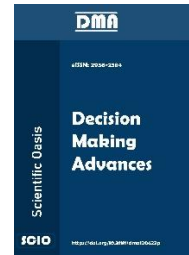




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Digital Twins as Socio-Technical Decision Systems: A Comparative Systematic Review of Supply Chain Management and Healthcare

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ARTICLE INFO	ABSTRACT
Article history: Received 30 May 2026 Received in revised form 7 July 2026 Accepted 2 August 2026 Available online 12 October 2026 Keywords: Digital Twins; Decision-making; Supply Chain Management; Healthcare; Value-complexity; Trade-off	Digital Twin (DT) technology is rapidly evolving from a digital representation of physical assets into a decision-support infrastructure that integrates real-time data, analytics, and simulation. However, existing research remains fragmented across application domains, limiting understanding of how DTs enable decision-making under different socio-technical conditions. This study presents a systematic literature review and decision-centric comparative analysis of DT applications in two contrasting decision environments: Supply Chain Management (SCM) and healthcare. Following a Systematic Literature Review (SLR) protocol, 193 peer-reviewed studies (95 SCM and 98 healthcare) were identified, screened, and synthesized across six analytical dimensions: application domains, technological integration, decision-making levels, business value, stakeholder involvement, and implementation challenges. The findings reveal fundamentally different decision logics despite a shared technological foundation based on Internet of Things (IoT), Artificial Intelligence (AI), and cloud computing. SCM-DTs primarily support coordination, optimization, resilience, and organizational scalability, whereas healthcare-DTs emphasize personalization, patient safety, and ethical governance under stringent regulatory constraints. Building on these findings, the study proposes a decision-centric comparative framework and a value-complexity perspective suggesting that value realization is increasingly associated with technological, organizational, and governance complexity as DT ecosystems mature. The paper advances the conceptualization of DTs as socio-technical decision systems and provides practical guidance for researchers, managers, and policymakers seeking responsible and effective digital transformation.

1. Introduction

The increasing complexity of modern organizations has intensified the need for intelligent decision-support systems capable of operating in dynamic, uncertain, and highly interconnected environments [1]. Among emerging digital technologies, DTs (virtual representations of physical entities, processes, or systems that are continuously synchronized with real-world data) have evolved from engineering simulation tools into powerful platforms for real-time monitoring, predictive

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analytics, scenario analysis, and decision support [2, 3]. Their growing importance is reflected in industry forecasts, with Gartner estimating that by 2026, more than 75% of large industrial organizations will deploy DT technologies to improve operational performance and decision-making capabilities by up to 10% [4]. By integrating sensing technologies, AI, simulation models, and cloud computing, DTs enable organizations to transform large volumes of heterogeneous data into actionable knowledge that supports operational, tactical, and strategic decision-making [5]. Consequently, DTs are increasingly viewed not merely as digital representations of physical assets but as socio-technical decision systems that bridge physical operations with digital intelligence.

Among the many domains adopting DT technology, SCM and healthcare represent two particularly important yet contrasting decision environments. [6]. Both are characterized by large-scale data generation, multiple interacting stakeholders, substantial uncertainty, and increasing dependence on digital technologies to support complex decisions [3]. However, they differ fundamentally in their objectives, governance structures, risk profiles, and decision consequences. SCM primarily seeks to coordinate distributed activities to optimize efficiency, resilience, sustainability, and economic performance across organizational networks [7]. Healthcare, conversely, focuses on patient-centered decision-making, where safety, personalization, ethical accountability, and regulatory compliance dominate clinical and organizational priorities [8, 9]. These contrasting characteristics make the two domains theoretically meaningful contexts for examining how DTs generate value through decision support.

Importantly, this study does not compare SCM and healthcare as equivalent industries. Healthcare represents an industry sector, whereas SCM is a cross-functional organizational capability spanning multiple industries [10, 11]. Accordingly, the unit of comparison in this study is not the industry itself, but the decision environment within which DTs operate. Within this perspective, SCM is conceptualized as a coordination-intensive decision-making environment, in which DTs primarily support synchronization, optimization, and resilience across distributed organizational processes. Healthcare is conceptualized as a personalization-intensive decision environment, in which DTs primarily support patient-specific decision-making under stringent clinical, ethical, and regulatory constraints. This terminology is adopted consistently throughout the remainder of the paper [12, 13]. Although both environments are highly data-driven and rely on continuous interaction between human and technological actors, they embody fundamentally different decision logics, providing a robust basis for comparative analysis.

