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Systematic Review

Digital Twins, Extended Reality, and Artificial Intelligence in Manufacturing Reconfiguration: A Systematic Literature Review

Anjela Mayer [1,*], Lucas Greif [1], Tim Markus Häußermann [2], Simon Otto [3], Kevin Kastner [2], Sleiman El Bobbou [1], Jean-Rémy Chardonnet [4], Julian Reichwald [2], Jürgen Fleischer [3] and Jivka Ovtcharova [1]

[1] Institute for Information Management in Engineering, Karlsruhe Institute of Technology, 76133 Karlsruhe, Germany; lucas.greif@kit.edu (L.G.); sleiman.bobbou@kit.edu (S.E.B.); jivka.ovtcharova@kit.edu (J.O.)
[2] Virtual Engineering Competence Center, Mannheim University of Applied Sciences, 68163 Mannheim, Germany; t.haeussermann@hs-mannheim.de (T.H.); k.kastner@hs-mannheim.de (K.K.); j.reichwald@hs-mannheim.de (J.R.)
[3] Wbk Institute of Production Science, Karlsruhe Institute of Technology, 76131 Karlsruhe, Germany; simon.otto@kit.edu (S.O.); juergen.fleischer@kit.edu (J.F.)
[4] Arts et Metiers Institute of Technology, LISPEN, 71100 Chalon-sur-Saône, France; jean-remy.chardonnet@ensam.eu
* Correspondence: anjela.mayer@kit.edu

Abstract: This review draws on a systematic literature review and bibliometric analysis to examine how Digital Twins (DTs), Extended Reality (XR), and Artificial Intelligence (AI) support the reconfiguration of Cyber–Physical Systems (CPSs) in modern manufacturing. The review aims to provide an updated overview of these technologies' roles in CPS reconfiguration, summarize best practices, and suggest future research directions. In a two-phase process, we first analyzed related work to assess the current state of assisted manufacturing reconfiguration and identify gaps in existing reviews. Based on these insights, an adapted PRISMA methodology was applied to screen 165 articles from the Scopus and Web of Science databases, focusing on those published between 2019 and 2025 addressing DT, XR, and AI integration in Reconfigurable Manufacturing Systems (RMSs). After applying the exclusion criteria, 38 articles were selected for final analysis. The findings highlight the individual and combined impact of DTs, XR, and AI on reconfiguration processes. DTs notably reduce reconfiguration time and improve system availability, AI enhances decision-making, and XR improves human–machine interactions. Despite these advancements, a research gap exists regarding the combined application of these technologies, indicating potential areas for future exploration. The reviewed studies recognized limitations, especially due to diverse study designs and methodologies that may introduce risks of bias, yet the review offers insight into the current DT, XR, and AI landscape in RMS and suggests areas for future research.

Keywords: reconfigurable manufacturing systems; digital twins; extended reality; artificial intelligence; human–machine interaction; cyber–physical systems

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1. Introduction

In recent years, the manufacturing industry has faced numerous challenges, including global pandemics, delivery shortages, and climate change [1]. Concurrently, product life cycles are becoming shorter, and there is an increasing demand for highly customized products [2]. These challenges and demands necessitate greater adaptability within manufacturing systems. Reconfigurable Manufacturing Systems (RMSs) offer a solution to this need. Initially proposed by [3]. RMSs present manufacturing systems designed to rapidly adapt their structure and control to meet changing demands and requirements [4,5]. In order to enable advanced RMS functions, Cyber–Physical Systems (CPSs) are applied. CPSs integrate physical components with data models and services by connecting the physical and digital worlds [6].

While RMSs have been integrated into the manufacturing industry, they continue to face significant challenges in the reconfiguration of production setups. These challenges include the need for more efficient reconfiguration procedures, reduced downtime during reconfiguration, and enhanced operator support during the process. Reconfiguration processes often involve mechanical, electrical, and software changes, typically performed by experts without methodological support, making the processes time-consuming and error-prone [7]. Advanced technologies such as Artificial Intelligence (AI), Digital Twins (DTs), and Extended Reality (XR) offer promising solutions to these challenges.

Various industries face increasing demands for highly customized products, creating the need for more sustainable and adaptable manufacturing systems, which has become critical [8]. The integration of AI, DT, and XR has transformative potential for manufacturing systems, enabling improvements in sustainability and adaptability [9,10]. For example, AI can optimize production workflows through predictive analytics and real-time decision-making [11], while DTs can provide dynamic virtual replicas of physical assets, enabling real-time monitoring and simulation [12]. XR technologies, including Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), can enhance human–machine interactions by providing intuitive interfaces and immersive environments [13]. Together, these technologies reduce resource consumption, improve operational efficiency, and enable sustainable manufacturing practices by minimizing waste and optimizing energy use.

The attainment of sustainable development goals (SDGs) within the manufacturing sector necessitates the implementation of groundbreaking methodologies that seamlessly incorporate advanced technologies alongside sustainability targets [14]. The valuable insights derived from these technologies empower manufacturers to make data-driven decisions aimed at minimizing energy use and emissions [15]. This alignment of production processes not only supports SDG 12, which emphasizes Responsible Consumption and Production, but also fortifies efforts toward achieving SDG 9, focusing on Industry, Innovation, and Infrastructure.

Despite their potential, research on the combined application of DT, XR, and AI in RMSs remains fragmented. While individual technologies have demonstrated their efficacy in specific domains [16], the synergistic benefits of integrating these technologies to address reconfiguration challenges are underexplored [17]. This gap underscores the need for comprehensive frameworks that bridge these technologies to create adaptive, sustainable, and efficient manufacturing systems. Addressing this gap is critical for advancing interdisciplinary research that supports sustainable development across industries.

1.1. Key Technologies in Reconfiguration of MS

In order to achieve seamless reconfiguration in manufacturing, several enabler technologies need to be considered, which include DTs, XR, and AI.

The concept of the DT was first introduced by Grieves in 2002. It describes a virtual representation named DT of a physical asset called a Physical Twin (PT). DTs and PTs share a unique bidirectional connection to exchange data and mirror each other's conditions and behavior in real-time [18]. DTs are dynamic virtual replicas of their physical counterparts, enabling the monitoring and simulation of real-world scenarios by replicating (either fully or partially) the state, functionality, and behavior of the physical entity. Michal Grieves introduced the three-dimension model of the DT in context of the PLM. This model of the

DT consists of the physical entity, the virtual representation, and the connection of both entities to each other. In current research, this model is extended to a five-dimensional model, adding the two dimensions: the data and service layer.

DTs have shown promise in reducing the reconfiguration time by up to 58%, increasing system availability, and enabling the manufacturing of customer-specific products [19]. ElMaraghy et al. [20] described the current evolutionary phase of manufacturing systems as being supported by Cognitive Digital Twins, which go beyond traditional DTs by enabling interconnected and adaptive systems with embedded sensors and software. Cognitive DTs represent a paradigm shift in human–machine interaction, facilitating interactions with increasingly intelligent and complex machines.

XR is an umbrella term that encompasses all immersive technologies, including Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). These technologies can be differentiated by their degree of immersion and interaction with the virtual and real worlds. AR enhances the real environment with digital overlays, MR allows virtual objects to coexist within and interact with the real world, and VR offers a completely immersive virtual experience that disconnects the user from the physical environment [21]. Within RMSs, XR technologies are increasingly relevant as they blend the digital and physical world, enable natural interaction with DTs, and support DT and AI models with operator data.

XR technologies have matured, offering intuitive possibilities for human–machine interaction, such as hand gesture recognition and tactile feedback mechanisms [22,23]. This technology provides interactive digital content to users with a high degree of immersion.

In our context, AI refers to computational techniques that enable machines to analyze data and make intelligent decisions autonomously. In reconfigurable manufacturing, AI leverages data generated by the DT and XR interfaces to optimize production workflows. By processing these data, AI algorithms can identify patterns, predict system failures, and recommend optimal reconfiguration strategies. This integration enhances RMSs by enabling predictive maintenance [24], streamlining production schedules [25,26], and supporting real-time decision-making [27]. Ultimately, AI makes RMSs more adaptive, efficient, and responsive to dynamic production demands [27,28].

The integration of AI, DT, and XR has significant potential to improve reconfiguration processes, as outlined in Figure 1. Recent advancements in Digital Engineering emphasize the role of these technologies in enabling real-time monitoring, predictive analytics, and simulation-driven decision-making [29]. For instance, the integration of AI and DTs has the potential to enhance system flexibility, efficiency, and automation, providing a broader perspective on their application in reconfigurable manufacturing. However, current research often focuses on individual technologies rather than their combined applications. Therefore, it is critical to elucidate how these technologies impact reconfiguration in manufacturing. Future DTs will serve not only as an accurate digital representation, but also as an intelligent companion to the physical system, incorporating AI, Machine Learning (ML), big data analysis, IoT, and smart sensors throughout their life cycle [20]. Combined with XR, such systems can provide a more intuitive interface for human workers, allowing faster analysis, on-the-fly emulation, and the methodological validation of reconfiguration possibilities.

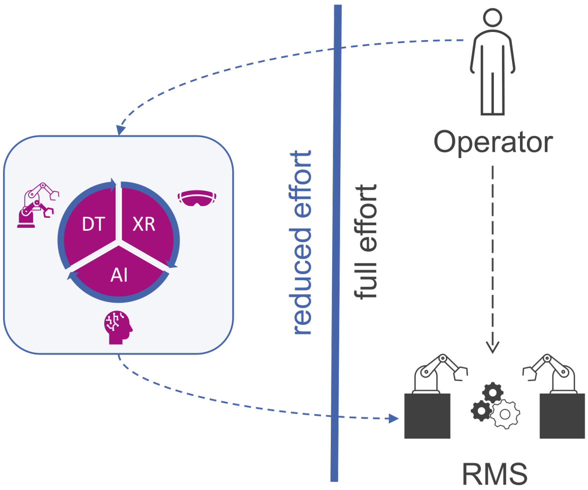

Figure 1. DT, XR, and AI in RMS.

1.2. Definitions

Mass Customization: This concept centers on the capability to meet diverse customer demands for product variety and customization without a proportional increase in cost or lead time [30].

RMS: RMSs, first proposed by Koren et al. (1998), are manufacturing systems designed for rapid adjustments in structure and control to respond to fluctuating market demands. RMSs differ from flexible manufacturing systems by emphasizing responsiveness within product families over expanding part variety, allowing for swift alignment with evolving requirements (Koren et al., 1998; Yang et al., 2022) [4], and "can rapidly adjust its structure and production configurations to meet new production requirements" [5].

CPSs: Cyber–Physical Systems (CPSs), integrate physical components, data models, and services for real-time data exchange and processing, linking the physical and digital realms to enable advanced RMS functions [6]. For reconfigurability within RMS, CPS requires both digital and physical adaptations, which increases the complexity and necessitates Cyber–Physical adaptation assistance.

DT: A Digital Twin (DT) consists of synchronized digital representations of physical assets within RMSs, encompassing (a) physical entities, (b) virtual counterparts, and (c) a connection layer that maintains alignment between physical and digital entities. DTs enable real-time monitoring, predictive modeling, and simulation, reducing reconfiguration time and enhancing system adaptability [31].

The process of creating a DT consists in general of three main steps: the Mirroring, the Shadowing and the Threading. The Mirroring step describes the virtual representation of the physical product. The physical product includes geometrical features as well as functionalities and behavioral dynamic properties. The shadowing step represents the connection between the virtual and the physical product.

XR: Extended Reality (XR) encompasses immersive technologies such as Augmented Reality (AR), Virtual Reality (VR), and Mixed Reality (MR), which enable enhanced interaction between physical and digital spaces within RMSs. According to Milgram's reality–virtuality continuum, XR technologies range from purely physical environments augmented with digital information (AR) to fully immersive digital environments (VR), with MR enabling a blend of both. In RMSs, XR supports real-time visualization, simulation, and control, providing intuitive interfaces that assist operators in complex reconfiguration tasks and enhance human–machine interaction [21].

AI: Artificial Intelligence (AI) pertains to the ability of machines, especially computer systems, to perform tasks that normally require human intellect. These tasks include learning from experience, understanding natural language, recognizing patterns, and making decisions [32].

To maintain simplicity and consistency, in this study, we will use the term AI as a collective reference to various related computational methods. This includes terms such as Machine Learning or Deep Learning, which are considered to be subcategories of AI [33].

