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Decision Support Within Digital Twins in Manufacturing Ecosystems: A Review

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ABSTRACT

The dynamic nature of manufacturing and evolving customer demands require agile adaptation within Manufacturing Ecosystems—interconnected networks of enterprises and institutions collaborating to develop market—oriented solutions. To support this adaptation, it is crucial to evaluate large volumes of data and assess alternative scenarios electively. Digital Twins (DTs) enable the replication of physical systems into virtual models, facilitating the exploration of such scenarios. In most applications, Decision Support (DS) is essential and can be considered intrinsic to DTs. By integrating DS within DTs, the loop can be closed—transforming simulation information into actionable decisions. This study investigates recent advances and trends in the use of DTs for DS in production processes, with a focus on applications in Manufacturing Ecosystems. A systematic review is conducted to examine how DTs contribute to complex and holistic decision-making, including tasks such as production planning, maintenance scheduling, and defect management. Special attention is given to how decisions are made within DT-based applications and the extent of their autonomy and complexity. The review contributes to the identification of current research directions and gaps regarding the integration of DTs and DS, with the aim of supporting more effective and adaptive manufacturing strategies.

1 | Introduction

Thanks to globalisation and rapid advancements in technology, Manufacturing Ecosystems have evolved tremendously in recent years. Manufacturing Ecosystems, are characterised by networks of interlinked and interdependent manufacturers, suppliers, and associated services that have become complex systems where collaboration and data exchange are crucial for the seamless production and delivery of goods [1]. However, the adaptation capabilities of manufacturing value chains are not keeping pace accordingly [2, 3]. Recent events, such as COVID-19 [4], geopolitical disruptions [5], supply chain shortages [6], among others, have shown that the Manufacturing Ecosystem is not fully prepared to anticipate problems and respond to those [7]. Within this landscape, there is an increasing effort to come up with updated technologies and new concepts, such as Industry 5.0 (I5.0) [8], and previously Industry 4.0 (I4.0) [9] to solve these challenges.

Industry 4.0 was initially introduced during the Hannover Fair in 2011; furthermore, it was officially announced in 2013 as a German initiative to take a pioneering role in industries which are currently revolutionising the manufacturing sector [10]. I4.0 has substantially changed the conventional industrial landscape, integrating cutting-edge design principles and advanced technologies [11–13], among which we can find Cyber-Physical Systems (CPSs) [14], Artificial Intelligence (AI) [15], and Internet of Things (IoT) [16]. These arose as a pivotal factor in enhancing efficiency, flexibility, and overall productivity [17]. Additionally, I4.0 contributes to agile production, customisation, and sustainable practices, making the manufacturing sector more competitive and innovative [18].

Following the advancements of Industry 4.0, the concept of Industry 5.0 has emerged as a response to the need for a more resilient, human-centric, and sustainable manufacturing paradigm. Officially recognised by the European Commission in 2021 [19], I5.0 builds upon the technological foundations of I4.0 while integrating principles that emphasise human–machine collaboration, environmental responsibility, and social well-being [20, 21]. Key enablers of this paradigm include collaborative robotics (cobots) [22], adaptive AI [23], and sustainable manufacturing approaches [22].

In this context of both I4.0 and I5.0, and thanks to the IoT and manufacturing processes becoming more digitalised, Digital Twins (DTs) emerge as a powerful tool for predictive analysis, performance optimisation and simulation-based testing [24]. DTs' importance became even more prominent in the COVID-19 pandemic, where DT-enabled remote commissioning and information interaction offered new solutions for enterprises in blocked or inaccessible areas [25]. DTs provide a virtual replica of physical assets that can reflect the life of its corresponding twin using physical models and data, ideally linked with the physical counterpart by a flow of data enabling the real-time update of the digital model [26].

DTs arise as a way to overcome the limitations found in static models, where there is no real-time communication with the system and every time it updates, the model needs to create a new model or adapt the existing one. In recent years, the application of Digital Twins in Manufacturing Ecosystems has significantly expanded. Previous reviews highlight that DTs have evolved to dynamic systems with real-time feedback capabilities, enabled by advances in IoT, artificial intelligence, and cloud computing [27, 28]. Their adoption in the manufacturing sector has led to measurable improvements in productivity, waste reduction, and time-to-market acceleration. For instance, industrial reports indicate productivity increases of up to 60%, waste reductions of 20%, and launch time reductions of up to 50% [29]. DTs are increasingly being adopted across a wide range of manufacturing applications due to their potential to provide real-time visibility, predictive insights, and operational optimisation. Their primary applications include real-time monitoring of equipment and processes, predictive maintenance based on sensor data, and virtual simulation of workflows to identify bottlenecks and optimise resource usage. DTs also support faster product development through virtual prototyping, enhanced workforce training via immersive environments, and improved sustainability by reducing energy consumption and carbon emissions [30]. According to recent industry surveys, 86% of manufacturing leaders recognise the value of DTs, with nearly half already deploying them [31]. This expansion is driven by the need for greater operational resilience, especially in response to workforce shortages and supply chain disruptions [32, 33].

Thus, the emergence and application of DTs have created great opportunities for interaction between the physical and virtual worlds [34]. I4.0 paves the way for DTs by facilitating the processing of vast amounts of data, so that DTs' underlying models can simulate systems' behaviours, predict future states and provide insights into performance, maintenance issues, among others. In turn, I5.0 extends the use of DTs to prioritise human-centric production systems. DTs, leveraging data from IoT devices worn by operators, can monitor their health in real time, prevent accidents, and provide recommendations to optimise their tasks, enhancing both productivity and quality of work life [35]. Going further, workplace well-being is not only about streamlining tasks but also about addressing the cognitive challenges posed by complex systems. Human perception and intelligence can often reach their limits when confronted with complex systems generating large amounts of data with many interdependencies. Therefore, advanced tools and technologies become essential to bridge the gap between data complexity and actionable insights. DTs address this need by providing an imminent feedback loop and the possibility to explore potential issues in systems performance, and integrating Decision Support (DS) as a core component. Accordingly, DTs can be used to help decision-makers cope with inherently complex problems or situations in the Manufacturing Ecosystem.

In fact, Manufacturing Ecosystems are becoming increasingly complex due to the need for production processes to adapt to constant shifts in demand and rising customer expectations for personalised products [36]. Consequently, there is a growing need for Decision Support Systems (DSSs) to navigate these complexities, selecting optimal adaptation strategies and evaluating their pros and cons [37]. When considering Decision Support as an integral part of Digital Twins, a realistic representation of the whole production system is available, allowing decision-makers to validate solutions and disregard nonoptimal strategies. In Manufacturing Ecosystems, DTs are already used to create a digital replica of the physical production systems, enabling comprehensive scenario exploration [38].

In this paper, our objective is to offer a thorough and updated examination of the applicability of Digital Twins for Decision Support. Rather than treating them as entirely separate concepts, we explore their interrelation, focusing on how DTs enhance DS capabilities. To structure our discussion, we define the following three research questions as key drivers:

- RQ1: What is the current approach for Decision Support feedback within Digital Twins in Manufacturing?
- RQ2: What are the key challenges in implementing real-time feedback mechanisms between Digital Twins and Decision Support systems in manufacturing?
- RQ3: Which strategy is adopted for addressing comprehensive decisions in a production process while considering intermediate decisions?

This review aims to demonstrate that DS should be considered an integral part of DTs. The main contribution of our work is to draw conclusions about the actual integration DTs and DS and its effectiveness. Additionally, we identify gaps in current research and potential areas for future investigation, offering a comprehensive understanding of the state-of-the-art in this rapidly evolving domain.

Previous research has explored DT applications and the separate roles of DT and DS, but our synthesis offers a comprehensive understanding of their integration. We emphasise how this integration benefits Manufacturing Ecosystems by closing the information loop, improving decision-making, and optimising processes. Our investigation identifies prevailing trends in these areas, offering valuable insights into the evolving decision-making landscape in Manufacturing Ecosystems' production processes.

This paper is organised as follows: In Section 2, we provide background information as a context for our review. Section 3 presents a detailed description of the methodology we followed to carry out our research. We discuss the relevant findings and propose future improvements in Section 4. Finally, we summarise our findings and outline our conclusions in Section 5.

2 | Background and Related Work

In this section, we provide a background on the trends related to Digital Twins in manufacturing systems, and specify how we define DTs, within the different trends in the field. Then, we describe the role of DS in DTs. Additionally, we provide a brief overview of decision-making processes in manufacturing to offer context. This section is relevant and lays the groundwork for the review presented in Section 4.

2.1 | Digital Twins in Manufacturing

As noted in the introduction, the role of DTs is of utmost importance for advancement in industry. In fact, some researchers consider DTs as one of the most innovative enabling technologies of I4.0 [39]. The concept of DT first appeared in 2002, introduced by Michael Grieves in the context of an industry presentation concerning product lifecycle management [40]. However, the first formal definition of a Digital Twin can be attributed to Glaessgen Stargel [41]. DTs are considered a catalyst that creates added value for various stakeholders [42, 43]. The importance gained by DTs has led to the emergence of many new research studies and inquiries, resulting in an increase in the number of existing definitions and some contradictions within them [44–46]. In this sense, from its inception, the concept has evolved and expanded [47]. For instance, while some authors define any digital model as a Digital Twin, others emphasise the need for a corresponding physical object or data exchange between the physical and digital realms [48, 49].

Therefore, it is essential to clarify our point of view around DT definition. A Digital Twin is a model in which automated data flows both from the physical object to its digital representation and vice versa. This allows the model to be automatically updated with any change in the system. When this bidirectional flow is absent, we refer to it as a *Digital Shadow*, where data flows only from the physical to the digital realm. Conversely, a *Digital Model* lacks automated data feedback altogether. Figure 1 illustrates these differences clearly.

