, Y. Digital twin in retail: An AI-driven multi-modal approach for real-time product recognition and 3D store reconstruction. In Proceedings of the 2024 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW), Orlando, FL, USA, 16–21 March 2024; IEEE: New York, NY, USA, 2024. [CrossRef]
95. Urgo, M.; Terkaj, W.; Simonetti, G. Monitoring manufacturing systems using AI: A method based on a digital factory twin to train CNNs on synthetic data. *CIRP J. Manuf. Sci. Technol.* **2024**, *50*, 249–268. [CrossRef]
96. Çapunaman, Ö.B.; Farrokhsiar, P.; Bilén, S.G.; Duarte, J.P.; Gürsoy, B. Vision-based sensing and digital twin technologies in conformal 3D concrete printing. *Constr. Robot.* **2025**, *9*, 4. [CrossRef]
97. Stürmer, J.M.; Graumann, M.; Koch, T. Demonstrating automated generation of simulation models from engineering diagrams. In Proceedings of the 2023 IEEE International Conference on Machine Learning and Applications (ICMLA), Jacksonville, FL, USA, 15–17 December 2023; IEEE: New York, NY, USA, 2023. [CrossRef]
98. Oyekan, J.; Farnsworth, M.; Hutabarat, W.; Miller, D.; Tiwari, A. Applying a 6 DoF robotic arm and digital twin to automate fan-blade reconditioning for aerospace maintenance, repair, and overhaul. *Sensors* **2020**, *20*, 4637. [CrossRef]
99. Sousa, T.; Ibusuki, U.; Del Conte, E. Development of a digital twin for spot welding quality inspection in an Industry 4.0 testbed of a Brazilian university. In Proceedings of the 12th Conference on Learning Factories (CLF 2022), Singapore, 11–13 April 2022.
100. Doroszuk, B.; Bortnowski, P.; Ozdoba, M.; Król, R. Calibrating the Digital Twin of a Laboratory Ball Mill for Copper Ore Milling: Integrating Computer Vision and Discrete Element Method and Smoothed Particle Hydrodynamics (DEM-SPH) Simulations. *Minerals* **2024**, *14*, 407. [CrossRef]
101. Döbrich, O.; Brauner, C.J.F. Machine vision system for digital twin modeling of composite structures. *Front. Mater.* **2023**, *10*, 1154655. [CrossRef]
102. Weckx, S.; Meyers, B.; Jordens, J.; Robyns, S.; Baake, J.; Lietaert, P.; De Geest, R.; Maes, D. Development and deployment of a digital twin for monitoring of an adaptive clamping mechanism, used for high performance composite machining. *IET Collab. Intell. Manuf.* **2022**, *4*, 112–122. [CrossRef]
103. Aiken, W.; Carden, L.; Bhabhrawala, A.; Branco, P.; Jourdan, G.V.; Berg, A. Strategic digitalization in oil and gas: A case study on mixed reality and digital twins. *IEEE Access* **2024**, *12*, 87248–87267. [CrossRef]
104. Yi, S.; Wu, Y.; Li, J.; Zhang, C.; Zhou, H. A vision-based human–robot collaborative system for digital twin. *Procedia CIRP* **2022**, *107*, 552–557. [CrossRef]
105. Arbabian, A.; Pezeshk, A.; Yang, K. Productivity enhancement in semiconductor manufacturing with AI-enabled operations digital twin platform. In Proceedings of the 2024 19th International Microsystems, Packaging, Assembly and Circuits Technology Conference (IM-PACT), Taipei, Taiwan, 22–25 October 2024; IEEE: New York, NY, USA, 2024.