Despite rapid growth in DT research, existing reviews remain largely domain-specific, concentrating on technical architecture, implementation approaches, or applications within individual sectors [9, 14]. Consequently, limited attention has been devoted to understanding how DTs support decision-making across contrasting socio-technical environments and whether the mechanisms through which they create value are domain-specific or transferable [15]. Without such comparative evidence, opportunities for cross-domain learning remain underexplored, and the theoretical understanding of DTs as decision-enabling systems remains fragmented [16]. Addressing this gap is increasingly important as DTs evolve into AI-augmented platforms that influence not only operational execution but also tactical planning, strategic decision-making, and organizational transformation. To address this gap, this study conducts an SLR and comparative synthesis of DT applications across SCM and healthcare, guided by the following research questions:

RQ1: How are DTs currently applied to support decision-making in SCM and healthcare?

RQ2: What benefits and business values do organizations in SCM and healthcare achieve through DT-enabled decision-making?

RQ3: How do DT-enabled decision environments differ, and what cross-domain lessons can be derived?

This study makes both integrative and conceptual contributions. At the integrative level, it organizes fragmented DT evidence across six established analytical dimensions: applications, technological integration, decision-making levels, business value, stakeholder involvement, and implementation challenges, within a common decision-centric comparative framework. The originality of the study, however, lies not in these dimensions individually, but in the explanatory relationships derived through their cross-environment comparison. Specifically, the synthesis conceptualizes SCM and healthcare as coordination- and personalization-intensive decision environments. It identifies how differences in decision focus, data-governance coupling, decision criticality and delegation tolerance, and value-realization logic shape DT adoption and decision-support roles. These relationships inform two conceptual evolution pathways: orchestration in SCM and personalization in healthcare, and the resulting value-complexity perspective, which explains how DT value realization is associated with differing technological, organizational, and governance demands. The comparison further generates reciprocal insights around scalable orchestration and responsible decision augmentation, providing a conceptual basis for future empirical testing and practical DT design.

The remainder of this paper, in Section 2, is structured to deepen the understanding of DT-enabled decision-making across domains progressively. Following the methodological discussion in Section 3, the demographic findings are discussed in Section 4. The description and systematic synthesis of DT applications in SCM and healthcare, and the cross-domain comparison that emphasizes differences in adoption maturity, value creation, and decision-making complexity, are discussed in Sections 5, 6, and 7. The discussion section, Section 8, then interprets these findings, drawing on existing theory and practice and highlighting implications for researchers, practitioners, and policymakers. Finally, the paper concludes in Section 9.

2. Background

2.1 Concept of Digital Twins

DTs are dynamic virtual representations of physical systems that integrate real-time data to simulate, predict, and optimize behavior [17]. This concept involves creating a precise model by merging data from sensors, devices, and numerous inputs to reflect the behavior and qualities of the underlying actual object or system [18, 19]. DTs are used across various industries, including manufacturing, aerospace, healthcare, and energy, to improve operational efficiency, optimize performance, and reduce costs [20].

DTs are distinguished from other similar concepts. 1) Digital models: A static or dynamic representation of a physical object or system, often used for design and analysis [21]. Unlike DTs, digital models do not necessarily involve real-time data updates or bi-directional communication with their physical counterparts [22]. 2) Simulations: The use of models to replicate the behavior of a system over time [23]. Simulations are typically used for specific scenarios and do not continuously update with real-time data like DTs [23]. 3) Digital shadows: A digital representation that reflects the current state of a physical object or system based on data collected from it [24]. Digital shadows are more passive and do not actively simulate or predict future states as DTs do [24]. 4) Digital threads: A communication framework that integrates data across the lifecycle of a product or system [25]. Digital threads focus on data integration and traceability rather than real-time simulation and optimization [25].

The functional architecture of DTs integrates three interdependent layers that enable cyber-physical synchronization across manufacturing and logistics systems. The physical layer spans assets from individual machines and manual assembly stations to interconnected networks of suppliers and production nodes [26, 27], with studies modeling bottleneck equipment [28], fine-grained assembly

operations [29], material handling subsystems [30], waste streams [31], and distributed production networks [32–34]. This physical foundation connects via the data and integration layer, primarily IoT sensing pipelines [28], Enterprise Resource Planning (ERP)/Manufacturing Execution Systems (MES) interfaces [30], and supplier/customer systems [35], which enables bidirectional feedback loops where virtual insights actively reshape machine settings and routing logic [31], with emerging blockchain architectures supporting multi-organizational data trust [36]. The virtual layer then transforms this data into dynamic representations through discrete-event simulation [26, 28], physics-informed models [29], or hybrid Machine Learning (ML)-optimization environments [30, 37], evolving beyond passive replicas into collaborative interfaces within augmented or metaverse environments [36] that support predictive analytics, scenario testing, and prescriptive decision-making [32, 37].