1.3. Research Aim

The rapid advancement of DTs, XR, and AI has opened new possibilities for RMSs. These technologies offer significant potential to improve flexibility, efficiency, and responsiveness in manufacturing processes. By systematically reviewing the current state of research, this article aims to identify how these technologies are being implemented, the benefits they provide, and the challenges faced in their integration. In addition, the review aims to highlight innovative approaches and propose future research directions to further advance this field. To address these goals, the following research questions are formulated:

RQ1: *How are DTs, XR, and AI being utilized, individually and in synergy, to enhance reconfiguration processes in RMSs?*

RQ2: *Which specific role do DTs, XR, and AI technologies play in supporting human operators during RMS reconfiguration?*

RQ3: *How can future advancements in DTs, XR, and AI further improve reconfiguration processes in RMSs?*

Therefore, this paper contributes to the understanding of how DTs, XR, and AI are used to enhance reconfiguration processes in RMS (RQ1); tgus involves examining their practical applications, both individually and combined, as well as their integration into existing systems. This includes identifying specific benefits such as improved process simulation, real-time monitoring, and predictive maintenance. The role these technologies play in supporting human operators (RQ2) is crucial, particularly in improving human–machine interactions, training efficiency, and decision-making during reconfiguration tasks. The future potential of these technologies (RQ3) will also be explored, focusing on advancements that can improve their integration and effectiveness in adaptive manufacturing systems.

The rest of the article is structured as follows. Section 2.1 evaluates the state-of-the-art and related literature reviews on the topic of reconfiguration and the research aim, questions, and contribution. The methodology used is described in Section 2.2. A detailed overview of the initial results is given in Section 3 and is followed by the analysis results in Section 4. Section 4.5 evaluates and discusses the results. Finally, the paper discusses some limitations and explores directions for future research in Section 5 and gives a conclusion of the literature review in Section 6.

2. Methodology

The literature review methodology consists of two main phases. In the first phase, a structured analysis of existing review articles on RMS was conducted to identify relevant contributions and assess potential research gaps in the integration of AI, DT, and XR for reconfiguration optimization.

In the second phase, a systematic literature review following the PRISMA approach was performed to identify and analyze primary research articles proposing specific solutions for RMS reconfiguration. As part of this process, further review articles were identified that were excluded from further analysis due to exclusion criteria but were retrospectively incorporated into the related work from the first phase. This ensured a more comprehensive examination of prior work and further refined the identification of research gaps. The results of the second phase are presented in Section 4, while the following Section 2.1 presents the findings of the first phase.

2.1. Related Work

A search of the academic literature was conducted to specifically identify reviews on RMS, with a particular focus on the role of AI, DT, and XR technologies in optimizing reconfiguration processes. The search was conducted in the Scopus Web of Science digital libraries with the search keys including Reconfigurable Manufacturing Systems and review and resulted in $N = 45$ review articles between 2017 and 2025. Retrospectively, $N = 9$ more articles were added that were found with the PRISMA approach and classified as review articles. However, many of the identified reviews were found to be only loosely related or not relevant to this specific topic. The identified reviews were screened and classified into four categories:

- not related: Articles containing search keys *"Reconfigurable Manufacturing System"* and *"Review"* without adding to this topic.
- partially related: Articles with a focus on RMSs but not on AI, XR or DT.
- related : Articles addressing one of the technologies AI, DT, or XR within the RMS context.
- very related: Articles addressing at least two of the technologies AI, XR, and DT within the RMS context.

The distribution of identified articles among these categories is depicted in Figure 2 and Table 1 provides representative examples of the reviewed articles.

Table 1. Summary of the most significant related work.

Title	Category	Main Reason
Napoleone et al. [34]	Very Related	Comprehensive review of AI, DT, and XR in reconfigurable manufacturing.
Napoleone et al. [35]	Very Related	Analyzes enablers such as AI, DT, and XR for reducing reconfiguration effort.
Leng et al. [36]	Very Related	Discusses XR and AI as key technologies for DT-based smart manufacturing.
Caesar et al. [37]	Related	Examines DTs for reconfiguration, but lacks broader RMS discussion.
Yelles-Chaouche et al. [38]	Related	Covers optimization in RMS, but AI and DT only mentioned in the outlook (and XR not at all).
Brahimi et al. [39]	Partially Related	Focuses on optimization, but does not discuss AI, DT, or XR.
Naz et al. [40]	Not Related	Discusses production repurposing, not manufacturing reconfiguration.
Zidi et al. [41]	Not Related	Focuses on supply chain reconfiguration, not manufacturing.

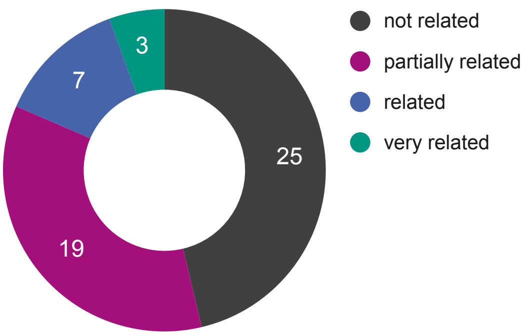

Figure 2. Results for Reconfigurable Manufacturing System reviews by their relevance in the context of this work.

2.1.1. Not Related Articles

Several articles ($N = 25$) addressed RMS-related topics but were classified as non-relevant, covering areas such as wireless and satellite communication antennas, supply chain networks and reconfiguration, production repurposing, sustainable or green RMSs, transition toward Industry 5.0, process planning, risk management, movable factories, reconfigurable steel structures, material processing, construction, agriculture and farming, and construction. Although these topics touched on aspects of manufacturing flexibility, they did not explore reconfigurability or reconfiguration within manufacturing systems.

2.1.2. Partially Related Articles

Some articles ($N = 19$) were identified as partially related. These reviews discussed RMS-related topics but did not integrate the role of AI, DT, or XR in optimizing reconfiguration. In contrast, some explored these technologies in manufacturing but did not specifically focus on reconfiguration optimization. Examples included topics such as wireless multirobot task assignment, which focused on robotic coordination but did not address reconfiguration optimization in RMSs [42]; cellular and modular manufacturing systems, which were not considered RMSs in this context [43,44]; RMS optimization, where the emphasis was on general system performance rather than reconfigurability [45]; and qualification requirements, management, and economic perspectives and disruption of RMSs, which discussed broader operational factors but did not engage with the technological optimization of reconfiguration [46–49]. Topics such as production process planning, specific machine reconfiguration, and CPS programming approaches were limited to specific technical setups without addressing system-wide reconfiguration [50–52].

One paper provides an in-depth review of RMS architectures and optimization techniques, while another categorizes optimization KPIs in RMS into four categories: process planning, layout design, reconfigurability, and planning and scheduling [39,53]. However, neither review includes AI, DT, or XR methods in their analysis and discussion.

A study investigating service-oriented DT in smart factories presents a framework for real-time knowledge access and decision-making support using DT and AR [54]. The service-oriented DT acts as an interface between Cyber–Physical Production Systems (CPPSs) and human operators, delivering real-time insights to enhance predictive maintenance, process optimization, and production setup efficiency. While these technologies improve operational performance, the study does not explore their role in optimizing reconfiguration processes or RMS.

In some cases, AI, DT, or XR technologies were briefly mentioned, but it not was discussed how they contribute to reconfiguration optimization. AI, DTs, and XR are usually listed among emerging technologies for Industry 4.0, where DTs act as connectors between a virtual simulation and its physical system [44,55–57]. Meanwhile, XR plays a role in human interaction with the physical system or its DT in real-time and improves changeability [58,59].

2.1.3. Related Articles

Several works ($N = 7$) were identified as directly relevant to the optimization of RMS, specifically addressing the role of DT, AI, and XR in improving reconfiguration processes.

A recent paper proposes a framework that uses DT as a management approach for reconfiguration, with the aim of improving operator support while offering a more comprehensive solution to the reconfiguration process [37]. Through a systematic literature review, both functional and non-functional requirements were identified. Functional requirements include operator support, customized optimization, reconfiguration trigger strategies, and a dynamically updated reconfiguration space. Meanwhile, the nonfunctional requirements emphasize solution neutrality, detailed task descriptions, clear definitions of reconfiguration tasks, and modularity. However, while the framework offers significant insight, it does not fully address the potential applications of AI and XR technologies. ML is briefly mentioned as a possible tool for estimating reconfiguration time using real-time data, but its integration remains unexplored in the current scope of the framework.

Similarly, another review highlights DTs as an emerging technology that supports real-time decision-making by continuously collecting, processing, and analyzing data to provide optimized decisions aimed at maximizing performance [38]. The authors suggest further research on how DTs can be applied in RMS configuration design and reconfiguration planning to enhance the adaptability and responsiveness of the system to market changes. Another review identifies the potential of DTs to improve the reliability of reconfiguration management [60]. However, a gap in holistic approaches that comprehensively integrate DTs to manage reconfiguration processes in manufacturing environments is emphasized.

The integration of DTs in the evaluation of RMSs is also considered in a separate review [61]. DTs enable the modeling of Programmable Logic Controller (PLC) operations, with a distinction proposed between entity DT and scenario DT. DTs are highlighted for their ability to automate reconfiguration, accelerate RMS responses to changing requirements, and conduct resilience analysis. In addition, DTs facilitate open reconfigurable architectures to support assembly line reconfiguration and can be used for optimization analysis, allowing rapid changes in manufacturing capacity and the integration of multiple processes into existing systems. However, several research gaps are noted, such as the fact that most DT models currently focus only on geometrical representations, with the limited modeling of behavior or consumption. Furthermore, data transmission capacities do not currently meet the accuracy and real-time requirements of DTs. AI and ML are suggested as potential tools to improve real-time evaluation, automate diagnostics and monitoring, and improve data acquisition and processing. However, XR technologies are not mentioned in this context.

In another study, the focus shifts to automating manufacturing steps to improve the feasibility of RMSs for Small and Medium-sized Enterprises (SMEs) in the control and switchgear production sector [62]. This research highlights the potential for AI and ML to automate manufacturing station reconfigurations, particularly in human–robot collaboration scenarios. By capturing human motions and predicting robot movements, the system facilitates collaboration and improves the adaptability of robots, optimizing processes such as collision prevention and task efficiency.

Another review investigates the application of AI and meta-heuristic optimization in the design and configuration of RMSs [63]. The study explores how different approaches with genetic algorithms, simulated annealing, and particle swarm optimization improve process planning, scheduling, and system configuration selection, with a focus on modularity, scalability, and integrability. Although the review provides insights into AI-driven RMS design, it does not address real-time reconfiguration processes or the integration of DT and XR technologies.

A review focusing on the human role in RMS emphasizes the collaboration between humans and robots as a recognized tool within the paradigm of changeability [64]. The literature review concludes that operators are widely regarded as key contributors to the flexibility of a manufacturing system. However, much of the research places greater emphasis on performance, safety, and ergonomics, with limited attention given to the operator's broader role. This indicates a need for further exploration of the role of the operator in changeable manufacturing systems, which is why this topic is included in our review.

2.1.4. Very Related Articles

Finally, $N = 3$ reviews were found to be particularly relevant, as they thematize the three technologies, DT, AI, and XR, within the context of RMSs.

DTs are the focus of a review, where they are considered an emerging technology that reduces the time and cost of physical reconfiguration by enabling semiphysical simulations during the design phase of smart manufacturing systems [36]. XR and industrial AI methods are mentioned as key enabling technologies for DT-based systems. AI, particularly ML, complements DTs to form smart Digital Twins. Deep Learning is presented as one of the most promising AI technologies for simulating and extending human intelligence to handle random occurrences in manufacturing. The review suggests that advanced industrial AI may, in the future, automatically generate new design solutions. XR is identified as a potential interface for human–computer interaction, supporting DT simulations, facilitating immersive robot path planning in AR, and facilitating immersive planning, monitoring, and optimization of manual work. In summary, DTs are seen as a key technology to improve reconfiguration in manufacturing, AI improving their capabilities for optimization and prediction, and XR providing a promising interface for interacting with these intelligent DTs.