It is important to clarify the role that temporality plays in the bidirectionality of data. Ideally, this bidirectionality would occur in real time; however, we consider the requirement of real-time communication as application-dependent. In our definition, a Digital Twin must include automated feedback between the physical and digital counterparts, but this does not necessarily imply instantaneous data exchange. In many industrial scenarios, especially those involving noncritical processes or long-cycle production systems, update frequencies in the range of minutes or even hours can still be considered consistent with a Digital Twin, as long as the loop remains automated and actively supports system updates and decision-making. This point of view is also supported by other research efforts. For instance [50], discuss how the bidirectional data flow between the physical and digital counterparts in a digital twin does not necessarily have to occur in real time, but rather should align with the temporal requirements of the specific application, whether that involves continuous, periodic, or event-driven updates. As an example [51], present a manufacturing use case where the Digital Twin is employed primarily as a pretrained model to support decision-making, without continuous updates from real-time physical data during execution.

The DT applicability spans across industries such as aerospace [52], energy [53], retail [54], among others, demonstrating its widespread adoption in diverse sectors. In this case, we focus on the DTs applied to the manufacturing sector as DTs provide great opportunities and powerful functionalities for the digitalisation of the manufacturing industry [55]. When examining production processes within a value chain that involves physical assets, there is a substantial production capacity alongside extensive historical process data. Nevertheless, without undergoing a digital transformation and implementing Digital Twins in technology, these data lose their utility for optimisation, scenario validation, predictive maintenance, and other essential activities [56].

DTs provide a more direct integration and synchronisation from the physical to the virtual world [57], which allows for virtual

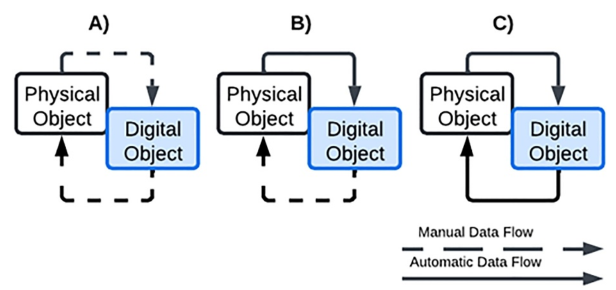

FIGURE 1 | (A) Dataflow in a digital model. (B) Data flow in a digital shadow. (C) Data flow in a digital twin. Same concept as presented in [44].

production control and process planning. The utilisation of Digital Twin technology extends throughout various stages of the product creation process, ranging from the design phase to end-of-life considerations. However, DT research tends to focus predominantly on the production/manufacturing phase [58]. A manufacturing DT offers an opportunity to simulate and optimise the production system, including its logistical aspects. It enables a detailed visualisation of the manufacturing process from single processes up to the whole production process.

Based on a recent study regarding the use of DTs throughout the production lifecycle [59], the primary applications of genuine Digital Twins in manufacturing are focused on production control, process evaluation and optimisation, and real-time monitoring. On the other hand, Digital Shadows are predominantly used for state monitoring, real-time production control, and predictive maintenance. Lastly, Digital Models are commonly employed for predicting workpiece performance and aiding production planning. The wide range of applications indicates the suitability of DTs to be applied in this area and the many opportunities that arise through them. It has already been stated that DTs enable complex manufacturing and allow production systems to be more autonomous, smart, and connected as a source of semantic information. Additionally, DTs can add value to various industries by accelerating time to market, streamlining processes, lowering maintenance costs, boosting user engagement, and integrating information technologies [60].

2.1.1 | Previous Literature Reviews

Existing literature reviews have laid a strong foundation in defining Digital Twins, classifying their applications, and exploring domain-specific uses (production optimisation, predictive maintenance, zero-defect manufacturing, etc.). A selection of these reviews, chosen based on their relevance and substantial citation count, is summarised in Table 1. Particular effort was made to identify reviews that address, even partially, the role of Digital Twins in supporting decision-making. However, as shown in the various columns of the table, these studies generally do not examine in depth the relationship between Digital Twins and Decision Support/Decision Support Systems to enable closed feedback loops. In our view, this convergence is critical to advancing the Industry 4.0 vision of self-optimising, intelligent manufacturing systems.

Although previous reviews have addressed key aspects of Digital Twin architectures, technological enablers, and domain-specific implementations, their treatment of Decision Support remains limited. For example, studies such as Kritzinger et al. [44] and Jones et al. [62] have advanced the conceptual understanding of DTs—clarifying definitions, levels of integration, and open research challenges. Likewise, reviews focused on areas such as predictive maintenance or smart manufacturing typically prioritise technical performance metrics over their contribution to systematic decision-making processes. This underscores a critical gap.

Another important dimension explored in our review is the presence—or absence—of closed feedback loops. Most of the Digital Twin systems reviewed by Kritzinger et al. or Lattanzi et al. [67] remain conceptual or operate in open-loop configurations. Our review expands on this point by identifying and evaluating studies in which Digital Twins are explicitly designed to provide feedback into the system—either through automation or human-in-the-loop architectures—and highlights the practical challenges encountered when attempting to close these loops. In addition, the set of articles considered distinguishes between real-world implementations and conceptual frameworks.

A further shortcoming of previous studies is the limited exploration of how Digital Twins integrate with existing industrial systems. Based on our experience working with industry, it is crucial to explore how Digital Twins can effectively interact with legacy systems—such as MES, ERP, or planning tools—to support decision-making and other key industrial functions. This review contributes by highlighting the ways in which Digital Twins can be connected to existing IT infrastructure to support decision-making, with particular emphasis on the practical challenges of implementation.

Taken together, these dimensions define the specific contribution of our work: a focused, up-to-date synthesis of the literature that bridges the gap between Digital Twin concepts and Decision Support applications, with special attention to practical implementations in real-world manufacturing ecosystems.

2.2 | The Role of Decision Support in Digital Twins

Decision Support is a broad and evolving concept that encompasses all aspects of assisting individuals in making informed decisions. It has been associated with various disciplines over time, including operations research, decision analysis, decision support systems, among others [68]. At its core, Decision Support involves providing relevant information, structuring problems, and facilitating the evaluation of alternatives to enhance decision-making processes. Decision-making itself refers to the entire process of selecting one option among multiple alternatives, typically involving problem assessment, information gathering, alternative identification, consequence evaluation, and final selection [69]. Importantly, Decision Support focuses on aiding human decision-makers rather than replacing them, distinguishing it from autonomous systems designed to make decisions independently. This distinction underscores the role of Decision Support in enhancing human judgement through structured methodologies, tools, and data-driven insights, ensuring that decisions are well-informed and logically sound [70].

A key component in modern Decision Support methodologies is the use of simulations and modelling, which have proven highly effective in analysing system behaviours and predicting future outcomes [71–73]. Moreover, simulation and modelling are widely used methods for assessing complex systems' design, operation, and performance [74]. This aligns with existing literature, which underscores simulation's versatility across different purposes and contexts, further emphasising its value in

TABLE 1 | Overview of key review articles on digital twins and decision support.

Review (year, outlet)	Main thematic focus	# Of papers analysed	Decision support?
Kritzinger et al. (2018; IFAC-PapersOnLine) [44]	Conceptual classification of DTs; defines Digital Model, Shadow, and Twin; highlights scarcity of true DTs with bidirectional data	Not explicitly stated (46 references cited)	No—Does not focus on DSS
Enders and Hoßbach (2019; AMCIS Conf.) [61]	Cross-industry DT applications; proposes 6-dim classification scheme; broader than manufacturing	87 applications analysed	No—No DSS focus
Jones et al. (2020; *CIRP J. Manuf. Sci. Tech.*) [62]	Derives 13 DT characteristics; identifies 7 research gaps incl. lifecycle and virtual integration	92 publications (2009–2019)	No—Concept and research gaps only
Melesse et al. (2020; *Procedia Manuf.*) [63]	DT in production, predictive maintenance, and after-sales; discusses use and challenges	25 studies (until mid-2019)	No—DSS not explicitly discussed
Errandonea et al. (2020; *Computers in Industry*) [64]	First DT-for-maintenance review; covers concepts and strategies across sectors	Not reported (~185 refs)	No—Focus on strategy, not DSS
van Dinter et al. (2022; *Info. & Software Tech.*) [65]	DTs for predictive maintenance; analyses platforms, twinning, and communication protocols	42 studies (to 2021)	No—Focus on engineering and PdM algorithms
dos Santos et al. (2021; *Int. J. Prod. Research*) [66]	DTs for decision support in production; systematic review of DES and ABS simulation models in DT-enabled manufacturing contexts	55 primary studies analysed	Yes—DSS via simulation tightly integrated with DT models
Lattanzi et al. (2021; *Int. J. Comp. Integ. Manuf.*) [67]	Smart manufacturing DTs; discusses implementation, optimisation, decentralised decisions	Not reported (132 refs)	No—Automated decisions mentioned, not DSS-specific

aiding decision-making processes [75–77]. Before the advent of Digital Twins, traditional simulation techniques were limited in their effectiveness. They offered specialised solutions and models that lacked real-time updates aligned with the dynamic nature of the entities being modelled [78, 79]. Consequently, these simulation models were static and dedicated solutions, unable to adapt to changes over time in the corresponding systems [80]. This situation led to the need for either frequently creating new simulation models or undertaking labour-intensive manual updates to existing ones, which were both challenging and expensive solutions.

To clarify the relationship between Digital Twins and Decision Support, it is essential to distinguish between them. A Digital Twin primarily serves as a dynamic digital representation of physical assets, capable of simulating behaviours, capturing real-time data, and predicting future states. In contrast, a Decision Support System is an interactive digital tool designed to assist human decision-makers in solving complex problems by integrating relevant data, analytical models, domain knowledge, and communication technologies in a flexible and adaptive way [81]. As described in the previous section, a defining feature of a true Digital Twin is the existence of a closed feedback loop with the real system. In our understanding of DT and DS, for this loop to be effective, Decision Support must be an integral part of the DT architecture, enabling simulation outcomes and analytical insights to translate into actions and continuous improvements as illustrated in Figure 2. Their integration occurs

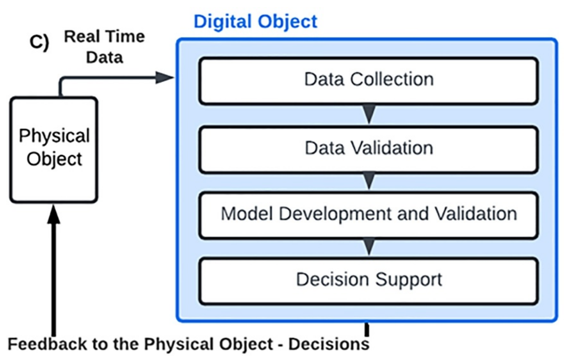

FIGURE 2 | Decision Support as a part of the DTs' elements.

when the DT's analytical and simulation capabilities are used to inform, validate, or trigger decisions, thereby embedding DSS functionalities within the DT architecture [82].