106. Rivera-Calderón, S.; Pérez-San Lázaro, R.; Vazquez-Hurtado, C. Online assessment of computer vision and robotics skills based on a digital twin. In Proceedings of the 2022 IEEE Global Engineering Education Conference (EDUCON), Tunis, Tunisia, 28–31 March 2022; IEEE: New York, NY, USA, 2022. [CrossRef]
107. Cheng, D.; Liu, Y.; Zhang, Y.; Han, J.; Zhang, W. A digital twin-driven guidance method for human–machine collaborative assembly operations based on machine learning and computer vision. In Proceedings of the 2024 International Conference on Networking, Sensing and Control (ICNSC), Hangzhou, China, 18–20 October 2024; IEEE: New York, NY, USA, 2024. [CrossRef]
108. Kovari, A.J. A framework for integrating vision transformers with digital twins in Industry 5.0 context. *Machines* **2025**, *13*, 36. [CrossRef]
109. Legaz, M.J.G.; Gaspar, H.M. Computer vision for reverse engineering in the design, simulation and operation of maritime systems. In Proceedings of the 38th ECMS International Conference on Modelling and Simulation (ECMS 2024), Cracow, Poland, 4–7 June 2024; European Council for Modelling and Simulation: Ostend, Belgium, 2024. [CrossRef]
110. Ward, R.; Soulatiantork, P.; Finneran, S.; Hughes, R.; Tiwari, A. Real-time vision-based multiple object tracking of a production process: Industrial digital twin case study. *Proc. Inst. Mech. Eng. Part B J. Eng. Manuf.* **2021**, *235*, 1861–1872. [CrossRef]
111. Ullah, A.; Younas, M.; Saharudin, M.S. Digital twin framework using real-time asset tracking for smart flexible manufacturing system. *Machines* **2025**, *13*, 37. [CrossRef]
112. Zhang, S. Application of computer vision 3D imaging sensing technology in GIS high-voltage power bushing gas composition detection and its device development. In Proceedings of the 2023 8th International Conference on Image, Vision and Computing (ICIVC), Dalian, China, 27–29 July 2023; IEEE: New York, NY, USA, 2023.
113. Pila, L.D. Image processing in digital twin solutions: A technical overview. *Int. J. Comput. Eng. Technol.* **2025**, *16*, 339–350. [CrossRef]

114. Kozin, E. Operational management of production for car maintenance and repair using digital twin technology. In *The Future of Industry: Human-Centric Approaches in Digital Transformation*; Springer: Cham, Switzerland, 2024; pp. 205–218.
115. Pavlosky, S. How Can Smart Factories Use Digital Twins to Learn and Test Before Deploying in a Real-World Environment. GE Vernova Blog. 2025. Available online: https://www.gevernova.com/software/blog/how-digital-twin-simulation-software-improves-manufacturing-operations (accessed on 27 August 2025).
116. Nvidia. Amazon Robotics Deploys First Fully Autonomous Robot with NVIDIA Isaac Sim. YouTube. 2023. Available online: https://www.youtube.com/watch?v=LUnZXBL_lqA (accessed on 27 August 2025).
117. Vimaan. The Role of Computer Vision in a Warehouse Digital Twin. Vimaan Blog. 2025. Available online: https://vimaan.ai/resources/blog/warehouse-digital-twin-explained/ (accessed on 27 August 2025).
118. Shyalika, C.; Prasad, R.; Jaimini, U.; Henson, C.; El Kalach, F.; Sheth, A. Multiagent CoPilot in industrial AI applications. In Proceedings of the 24th Int Conf Autonomous Agents and Multiagent Systems (AAMAS), Detroit, MI, USA, 19–23 May 2025.
119. National Ocean Channel. Industrial Digital Twins for Simulating Robot Fleets. YouTube. 2022. Available online: https://www.youtube.com/watch?v=IuWk0C3MzBQ (accessed on 27 August 2025).
120. Zheng, O.; Abdel-Aty, M.; Yue, L.; Abdelraouf, A.; Wang, Z.; Mahmoud, N. CitySim: A drone-based vehicle trajectory dataset for safety-oriented research and digital twins. *Transp. Res. Rec.* **2024**, *2678*, 606–621. [CrossRef]
121. Ghosh, A.; Acharya, A.; Saha, S.; Jain, V.; Chadha, A. Exploring the frontier of vision–language models: A survey of current methodologies and future directions. *arXiv* **2024**, arXiv:2404.07214.
122. *ISO 9001:2015*; Quality Management Systems—Requirements. International Organization for Standardization: Geneva, Switzerland, 2015.
123. *ISO 14001:2015*; Environmental Management Systems—Requirements with Guidance for Use. International Organization for Standardization: Geneva, Switzerland, 2015.
124. Heras-Saizarbitoria, I.; Boiral, O. ISO 9001 and ISO 14001: Towards a research agenda on management system standards. *Int. J. Manag. Rev.* **2013**, *15*, 47–65. [CrossRef]
125. Kandie, C.J. Effect of ISO 9001:2008 Standard Certifications on Sustainable Performance of Kenyan Public Universities. Master's Thesis, University of Eldoret, Eldoret, Kenya, 2019.
126. Sundby, T.; Graham, J.M.; Rasheed, A.; Tabib, M.; San, O. Geometric change detection in digital twins using 3D machine learning. *Digital* **2021**, *1*, 111–129. [CrossRef]
127. Webb, A.M.; Brown, G.; Luján, M. ORB-SLAM-CNN: Lessons in adding semantic map construction to feature-based SLAM. In Proceedings of the Annual Conference Towards Autonomous Robotic Systems, London, UK, 3–5 July 2019; Springer: Cham, Switzerland, 2019; pp. 221–235.