There are several enabling technologies for DTs. 1) IoT: IoT devices and sensors collect real-time data from physical objects, which is crucial for updating DTs and enabling real-time monitoring and control [38]. 2) AI: AI algorithms analyze data from DTs to detect anomalies, predict maintenance needs, and optimize performance. AI enhances the decision-making capabilities of DTs by providing insights and predictive analytics [39]. 3) Big data: The vast amounts of data generated by IoT devices and other sources are processed and analyzed to provide accurate and comprehensive insights into the physical system's behavior. Big data analytics is essential for understanding patterns and making data-driven decisions [40]. 4) Cloud computing: Cloud platforms offer the computational power and storage needed to handle the large volumes of data generated by DTs [41]. They enable scalable and flexible data processing, storage, and analysis, facilitating real-time updates and complex simulations [42, 43].

2.2 Evolution of Digital Twins

DT technology originated in the aerospace industry, with NASA being a pioneer. The concept was first introduced during NASA's Apollo Space Program in the 1970s and was formally defined in 2002 by Michael Grieves [19, 44]. Initially, DTs were used for product lifecycle management within aerospace, allowing for the creation of virtual models to enhance the safety and reliability of space missions [45, 46]. Companies like Siemens and GE have also been instrumental in advancing DT technology, particularly in manufacturing and industrial applications [47]. DTs have expanded beyond their initial engineering applications to various other domains, as summarized in Table 1. In SCM, DTs are used to create virtual models, enabling real-time monitoring and optimization of supply chain dynamics [48]. In healthcare, DTs are employed for personalized medicine, disease modeling, and treatment simulations, leveraging AI and big data for predictive analytics [49, 50]. In smart cities, DTs are used in urban planning and infrastructure management to improve city planning, public safety, and emergency response strategies [51, 52]. Moreover, the principles of DTs can be applied to financial systems for risk assessment and predictive modeling [51].

DTs enhance predictive analytics and prescriptive modeling. For example, DTs use real-time data and advanced analytics to predict future conditions and events. This capability is crucial in various sectors, including construction, where it helps predict equipment failures and optimize maintenance schedules [53]. Moreover, by integrating AI and ML, DTs can provide prescriptive insights, suggesting optimal actions based on predictive data. This is particularly evident in healthcare, where DTs help optimize treatment plans and improve patient outcomes [49]. Furthermore, in manufacturing, DTs enable real-time monitoring and optimization of production processes, leading to improved efficiency and reduced downtime [54].

Table 1
Applications for DTs

Domain	Applications	Benefits
Aerospace [19, 44]	Product lifecycle management, mission planning, safety enhancement	Improved reliability, safety, and efficiency of space missions
Manufacturing [47]	Real-time monitoring, predictive maintenance, design optimization	Enhanced production processes, reduced downtime, improved product quality
Supply chains [48]	Real-time monitoring, optimization of supply chain dynamics	Increased efficiency, reduced costs, improved resource management
Healthcare [49, 50]	Personalized medicine, disease modeling, treatment simulation	Optimized treatment plans, improved patient outcomes, proactive patient management
Smart cities [51, 52]	Urban planning, infrastructure management, public safety	Efficient city planning, improved emergency response, enhanced public safety
Finance [51]	Risk assessment, predictive modeling, portfolio optimization	Enhanced decision-making, improved risk management, optimized investment strategies

2.3 Digital Twins in Business Decision-Making

DTs are increasingly recognized as essential tools for enhancing business decision-making. By providing operational, tactical, and strategic support, they empower managers to make informed decisions based on real-time data and predictive insights.

- i. DTs provide accurate, real-time data and simulations. This technology allows managers to visualize and analyze complex systems, leading to better-informed decisions and improved resource management [55, 56]. DTs also facilitate collaboration and communication among stakeholders, which is essential for effective decision-making and value co-creation [57, 58].
- ii. DTs enable continuous monitoring of physical systems, providing insights into performance metrics and potential issues [59]. This helps with early anomaly detection and proactive maintenance, reducing downtime and maintenance costs. By simulating different scenarios, DTs optimize operational processes, identify bottlenecks, and enhance overall efficiency [60]. For example, in SCM, DTs improve visibility and productivity, leading to better customer satisfaction and lower costs [61].
- iii. DTs support tactical decision-making by aiding in resource allocation and planning. DTs help managers allocate resources more effectively by providing detailed insights into system performance and potential issues [62]. This ensures optimal use of resources and minimizes waste. DTs facilitate scenario planning and risk assessment, allowing organizations to simulate the impacts of different strategies and operational changes [63]. This helps make informed decisions and improve operational flexibility.
- iv. DTs provide strategic support through long-term forecasting and risk management. DTs enable predictive analytics, helping organizations forecast future trends and plan accordingly [64]. This is particularly useful in industries like manufacturing and urban management, where long-term planning is crucial [65]. DTs enhance risk management by simulating potential risks and their impacts, allowing organizations to develop proactive mitigation strategies [66]. This improves resilience and preparedness for crises [67].