Another review focuses on reconfigurability enablers in human-centric RMSs, emphasizing the integration of DTs, AI, and XR to reduce the reconfiguration effort [35]. The review outlines three key components of the reconfiguration effort: reconfiguration cost, reconfiguration time, and ramp-up time—the time taken by the system to reach a normal production state after reconfiguration. In addition to physical enablers, such as adjustable layouts, logical enablers such as DTs, AI, and XR play a critical role in supporting operators during reconfiguration. DTs for both products and RMSs enable the design and analysis of configurations with minimal effort, significantly reducing the reconfiguration effort. Human–machine interfaces (HMIs) support the dynamic acquisition of context-relevant information, with VR helping to reduce ramp-up time by simulating configurations or tracking operators during reconfiguration execution, providing real-time support and guidance. The review also highlights the importance of standardized software and hardware components in enabling decentralized control architectures, which further reduce the reconfiguration effort. HMIs allow bidirectional feedback loops between the RMS and the operator, allowing operators to report problems and ML algorithms to automate problem detection and machine reprogramming. This combination of sensory devices and ML facilitates real-time decision-making and rapid responses during ramp-up. Additionally, HMIs such as AR provide guidance during task execution, while ML can integrate operator experience and context-related information to support reconfiguration. In this context, VR and digital feedback improve operator training, allowing them to quickly adapt to new tasks.

Finally, an article by the same authors discusses how CPS technologies support reconfigurability capability in RMSs [34]. The reconfigurability characteristics defined include modularity, integrability, diagnosability, scalability, convertibility, and customization, and the article discusses how these can be enabled. Seven classes of CPS technologies are identified, with AI, DT, and XR grouped into distinct but complementary categories. One class focuses on simulation, AI, and ML for data storage, data analytics, and knowledge extraction, where simulations evaluate system performance across various parameters. AI typically aids in learning and reasoning tasks, serving as a basis for decision-making, while ML supports predictive analytics by processing historical data. Reinforcement learning improves knowledge extraction through reasoning and data-driven insights. Another class covers advanced monitoring and DT, which provide visualization and real-time feedback loops between the physical and virtual worlds, supporting decision-making throughout the manufacturing lifecycle. DTs bridge the physical and cyber worlds by offering the real-time virtualization of production, allowing stakeholders to monitor progress throughout the lifecycle. They support various activities, including modeling, design, monitoring, validation, failure prediction, and decision-making. XR, together with ubiquitous computing and assistance systems, is part of a class that includes AR, VR, and HMI, enabling enhanced visualization, decision-making, and real-time interaction with the manufacturing process.

2.1.5. Research Gap

The literature review on RMSs reveals that while a substantial number of review articles discuss various aspects of RMSs, many do not fully explore how emerging technologies such as AI, DT, and XR are specifically applied to optimize reconfiguration processes. Several reviews focus on topics tangential to RMS, such as wireless communications, process planning, or sustainable manufacturing, without addressing the specific challenges and opportunities associated with reconfiguration. Even when reviews cover DT, AI, and XR, they usually do not investigate how these technologies can specifically improve the flexibility and adaptability of RMSs.

Reviews that discuss the application of DTs highlight their potential for real-time decision-making and system reconfiguration but frequently emphasize the absence of a comprehensive framework that integrates AI and XR technologies. While AI and ML are recognized as enablers of predictive analytics and decision-making, their role in optimizing real-time reconfiguration processes remains underexplored, particularly in combination with DT and XR. Similarly, XR technologies are acknowledged for their potential in improving human–machine interaction, yet the literature lacks detailed analysis of how XR supports immersive reconfiguration processes and assists operators in real-time adjustments.

Therefore, current research indicates a notable deficiency in systematically examining the application of AI, DT, and XR technologies to improve RMS reconfiguration. Our work aims to fill this gap by investigating how these technologies are currently applied to optimize reconfiguration processes and by providing an in-depth analysis of their role in supporting human operators during RMS reconfiguration. Through this review, we contribute to a better understanding of the practical applications of AI, DT, and XR in RMSs.

2.2. Bibliometric Analysis

This review systematically explores the role and impact of Digital Twins (DTs), Extended Reality (XR), and Artificial Intelligence (AI) in enhancing reconfiguration processes within RMSs. By adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, the review rigorously examines literature published since 2019, encompassing both theoretical frameworks and practical applications [65]. The objective is to provide a comprehensive analysis of how these advanced technologies contribute to improving reconfiguration efficiency, reducing downtime, and supporting human operators while also identifying gaps in current research and suggesting future directions. The review procedure is illustrated in Figure 3.

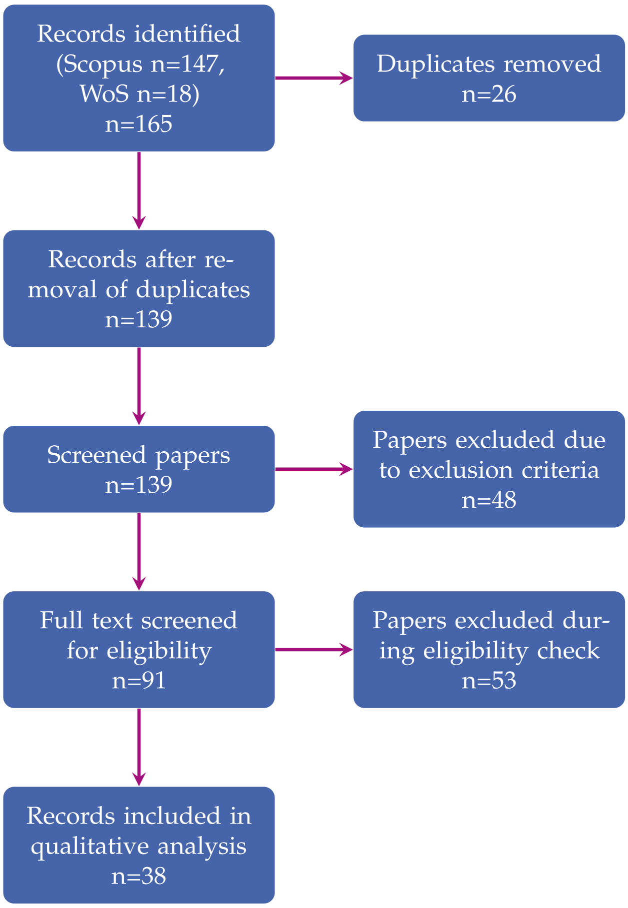

Figure 3. PRISMA flow diagram.

2.2.1. Search Strategy

A comprehensive search was conducted using the Scopus and Web of Science (WoS) databases, known for their extensive coverage of peer-reviewed literature, including key journals such as *Procedia CIRP*, Lecture Notes in Computer Science, Applied Sciences (Switzerland), Lecture Notes in Mechanical Engineering, and *Journal of Manufacturing Systems*. The search was last performed on 3 March 2024 and focused on identifying studies published from 2019–2025. By beginning our search in 2019, we ensure that all studies reflect the recent developments rather than referencing potentially outdated approaches. Second, the upper limit of 2025 allows us to include both the most recent publications available at the time of our final search and any manuscripts that are "in press" or are slated to be published in the near term.

Prior to the search, relevant search keys were identified from related works, which are detailed in Table 2. These keys included specific terms related to RMS, DT, XR, and AI. Boolean operators were used to combine these keywords into search expressions like *{RMS} AND {DT} AND {XR} AND {AI}*. Since this comprehensive search initially returned only two results, the search strategy was adapted to include three separate searches: *{RMS} AND {DT}*, *{RMS} AND {XR}*, and *{RMS} AND {AI}*, as detailed in Table 3. The combined results from these searches yielded a total of 283 articles, including the two from the initial comprehensive search.

Table 2. Identified keywords from major related work.

Topic	Keywords
{RMS}	Adaptable Manufacturing, Smart Manufacturing, Reconfiguration, Reconfigurable, Manufacturing, Production, Cyber-Physical
{DT}	Virtual Twin, Virtual shadow, Digital Shadow, Virtual Replica, Hybrid Twin
{XR}	Extended Reality, XR, Virtual Reality, VR, Augmented Reality, AR, Mixed Reality, MR
{AI}	Artificial Intelligence, AI, Machine Learning, Neural Networks, Reinforcement Learning, Deep Learning

Table 3. Boolean search expressions combining identified keywords.

Topic	Search Expression
RM	((reconfigurable OR cyber physical OR cyber-physical OR cognitive OR changeable OR smart OR adaptive) AND (manufacturing OR production)) OR ((“industry 4.0” OR manufacturing OR production) AND reconfiguration)
DT	“Virtual twin” OR “virtual replica” OR “Digital Twin” OR “digital shadow’ OR “hybrid twin”
XR	VR OR “virtual reality” OR AR OR “augmented reality” OR MR OR “mixed reality” OR XR OR “Extended Reality”
AI	AI OR “Artificial Intelligence” OR “Machine Learning” OR “neural networks” OR “reinforcement learning” OR “deep learning”

Filters were applied to refine the search results: only peer-reviewed articles in English were included, and review articles, as well as conference reviews, were excluded. This filtering process reduced the number of articles to 165. An overview can be found in Table 4. The individual search results were then exported to BibTeX files that were merged, sorted, and cleaned of duplicates. This process identified and removed 26 duplicate records, leaving 139 unique articles for the screening process.

Table 4. Results by Boolean expression combinations with reconfigurable manufacturing.

Combination	Results	Filtered Results
DT	90	64
XR	37	12
AI	118	70
DT AND XR AND AI	38	19
Total	283	165

2.2.2. Selection Process

The titles and abstracts of the 139 unique articles were screened against predefined inclusion and exclusion criteria, as summarized in Table 5. This initial screening resulted in the selection of 91 articles for further eligibility assessment. During the eligibility phase, the full texts of these 91 articles were thoroughly examined to ensure that they provided meaningful information on the integration of AI, DTs, and XR in RMS. The focus was on identifying studies that offered theoretical and practical advances in this field. During this phase, 53 articles were excluded due to factors such as limited scope, lack of evaluation or validation, or insufficient relevance to reconfiguration processes within RMS. As a result, 38 articles satisfied all the criteria and were incorporated into the final qualitative and quantitative analysis.

Table 5. Summary of exclusion and inclusion criteria for article selection.

	Exclusion Criteria		Inclusion Criteria
Filter	Not in English, not peer-reviewed, published before 2019, review paper, not open-access	Closely related	AI, DT, or XR enhance reconfiguration processes.
Loosely related	Manufacturing context, but unrelated to reconfiguration (e.g., network reconfiguration).		AI, DT, or XR support human operators in reconfiguration processes.
Non-related	Not in the manufacturing or reconfiguration context (e.g., energy production).	Parti-ally related	AI, DT, or XR generally improve RMS.
Insuf-ficient	Limited scope or lacks evaluation or validation.		AI, DT, or XR generally support operators in RMS.

2.2.3. Data Extraction

During the screening and eligibility assessment, a detailed data extraction process was performed to systematically capture all relevant aspects of each study. The extracted data were organized into a structured table, which included various categories, including basic study information such as publication year, author(s), title, and comments on selection and eligibility assessment decisions.

The extraction process also focused on key definitions, capturing how the authors defined "reconfiguration" and identifying the specific characteristics of the reconfiguration processes involved. The problem statement of each paper was summarized, emphasizing its relevance to the reconfiguration of the RMS. Additionally, summarized descriptions of the solution and insights into the suggested AI, DT, and XR solutions were recorded in the table, along with their impact on improving reconfiguration processes.

2.2.4. Synthesis and Reporting

To minimize bias in the selection and evaluation of studies included in this systematic review, several strategies were used throughout the process. First, strict inclusion and exclusion criteria were established and rigorously applied to ensure consistency and objectivity in the study selection. These criteria were designed to focus on studies that were highly relevant to the research questions and demonstrated methodological rigor.

A team of six researchers from three distinct research facilities collaboratively carried out the screening and assessment, reducing bias and guaranteeing thorough reviews of each article. The findings were documented in an Excel table that captured key aspects such as the implementation and advantages of AI, XR, or DT technologies in RMS. This collaborative approach was further supported by frequent discussions among researchers, which were essential to resolve any uncertainties or potential biases during the screening and evaluation phases. The discussions also ensured transparency and consistency in decision-making.

3. Overview of Reviewed Publications

This section provides an initial overview of the identified and reviewed publications, summarizing publication trends, key technologies, and insights from the systematic review of RMSs.

3.1. Sources

This review includes a balanced representation of high-quality journals and conference proceedings to capture the breadth of research in RMSs. In total, $N = 86$ journal articles and $N = 79$ conference proceedings were included. The most frequently appearing sources include Procedia CIRP ($N = 21$), *Lecture Notes in Computer Science* ($N = 11$), *Journal Of Manufacturing Systems* ($N = 10$), *International Journal Of Advanced Manufacturing Technology* ($N = 7$), and *Applied Sciences Switzerland* ($N = 7$), alongside other prominent publications like *Sustainability* and *Mechanical Engineering*. This distribution ensures that influential journals and conferences are represented, as each significantly contributes to the field's core technological advances (AI, DT, XR). In an emerging field like RMSs, high-quality conference proceedings are also essential, as conferences often serve as venues for idea generation and the early dissemination of new methods and technologies. As recommended and performed in similar reviews articles, conference proceedings were also included [66,67].