In Manufacturing Ecosystems, this fusion allows Digital Twins to go beyond passive mirroring and function as prescriptive systems that support strategic, tactical, and operational decisions. The combination leverages the DT's real-time responsiveness along with the DSS's structured decision-making logic, forming a closed-loop system. DTs can significantly enhance decision-making processes [58]. In this paper, we specifically examine the potential for Decision Support offered by DTs within applications in Manufacturing Ecosystems' value chains.

As an introduction, we now outline some challenges faced in manufacturing processes' decisions and expose how Digital Twins can effectively address them:

- As stated above, Manufacturing Ecosystems continuously change, leading to corresponding shifts in their value chains and production processes. This makes it difficult for static models to adapt and provide accurate replicas of the processes involved in these value chains. Because of DTs' ability to replicate processes and their changes in real-time, more up-to-date information and models are available, which allows for better-informed decisions. This, in turn, can positively impact the achievement of associated performance goals [83].
- The intricacy of manufacturing processes is on the rise due to the emergence of reconfigurability. Consequently, decision-making becomes more challenging because of the multitude of variables and involved factors requiring careful consideration and analysis. DTs help by allowing for the analysis of intricate processes, offering insights into performance, and facilitating predictive capabilities [84].
- When confronted with complex processes, physically testing various scenarios to determine optimal solutions can be impractical. Yet, decision-makers greatly benefit from this information to enhance the reliability and insightfulness of their decision-making processes. DTs emerge as a solution by enabling decision-makers to simulate diverse scenarios in a virtual setting, eliminating the need for expensive and time-intensive physical tests. This is based on the DTs' ability to complete offline 'what-if' analysis in a close-to-reality virtual environment before implementing tested actions in actual operations [85].
- In complex manufacturing systems, the DTs can serve not only for modelling the processes within value chains but also for controlling systems as part of a more comprehensive framework. Their advantages span from real-time monitoring of machine status and enhanced reliability to facilitating predictive maintenance, among other benefits. These collectively contribute to a better understanding of the decisions required to control the systems [86].

Considering the above, DTs empower decision-makers with comprehensive insights, enabling more informed and efficient decision-making when facing complex manufacturing challenges. In literature, the application of Decision Support throughout DTs has already been studied [87].

2.3 | Decisions in the Manufacturing Ecosystem

It is worth mentioning that the types of decisions encountered in the manufacturing realm are vast and varied. These decisions range from selecting the appropriate materials/parameters for a specific process or machine (*low-level*) to choosing the most suitable supplier (*high-level*) in order to optimise both manufacturing efficiency and costs [88]. Decision makers have to consider costs and maximum capacity of the production, but also sustainability aspects [89], task scheduling [90], and the optimal routing determination of a product through the production process [91]. Another classification of decisions can be made according to the different levels at which they take place within an organisation: *strategic, tactical, and operational* [92]. Strategic decisions focus on long-term planning, investment, and policy-setting to ensure competitiveness and sustainability. Tactical decisions deal with mid-term process optimisation, resource allocation, and efficiency improvements. Operational decisions are short-term and involve day-to-day production management, machine control, and real-time troubleshooting.

As stated in the introduction, in order to meet the challenges of global competitiveness, manufacturing organisations now face the complex task of selecting appropriate manufacturing strategies, product and process designs, manufacturing processes and technologies, as well as machinery and equipment [93]. These choices become increasingly complex as decision-makers in the manufacturing environment must evaluate a wide array of alternatives based on a set of often conflicting criteria [94]. Managing these ultra-high-dimensional data, unlocking its potential value, and developing a data flow model suitable for the modern manufacturing environment presents a significant challenge [95]. Consequently, understanding and improving the decision-making processes in manufacturing is crucial for achieving long-term success in an increasingly competitive and dynamic global market. In this context, Decision Support is endorsed by Digital Twins across diverse levels [96]. In Section 4, we provide an extensive review of the DS approaches that are used in or related to DTs within manufacturing applications.

3 | Materials and Methods for the Review

In this review, we employed a systematic methodology to ensure a comprehensive and unbiased examination of the relevant literature. Our objective was to provide reliable insights into current trends in Digital Twins and Decision Support in Manufacturing, mainly focusing on the feedback loop created to the replicated systems. To this end, we followed a structured search process across major academic databases, using predefined keywords and search strings to identify pertinent studies. The overall methodology was inspired by the systematic review guidelines proposed by Kitchenham et al. [97] for the software engineering domain, which offer a robust framework well-suited to technology-driven fields characterised by conceptual and terminological heterogeneity. Detailed processes for the literature review and the criteria used to determine the eligibility of studies are discussed in subsequent sections.

3.1 | Definition of the Keywords

We embarked on a comprehensive articles review, targeting research at the intersection of the topics that we have been introducing. We conducted the research in Scopus, IEEE, Science Direct and Web of Science in order to gain a comprehensive overview of the issue. We accessed the databases in February 2025. The selection of keywords for this study was not arbitrary but rather the result of a structured approach. For the selection of keywords, we first conducted an initial screening of the most commonly used terms that linked Decision Support with Digital Twins in Scopus. This preliminary analysis revealed that the thematic coverage of these concepts is highly diverse, encompassing multiple disciplines and application areas. A visual representation of this first analysis can be observed in Figure 3, generated using VOSviewer.

Figure 3 therefore illustrates the co-occurrence network of key terms found in the literature. Each node represents a keyword, with its size proportional to the frequency of occurrence, while the edges indicate co-occurrence relationships between keywords within the same documents. The colours correspond to clusters identified by VOSviewer's clustering algorithm, which groups terms that tend to appear together in the literature, thus revealing thematic areas within the field. In this case, five main clusters were identified: One cluster (in red) is centred around *artificial intelligence*, *data analytics*, and *production control*, suggesting a strong focus on AI-driven decision-making in manufacturing. Another cluster (yellow) gathers terms such as *cyber-physical systems*, *embedded systems*, and *real-time*, indicating enabling technologies that support the implementation of Digital Twins. A third group (green) emphasises application-oriented aspects, with keywords such as *performance*, *feedback*, and *manufacturing industries*. The blue cluster reflects operational concerns such as *predictive maintenance*, *quality control*, and *efficiency*, while the purple cluster connects terms such as *machine learning*, *digital transformation*, and *forecasting*, pointing to data-centric and algorithmic approaches underlying both DTs and DSS. This clustering offers a high-level visual summary of the main research directions in the field, helping to contextualise how different technological concepts interrelate and where current research efforts are concentrated.

Given that our objective was to explore how these two domains interact and complement each other, we needed to refine our keyword selection to capture studies that specifically examine the interplay between Decision Support Systems and Digital Twins. To achieve this, we selected the following set of keywords: (‘Decision Support’ OR ‘Recommendations’ OR ‘Feedback Loop’) AND ‘Digital Twins’ AND ‘Manufacturing’. The keywords selected allow us to capture the essence of the Decision Support by taking into account synonyms that could refer to the same aspect, that is ‘recommendations’ and ‘feedback loop’. These keywords were applied to the TITLE-ABS-KEY (title, abstract, and keywords) field in the selected databases to maximise relevance. The initial database search, after the removal of duplicates, resulted in a total of 358 documents, confirming the relevance and multidisciplinary interest in the topic. To ensure consistency and academic rigour, we established a set of inclusion and exclusion criteria that is further explained in the next section.

To gain a clearer view of the underlying thematic trends beyond the dominant term ‘digital twin’, we generated an alternative word cloud (Figure 4) in which this keyword and its variations were intentionally excluded. This approach allows for a more nuanced analysis of the remaining recurring concepts within the dataset. As shown in the visualisation, terms such as ‘machine learning’, ‘predictive maintenance’, ‘simulation’, ‘control’, ‘decision support’, and ‘big data’ emerge prominently. These keywords reflect the themes and technologies associated with the topic of the review. The resulting distribution aligns well with the research objective of exploring how Decision Support Systems are integrated and operationalised in manufacturing contexts. By removing the central term, this figure validates the relevance of the broader ecosystem of concepts captured by our keyword strategy and confirms the coherence of our dataset with the intended scope of the study.

Figure 5 shows the annual distribution of the articles retrieved for this review. As illustrated, there has been a steady increase in the number of publications over the years, reflecting a growing academic interest in the intersection of Digital Twins and Decision Support within the manufacturing domain. From

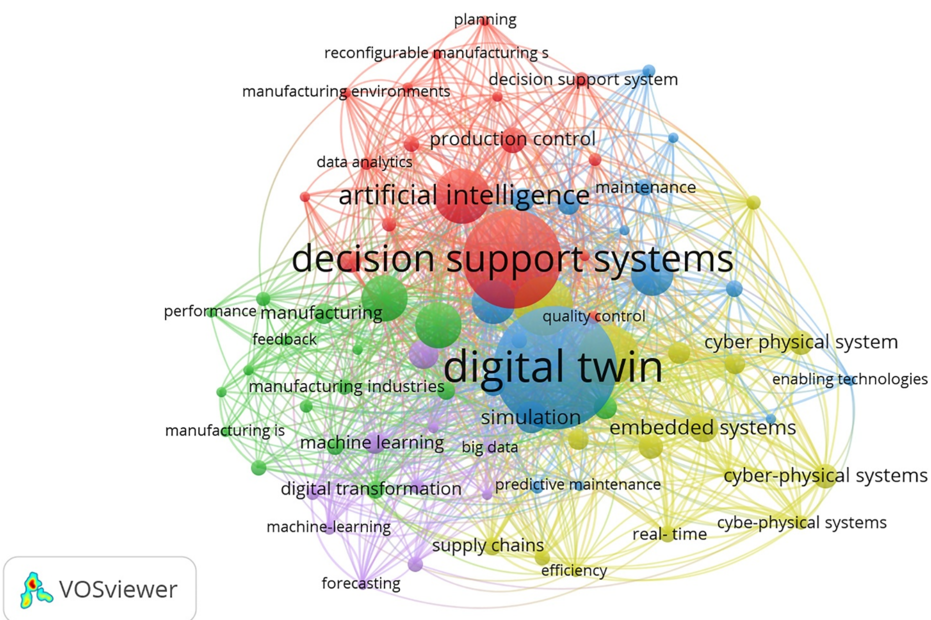

FIGURE 3 | Co-occurrence network of key terms related to decision support systems and digital twins in Scopus, generated using VOSviewer.