Despite the clear benefits, the adoption of DTs in business decision-making is still fragmented. Many organizations face challenges related to data integration, cybersecurity, and the complexity of implementing DTs [68, 69]. Comparative research is needed to understand the best practices and overcome these challenges, ensuring a smoother integration of DTs into business processes [15, 70].

2.4 Theoretical Foundation

This study conceptualizes DTs as socio-technical decision-support systems that transform real-time data into actionable intelligence across operational, tactical, and strategic decision-making contexts. To support this perspective, the study integrates four complementary theoretical lenses: Decision Support Systems (DSS) theory, bounded rationality, socio-technical systems theory, and value–complexity logic.

2.4.1 Decision Support Systems Perspective

DSS theory explains how information technologies improve managerial decision-making by transforming data into relevant insights for planning, monitoring, and control [55, 56]. DTs extend traditional DSS capabilities by combining real-time sensing, simulation, predictive analytics, and scenario evaluation within a continuously synchronized virtual environment. Through these capabilities, DTs support operational decisions through monitoring and control, tactical decisions through planning and resource allocation, and strategic decisions through forecasting and risk assessment [62, 64]. Consequently, DTs can be viewed as next-generation DSS platforms capable of supporting complex decision environments characterized by uncertainty, interdependence, and dynamic change [15, 71].

2.4.2 Bounded Rationality and Decision Complexity

The theory of bounded rationality suggests that decision-makers face cognitive limitations when processing large volumes of information under uncertainty [72]. Both SCM and healthcare operate in environments characterized by high information intensity, multiple stakeholders, and rapidly changing conditions. DTs help mitigate these limitations by integrating heterogeneous data sources, reducing information fragmentation, and enabling the simulation of alternative scenarios before decisions are implemented [63, 66]. In this sense, DTs augment human decision-making by reducing uncertainty and supporting evidence-based judgment rather than replacing managerial or clinical expertise.

2.4.3 Socio-Technical Systems Perspective

While often presented as technological artifacts, DTs function within broader socio-technical systems composed of technologies, people, organizational processes, governance structures, and external stakeholders [72]. Successful DT deployment depends not only on technical performance but also on stakeholder collaboration, data governance, organizational readiness, and trust in model outputs [57, 58]. This perspective is particularly relevant when comparing SCM and healthcare, as both domains rely on complex interactions between technological infrastructures and human decision-makers operating under different regulatory, operational, and ethical constraints.

2.4.4 Value–Complexity Logic

Building upon the preceding theories, this study introduces value–complexity logic as an interpretive lens for understanding DT adoption across domains [73]. The comparative findings indicate that higher levels of DT-enabled value are often associated with increasing organizational, stakeholder, and governance complexity [73]. Asset-level DTs typically generate operational efficiency and process optimization benefits, whereas enterprise-wide and ecosystem-level DTs enable resilience, sustainability, and strategic transformation [3]. However, realizing these benefits requires greater interoperability, stakeholder coordination, regulatory compliance, and governance maturity. The value–complexity logic therefore provides an interpretive basis for examining why DT adoption trajectories may differ between SCM and healthcare and why higher-value applications may

face greater implementation challenges. Figure 1 summarizes the proposed theoretical framework linking DT architecture, decision-making levels, socio-technical complexity, stakeholder involvement, and value realization.