3.2. Distribution of Papers According to Our Categories

Figure 4 visualizes the distribution of the screened articles. Initially, articles were categorized based on the search terms they resulted from. However, since many studies address multiple technologies simultaneously (e.g., AI-driven Digital Twins), a more precise categorization was conducted during the in-depth analysis. In cases where an article covered multiple categories, it was assigned to the category that best reflected its primary focus. The majority of screened articles relate to AI (43.2%, $N = 60$) and DT (48.9%, $N = 68$) technologies, while XR is underrepresented (7.9%, $N = 11$). This screening phase helped narrow the scope by excluding studies that were unrelated to reconfigurable manufacturing, lacked empirical evidence, or did not substantially contribute to the primary technologies of interest. Out of $N = 139$ screened articles, only 38 were included in the final analysis.

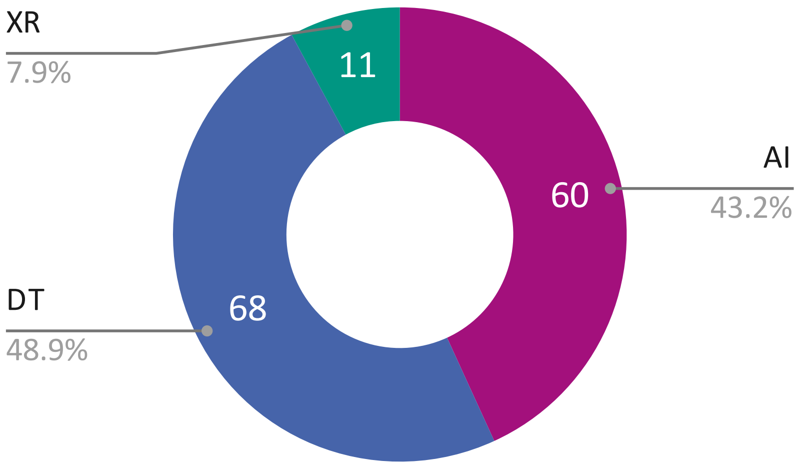

Figure 4. Distribution of screened articles.

Figure 5 depicts the included articles' distribution by technology. Among AI-related articles, 75.0% ($N = 45$) were excluded, in DT 73.5% ($N = 50$), and in XR 45.5% ($N = 6$), resulting in $N = 15$ AI articles, $N = 18$ DT articles, and $N = 5$ XR articles. After the screening, DT emerged as the dominant focus, with XR gaining a small but slightly improved representation, as shown in Figure 6. Together, these visualizations depict the role of each technology within reconfigurable manufacturing and the range of approaches observed across the studies. The majority of included papers explored DT due to its direct alignment with RMS digital needs, followed by AI, with XR representing an emerging yet limited field of application.

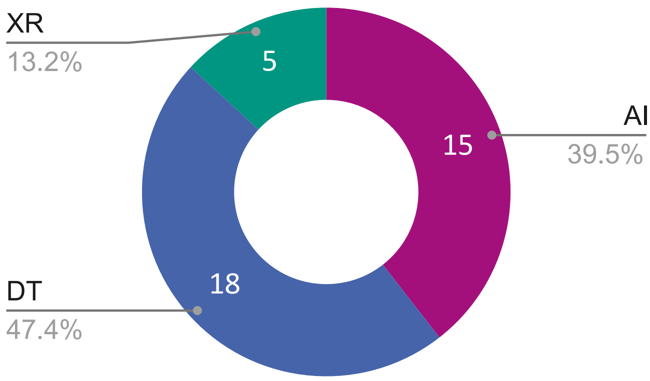

Figure 5. Included articles.

Among the included articles, the five most cited papers were identified and are listed in Table 6, providing insights into the foundational and influential studies within the field. Two DT articles are highly cited with over 200 citations as of March 2024. The remaining articles present AI approaches to reconfiguration with fewer than 100 citations, showing a quick drop in citation numbers within this group. One of the AI articles also incorporated XR technologies and has 70 citations. Note that only articles published after 2019 were reviewed, reflecting a relatively recent body of work, which contributes to the lower citation counts.

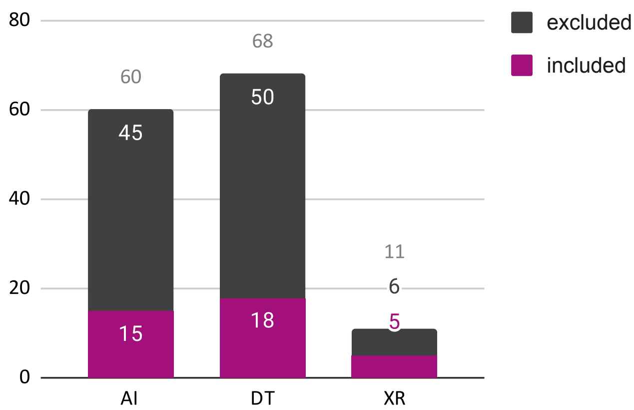

Figure 6. Included and excluded articles.

Table 6. Top 5 highly cited articles.

Articles	Year	Citations
Leng et al. [68]	2020	251
Liu et al. [69]	2021	211
Villalonga et al. [70]	2020	73
Dimitropoulos et al. [71]	2021	70
Kousi et al. [72]	2021	65

3.3. Technology Relations

The Sankey diagram in Figure 7 presents the distribution of included papers based on reconfiguration type (digital, physical, or mixed), technology focus, and the specific methods and approaches employed. Identified articles were grouped by whether they focus on digital, physical, or mixed reconfiguration types. The majority (63.2%, $N = 25$) focus on digital reconfiguration, while physical approaches are underrepresented (2.6%, $N = 1$). Some approaches recognize the mixed character of CPS reconfigurations (31.6%,

$N = 12$), and in one article, the reconfiguration type was not specified. Both digital and mixed approaches utilize all the core technologies, while the single physical reconfiguration approach focuses exclusively on XR application.

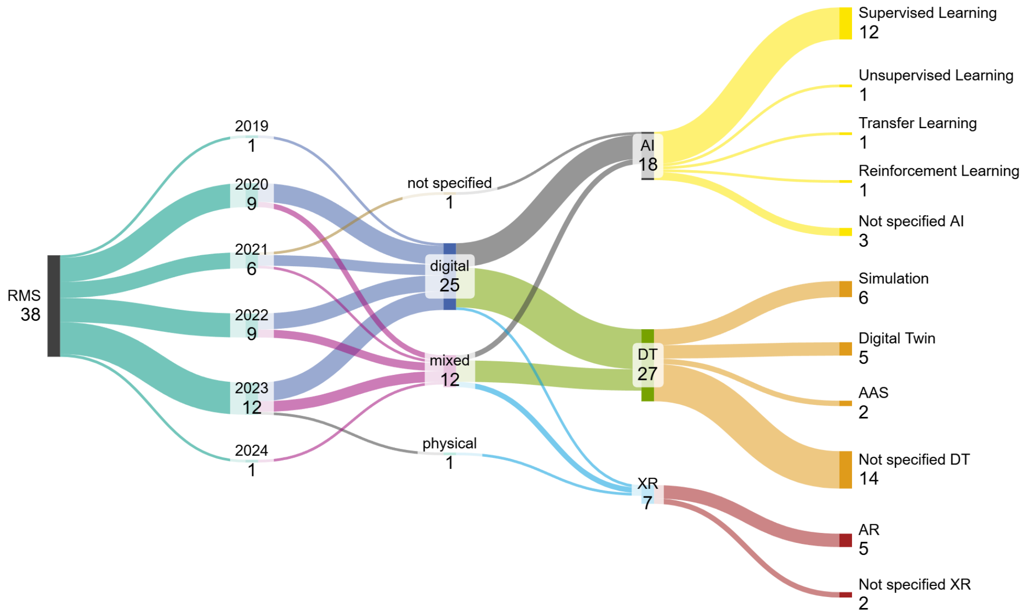

Figure 7. Sankey diagram of the included papers.

Additionally, the Sankey diagram highlights specific methods within each technology branch. Among the articles using AI, 47.4% ($N = 18$) of approaches predominantly used supervised learning (66.7%, $N = 12$), with unsupervised, transfer, and reinforcement learning each appearing in 5.6% ($N = 1$) of studies. In three articles (16.7%), the AI method was not specified. DTs were utilized in 71.1% ($N = 27$) of the articles, with 51.9% ($N = 14$) not further specifying the DT technology, 18.5% ($N = 5$) adhered to the DT as per its definition, 22.2% ($N = 6$) implemented simulations, and 7.4% ($N = 2$) employed an Asset Administration Shell (AAS). XR was used in 18.4% ($N = 7$) of the reviewed studies, where 71.4% ($N = 5$) used AR, and the remaining articles (28.3%, $N = 2$) did not specify the XR technology.

3.4. Human Involvement

Table 7 provides an overview of human involvement across the studies, distinguishing between technology-centric and human-centric approaches. In 42.1% ($N = 16$) of articles, the operator is involved in the reconfiguration approach. In most cases, the human is in a supporting role, such as being "in the loop" (25.0%, $N = 4$) or cooperating with robots (37.5%, $N = 6$). A smaller subset involves humans in more central roles, such as CPS–human systems (12.5%, $N = 2$) or human-centered systems (25.0%, $N = 4$). In one article, the human's role in the method was unclear, while in $N = 21$ articles (55.3%), human involvement was not considered.

Table 7. Publications related to Reconfigurable Manufacturing Systems, Digital Twins, Extended Reality, and Artificial Intelligence.

Article	Year	AI, XR, DT Method	Characteristic	Human Involvement
Abadi et al. [73]	2023	DT	Mixed	No involvement
Alexopoulos et al. [74]	2023	AI, DT, XR	Digital	Human-centered System
Ali et al. [75]	2023	DT	Digital	No involvement
Arnarson et al. [76]	2022	DT	Mixed	No involvement
Ashtari Talkhestani and Weyrich [19]	2020	DT	Mixed	Human-in-the-Loop
Bavelos et al. [77]	2022	DT, XR	Digital	No involvement
Begout et al. [78]	2022	DT, XR	Mixed	Human-in-the-Loop
Braun et al. [79]	2020	DT	Digital	No involvement
Caesar et al. [37]	2023	DT	Mixed	No involvement
Chen et al. [80]	2023	AI	Mixed	No involvement
Eswaran et al. [81]	2024	XR	Mixed	Human–Robot Cooperation
Garcia et al. [82]	2021	AI	Not specified	Human–Robot Cooperation
Gundall et al. [83]	2021	XR	Digital	No involvement
Huang et al. [84]	2021	DT	Digital	Not specified
Iglesias et al. [85]	2020	AI	Digital	No involvement
Izquierdo-Domenech et al. [6]	2023	AI, XR	Physical	Human-centered System
Jazdi et al. [86]	2020	AI, DT	Digital	No involvement
Kernan Freire et al. [87]	2023	AI	Mixed	Human-centered System
Khalifa et al. [88]	2019	AI	Digital	Human-centered System
Kombaya Touckia et al. [89]	2022	DT	Digital	No involvement
Kousi et al. [90]	2020	AI, DT	Digital	Human–Robot Cooperation
Kousi et al. [72]	2021	DT	Digital	Human–Robot Cooperation
Leng et al. [91]	2023	DT	Digital	Cyber–Physical–Human System
Leng et al. [68]	2020	DT	Mixed	No involvement
Liu et al. [69]	2021	DT	Mixed	No involvement
Maschler et al. [92]	2022	AI, DT	Digital	No involvement
Mo et al. [93]	2023	AI	Digital	Human-in-the-Loop
Nikolakis et al. [94]	2022	AI, DT	Digital	No involvement
Pereira et al. [95]	2020	AI, DT	Digital	Human–Robot Cooperation
Sartori et al. [96]	2023	DT	Digital	Human-in-the-Loop
Scrimieri et al. [97]	2023	AI	Digital	Cyber–Physical–Human System
Talkhestani et al. [98]	2020	DT	Digital	No involvement
Villalonga et al. [70]	2020	AI	Digital	No involvement
Xu et al. [99]	2023	DT	Digital	No involvement
Yang and Xu [5]	2022	AI	Digital	No involvement
Yang et al. [100]	2022	DT	Digital	No involvement
Zhu et al. [101]	2022	DT	Mixed	No involvement
Dimitropoulos et al. [71]	2021	AI, XR	Mixed	Human-centered System

3.5. Commonalities in Studies

Many papers use Digital Twins as the main technology, particularly for tasks directly related to reconfiguration, such as simulation, planning, and real-time optimization. On the other hand, AI and XR are instead used to serve a supportive or enabling function rather than being directly involved in reconfiguration processes. For example, they are often used to assist with predictive maintenance or optimize system configurations indirectly.