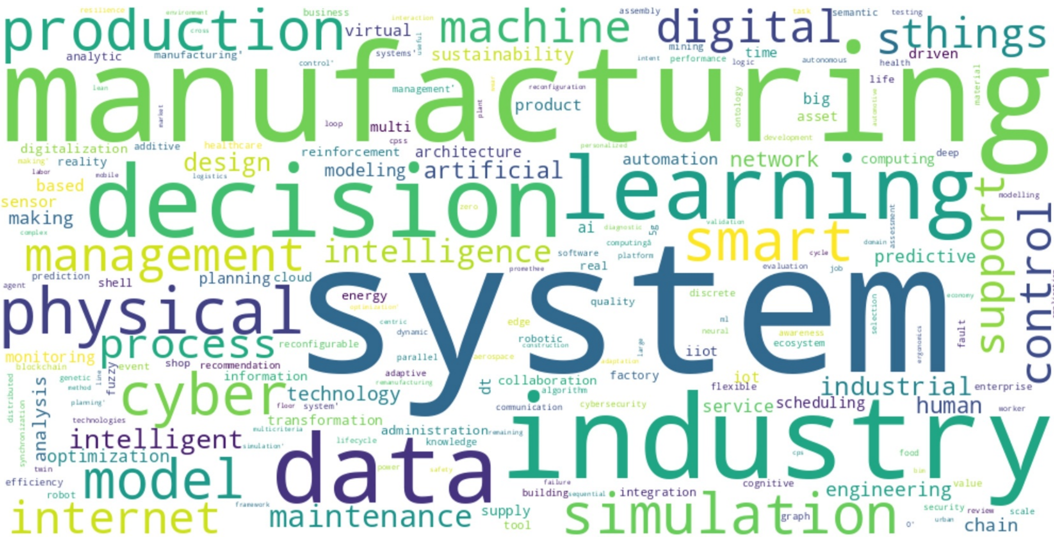

FIGURE 4 | Cloud of keywords from the resulting articles, generated with python, not taking into account 'Digital Twin'.

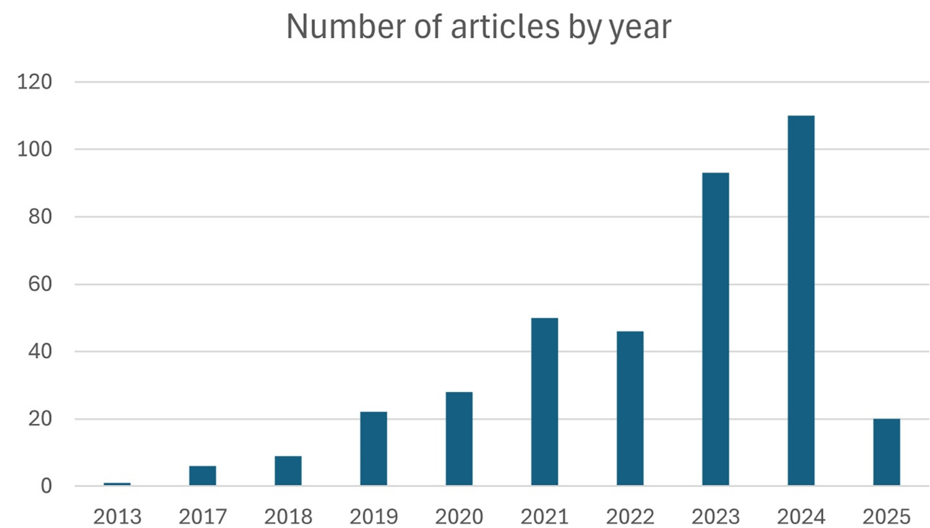

FIGURE 5 | Articles published by year after applying first step criteria.

2019 onwards, the number of publications began to rise more significantly, with a notable surge starting in 2021. This trend accelerated in 2023 and 2024, which together account for the highest volume of contributions, indicating that the topic has become highly relevant in recent years. The partial count for 2025, based on data collected up to January, already shows a promising number of publications, suggesting that research in this area is likely to continue expanding.

In addition to the yearly distribution, Figure 6 also distinguishes between journal articles and conference papers, offering insights into the type of publications that dominate this research field. As observed, conference papers consistently outnumber journal articles throughout the period, accounting for 64% of the total documents obtained. This dominance suggests that the field is still highly dynamic, with many contributions being disseminated through conferences, likely due to the fast-evolving nature of digital twin technologies and their application in decision support systems. However, the number of journal articles has

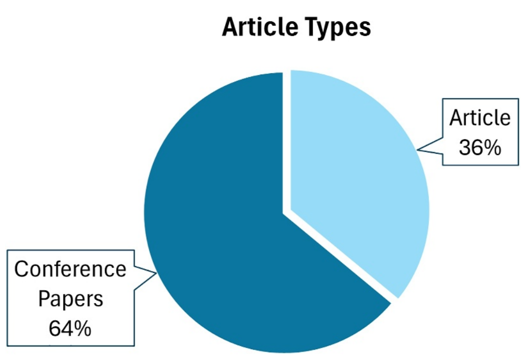

FIGURE 6 | Papers stratified by type of publication.

also increased steadily, particularly from 2021 onwards, which may indicate a gradual consolidation and maturation of the research. Figure 7 presents the evolution of both publication types over time, showing parallel growth patterns. Although conference papers led the early development of the field, journal publications have gained significant traction in the most recent years, notably in 2023 and 2024. This shift could reflect a transition from exploratory studies to more consolidated research, with scholars increasingly seeking to publish in peer-reviewed journals. The continuous rise in both types of publications highlights the growing academic engagement with the integration of digital twins and decision support systems in manufacturing and related domains.

3.2 | Eligibility Criteria and Results Overview

The article selection process can be divided into two steps, the first being automatised and the second manual, the summarised process can be found in Figure 8. These specific eligibility criteria are designed to ensure the relevance and quality of articles included in our review. Firstly, we limited our selection to peer-reviewed papers and conference proceeding papers published in English between 2017 and 2025. The year 2017 was chosen as the starting point, based on the results of our initial automated search, which showed a notable increase in the number of publications addressing our topic. Only a single isolated contribution appeared in earlier years (see Figure 5), therefore 2017 marked the beginning of more consistent and thematically aligned research. Applying these filters resulted in a total of 350 articles, which then proceeded to the manual screening stage.

Figure 9 helps to illustrate the distribution of the reviewed articles by subject area. The majority of contributions come from Engineering (30%) and Computer Science (25%), confirming the technological and applied nature of the research focus. Other well-represented fields include Mathematics (6%), Decision Sciences (4%), and Materials Science (4%), all of which are strongly connected to modelling, optimisation, and system development relevant to digital twin and decision support research. Smaller but notable contributions come from areas such as Automation and Control Systems (3%), Business and Economics (3%), and Operations Research and Management Science (2%), reflecting the interdisciplinary approach and the importance of decision-making frameworks in industrial and manufacturing contexts.

A significant portion of the articles (11%) is grouped under the category 'Other', which includes a wide range of disciplines with very low individual representation. These fields, such as Psychology, Medicine, and Public Administration, each contribute a minimal number of articles and are generally less

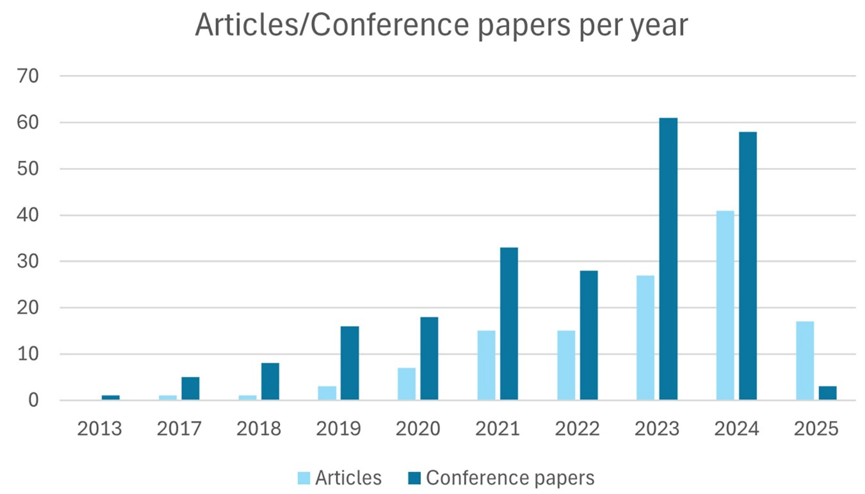

FIGURE 7 | Papers stratified by type of publication and distribution throughout years.