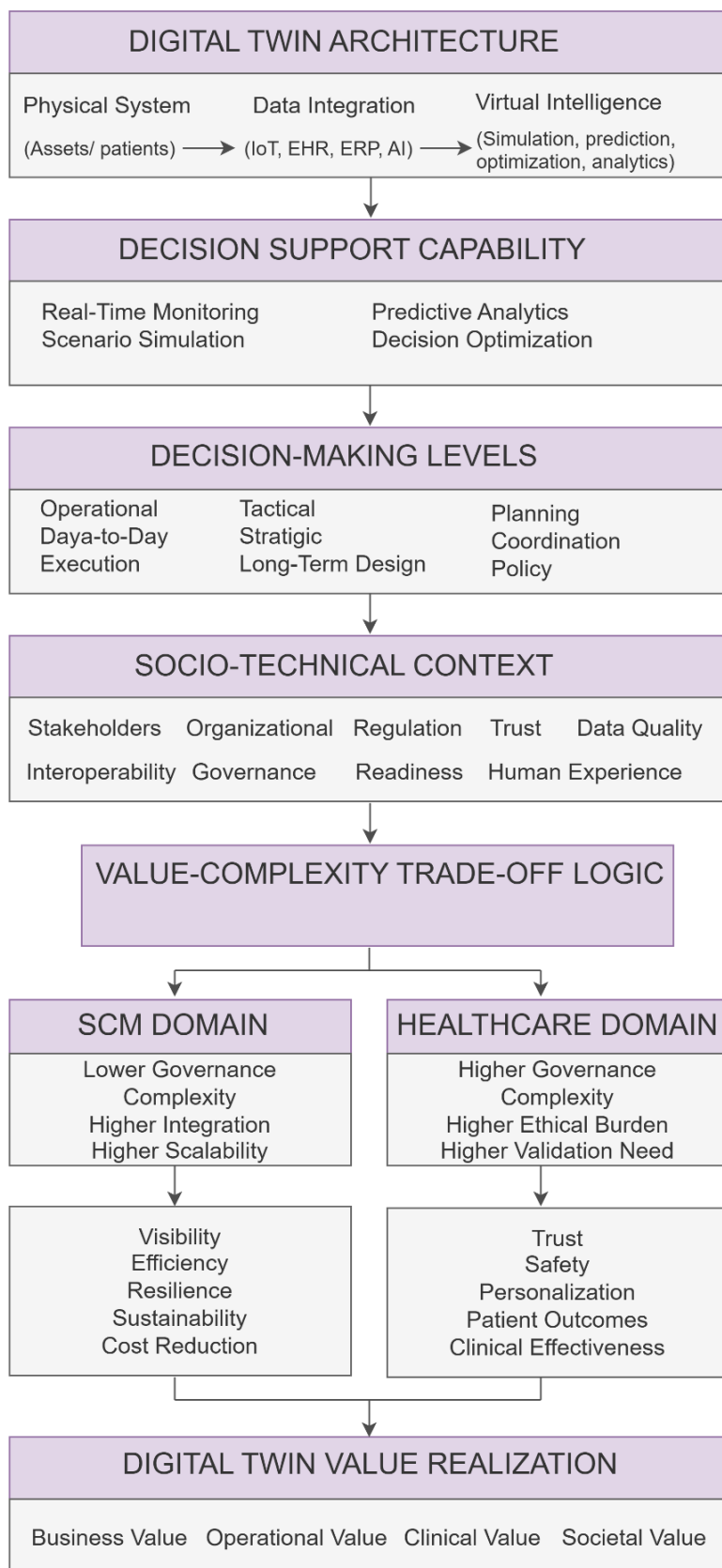


Fig. 1. Theoretical framework of DT-enabled decision-making across domains

3. Methodology

The methodological process followed the five SLR stages for management and information systems reviews [74]:

- Planning the review – defining scope, objectives, and review protocol.
- Identification – developing search strings and selecting databases.
- Screening – applying inclusion and exclusion criteria at the title and abstract levels.
- Eligibility and data extraction – full-text assessment and systematic coding.
- Synthesis and interpretation – integrating findings through structured narrative synthesis.

The structured narrative element was incorporated into Stage 5, where coded findings were analyzed thematically and interpreted within a decision-support theoretical lens [75].

3.1 Research Design

This study adopts a focused SLR with structured narrative synthesis to examine how DT technologies support business decision-making in SCM and healthcare. The review is intentionally focused rather than exhaustive. The study focuses on literature that explicitly links DT implementations to operational, tactical, or strategic decision-making outcomes in healthcare and SCM. This positioning aligns with established guidance for management and information systems reviews, where focused systematic approaches are recommended to enable theory-building and cross-domain synthesis without compromising methodological transparency [74, 76]. To operationalize the research questions presented in the introduction, the review examines decision levels (strategic, tactical, operational), DT configurations, performance outcomes, contextual moderators, challenges, and ethical–human factors. This layered questioning structure supports systematic progression from mapping DT-enabled decision-making (RQ1), through evaluating the resulting business value (RQ2), to comparing the contextual factors and transferable insights across the two decision environments (RQ3).

Structured narrative synthesis is employed at the synthesis stage to systematically interpret coded evidence from decision-support and digital decision intelligence perspectives. This enables the study to move beyond descriptive aggregation toward explanatory and comparative insights, consistent with contemporary review designs in DSS and information systems research [71]. Moreover, this approach enables the identification of patterns, relationships, and explanatory mechanisms across heterogeneous studies and contexts [77]. This integrative methodology aligns with recent calls for hybrid review designs in information systems research [78], which encourages combining systematic and interpretive synthesis to produce actionable theory and decision frameworks [77].

3.2 Data Sources and Search Strategy

A comprehensive search was conducted across five major academic databases to ensure coverage of both technical and managerial DT research: Scopus, Web of Science, IEEE Xplore, ScienceDirect, and PubMed [79]. The database searches were completed in January 2026 and covered publications published between January 2021 and December 2025. The same Boolean search expression was applied consistently across all five databases using the title, abstract, and keyword search fields: ("Digital Twin" OR "digital-twin") AND ("decision-making" OR "decision support" OR "business intelligence") AND ("supply chain" OR "logistics" OR "healthcare" OR "hospital management"). Where required by the database interface, the expression was entered using the corresponding title, abstract, and keyword search fields without altering the underlying search terms or Boolean logic. The detailed screening, eligibility assessment, and final study selection are presented in Section 3.4 and summarized in the PRISMA flow diagram (Figure 2).