3.6. Divergence in Technology Applications

While DT and AI technologies aim to reduce human involvement (e.g., automation-focused DT applications), XR is explicitly designed to support human tasks, such as systems providing augmented reality (AR) guidance for technicians.

4. Results and Discussion

The landscape of RMSs is increasingly defined by the convergence of advanced technologies aimed at improving the flexibility, efficiency, and adaptability of production environments. Across various research efforts, there is a clear focus on developing systems that can respond dynamically to the evolving demands of modern manufacturing, whether through digital reconfiguration, physical adjustments, or a combination of both.

4.1. RQ1: How Are DTs, XR, and AI Being Utilized, Individually and in Synergy, to Enhance Reconfiguration Processes in RMS?

The overarching goal in RMSs is to enhance the flexibility of these systems, enabling them to adapt to changing production demands and distributed production environments. This broad goal is reflected across several studies, each tackling different aspects of flexibility, efficiency, and the role of human operators. Table 8 provides an overview of the sub-objectives.

Table 8. Summary of usually enhanced and minimized factors in RMS optimization.

Enhanced Factors	Minimized Factors
Performance, Knowledge Sharing, Flexibility, Adaptability, Robustness, Reliability, Human–Machine Interaction, Efficiency, Real-Time Decision-Making, Real-Time Operator Guidance, Situational Awareness	Human Intervention, Time, Delays, Cost, Training, Errors, Physical Strain, Reliance on Experts

4.1.1. Reconfiguration of Highly Flexible Manufacturing Systems

A central objective shared by many studies is the reconfiguration of highly flexible manufacturing systems, which allows for the seamless adaptation of production processes to new conditions and requirements. This general goal is evident in a paper where the focus is on enabling the reconfiguration of distributed production systems through the integration of data-driven methods and capability management [97]. The idea is to create systems that can autonomously adapt to changing production needs with minimal human intervention, thereby increasing overall system flexibility and efficiency.

In order to find the optimal solution for the reconfiguration of a single manufacturing transfer line, a simulation based on multiple objectives was utilized [75]. The reconfiguration of manufacturing systems was enhanced by the DT, as demonstrated by comparing the reconfiguration process with and without the DT. The utilization of the DT technology increases the reconfiguration efficiency by reducing time and improving the system's availability and flexibility [19]. The improved speed and accuracy of reconfiguration assessments were aimed for by utilizing a DT-based application that synchronizes manufacturing data and automates simulations [100]. Similarly, reconfiguration time was reduced, and system efficiency was enhanced in a study where a synchronized DT was facilitated by the Anchor-Point Method for the reconfiguration of an automation system [98]. To enhance the reconfiguration of robotic mixed-model assembly lines, DT technology was applied, and a virtual reconfiguration method based on an Adaptive Neighborhood Search Bee Algorithm (ANSBA) was proposed. This method was utilized to optimize the reconfiguration solution with the objective of reducing costs and achieving balanced workloads [99].

4.1.2. Increasing Flexibility Through Dynamic Systems

Flexibility can be further enhanced by developing systems that are inherently more dynamic and capable of responding to real-time changes. For instance, this is explored by developing a reconfiguration framework for CPPSs that emphasizes remote reprogramming [95]. This approach allows for the dynamic adjustment of production processes without requiring physical changes, thus enhancing system adaptability. Similarly, another approach focuses on dynamic monitoring and control of production lines to handle different product models and operational disturbances [80]. By continuously monitoring equipment performance and applying Deep Learning algorithms for real-time adjustments, this approach ensures that production lines remain flexible and responsive to changing conditions. Another paper adds to this goal by introducing an AI-driven algorithm for intelligent job scheduling in adaptive production lines, which improves the system's ability to adapt to varying demands and optimize scheduling efficiency [5].

Despite the potential of these technologies, there is still limited research on how DT can be used to monitor the entire product lifecycle or how generic algorithms can improve the production process [91]. This research gap implies that, while significant progress has been made in using DTs for specific tasks, there is a need for further investigation of their broader applications in production monitoring and lifecycle management.

One study introduced an approach for synchronizing the physical production line with its DT. This approach is designed to automatically update the DT in order to map changes made to the real production line by transforming the coordinates of each component into a global coordinate system [79]. Another study presented a framework focused on the reconfiguration of production systems and networks. It aims to improve decision-making and improve the ability of the manufacturing system to withstand disruptions [74].

4.1.3. Efficient Knowledge Sharing and Operator Support

Efficient knowledge sharing and enhanced situational awareness are crucial to improving the efficiency of human-involved processes in manufacturing. These aspects are interrelated, as both aim to provide operators with the information and tools they need to perform their tasks effectively. This is addressed by an AI cognitive assistant called CLAICA that is designed to facilitate knowledge sharing and provide real-time support to operators in agile production environments [87]. This approach not only improves task execution but also reduces training time, thereby enhancing overall efficiency in environments where human involvement is significant. Similarly, a human–robot collaboration system using AI-driven perception and wearable XR devices has been proposed to enhance real-time operator support [71]. The system leverages a convolutional neural network (CNN)-based action perception to recognize operator intent and adapt robotic assistance accordingly.

A hybrid model is proposed that combines various technologies, including Object Linking and Embedding for Process Control (OPC) and industrial internet-based protocols, to create a cohesive system for manufacturing automation [69]. The design steps outlined in optimization decoupling address various discrete optimization challenges to enhance the efficiency and effectiveness of manufacturing processes, including order-batch grouping, blanking optimization, and operation planning.

AR was integrated with a semantic AI layer to enhance situational awareness and multimodal interaction within industrial applications [6]. This system provides operators with real-time anomaly detection and natural language interaction, further supporting the efficient sharing of critical information. By combining these technologies, the approach ensures that operators can make informed decisions quickly and effectively, reducing the cognitive load on human workers and improving overall operational efficiency.

4.1.4. Automation and Mitigation of Human Involvement

Conversely, some studies aim to automate as much of the reconfiguration process as possible to improve efficiency, flexibility, and system autonomy. This is particularly evident in the EECG system that automates the reconfiguration process by continuously monitoring equipment performance and making real-time adjustments without manual intervention [80]. The goal here is to minimize the need for human involvement, thereby reducing the potential for human error and increasing the reliability of the system. The reconfiguration of PLCs is being automated using knowledge graphs and Graph Neural Networks (GNNs), which reduces the time and errors associated with manual reconfiguration, thereby improving overall system efficiency and reliability [93].

Additionally, Web Ontology Language (OWL) was utilized for capability matching to automate the reconfiguration and operation of flexible production lines by abstracting production workflows without human involvement [84]. To enable a more flexible and efficient robot assembly process, a study proposed a method for automatic robot program generation using a visual programming editor. This approach allows for a quick reconfiguration of a robotic assembly and adaptation to product variants without manually programming robot poses [96]. In another study, an autonomous RMS that integrates DT technology, mobile robots, and wireless power transfer (WPT) was proposed. The objective was to improve flexibility, increase system reconfigurability, and reduce human intervention [76].

4.2. Improved PI

Research on RMSs has focused on optimizing various performance indicators to enhance overall efficiency, reliability, flexibility, and decision-making processes, as summarized in Table 9.

Table 9. Categorized overview of research articles on reconfigurable manufacturing systems.

Goals	Articles
Efficiency	[5,6,19,71,93,96–100,102]
Flexibility and Adaptability	[71,76,80,84,95,102]
Error reduction and Reliability	[80,93,97]
Knowledge and Decision-Making	[6,71,74,75,87]

4.2.1. Efficiency

A significant aspect of this optimization is efficiency, which encompasses time, cost, and operational factors. Specifically, progress has been achieved in enhancing time efficiency by minimizing the duration of reconfiguration, thanks to DT simulations and data-driven techniques [97,102]. Furthermore, enhancing real-time scheduling efficiency in adaptive production lines ensures that job processing is handled promptly and efficiently [5]. Another contribution to this category is the automation of the generation of PLC codes that significantly reduces the time associated with manual reprogramming [93].

The efficiency of reconfiguration is expected to be improved by reducing the time required and increasing the availability of the system [19,98,100]. One study focused on reducing the cost of reconfiguration, while another provided a more flexible and efficient robot assembly process to increase system efficiency [96,99]. AI-driven human–robot collaboration has demonstrated a 6% reduction in cycle time through real-time robotic motion adaptation and predictive operator support [71].

Cost efficiency has been another critical area of focus, with the aim of reducing the costs involved in the reconfiguration process by minimizing human intervention and optimizing the overall process through Machine Learning techniques [97].

Operational efficiency is also a key performance indicator targeted by several studies. Operational performance is improved by introducing intelligent job scheduling algorithms that improve the adaptability of production lines to changing demands [5,69]. Furthermore, operational efficiency is improved by streamlining human–machine interaction, while

AR and semantic AI were used to increase situational awareness and decision-making, ultimately leading to more efficient industrial processes [6,93].

4.2.2. Error Reduction and Reliability

Error reduction and reliability are addressed by minimizing errors through the application of Machine Learning, which ensures a more reliable and consistent system performance [97]. Similarly, automating the monitoring and adjustment of equipment performance improves system reliability, while error reduction in the generation of PLC codes contributes to more reliable and fault-resistant reconfigurations [80,93].

4.2.3. Flexibility and Adaptability

Flexibility and adaptability are essential for systems that need to handle diverse production demands and adjust to new products. A work highlights the role of DT models in improving system flexibility, making it easier to scale and adapt to new market requirements [102]. On-demand reconfiguration in CPPS is supported in another work, enabling remote reprogramming and enhancing the system's adaptability [95]. Furthermore, the need for dynamic adjustments in production lines is addressed to ensure that systems can respond effectively to variations and disturbances [80].

One study featured an approach to increase flexibility and reconfigurability while reducing human involvement [76]. Alternatively, AI-supported human-in-the-loop learning enhances robotic adaptability by dynamically adjusting motion based on operator intent and task changes [71]. Furthermore, another used a capability-based approach to allow more flexibility within manufacturing [84].

The bin-picking task can increase their flexibility and adaptability through AI. Objects can be picked from chaotic ordering instead of predefined places through pattern-matching, and adapting to new objects only requires CNN retraining and a CAD change [85].

An additional study suggests breaking down the plan for an object manufacturing task using a digital mock-up, allowing comparison with familiar objects to reduce reconfiguration by leveraging existing knowledge [73].

4.2.4. Knowledge and Decision-Making

The Knowledge and Decision-Making category is pivotal in optimizing RMSs. Knowledge sharing and training through an AI cognitive assistant that supports operators by providing real-time recommendations reduces training time and improves knowledge sharing [87]. Integrating AR with semantic AI has been shown to enhance situational awareness and real-time decision-making by reducing cognitive load and reliance on human experts, thereby optimizing operational decision processes [6,71].

A study introduced an approach to support the production planner in the decision-making process for reconfiguration by providing the optimal solution [75]. At the same time, another study presented a framework that provides a quicker and more focused decision process for shop floor reconfiguration [74].

The integration of DT technology into manufacturing has led to substantial improvements in knowledge management and decision-making processes by leveraging real-time data and advanced algorithms [69]. Manufacturers can optimize operations, reduce costs, and improve system adaptability. Future developments are expected to further automate decision-making and improve the overall efficiency of manufacturing systems.

4.3. RQ2: Which Specific Role Do DTs, XR, and AI Technologies Play in Supporting Human Operators During RMS Reconfiguration?

4.3.1. Role of Human Operator Within RMSs

Two distinct trends emerge regarding the role of human operators in RMS. One trend focuses on fully automating processes, minimizing human involvement in reconfiguration, while the other highlights the importance of human involvement and seeks to enhance human–machine interaction by making CPS more accessible and user-friendly.