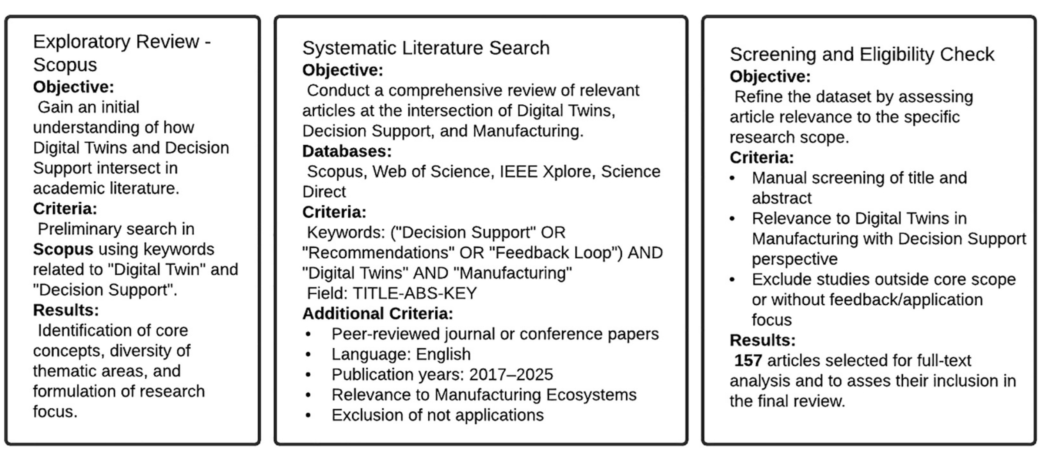

FIGURE 8 | Summary of procedures performed for the review process.

central to the core topic of the study. For example, studies from the medical domain, despite discussing the use of Digital Twins and decision-making, were not considered relevant to our scope. These selection criteria were applied to ensure that the articles included made a meaningful contribution to understanding Decision Support aspects related to Digital Twins in Manufacturing Ecosystems. Therefore, we prioritised articles that provided insights into the practical applications and implications of Digital Twins within Manufacturing Ecosystems, emphasising the role of Decision Support and feedback mechanisms. Table 2 shows the eligibility criteria described above.

The manual process began with a title and abstract screening in order to narrow down relevant studies. During this phase, members of the research group individually examined the titles and abstracts of the retrieved articles to assess their alignment with the review's thematic focus. Articles clearly unrelated to the core subject, were excluded. This collaborative filtering step ensured that only studies with substantial relevance were retained for full-text analysis. The research team excluded papers that primarily focused on low-level oriented Digital Twin creation without considering feedback mechanisms, as well as those that were not application-driven. Furthermore, some articles were excluded for falling outside the core scope of the review, which centres on Manufacturing Systems.

As a result of the manual screening conducted by the research team, a total of 157 articles were identified as fully meeting the inclusion criteria for full-text review. However, not all of them were ultimately referenced or thematically classified in the subsequent analysis. During the in-depth reading phase, some of the initially selected studies were excluded due to insufficient detail regarding the feedback mechanisms between Digital Twins and Decision Support Systems, or a lack of explicit contributions relevant to the objectives of this review. Accordingly, only those works that provided substantial and concrete insights were retained for the final synthesis, which are listed in the tables presented in Section 4. These studies represent practical or conceptual applications situated within the manufacturing domain, and they specifically address the integration of Decision Support mechanisms in the context of Digital Twin technologies.

4 | Literature Review

A systematic approach has been employed to address each research question introduced in Section 1. To ensure a structured analysis, a dedicated subsection has been created for answering each research question. At the end of the section, the lists of articles organised by key decision-related application areas offer a comprehensive summary of the literature review findings. These lists classify the selected studies based on the

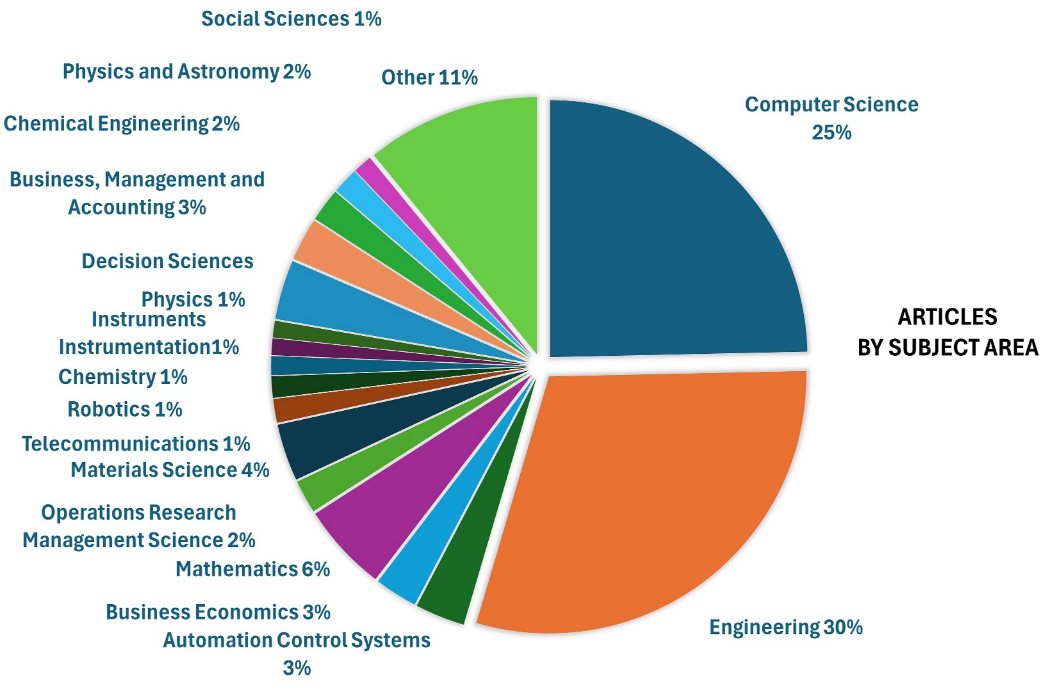

FIGURE 9 | Articles by subject area.

TABLE 2 | Review criteria and details.

Protocol	Details
Criteria for inclusion	Articles taking into account Decision Support/Feedback coming from the DTs, and applications in Manufacturing Ecosystems. Articles published in journals
Criteria for exclusion	Low-Level Oriented Digital Twins creation focused papers, disregarding feedback to the systems. Conference proceeding papers. Non-English texts

type of technology associated with Digital Twin, clearly distinguishing between conceptual frameworks and practical implementations. Furthermore, the articles are categorised according to the specific application domains in which the developed technologies are applied.

4.1 | Perspectives on Decision Support Within Digital Twin: Definitions

Our research started by examining how Decision Support is addressed within the various definitions of DTs. Although the concept of Digital Twin itself varies widely in the body of knowledge [98], and even though a consensus seems to have been reached, as explained in Section 2.1, it was interesting to observe that despite the different concepts, we found a common factor regarding how researchers also define DTs as considering or not Decision Support. All the articles reviewed reflect that Digital Twins are related to and assist in the decision-making process in manufacturing. Overall, we can conclude that most authors define DT as a tool for enhancing decision-making processes by serving as a simulation model. Examples of it are [99–104], who define how DTs' scenario simulation allows obtaining valuable information for decision-making.

We can highlight a reduced quantity of authors [105, 106], who agree with an interesting definition of the Digital Twin, emphasising five dimensions. This conceptual idea was introduced by [107]. The DT is formed by: Physical Space (PS), Virtual Space (VS), Digital Twin Data (DTD), Service System (SS) and the connections between them (CN). The Physical Space (PS) encompasses industry's physical assets, setups, processes, and human resources. The Virtual Space (VS) mirrors PS digitally, constantly updated via information exchange to reflect PS's current state. DTD comprises PS data, VS data, and fused data combining both PS and VS information. According to them, the SS is responsible for providing various services based on the demands of PS and VS. This way, the SS integrates Enterprise Information Systems, computer-aided tools, models and algorithms. Decision Support within this integrated DT definition ensures that interactions between PS, VS, and SS are aligned and optimised over time through continuous feedback loops and iterative improvements.

Related to Decision Support, they explain how the DT could help in multiple manufacturing stages, covering design, manufacturing, product use, and maintenance. For instance, regarding the design stage, the DT aids in control processes. In manufacturing, VS models use process and planning data coming from the DTs, which include continuous monitoring of status and capacity to ensure efficient production. Altogether, they optimise manufacturing plans leading to high-quality finished products in the PS. During the product use phase, it utilises available information to identify value-added functions of the products, incorporating user feedback. Additionally, for maintenance, the DT can act as a diagnostic model to create effective maintenance schemes.

In comparison, Khan et al. [108] introduce a comprehensive approach to advancing smart manufacturing through the Spiral Digital Twin Framework and a novel blockchain system called Twinchain. The Spiral DT Framework extends traditional DT models by incorporating six dimensions that enable continuous optimisation and real-time synchronisation between physical products and their digital counterparts; these are: the Physical Product (PP), its Virtual Product (VP), the Performance Data (PD) collected throughout the lifecycle, Optimisation Utilities (OU) that enhance performance, Spiral Rings (SR) representing iterative improvement cycles, and Dynamicity (DY), ensuring constant alignment between the physical and virtual entities. It emphasises iterative improvement cycles, supported by performance data and optimisation tools. Complementing this, they propose the Twinchain which is a quantum-resistant blockchain designed specifically to ensure secure, fast, and reliable management of DT data, addressing the limitations of conventional cloud and blockchain systems. Together, these innovations aim to provide a robust foundation for dynamic, data-driven manufacturing environments. Decision-making is treated as a traceable and data-driven process, where each design decision is recorded as a transaction within the Twinchain and linked to specific performance requirements, enabling continuous feedback and iterative improvements throughout the product's lifecycle.

Finally, we have also found that [109] backs up our initial statement, in which DS is an integral part of the DT. They consider Decision Support as an intrinsic aspect of Digital Twins. In this sense, they declare that the objective of a Digital Twin within a manufacturing system is to facilitate the decision-making process and enable decision automation by simulating specific elements or processes within the real system.

4.2 | Feedback Loop to the Physical Systems: Answering RQ1

For the DS to be an integral part of Digital Twins, the feedback, as also stipulated in the original DT definition [110], needs to be automated. This automation significantly impacts how decisions are made. Consequently, it is essential to analyse how the feedback loop is currently closed to manage the physical counterparts and, by extension, how decisions are made. Not only should information automatically flow from the system to the DT, but the DT must also transmit information, improvements, or decisions back to the system to perform DS. This setup ensures automated decision-making processes, enhancing the responsiveness and efficiency of Manufacturing Ecosystems.