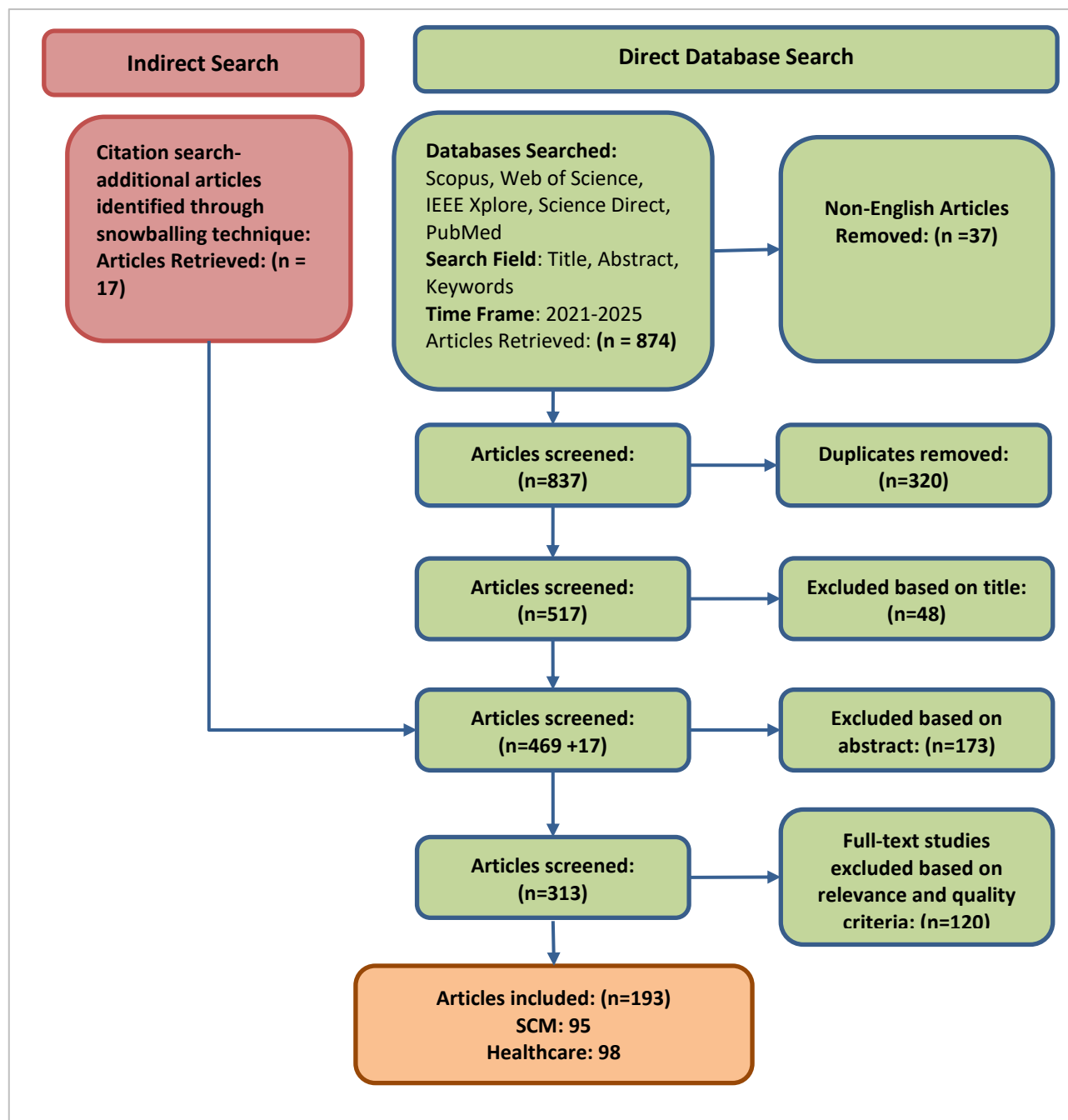


Fig. 2. PRISMA flow diagram of the study selection process

The initial search returned 874 records for DT research in healthcare and SCM. However, a substantial proportion of these studies focused primarily on technical model development, domain-specific simulations, or system architecture without explicit consideration of decision-making processes. In line with the study's decision-centric objectives, a focused, systematic selection was applied to retain only studies that explicitly examined DT as decision-support systems at the operational, tactical, or strategic levels. Backward and forward snowballing was applied to key articles to identify additional relevant studies. While initial searches yielded a large volume of results, particularly in healthcare, the focused scope ensured retention only of studies explicitly addressing DT-enabled decision processes. The final set of selected studies is summarized in Table A1 - Appendix A (healthcare) and Table B1 - Appendix B (SCM).