In some cases, human involvement is minimized, and operators primarily monitor and supervise the system. A common argument is that automating reconfiguration is more efficient and less prone to error, allowing faster adjustments compared to manual interventions [95]. For example, operators can initiate digital reconfiguration remotely using systems integrated with DTs, interacting with virtual replicas of the store floor, while physical reconfiguration is automated [97]. The vision here is to move toward highly automated systems that minimize human intervention while still maintaining oversight capabilities [103].

When human operators are involved, they are assisted during the reconfiguration process through systems that continuously learn from the operators and provide real-time recommendations and knowledge sharing [87]. VR enables operators to explore and design optimal layouts virtually, while AR ensures spatial accuracy and ergonomic considerations by allowing operators to verify layouts on-site [81]. AR also provides real-time support during the reconfiguration process, guiding operators through the adjustment of physical components with visual overlays that highlight task sequences, assembly points, and safety zones. This real-time feedback ensures that the reconfiguration is in line with the planned design, enhancing both accuracy and efficiency.

In addition to layout planning, AR enables dynamic interaction with additional assistive systems, such as AI, allowing operators to use natural language commands to ask questions or trigger actions, and the system provides immediate feedback to optimize task completion and process accuracy [6]. This combination of natural language interfaces and AR enhances operator engagement during reconfiguration by offering context-sensitive information superimposed on the physical environment, guiding them through processes such as machine activation, monitoring operational values, and performing real-time adjustments.

One study presented a human-centered decision support system that aids in reconfiguration planning by assisting operators in making informed decisions [74]. In another approach, non-experts were able to adapt an assembly process using a visual programming editor, reducing the complexity of reconfiguration tasks [96]. Human operators are also involved in verifying changes and validating adjustments during the reconfiguration process [19]. Despite the growing automation in manufacturing systems, the expertise of human operators remains indispensable, as they balance advanced technological systems with their knowledge to improve manufacturing efficiency and adaptability [69].

4.3.2. Role and Implementation of AI

AI is a crucial and pervasive element in the transformation of industrial processes, as emphasized in the reviewed literature. This section outlines the implementation to enhance reconfiguration processes.

The DINASORE framework provides a Python 3.6-based environment that is compliant with the industrial standard IEC 61499, allowing the modular and scalable deployment of DT and ML algorithms directly on the shop floor [95]. By integrating with ML libraries such as TensorFlow, PyTorch, and Keras, DINASORE facilitates the incorporation of advanced AI techniques, such as random forests, Artificial Neural Networks (ANNs), and

Support Vector Machines (SVMs) into industrial processes, enabling real-time reconfiguration, collision detection, and distributed control. Although DINASORE primarily serves as a tool for enabling these AI applications rather than directly applying them, it has also been tested in various scenarios. These include collision detection for a robotic arm, where Random Forests were used to accurately detect and respond to overload conditions and control a UR5 robotic arm and a 3D-printed gripper in a synchronized manner, demonstrating its capability to manage distributed control tasks effectively. Furthermore, DINASORE was evaluated in a simulated manufacturing production line, where its scalability and performance were validated as it handled an increasing number of function blocks without significant degradation in system performance.

AI has been applied to improve human–robot cooperation in flexible assembly systems. In one study, an AI framework was developed to monitor human actions and predict subsequent steps, allowing robots to dynamically adjust their behavior [82]. Reinforcement learning enabled the system to improve predictions based on feedback from previous actions. The proposed framework was tested in a simulated environment, demonstrating significant reductions in human intervention and improvements in task efficiency. Similarly, an AI-driven action perception system combined with XR-based real-time operator guidance has been proposed to enhance human–robot collaboration, enabling predictive robotic motion adaptation and reducing ergonomic strain [71]. The proposed framework was tested in a simulated environment, demonstrating significant reductions in human intervention and improvements in task efficiency.

CLAICA is presented as a continuously learning cognitive assistant AI designed to support workers in agile production environments, employing a conversational user interface and a knowledge graph to facilitate the acquisition and sharing of knowledge directly on the shop floor [87]. The system's natural language understanding and context awareness capabilities enable it to interact efficiently with users, offering real-time assistance with tasks such as troubleshooting, machine-setting adjustments, and issue reporting. In a user study involving 83 participants, including factory workers, researchers, and students, CLAICA was found to improve task efficiency by 18% compared to traditional methods without AI assistance for users who had no prior training. Usability was rated positively, with 75% of the participants expressing satisfaction with the ease of use of the system. However, the study also revealed that users with prior training experienced a 12% higher perceived workload, and the system faced challenges with divergent phrasing and conversation breakdowns, indicating areas for further improvement in natural language capabilities.

The integration of human resource management into the reconfiguration of RMS has been explored through modeling and simulation. A human resource model was developed to map roles, skills, and capabilities to specific tasks within the RMS [88]. Simulation-based testing allowed one to evaluate how different human resource allocations impacted system performance. Optimization algorithms were used to identify the optimal configuration of human and machine resources, demonstrating that effective human involvement can significantly enhance system performance during reconfiguration.

AI techniques have also been used in reconfigurable inspection systems within RMSs. An approach integrated Support Vector Machines for defect classification and Deep Convolutional Neural Networks (DCNNs) for image recognition and defect detection [104]. In addition, LS methods were used to optimize reconfiguration by minimizing discrepancies between predicted and actual outcomes. The effectiveness of the system was validated in a controlled RMS environment, where the inspection parameters were dynamically adjusted in response to production changes.

A system has been introduced to employ Equipment Electrocardiogram (EECG)-based defect detection, utilizing Convolutional Neural Networks (CNNs) and Deep Learning [80].

This innovative approach leverages the electrical signals of the equipment, much like a medical ECG, to monitor and diagnose the health of intelligent production lines. The system was validated on a laboratory assembly line prototype, where it was used to classify signals as normal or indicative of a defect, achieving a classification accuracy of 95.24% and demonstrating robust operation under varying conditions. These results contribute to effectively preventing downtime and ensuring continuous production.

Cloud-based industrial CPSs have been proposed as a solution to optimize manufacturing processes. A cloud-based platform was used to store and process data from edge devices equipped with sensors and actuators [70]. The system dynamically reconfigured itself based on real-time data analysis, adjusting machine settings and production schedules to enhance performance. Machine Learning models were used to analyze historical and real-time data, guiding reconfiguration decisions. A case study demonstrated the system's ability to improve efficiency and adaptability in a real-world manufacturing setup.

Building on the concept of dynamically adjusting systems, another approach is focused on self-adaptability within reconfigurable manufacturing [93]. The presented methodology employs a graph database that models the entire manufacturing process, including PLC code, combined with knowledge graphs and Graph Neural Networks (GNNs), specifically the GraphSAGE model. This AI-driven approach allows the system to learn from the knowledge graph, effectively predicting optimal configurations and sequences for new production processes. By automating the generation and testing of PLC code, the system can self-adapt to new product requests or process changes with minimal human intervention. Their validation involved implementing the approach in a case study focused on an adaptive assembly facility for aircraft parts. The results demonstrated that the system could automatically generate and test PLC code, effectively handling new production requests without the need for manual programming, suggesting potential reductions in time and errors. However, the study did not include a comparative analysis to explicitly quantify these reductions.

A related approach explores self-adaptability within reconfigurable manufacturing through a multi-agent system (MAS) that uses Machine Learning to enhance the reconfiguration process [97]. The MAS utilizes an experience base to learn from past reconfigurations, employing the k-Nearest Neighbor (kNN) algorithm to classify machine states and recommend optimal adjustments. Although the study primarily uses kNN for this purpose, it acknowledges the potential of other techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Decision Trees for similar tasks. The MAS's ability to autonomously adjust resource configurations and optimize performance was validated in a robotic assembly system, where it demonstrated an ability to reach target performance levels more efficiently compared to manual reconfiguration. However, the paper focused on demonstrating automation and learning capabilities rather than conducting a detailed comparative analysis of these Machine Learning techniques or explicitly measuring time and error reductions.

In summary, AI's role in RMS reconfiguration is multifaceted, ranging from enabling modular, scalable control frameworks like DINASORE to enhancing human–robot cooperation, human resource management, and defect detection. These applications, supported by techniques such as reinforcement learning, Machine Learning, and neural networks, demonstrate advancements in system adaptability, task efficiency, and autonomous decision-making. Table 10 presents an overview of AI usage in various fields. However, limitations in natural language processing and the need for further validation in practical applications indicate opportunities for further refinement in the integration of AI within industrial processes.

Table 10. Overview of AI usage in various fields.

Overview Field	Database	Exact Methods Used	Specific Task
Optimization	Real-time Shopfloor Data	Heuristic Algorithms	Task sequencing and robot motion planning [90]
Automation	Video data of operator, graph database that represents the manufacturing process (PLC-code) [93], experience base, machine states [97]	Machine Learning (not further specified), deep neural networks [82], knowledge graphs combined with Graph Neural Networks (GNN) (GraphSAGE model) [93], k-Nearest Neighbors (kNN) [97]	Object/person recognition [94], learn from knowledge graph and predict optimal configurations and sequences for new production processes [93], finding the best adjustments by comparing new machine states with past experiences [97]
Defect detection	EECG signal data [80]	Convolutional Neural Networks (CNNs), Deep Learning [80]	Real-time equipment monitoring, anomaly detection, predictive maintenance [80]
Operator Support	Knowledge Graph, Worker Feedback [87]	Natural Language Understanding (NLU) [87]	Real-time knowledge acquisition and sharing, task assistance [87]

4.3.3. Role and Implementation of DT

This section outlines the role and implementation of DTs in the reconfiguration of manufacturing systems. The technology has been applied in various contexts to create a digital representation of physical entities, facilitating simulations and enhancing the reconfiguration process.

In one study, DT technology was used to create a digital version of a production line that also included robots. This digital version has been used to store and display the automatically created layout of the production line [79]. Another study used a DT as a simulation for reconfiguration planning of a single manufacturing transfer line utilizing MATLAB. The simulation was used to find the optimal configuration based on multiple objectives [75].

The DT derived from the Asset Administration Shell (AAS) was utilized for capability and skill representation, as well as to provide semantic descriptions and matching [84]. In addition, DT based on AAS served as a middleware to exchange data between manufacturing companies, enabling predictions about the impact on the supply chain from reconfiguration on the shopfloor level [74]. Another study presents DTs implemented using Python-based function blocks, which provide control logic and interaction for the real-time operation of physical systems, such as robotic arms, within the manufacturing cell [95]. This implementation enables efficient reconfiguration, on-demand adjustment, and even remote reconfiguration, thanks to the modular nature of the function blocks.

DTs have also been used to facilitate annotation, simulation, and reconfiguration to improve the assembly of robotic systems [96]. Additionally, DTs were applied to enhance reconfigurable systems in manufacturing tools by providing simulations [91].

DTs were also used to enable simulations and analysis during the planning and validation of the reconfiguration process [19]. Another study used DT technology to simulate reconfiguration and identify the optimal solution [100].

Further applications of DT technology included the running of simulations and the provision of an integration platform to synchronize DT with the real manufacturing system [98]. DT technology was also used for simulation, planning, and real-time control to enable automated reconfiguration utilizing mobile robots [76]. Lastly, DT served as an integration platform to solve the virtual reconfiguration problem of the mixed model assembly line [99].

Below, the implementations are categorized based on the communication, synchronization, and types of implementation proposed.

The communication of the DT implementation can be divided into unidirectional and bidirectional communication between the physical and digital entity. The results of the analysis are presented in Table 11. Most of the implementations presented can be classified as bidirectional. This communication scheme is often referred to as synchronization and features a continuous data flow between a physical and a digital entity. Only two articles use unidirectional communication to transfer data from the physical entity to its digital model [75,79].

Table 11. Overview of communication in Digital Twin implementations.

Communication	Articles
Unidirectional	[75,79]
Bidirectional	[19,76,91,95,98–100]
Unspecified	[74,84,96]

The next aspect of the DT implementation is the synchronization between the physical and digital entities. Here, two types of synchronization can be observed: synchronized and static. Synchronized implementations update state, conditions, and measurements continuously. Static implementations, which can be referred to as created once, extract the data but do not update them. An overview of the synchronization within the DT implementations is given in Table 12.

Table 12. Overview of synchronization in Digital Twin implementations.

Synchronization of Implementation	Articles
Synchronized	[19,74,76,79,91,95,98–100]
Static/created once	[75,96]
Unspecified	[84]

The final aspect of DT implementations is the types of implementation used in the articles presented. These are divided into three categories that are illustrated in Figure 8: Simulation, Digital Shadow, and Digital Twin. The classification follows the given definition of a DT and a Digital Shadow. Table 13 displays the categorization.