Therefore, to solve our first research question (RQ1: What is the current approach for Decision Support feedback given Digital Twins in Manufacturing?), we investigated how researchers approached this particular aspect by examining how the reviewed articles addressed the feedback loop. In what automated Decision Support refers to, we realised there is a lack of automated feedback and consequent automated actions within the systems when utilising Digital Twins. Thus, despite the advanced capabilities of DTs to simulate and predict various manufacturing scenarios, the current applications broadly fall short of incorporating automated response mechanisms. As a result, while Digital Twins are proficient in data collection and simulation, the transition from data and simulation insights to action in manufacturing systems remains underdeveloped.

The nearest applications with automated feedback that we found were the contributions from refs. [109, 111]. These studies utilised the OPC Unified Architecture (OPC UA) protocol to enable automated interaction with the system. In the case of Glatt et al., they state that the objective of a digital twin in a manufacturing system is to enhance decision-making and enable decision automation by simulating various elements and processes of the real system. They found other works that addressed DT feedback also using the OPC UA protocol [112–114]. Additionally, in their work, DT implementation facilitated three main aspects: prediction, monitoring, and diagnostic functions. Novák et al., on the other hand, leveraged this technology for on-the-fly production planning. In their case, the feedback to the manufacturing line is derived from an intermediate, the Distributed Manufacturing Execution Systems (DMES). Both contributions highlight the importance of bidirectional feedback, where the Digital Twin continuously simulates new actions in real-time to obtain updated information and provide useful insights.

Additionally, Abed et al. [115] propose a framework where the Digital Twin operates in a continuous feedback loop, with Digital and Physical spaces exchanging information. In this system, the Digital Twin simulates the toolpath of a milling machine and directly interacts with the machine controller to correct any deviations. Based on the simulation results, a toolpath algorithm generates G-code, which consists of instructions guiding the CNC machine on adjusting the tool to correct predicted errors. They emphasise the critical importance of real-time and rapid simulation to enable swift responses and prevent defects and state this as a vital aspect for DS and DTs integration.

Another related aspect to consider is how the sensor evolution within Manufacturing Ecosystems will affect bidirectionality. As sensor technology advances, the ability to gather and utilise data becomes increasingly sophisticated, enabling more effective and precise interactions between Digital Twins and physical systems. In this sense, we found works such as the one from [116, 117], which take advantage of Industrial Internet of Things (IIoT) sensors and infrastructure to provide a bi-directional flow of information. Their studies illustrate how IIoT sensors can collect real-time data from the manufacturing process and feed it back into the Digital Twin. Then, in the opposite direction, it facilitates the transfer of insights from the virtual model to the actual production lines. This allows for analysing constraints and critical assets, running simulations for alternative scenarios, performing diagnostics, identifying defective assets, triggering predictive maintenance, and undertaking performance monitoring to improve operations continuously. Specifically, Guo et al. emphasise the critical role of synchronisation in manufacturing systems. Decision-making is facilitated by IIoT and Digital Twin technologies through a synchronised ticket pool that orchestrates job, setup, operation, and logistics tasks in real time. This approach ensures seamless coordination between physical and digital processes. The Digital Twin continuously processes data from the physical environment and generates actionable insights, creating a closed-loop system of real-time information exchange and feedback.

However, the prevalent pattern is the reliance on Digital Twins to provide feedback that supports user-driven decision-making rather than automated actions, as seen in the work of [118, 119]. The feedback generated by DTs primarily consists of information presented to users, who then make strategic decisions based on these insights [120, 121]. This user-centric approach leverages DTs' analytical and predictive capabilities to enhance human decision-making processes but stops short of fully autonomous systems. This pattern reflects a cautious approach towards full automation, possibly due to concerns regarding reliability, complexity, and the critical nature of manufacturing processes.

Thus, the literature consistently indicates that DTs are used as sophisticated simulation decision support tools. Some examples of this are the work from [122], which focuses on improving the resiliency of Factories of the Future (FoF), where the DT enables, among other capabilities, to comprehend the complexity of event propagation from physical assets to digital networks and this information is used for DS. Furthermore, the contribution of ref. [123] focused on preventive maintenance scheduling. They provide Decision Support through the periodic running of short-term process simulations based on their updated model (DT) of the shop-floor and on the specific opportunity events that unfold in real-time. Moreover, the work from [124] wants to provide a more comprehensive scenario in decision-making related to planning, equipment maintenance, and dynamic deployment of resources, among others. Their proposed system evaluates production scenarios and optimises the processes using DT-based simulations. The decision-making steps include describing possible actions, evaluating those through simulation, and selecting the preferred action.

A middle ground between the tendencies described in the previous paragraphs is also derived from the articles analysed, which combines the DT with further technology, such as, but not limited to, Decision Support System techniques and concretely Machine Learning (ML) models such as Reinforcement Learning (RL). RL is a technique where agents learn to make decisions by performing actions and receiving feedback from the environment [125]. Therefore, having a DT model as the environment to test the actions is highly beneficial. RL has shown great potential in this context [126–128]. By integrating RL with Digital Twins, manufacturers can develop systems that not only simulate and predict outcomes but also learn and adapt from past actions to optimise future decisions [129, 130]. This combination enables the DT to move beyond static simulations to dynamic, self-improving systems that continuously refine their decision-making processes based on real-time data and historical performance [131, 132].

In this case, we can talk about the works presented by Padovano et al. and Pires et al. [120, 133, 134]. The former proposes a Recommender Module, leveraging Digital Twin's simulation data to propose maintenance and production strategies. In contrast, the latter suggests an RL algorithm aimed at selecting the most suitable scenario for the user, combined with similarity measures from other actions and considering the users' trust in the DT-based recommendation. This last aspect sheds light on how users' hesitancy in adopting strategies suggested by a DT-driven recommendation system could also be considered an issue, as it may impede the effective implementation and utilisation of advanced decision-making tools.

Building on the previously discussed studies, these cases help illustrate the practical challenges and varying levels of maturity in implementing feedback loops between DTs and DSS. For instance, Meierhofer et al. identified limitations in maintaining real-time data exchange and model coherence across heterogeneous systems, despite enabling performance monitoring and scheduling decisions [118]. Similarly, Latif et al. reported difficulties in synchronising data flows and preserving simulation fidelity when interacting with human-in-the-loop scenarios [103]. A more recent example by Chen et al. presents a closed-loop DT for additive manufacturing, which integrates model predictive control with time-series deep neural networks to dynamically adjust melt pool parameters in real time and reduce defects. However, this approach required highly efficient surrogate modelling to meet latency constraints and preserve operational responsiveness [135]. Collectively, these studies reinforce the idea that while bidirectional feedback is technically achievable and actively pursued, its practical deployment still encounters significant challenges related to latency, interoperability, and computational demands.

Therefore, RQ1 can be answered by acknowledging that the feedback loop to physical systems is still predominantly unidirectional; Digital Twins generate insights and recommendations, but the final decisions and actions are mostly carried out by human operators. Although some advanced implementations show partial automation, leveraging technologies such as OPC UA, IIoT, and reinforcement learning for real-time, bidirectional interaction, fully automated feedback loops remain rare. This trend highlights not only the technical challenges of achieving complete automation, but also the ongoing preference to keep humans actively involved in decision-making processes within manufacturing environments.

4.3 | Challenges for Decision Support: Answering RQ2

In response to the second research question (RQ2: What are the key challenges in implementing real-time feedback mechanisms between Digital Twins and Decision Support systems in manufacturing?), several critical barriers emerge, both technological and organisational.

From a technical standpoint, one of the primary challenges is the integration and interoperability of heterogeneous systems. Current manufacturing environments often lack unified protocols that enable Digital Twins to communicate actions directly back to physical systems. As the literature shows in the former section, only a few implementations achieve true closed-loop feedback, typically relying on middleware platforms such as OPC UA or intermediate execution systems such as DMES to mediate between the virtual and physical layers. Another major challenge is the technical complexity required for real-time responsiveness. Real-time bidirectionality demands high data quality, robust synchronisation, and especially low-latency communication between digital and physical environments [117]. However, these requirements are difficult to fulfil when Digital Twins involve complex, large-scale models that require intensive simulations, which in turn can delay feedback and hinder time-sensitive decision-making processes.

Beyond technological issues, organisational and human factors also play a significant role. Most current Decision Support approaches remain human-centric, with DTs primarily acting as analytical tools to assist, rather than replace, human decision makers. This reliance on human interpretation introduces trust-related challenges, as operators may be hesitant to accept or act on autonomous recommendations. Moreover, the evolving nature of DT design adds further complications as many implementations lack standardisation in services, data structures, and feedback protocols, making consistent integration across systems difficult.

Another critical aspect identified through the authors' own experience working with industrial partners is the interpretability of simulation results. In many cases, understanding the output generated by Digital Twins requires additional support, either in the form of external tools or the involvement of human expertise to contextualise the data and translate them into actionable knowledge. This highlights a key barrier to the broader adoption of automated Decision Support: if the results of simulations are not easily interpretable, their value for timely and effective decision-making diminishes. Therefore, ensuring that DT outputs are not only accurate but also understandable is essential for fostering trust and enabling practical use in real-world manufacturing environments.

4.4 | Types of Supported Decisions: Answering RQ3

Finally, an important aspect we explored in our research was the type of decisions that researchers entrusted to, or supported with, the use of DTs. We found a wide range of sectors and decision types, summarised in clear boxes at the end of the section. It is worth highlighting some works that address specific decisions, such as the work of [136], where the DT assisted operators in determining the parameters to use according to the expected quality of a part formed through Additive Manufacturing (AM). Furthermore, we can discuss other works that address slightly more complex decisions, such as [137], who tackle assembly decisions. Their proposal effectively identified the assembly design most likely to fulfil an industrial lifeboat hook's nonfunctional requirements, such as assembly time and assembly displacement error.