3.3 Inclusion Criteria and Quality Assessment

To ensure consistency and relevance, the following criteria were applied across both domains. A dual independent screening process was conducted, with disagreements resolved through consensus. Inter-rater reliability exceeded accepted thresholds (Cohen's Kappa, $\kappa > 0.80$) [80], ensuring robustness of the selection process. The inclusion criteria are as follows:

- Focus on SCM, logistics, or healthcare contexts
- Explicit application of DTs to support business, operational, or decision-making. Studies were excluded if they focused on addressing digitalization or simulation without DT conceptualization. Engineering-only or hardware-focused modeling with no decision context was also excluded.
- Peer-reviewed journal articles or high-quality conference proceedings/book chapters. Editorials, abstracts, practitioner reports, or non-peer-reviewed content were also excluded.
- English-language publications
- Published between January 2021 and December 2025. This period was selected to capture the recent phase in which DT technologies increasingly progressed from conceptual and engineering-oriented models toward operational, organizational, and clinical decision-support applications. The focus is therefore on the contemporary decision-centric development of DTs rather than on reconstructing their complete historical evolution. This boundary is particularly relevant to the comparative purpose of the review, as DT adoption in healthcare accelerated substantially during and after the COVID-19 period, while SCM applications increasingly expanded toward enterprise and network-level decision support. As an additional indication of this shift, the database searches identified only 35 healthcare and 42 SCM studies before 2021 under the applied decision-focused search criteria.

Following eligibility screening, the retained studies underwent a structured quality assessment across four dimensions: conceptual clarity, theoretical contribution, methodological rigor, and relevance to decision-support research. These dimensions were operationalized through the following assessment questions. Each criterion was assessed as Yes, Partially, or No during full-text review. Studies demonstrating insufficient relevance of decision support or substantial deficiencies in conceptual clarity and methodological reporting were excluded during the final relevance and quality assessment stage.

- Conceptual clarity: Does the study clearly define or operationalize the DT concept and distinguish it from conventional simulation or digitalization?
- Theoretical contribution: Does the study provide a clear conceptual, analytical, or decision-oriented contribution relevant to DT-enabled decision-making?
- Methodological rigor: Are the research design, data sources, analytical or simulation procedures, and validation approach sufficiently described to support the reported findings?
- Decision-support relevance: Does the study explicitly demonstrate or discuss how the DT supports operational, tactical, or strategic decision-making in SCM or healthcare?

3.4 PRISMA Flow and Study Selection Narrative

The study selection process followed the PRISMA 2020 guidelines to ensure transparency and traceability of the focused systematic review [81, 82]. The initial database search across Scopus, Web of Science, IEEE Xplore, ScienceDirect, and PubMed yielded 874 records [83]. After removing 37 non-English records and 320 duplicates, 517 unique records remained for screening [84]. Title screening excluded 48 records that lacked explicit DT conceptualization or decision-making relevance, or had a purely technical or engineering focus, leaving 469 database records.

Backward and forward citation searching identified an additional 17 potentially eligible studies, which were assessed against the same inclusion criteria and added to the abstract-screening pool, resulting in 486 records for abstract-level assessment. At this stage, 173 records were excluded, leaving 313 studies for full-text relevance and quality assessment. A further 120 studies were excluded because of insufficient discussion of decision-support outcomes, misalignment with the SCM or healthcare decision environments, or failure to meet the predefined quality criteria. The final corpus therefore comprised 193 studies, including 95 SCM and 98 healthcare studies, which formed the evidence base for systematic coding and structured narrative synthesis. The complete selection process is summarized in the PRISMA flow diagram (Figure 2).

3.5 Data Extraction and Coding

Data extraction was guided by a predefined data extraction framework (Table 2), designed to operationalize the study's analytical dimensions and ensure consistent coding across domains. The framework captures bibliometric, technological, decision-oriented, contextual, and ethical variables, enabling systematic comparison between SCM and healthcare literature. Methodological rigor was established through adherence to predefined protocols, comprehensive documentation, and iterative validation mechanisms [74]. Theoretical grounding of research questions and consistent operational definitions strengthened construct validity throughout the review process. To enhance reliability, dual independent screening and coding were performed by multiple reviewers, with discrepancies resolved through structured consensus discussions [77]. Together, these systematic safeguards ensure the review's methodological integrity, facilitate replication by other researchers, and provide a solid empirical foundation for comparative theory development for DT-enabled decision-support systems.