The category of Digital Twin implementations contains a subcategory, AAS. This type of implementation is used in [74,84].

Table 13. Overview of types in Digital Twin implementations.

Type of Implementation	Articles
Simulation	[75,79,96,100]
Digital Shadow	-
Digital Twin	[19,74,76,84,91,95,98,99]

In summary, the implementation of DTs in RMSs is varied, with applications ranging from simulation-based planning to real-time synchronization and reconfiguration. Most implementations employ bidirectional communication and synchronized states, facilitating dynamic adjustments and continuous data flow. DTs have proven effective in optimizing system performance and enabling autonomous reconfiguration, although challenges remain in areas such as improving synchronization accuracy and enhancing interoperability across different manufacturing platforms.

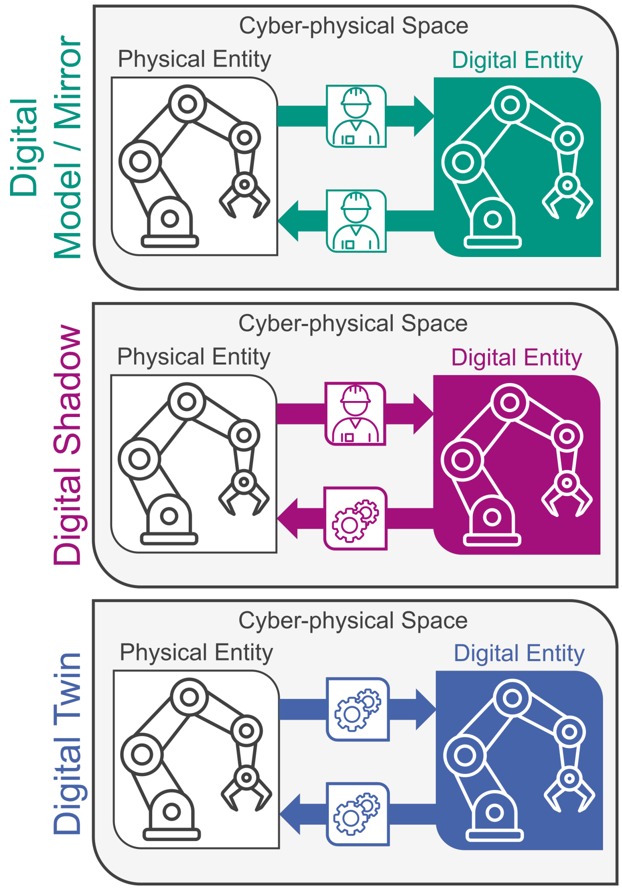

Figure 8. Different aspects of DT implementations.

4.3.4. Role and Implementation of XR

In industrial environments, AR is increasingly being used to enhance situational awareness and enable real-time interaction between operators and machines. An AR system was implemented to provide operators with contextual information overlaid on real-world objects [6]. The system utilized Simultaneous Localization and Mapping (SLAM) and image tracking, allowing the system to understand its surroundings and accurately align digital content with physical elements in the environment. An AI-driven human–robot collaboration system has integrated HoloLens-based AR to provide real-time operator assistance during assembly tasks [71]. The system overlays interactive AR guidance on physical workspaces, improving task execution, reducing cognitive load, and enhancing safety through predictive robotic adaptation. Operators were guided through processes such as maintenance, repair, and reconfiguration by viewing real-time data superimposed directly on the equipment, helping to reduce errors, improve safety, and speed up tasks. The ability to track the operator's position and recognize objects allowed a precise alignment of the information with the actual physical system.

Another work uses both AR and VR for optimal layout planning in human–robot collaborative systems [81]. VR is initially used for layout planning in collaborative human–robot assembly systems. Designed and simulated assembly layouts can be designed in a fully immersive virtual environment. This allows for the early-stage planning and exploration of different configurations without the constraints of the physical workspace. Once the layout is designed in VR, AR is used to validate the planned layout in the real environment. Using AR, planners can visualize the proposed layout directly in the physical workspace, ensuring that the design integrates seamlessly with real-world constraints. This process helps identify potential issues such as spatial conflicts, ergonomics, and safety clearances. The combination of VR for planning and AR for real-time validation provides an efficient workflow, enabling on-site adjustments based on real-time feedback from the AR system.

In summary, XR technologies, including AR and VR, show significant potential in improving situational awareness, optimizing planning, and enabling real-time interaction in industrial settings. AR supports the precise alignment of digital information with physical systems, while the combination of VR for immersive planning and AR for real-world validation streamlines workflows in human–robot collaboration. Despite these clear benefits, the use of XR technologies in this context remains underrepresented, indicating a gap in their broader adoption and integration into industrial processes.

4.4. Combination of Technologies

This section explores the integration of AI, DTs, and XR in RMSs, highlighting both the benefits and challenges of combining these technologies. AI and DTs are frequently paired to optimize system reconfiguration, with DTs providing real-time data and virtual representations of physical systems, while AI models analyze these data to predict failures, detect anomalies, and recommend reconfiguration strategies. XR technologies, such as AR and VR, complement these systems by enabling intuitive human-driven decisions and problem-solving.

The relationship between these technologies resides in their complementary functions, which provide a cohesive framework for system reconfigurability. XR provides operators with immersive, real-time interfaces that overlay digital information onto physical systems, while AI assists by offering contextual guidance and anomaly detection. In turn, DTs keep the digital and physical worlds synchronized, ensuring the accuracy and relevance of the displayed data. However, the combination of these technologies, particularly AI, DT, and XR together, remains underexplored in the reviewed literature.

4.4.1. AI and DTs

The combination of AI and DT technologies is critical to enabling flexible and efficient reconfiguration in manufacturing. The following examples show how AI and DTs are being combined to enable more flexible and efficient reconfiguration in manufacturing.

AI and DTs are utilized to elicit the capabilities of current manufacturing systems and the reconfigured system. When a mismatch is identified, reconfigurations are suggested [103].

In a Digital-Twin-enabled CPS approach for mixed packaging, DTs serve as the core technology to orchestrate production operations and enable autonomous reconfiguration. This is achieved by simulating and validating alternative strategies for handling and packaging scenarios based on new requirements. ML is applied to automate the packaging process from object recognition to robot control, improving the system's adaptability and flexibility [94].

AI techniques are used for efficient task sequencing and the generation of a collision-free path on flexible robotic assembly lines. DTs therefore provide a digital representation of the physical floor of the store, allowing direct simulation and testing of reconfiguration scenarios [90].

Additionally, a dynamic intelligent reconfiguration tool for CPS is presented based on Python function blocks. By integrating AI with DTs, a dynamic and adaptable manufacturing system is created, allowing the quick and on-demand reconfiguration of the CPS, performed on DTs [95]. There, DTs act as virtual replicas of physical entities on the shop floor, enabling real-time monitoring and integration with information systems such as MES and ERP. This integration allows for improved data sharing and process optimization.

The synergy between DTs and AI is achieved through the utilization of data provided by DTs, which AI models analyze to make real-time decisions, such as detecting anomalies and predicting equipment failures.

4.4.2. XR and AI

XR technologies combined with AI provide the foundation for intuitive operator interaction in complex manufacturing environments. AI-driven AR has been applied in human–robot collaboration, where real-time operator action recognition enables adaptive robotic movement and ergonomic optimization. The system integrates AR with AI-based perception models, using CNNs for hand and object tracking, and reinforcement learning for robot posture adjustment [71]. By dynamically responding to operator actions, the system reduces cognitive load and enhances efficiency.

AR and semantic AI are used to assist the operator in a highly automated environment [6]. Various AI methods are used, including ML and DL techniques such as NLP to promote natural interaction, CNNs to help the operator understand the environment, and ML for anomaly detection. AR systems are often used to connect to a remote expert who helps and guides on-site operators. The hypothesis is that many possibilities provided by a remote expert can also be solved by adding a semantic layer. An architecture consisting of several layers is proposed: a user interaction layer, an AR physical layer to align the physical and virtual worlds, and a semantic layer supporting step-by-step guidance, decision-making, and anomaly detection. The technologies in this architecture complement each other, allowing the device to retrieve context information from the environment, such as reading states or values from non-sensorized controls and validating the operator actions. Advances in NLP techniques, chatbots, and new architectures based on transformers enable operators to access valuable context information in natural language, with responses returned in a natural form to better comprehend the actions carried out. ML-based anomaly detection techniques accelerate the determination of errors or the identification of risk situations in scenarios with a large amount of information from sensors and images retrieved by AR devices.

These applications show how AI-enhanced XR interfaces empower operators in making informed decisions and maintaining system efficiency.

4.4.3. DT and XR

The combination of DT and XR technologies seamlessly bridges the gap between physical and digital systems, enabling real-time updates and operator support. The examples below illustrate this combination.

An approach has been presented to intuitively update the digital shadow of a showroom using AR [78]. The operator can place additional geometry where the physical shop floor was changed, allowing for easy and intuitive updates to the digital shadow. An AR-based application integrated with an Asset Administration Shell (AAS) framework to support human operators has been described [77]. This solution provides digital instructions, malfunction alerts, and resource status visualization, enhancing reconfiguration by enabling seamless communication between different components and providing real-time support to operators.

These examples demonstrate that DTs and AR complement each other in enabling interactive and adaptive manufacturing environments.

4.4.4. AI, DT, and XR

An industrial data-space framework for resilient manufacturing value chains integrates DTs, XR, and AI to create a comprehensive and adaptive system [74]. These technologies are integrated as follows: DTs model data using the AAS model approach and Gaia-X specifications, which utilize the serialization format JSON-LD for asset modeling. The knowledge base incorporates skills from human experts, product or process information, and human–machine interaction schemes. VR/AR technologies are used to convey necessary reconfiguration steps or problem-solving strategies to the user in an intuitive and interactive manner. AI uses information from tools, prior knowledge, and decisions made by machine experts regarding process reconfiguration. This forms an AI-based knowledge base capable of predicting disruptions, determining reconfiguration strategies, and intuitively communicating these to the machine user. As illustrated in Figure 9, a comprehensive overview of the interplay among these technologies and their respective roles is provided.

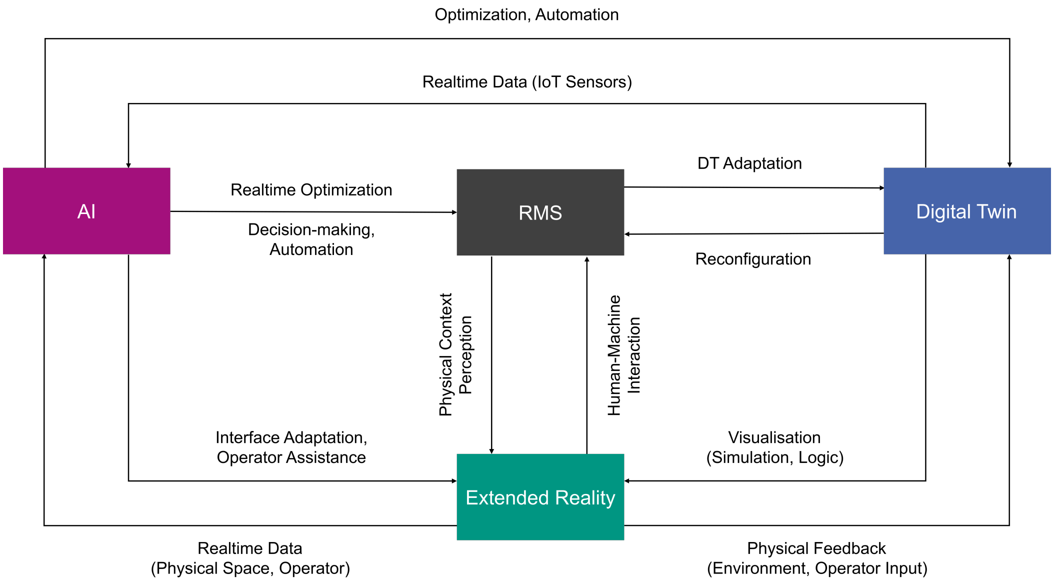

Figure 9. Diagram showing the interactions between AI, RMS, DT, and XR in real-time data and context adaptation.

This integration of AI, DTs, and XR exemplifies how these technologies enhance the adaptability, efficiency, and resilience of manufacturing systems by combining real-time data, predictive analysis, and immersive interaction.