We can also highlight works that tend to focus the decisions on the scheduling of tasks [111, 121] and the scheduling of maintenance repairs [101, 123, 138, 139], which require a comprehensive overview of both the tasks and the status of the machinery. These studies often employ Digital Twins to create detailed, real-time simulations of the production environment, allowing for precise planning and optimisation. For instance, task scheduling involves allocating resources and timing activities to maximise efficiency and minimise downtime. DTs can identify potential bottlenecks and suggest optimal schedules by simulating various scenarios. Similarly, the scheduling of maintenance repairs benefits greatly from the integration of DTs. They enable proactive maintenance planning by continuously monitoring the condition of machinery and predicting potential failures. This predictive maintenance approach helps avoid unexpected breakdowns and extends the lifespan of equipment.

From maintenance scheduling decisions, we can highlight the framework proposed by [140]. They rely on a Digital Twin Shopfloor (DTS), which integrates physical and virtual processes through real-time data collection and analysis, allowing for predictive maintenance based on historical data from physical manufacturing tasks. Maintenance is defined as one of the critical manufacturing tasks for efficient operation. The DTS's predictive capability ensures timely and accurate maintenance scheduling, reducing unexpected downtime and optimising resource allocation. They propose an ontology-based semantic model that supports dynamic and real-time updates, facilitating effective maintenance task management by aligning it with other manufacturing processes. This approach ensures that maintenance scheduling is proactive and data-driven, contributing to the overall efficiency and reliability of the manufacturing system.

On the other hand, an example of production planning is the work of [141], whose method leverages complete DT data for accurate prediction and visual simulation. The DT system is powered by Graph Neural Networks (GNNs). The core of this approach is a planning model that utilises an attention mechanism to process and characterise disjunctive graphs, which represent the complex relationships between operations and machines. They mitigate unexpected factors that typically interfere with scheduling. As a result, their approach achieves rapid processing and just-in-time completion of production tasks. The proposed model has been validated in structural assembly and welding workshops, showing superior precision and speed compared to traditional scheduling rules and heuristics.

A comprehensive framework taking into account both DSSs and MES or ERP planning con be found in ref. [142]. They explain that the DT represents the virtual aspect of the cyber-physical systems (CPS). When multiple such systems are integrated, they form Cyber-Physical Production Systems (CPPS). In CPPSs, several DTs can be connected hierarchically, providing a comprehensive overview of the manufacturing processes. However, they emphasise that the DT must interface with decision support systems (DSSs) to perform decision support effectively. This integration requires incorporating comprehensive information from manufacturing execution systems (MES), enterprise resource planning (ERP) systems, Bills of Materials, and other relevant data. Additionally, they highlight that the DT can aid in prediction, safety, and diagnosis within manufacturing production processes.

Moreover, in the same line, in the work from [143], the DT acts as a dynamic replica of the physical manufacturing environment, continuously updated with data from MES or ERP systems. This integration allows for real-time monitoring and simulation of production scenarios, optimising production schedules, predicting potential issues, and proactively implementing corrective measures. Key performance indicators (KPIs) generated by simulations provide valuable insights that guide the MES in generating efficient production plans, thereby improving overall operational efficiency and flexibility in responding to changing manufacturing conditions.

In conclusion, most of the articles analysed focus on improving various aspects of the production as a whole, such as monitoring processes, controlling efficiency, and managing material handling, among others (see Production as a Whole for more details). This primary focus is followed by research aimed at enhancing maintenance planning. There are fewer contributions in other critical areas of production, including defect management [144], product rerouting [145], and assembly [137]. However, these areas also demonstrate significant potential for improvement by applying Digital Twins technology. The comprehensive data integration and real-time analysis capabilities of DTs offer substantial advantages in optimising decision-making processes. In response to RQ3 (Which strategy is adopted for addressing comprehensive decisions in a production process while considering intermediate decisions?), the literature indicates that integrating DTs with systems such as DSSs, MES, and ERP allows for coherent, multi-level decision-making. This integration ensures that strategic production planning is aligned with real-time, task-level decisions, promoting both responsiveness and overall efficiency. Overall, the findings highlight the vast potential of DTs to revolutionise production management and operational performance across diverse sectors of the manufacturing industry.

Supply Chain Related

[REF]: Implemented (I)/Concept (C); Areas under consideration within Supply Chain; Application Domain; Is the DT linked to external technologies or interfaces with other tools?

- [146]: I; Supply chain in general; 3-Level Agri-food Supply Chain; External user provides risks, potential strategies before start.
- [147]: I; Procurement strategies, supplier categorisation, and dynamic cooperation; Stratified fuzzy Best-Worst Method (SF-BWM) algorithm.
- [148]: I; Disruption management (recalibrating supply routes, production scheduling, inventory management, and overall resource distribution); Fast-Moving Consumer Goods; Potential solutions obtained from a database.
- [149]: I; Service Provider; Provider selection based on criteria, scheduling and coordination of service requests, and updates to product design and maintenance strategies based on collected data; Boiler repair services; Service Recommendation algorithms.

(Continues)

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Preventive Maintenance Scheduling and Machine Prognostics Related

[REF]: Implemented (I)/Concept (C); Application Domain; Is the DT linked to external technologies or interfaces with other tools?

- [100]: I; Manufacturing of Sheet Material; Connected with MES.
- [101]: I; Drilling Machine; Coefficient statistical method for calculating RUL.
- [106]: C; —; NLP to process and analyse Maintenance Work Orders (MWO).
- [123]: I; Furniture Manufacturer; —.
- [118]: C; Industrial Processes; —.
- [120]: I; Smart Cyber Physical Production Environment; Production Planning and Control (PPC) and ML.
- [105]: I; Industrial System; Optimisation Algorithms.
- [139]: I; Semiconductor; DT as part of a comprehensive software.

Management Related

[REF]: Implemented (I)/Concept (C); Application Domain; Specific Decision Area; Is the DT linked to external technologies or tools?

- [143]: I; Injection and Assembly Line; Management (intelligent design, monitoring, and optimisation of production processes); Plant Layout and MES.
- [150]: C; High precision weight industry; Management (system efficiency, customer specific delivery times, and overall production network coordination); Asset Administration Shell (AAS).
- [151]: C; Virtual Factories; Management (strategic, tactical, and operational levels); Offline KDO (knowledge-driven optimisation).

Production Planning/Scheduling Related

[REF]: Implemented (I)/Concept (C); Application Domain; Is the DT linked to external technologies or interfaces with other tools?

- [133]: I; Battery-Pack Assembly Line; Reinforcement Learning and Similarity Measures.
- [111]: I; Industry 4.0 Testbed; ERP + MES; use of Planning Domain, AI planner and Definition Language (PDDL).
- [140]: I; Body-in-white Manufacturing process; Manufacturing Task Semantic Modelling and Manufacturing Resources recommendation.
- [121]: I; Railway Sector; Multi-Objective Optimisation Method + KPIs.

(Continues)

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- [152]: I; Lab-scale and experimental framework; Virtual Reality.
- [141]: I; Structural assembly and welding workshops; Graph Attention Network (GAT) model.
- [102]: I; Manufacturing sector; Decision Support System (DSS).
- [153]: I; Assembly, Welding, Grinding; AI, optimisation via ProSeqqo, visual serving, human collaboration.
- [154]: I; Smart poultry feed plant case study; Knowledge graphs and AI.

Production Processes Related

[REF]: Implemented (I)/Concept (C); Application Domain; Specific Decision Area; Is the DT linked to external technologies or tools?

- [155]: I; Thermoformed FRTP sheet; Product Development; —.
- [156]: I; 3D Laser Scanner; Product Development; —.
- [157]: I; Manufacturing cell testbed; Production (re) routing; ERP, MES, SDC framework, Anomaly detection app (MILP).
- [145]: I; Industrial conveyor—Pallets re-routing; Production routing; —.
- [144]: I; Aerospace Industry; Rework—Defects; DSS + 3D visualisation and analytics dashboards.
- [115]: I; End-milling processes; Defects (Detect Production Anomalies); Connected to CNC controller using G-code algorithm for toolpath.
- [158]: I; University Laboratory; Defects (Detect Production Anomalies); —.
- [136]: I; Additive Manufacturing; Machine Parameters; —.
- [159]: I; Mobile Robot Manipulator; Machine Parameters; —.
- [160]: I; Monitoring tool wear; Machine Parameters; —.
- [161]: I; Plastic Extrusion; Machine Parameters; Comparison between DT and real world experiments.
- [137]: I; Life boat hook assembly; Assembly; Virtual Reality; Axiomatic Design Principles.

Production as a Whole

[REF]: Implemented (I)/Concept (C); Application Domain; Specific Decision Area; Is the DT linked to external technologies or tools?

- [122]: I; Aerospace System; Resiliency; Hierarchical Digital Twins.
- [162]: I; Five diverse use cases; Resiliency; AI, user-friendly interfaces.

(Continues)

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- [142]: C; Dynamic scheduling, delivery date calculation, pricing; Order Management; Suggests including data from MES, ERP + DSS.
- [109]: I; Material handling and Physical disturbances; Prediction, Monitoring, Diagnosis; Interfaces.
- [116]: I; Production of Electro-Mechanical Devices; Bottleneck analysis, Root Cause Analysis, Preventive Maintenance; —.
- [163]: I; Flexible Production Cell; Best strategy when a problem arises; —.
- [124]: I; Reconfigurable production lines; Planning, equipment maintenance, resource deployment, optimisation, emergency response; —.
- [164]: I; Production Logistics; Resource allocation, control, synchronisation; Blockchain, Optimisation Techniques.
- [165]: C; Sustainable production lines; Efficiency, resource management; Artificial Intelligence.
- [166]: I; Manufacturing Lines; Process planning, scheduling, real-time control; Artificial Intelligence, Optimisation Techniques.
- [167]: C; —; Control of the production; Artificial Intelligence, Feedback Module, Control Techniques.
- [168]: C; Medical products; —; AI algorithms.
- [169]: C; Transportation, manufacturing, logistics, supply chains; Resource management, forecasting, real-time adjustment; —.
- [170]: I; CTO production environment; Resource management, forecasting, optimisation; Microservices and event triggers.
- [171]: C; —; Process monitoring, diagnostics, control, predictive maintenance; Blockchain Technology, IIoT services.
- [172]: I; Industrial Processes; Design, operation, maintenance of systems; —.
- [173]: C; —; Operational efficiency, security, resilience; Big Data analytics.
- [174]: C; —; Operational control, optimisation, real-time adjustments; —.
- [175]: C; —; Efficiency, downtime reduction, quality improvement; Optimisation Algorithms.
- [176]: Simulated; —; Material handling on the plant floor; Reinforcement Learning.
- [119]: Simulated; —; Material handling on the plant floor; Reinforcement Learning.
- [177]: I; Reconfiguration of brownfield manufacturing systems; Reconfiguration, system understanding, and model generation for engineering purposes; PLC, ML-based methods.