The combination of AI, DTs, and XR is still emerging, but the practical applications discussed here demonstrate the potential of combining these technologies and provide a foundation for future research in RMSs.

4.5. Implications

RMSs have undergone extensive development in recent years with the aim of optimizing reconfiguration processes to meet the dynamic demands of modern manufacturing. Common goals in this field include improving key performance indicators (KPIs) such as reducing reconfiguration time and errors, enhancing accuracy, enabling anomaly detection and prediction, increasing automation and remote operation capabilities, and increasing flexibility and availability. Objectives like cost reduction, balanced workload and job scheduling, real-time adaptability to changes, and minimizing physical alterations are also paramount. Achieving these goals critically depends on the synchronization of Digital

Twins (DTs) with manufacturing systems and the implementation of dynamic monitoring and control mechanisms.

4.5.1. Current State of Technology Use in RMS

This section summarizes our analysis results on how DTs, XR, and AI are utilized, individually and in synergy, to enhance reconfiguration processes in RMS, as was stated in RQ1, and provides an overview that specific roles they play in supporting human operator during reconfiguration tasks (RQ2).

Regarding the technology use (RQ1), AI and DTs are the predominant technologies used in RMS research today. AI contributes significantly to optimizing RMS efficiency through real-time monitoring, predictive maintenance, and effective decision-making processes. Through ML algorithms, AI can predict potential system failures, schedule jobs dynamically, and adapt workflows to changing demands. This significantly reduces downtime, minimizes reconfiguration errors, and enhances overall system performance. Cognitive AI tools, such as those integrating natural language processing (NLP), allow operators to interact with RMSs more intuitively, bridging the gap between complex system controls and human decision-making. Additionally, AI supports the analysis of large datasets, enabling the continuous improvement of reconfiguration strategies over time.

DTs facilitate virtual representations of physical assets, enabling simulation and analysis that support system optimization. These virtual models enable manufacturers to test reconfiguration scenarios, predict outcomes, and validate processes before physical implementation, reducing the risks and costs associated with trial-and-error approaches. Synchronization between physical systems and DTs allows for real-time updates, empowering operators and automated systems to respond to changes dynamically. Furthermore, DTs contribute to long-term system optimization by capturing data throughout the product lifecycle, which can be used to refine manufacturing strategies and enhance predictive capabilities.

In contrast, XR remains underutilized in RMS, despite its acknowledged potential to enhance human–machine interaction and provide immersive reconfiguration simulations. When implemented, XR can improve situational awareness, facilitate knowledge sharing, offer real-time support and training, and enable natural language processing and decision-making through immersive experiences. For example, VR can be used for reconfiguration planning and optimization in a risk-free environment, while AR overlays critical real-time information onto the physical workspace, guiding operators during complex tasks or in human–robot collaboration [71,105]. XR tools incorporating NLP and AI can provide real-time feedback and anomaly detection, further assisting operators in achieving more accurate and efficient reconfiguration outcomes.

While DTs, AI, and XR each contribute uniquely to enhancing RMS reconfiguration processes, integrating these technologies creates a cohesive system that enhances decision-making and empowers operators beyond their separate abilities. Thereby, DTs serve as a foundation for AI and XR integration by providing continuous real-time data of the on-site system. By capturing and synchronizing data from physical systems, DTs enable AI algorithms to analyze performance trends, detect anomalies, and recommend optimal reconfiguration strategies.

Regarding operator support (RQ2), XR interfaces are essential for operator inclusion and can utilize data produced by DTs to deliver immersive, real-time visualizations, enhancing situational awareness and operator comprehension, while also facilitating sophisticated interactions between humans, machines, and AI. While DTs provide data for the virtual representation of the physical system, AI offers assistance and guidance based on the scanned physical environment from the XR system and the real-time data of the system from the

DT. Here, XR acts as an intuitive interface for human operators, translating complex DT and AI outputs into actionable, user-friendly formats. The integration of DTs, AI, and XR significantly enhances human–machine collaboration in RMSs and secures the operator's central role. By combining the predictive power of AI, the virtual testing capabilities of DTs, and the intuitive interfaces of XR, RMS can achieve real-time adaptability to changes in production demands. For example, DTs synchronized with AI can continuously analyze system performance and identify the need for reconfiguration, while XR ensures that operators can execute these changes efficiently and accurately.

4.5.2. Challenges and Emerging Trends

This section summarizes the limitations and issues in current research and outlines how future advancements in DT, XR, and AI can further improve processes in RMS (RQ3).

A significant issue identified in the field is the lack of generalizable frameworks that can be applied across different contexts. Many studies develop their own customized frameworks optimized for specific applications, which hinders broader application and standardization. Similar challenges are observed in the broader field of Digital Engineering, where achieving seamless interoperability between digital tools, models, and platforms remains a major research focus [29]. This proliferation of proprietary frameworks leads to fragmentation, making knowledge sharing and collaboration more challenging. The absence of universal or generalizable frameworks that meet the needs of diverse manufacturing setups represents a critical gap in the literature and should be addressed in future research to facilitate standardization and enhance collaboration among different sectors.

In addition, many existing systems rely on complex and inflexible pipelines to integrate data from different sources into RMSs. Although effective in specific scenarios, these pipelines can be cumbersome and lack adaptability. Limitations persist in monitoring entire Programmable Logic Controllers (PLCs) and enhancing support for generic algorithms, which are essential for broader applicability and scalability.

Despite the potential benefits of integrating AI, DT and XR technologies, significant challenges are associated with their combined use. Although several papers utilize each technology individually, few studies combine them to leverage their synergies, and only one paper was found to use all three technologies together. This indicates a substantial gap and opportunity in research for integrating these technologies to create more advanced and effective RMS solutions.

The integration of AI, DT, and XR poses considerable interdisciplinary challenges. Researchers in different domains must collaborate to develop cohesive systems that take advantage of the strengths of each technology. Cross-disciplinary collaboration is difficult due to the varying methodologies, terminologies, and research priorities among fields. Furthermore, the trend of developing individual frameworks exacerbates fragmentation and hinders the standardization necessary for widespread adoption.

4.6. RQ3: How Can Future Advancements in DTs, XR, and AI Further Improve Reconfiguration Processes in RMS?

Emerging research suggests that models utilizing multimodal data, combining input from images, sensor readings, text, and other sources, have the potential to outperform traditional pipelines. These multimodal systems enable more adaptive and dynamic reconfiguration processes, adjusting in real time on the basis of a variety of inputs. This approach promises greater scalability and flexibility, aligning with the future needs of the industry.

Another significant emerging trend is the incorporation of Large Language Models (LLMs) into RMS. LLMs offer the opportunity to process and interpret complex and multimodal datasets, providing insights that were previously difficult to extract. They could serve as key drivers for intelligent decision-making systems, potentially simplifying interactions between operators and AI systems and automating more complex tasks. However, there is still limited research that uses the capabilities of LLMs in RMS, which highlights a significant opportunity for future exploration.

Furthermore, similar trends can be observed in other domains. For example, City Digital Twins (CDTs), which are digital representations of urban environments, aim to integrate heterogeneous data, enable multi-system interactions, predict dynamic changes, and facilitate bi-directional feedback between digital and physical urban operations. Their implementation faces similar challenges to RMSs such as data integration and interoperability issues, cross-sectoral coordination difficulties, and concerns about social justice, privacy, and data bias. Moving forward, CDTs must also align with the SDGs by enhancing data-driven decision-making, fostering inclusivity, and ensuring equitable urban governance [106].

Automated Machine Learning (AutoML) is also gaining attention in the context of RMS. AutoML techniques can automate the process of selecting and tuning Machine Learning models, alleviating some of the challenges associated with developing customized algorithms for specific applications. Incorporating AutoML into RMSs could enhance the development of generic algorithms, improve support and performance across various contexts, and contribute to the creation of more adaptable and efficient systems.

In the realm of Digital Twins, the concept of a bidirectional twin, where the DT not only mirrors the physical system but can also influence it, is not yet fully realized in RMS. The development of bidirectional twins could significantly enhance dynamic monitoring and control, enabling real-time synchronization and interaction between physical and virtual systems. Future directions point toward the implementation of the Asset Administration Shell (AAS), which could facilitate standardized communication and data exchange between physical assets and their digital counterparts, further advancing the capabilities of DTs in RMS.

Despite increasing levels of automation in manufacturing systems, human operators seem to remain in the loop. As automation advances, the complexity of these systems also increases, leading to greater cognitive demands on operators. To maintain efficiency and reduce the likelihood of errors, operators are increasingly relying on assistive technologies. Extended Reality (XR), including Augmented Reality (AR) and Virtual Reality (VR), provides an intuitive interface for connecting operators with digital models such as DTs and AI. XR improves situational awareness by overlaying real-time information onto physical environments, supporting operators in performing reconfiguration tasks with real-time feedback. As RMS systems evolve and integrate multimodal data, XR offers a more seamless and intuitive method for human–machine interaction, especially in combination with DTs and AI systems.

5. Limitations and Future Research

While this review offers a comprehensive analysis of Digital Twins (DTs), Extended Reality (XR), and Artificial Intelligence (AI) in Reconfigurable Manufacturing Systems (RMSs), several limitations must be acknowledged.

First, the inclusion criteria focused on studies published since 2019, which means that earlier relevant work may have been unintentionally excluded. Although we are unaware of older studies directly addressing the integration of DTs, XR, and AI in RMS, it is plausible that such research exists and could provide a valuable historical context or foundational insights into these technologies. Regarding the review process, Scopus was selected as the primary database due to its comprehensive coverage of peer-reviewed literature, which generally includes studies also indexed in other major databases like IEEE Xplore and

ACM Digital Library. While this choice significantly reduces the likelihood of missing key publications, it is still possible that some relevant studies, particularly those in the grey literature or emerging areas, have been overlooked. Furthermore, although a non-English article was excluded, this is unlikely to have significantly limited the scope of the review, as the vast majority of relevant studies were published in English.

Another limitation stems from the variation in the methodologies and study designs between the included articles. This heterogeneity introduced challenges when synthesizing findings in different industrial settings and technological applications. Some studies provided only conceptual frameworks or simulation-based results without real-world validation, which could affect the generalizability of the conclusions drawn from this review. Finally, potential biases in the selection process, such as the reliance on keyword-based searches and the exclusion of grey literature, may have limited the identification of emerging research or work that has not yet been peer-reviewed. While the PRISMA methodology was rigorously followed, future research could benefit from expanding the search to include grey literature and other databases to ensure a broader capture of relevant studies.

This review has primarily focused on the application of DTs, AI, and XR in RMSs. However, the potential of these technologies extends beyond manufacturing, and future work could expand the search to include other domains that are increasingly utilizing these three technologies, such as robotics, the medical field, education, architecture and construction, logistics and supply chain management, aerospace, and the energy sector. These domains have been exploring innovative solutions with DTs, XR, and AI that could be adapted and applied to manufacturing systems. By examining cross-domain applications, it is likely that new methods and frameworks could be identified, which are transferable and beneficial for enhancing reconfiguration processes in RMS.

6. Conclusions

The integration of Digital Twins (DTs), Extended Reality (XR), and Artificial Intelligence (AI) presents significant potential to advance Reconfigurable Manufacturing Systems (RMSs). This review has systematically analyzed their role in improving the flexibility, efficiency, and responsiveness of manufacturing processes. Through the application of DTs, real-time simulation and predictive modeling have been made feasible, reducing reconfiguration time and increasing system availability. AI has optimized decision-making processes, allowing for more adaptive and intelligent manufacturing systems, while XR has enhanced human–machine interaction, providing immersive environments that facilitate intuitive reconfiguration and training.

However, despite the promising individual contributions of these technologies, their combined applications remain underexplored. This gap represents a crucial research opportunity, especially as future manufacturing systems demand more holistic and interoperable solutions. The development of frameworks that enable the seamless integration of DT, XR, and AI will be essential to address current limitations, such as the lack of generalizable models and the reliance on proprietary solutions. Moreover, as advanced technologies such as large language models (LLMs) and automated Machine Learning (AutoML) continue to evolve, they offer promising avenues to enhance the adaptive capabilities of RMS.

In conclusion, while significant progress has been made, the field is on the cusp of a new era where the synergistic application of DTs, XR, and AI could redefine the capabilities of RMSs. Future research should focus on bridging the integration and standardization gaps, thereby driving innovation toward more adaptable, efficient, and intelligent manufacturing processes.

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