(Continues)

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- [178]: I; Fault Diagnosis of rotating machinery; Predictive maintenance; VMD, and CNN-based classification.
- [134]: I; Assembly Line; Intra logistics; Reinforcement Learning.
- [179]: I; Automotive machining line; Corrective maintenance tasks; -.
- [180]: I; Diverse Industrial scenarios; Resource allocation, scheduling, reconfiguration, maintenance prioritisation; SAC reinforcement learning.
- [181]: I; In-lab scale demonstration; Sustainable manufacturing/Maintenance and energy integration; IoT.

4.5 | Future Research

All in all, this research has allowed us to identify this field's current gaps that can be summarised as opportunities for future research and improvements:

— As has been observed in the field of Digital Twins, there is still a lack of consensus regarding the interpretation of the concept itself and what it encompasses. This issue extends to how Decision Support is interpreted and its relationship with DTs. These diverse interpretations lead to a fragmented view of their potential and applications.

— Although several studies highlighted the potential for DTs to revolutionise manufacturing through real-time monitoring and predictive maintenance, and, therefore, on-the-fly Decision Support; the implementation of automated corrective actions, where the system independently adjusts processes based on the insights provided by the DT, is scarcely observed.

— The current frameworks often use DTs to identify issues and recommend solutions, but the ultimate decision-making authority remains with human operators. Although beneficial for ensuring oversight and accountability, this human-in-the-loop approach limits the efficiency and responsiveness that fully autonomous DT systems could provide.

The DT definition inconsistency underscores the need for a standardised framework or guidelines to unify interpretations and facilitate more effective utilisation of DTs in supporting decision-making processes. Establishing such a consensus would enhance collaboration and innovation across various sectors employing DT technology. In this context, the Asset Administration Shell (AAS) emerges as a promising solution to address the fragmentation in Digital Twin definitions [182]. As a standardised, technology-neutral framework developed within the Industry 4.0 paradigm, the AAS provides a consistent structure for representing assets and their attributes through interoperable submodels. By offering a common semantic foundation and standardised APIs, it can unify how digital representations are built, accessed, and integrated across systems. This not only helps align interpretations of what constitutes a Digital Twin, but also fosters greater interoperability, traceability, and trust, key enablers for effective decision-making.

Moreover, there is a need for further research and development to fully harness the capabilities of DTs in creating autonomous systems that not only predict and diagnose issues but also execute corrective measures without human intervention. The body of knowledge should conduct research to enable a seamless, bi-directional communication flow, developing frameworks for systems that could autonomously adjust operations in real time based on the insights provided by the DT. By achieving this level of automation, industries could significantly enhance efficiency, reduce downtime, and optimise resource use, embodying Digital Twin technology's full potential. Additionally, fewer applications have been identified in areas such as quality control and supply chain optimisation, possibly due to the preciseness of these domains and the inherent complexity of automating or accurately replicating them. Nevertheless, we strongly believe in the importance and potential of including Decision Support in DT tools, particularly as integral components of feedback loops aimed at improving efficiency and precision in these specific areas.

It is crucial to recognise that not all decisions can or should be entirely entrusted to an automated system. Human oversight remains vital in many contexts to ensure safety, ethical considerations, and nuanced judgement that machines cannot replicate. Therefore, developing and implementing semi-automated applications should be considered a viable approach. It has been demonstrated that the research field is already exploring these hybrid systems, where automated processes are complemented by human decision-making. This approach aligns well with initiatives such as Industry 5.0, introduced at the beginning. Building on this perspective, further research is needed to better understand the implications of joint Digital Twin and Decision Support applications, particularly in relation to the evolving role of workers. These systems demand new skills, from data literacy to supervisory and analytical capabilities, placing new requirements on workforce training. Besides the technical and operational advantages, questions surrounding responsibility and accountability in cases of failure or unintended outcomes must be addressed. Clarifying liability; whether it falls on human operators, system developers, or automated components, is essential to ensure trust, safety, and ethical deployment in manufacturing environments. This symbiotic relationship could, in our view, ensure that the strengths of both humans and technology are leveraged, leading to more resilient and adaptive manufacturing processes.

In the context of this review, we have observed that integrating Digital Twins with Decision Support Systems and Artificial Intelligence algorithms presents a significant opportunity to bridge the existing gaps in the field. This integration can enhance both automated and semi-automated feedback frameworks. For fully automated systems, combining both will allow to perform complex reasoning and decision-making tasks that typically require human intelligence. This can lead to more sophisticated and responsive automated processes, improving efficiency and reducing the need for constant human intervention. For referred-above semi-automated systems, integrating DTs with DSS plays a crucial role in augmenting human decision-making. These algorithms can provide comprehensive, real-time, actionable insights to users, facilitating better-informed decisions. This support is precious in scenarios where human judgement is indispensable, ensuring operators can access the best possible data and analysis to guide their actions. DSS integration also contributes to bridging the gap towards interactive feedback, supporting a more dynamic exchange between the Digital and Physical layers. Importantly, it enhances the interpretability of simulation results, an aspect that, as discussed in Section 4.3; is not always straightforward.

By leveraging DSS technologies, DTs can become more versatile and practical, supporting a more comprehensive range of applications and decision-making contexts. Moreover, in labour-intensive production systems, where human skills and adaptability are paramount, and fully-automation will not be possible, the enhanced decision support provided by integrated DTs and DSS can lead to more efficient and resilient operations.

5 | Conclusion

In this article, we have reviewed how researchers currently address decision support related to Digital Twins in Manufacturing Ecosystems. We first performed a keyword search and then selected articles based on specific criteria presented in Section 3.1. Only direct applications in Manufacturing Ecosystems were considered. We analysed how the body of knowledge is currently approaching the feedback from the DT's information and insights into the physical systems. We have provided a classification based on whether the reviewed article discussed an actual implementation or a concept/simulation. We also considered the type of decisions for which the DT feedback was used and whether the DT is complemented by external technologies to fulfil the DS function.

We realised that there is a gap regarding this feedback loop, which is rarely automated. There is a significant reliance on an intermediate user who makes the final decisions based on the information provided by the DT. Therefore, the usage given to the DTs is mainly like a real-time updated model of the actual systems. Thus, DTs' capabilities for improvement and problem resolution remain partly unused. In this sense, the primary challenge regarding the automation of the feedback lies in giving DTs the autonomy to communicate with systems. On the one hand, some tendencies to solve this gap have been spotted, by using dedicated industrial protocols (OPC UA, TCP, etc.) in order to provide the DT with means to interface the systems. However, the contributions in this venue are limited. On the other hand, some contributions rely on the opportunities provided by AI algorithms to showcase the best strategies among the simulated scenarios from the DTs, acting as an interpreter and giving the best solutions. In this sense, the AI algorithms will hold the users' role in a DT framework.

We analysed the kind of decision applications and application fields to see this topic's potential. We observed that they range from specific and low-level applications, such as machine modelling and parameters selection, to high-level ones, related to whole production modelling and decisions related to maintenance, order processing, among others.

Overall, we can say that the area of research shows promising interest, given the number of recent studies addressing the issue. There is a need to reach a consensus regarding the consideration of Decision Support in Digital Twins, as it has been observed how it is broadly used in manufacturing. This aligns with our definition: DS is an integral aspect to be considered in the DTs. The suitability of this approach is demonstrated by the potential and diverse applications identified. As such, we advocate for further exploration and acknowledgement of DS's role within DT frameworks.

Although this review followed a rigorous and systematic methodology, future research should aim to address some inherent limitations, particularly those related to the scope and terminology of the field. The absence of standardised definitions for both Digital Twins and their integration with Decision Support Systems introduces ambiguity and hampers consistent interpretation across studies. Advancing this research area requires efforts to establish a shared vocabulary and ontologies that facilitate more precise classification and comparison of contributions.

Additionally, building on the insights gathered from reported conceptual models and implementations, future research could extend this foundation through empirical validation in real-world manufacturing environments. Case studies, pilot deployments, and experimental evaluations would offer valuable evidence regarding the operational performance, maturity, and scalability of DT-based DS systems. Such investigations can also help uncover context-specific enablers and barriers, contributing to more informed and practical design choices.

Finally, the diversity of application domains, decision levels (strategic, tactical, operational), and enabling technologies revealed in the literature indicates a fragmented landscape lacking unified integration frameworks. Future work should explore the development of interoperable architectures, domain-independent evaluation metrics, and guidelines that support replicability and scalability. Establishing such foundations would enable more structured and comparative investigations, accelerating the adoption of robust DT-based decision support solutions across manufacturing ecosystems.

Author Contributions

Lucía Gálvez del Postigo Gallego: conceptualization, data curation, formal analysis, investigation, methodology, writing – original draft, writing – review and editing. **Sanja Lazarova-Molnar:** conceptualization, formal analysis, methodology, supervision, validation, writing – review and editing. **Alejandro del Real Torres:** formal analysis, supervision, writing – review and editing. **Luis E. Acevedo Galicia:** supervision, visualization, writing – review and editing.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The authors confirm that the articles supporting the findings can be accessed through the databases referenced in Section 3.

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