The included studies were coded and thematically synthesized rather than assigned an aggregate numerical score. Frequency counts and percentages were used only for directly quantifiable coded categories. At the same time, comparative interpretations of value, complexity, governance, and related dimensions were derived qualitatively from recurring patterns across the coded evidence rather than from a weighted scoring model.

A mixed deductive–inductive coding strategy was employed. Deductive coding operationalized the theoretical foundations of the study through observable analytical dimensions: DSS theory informed the coding of decision-support mechanisms and performance outcomes; bounded rationality informed the examination of how DTs extend information processing, prediction, simulation, and decision support across operational, tactical, and strategic levels; and the socio-technical perspective informed the coding of stakeholder involvement, organizational readiness, governance, interoperability, and ethical–human factors. Inductive coding captured recurring themes emerging from the reviewed studies, including explainability, trust, human–AI collaboration, and domain-specific constraints [78]. Two reviewers independently coded all included studies, achieving a Krippendorff's $\alpha = 0.84$, indicating high inter-coder reliability [75]. The coded evidence was subsequently synthesized through thematic clustering and cross-domain comparison, allowing recurring relationships among decision characteristics, technological integration, governance requirements, stakeholder configurations, and reported value to inform the explanatory mechanisms and value–complexity perspective developed in Section 7. Coding and visualization were performed using NVivo 14, following a structured narrative synthesis protocol [71].

Table 2
Data extraction framework

Category	Variable/field	Purpose
Bibliometric details	Author(s), year, title, journal, country, DOI	Basic reference information; supports trend analysis
Study type	Conceptual / empirical / simulation / case study / framework development Decision context: Decision type (strategic/tactical/operational); decision domain (planning, scheduling, diagnosis, optimization, etc.)	Distinguishes theoretical vs. practical applications Links DT applications and functions to decision levels
RQ1 (Applications; technological integration)	Decision-support mechanisms: Predictive analytics, optimization models, simulation, visualization, cognitive augmentation	Operationalizes DSS and bounded-rationality perspectives by identifying how DTs augment information processing and decision-making
RQ2 (decision-making levels; performance outcomes)	DT characteristics: Type (physical twin, digital shadow, hybrid twin), level of integration (data-driven, model-driven, hybrid), real-time capability Performance outcomes: Accuracy, cost reduction, risk resilience, patient safety, throughput, decision quality	Captures technological configuration and integration Captures reported operational, clinical, organizational, and decision-related value
RQ3 (Challenges; stakeholders; contextual factors)	Contextual factors: Regulatory constraints, organizational readiness, data governance, interoperability issues, stakeholder involvement, and decision authority Ethical & human factors Transparency, interpretability, bias, trust, accountability	Operationalizes socio-technical conditions shaping DT-enabled decision-making Captures human, ethical, trust, and accountability dimensions of socio-technical decision systems
Key findings from RQ1-RQ3, limitations	Methodological details; key findings and contributions; limitations	Enables methodological comparison

4. Demographic Findings

This section presents an overview of common publication-related statistics to establish a clear picture of the research landscape. In general, studies on healthcare outpaced those on SCM during the search period. Journals dominate as the primary publication venue in both domains. Thematic analysis reveals distinct priorities: Healthcare-DT research emphasizes data processing, health monitoring, and personalized medicine, with a focus on patient-specific modeling, real-time diagnostics, and treatment optimization. In contrast, SCM DT literature centers on Industry 4.0 integration, digital transformation, and simulation, with a focus on operational resilience, logistics efficiency, and disruption response. While both fields leverage real-time data and predictive analytics, their end goals seem to differ. Healthcare prioritizes clinical outcomes and individualized care, while SCM emphasizes system-wide efficiency, cost reduction, and sustainability. The demographic overview and the functional architecture of digital twins in the selected domains are presented below.

4.1 Selected Studies Overview

Figure 3 compares the publication trends, database sources, and channel distribution of DT research in healthcare with those of the SCM-selected articles reviewed in this paper. It reveals that while both fields show strong growth peaking in 2025, healthcare research is more fragmented across publishers and relies heavily on journals. In contrast, SCM research is dominated by a few major

publishers, such as Elsevier, and shows greater journal dominance. The figure reveals a sharp surge in DT research for both healthcare and SCM, peaking in 2025. Healthcare publications (56 in 2025) slightly outpace SCM (33). In both domains, Elsevier is the dominant publisher, followed by IEEE and MDPI. Journals are the primary dissemination channel, accounting for 75% of healthcare and 82% of SCM studies, reflecting academic maturity. Conferences play a minor role (4% in healthcare, 8% in SCM). The concentration in major publishers indicates high competition and validation standards. While both fields are rapidly growing, healthcare's higher publication volume and broader publisher base indicate greater research activity and diversification compared with SCM.

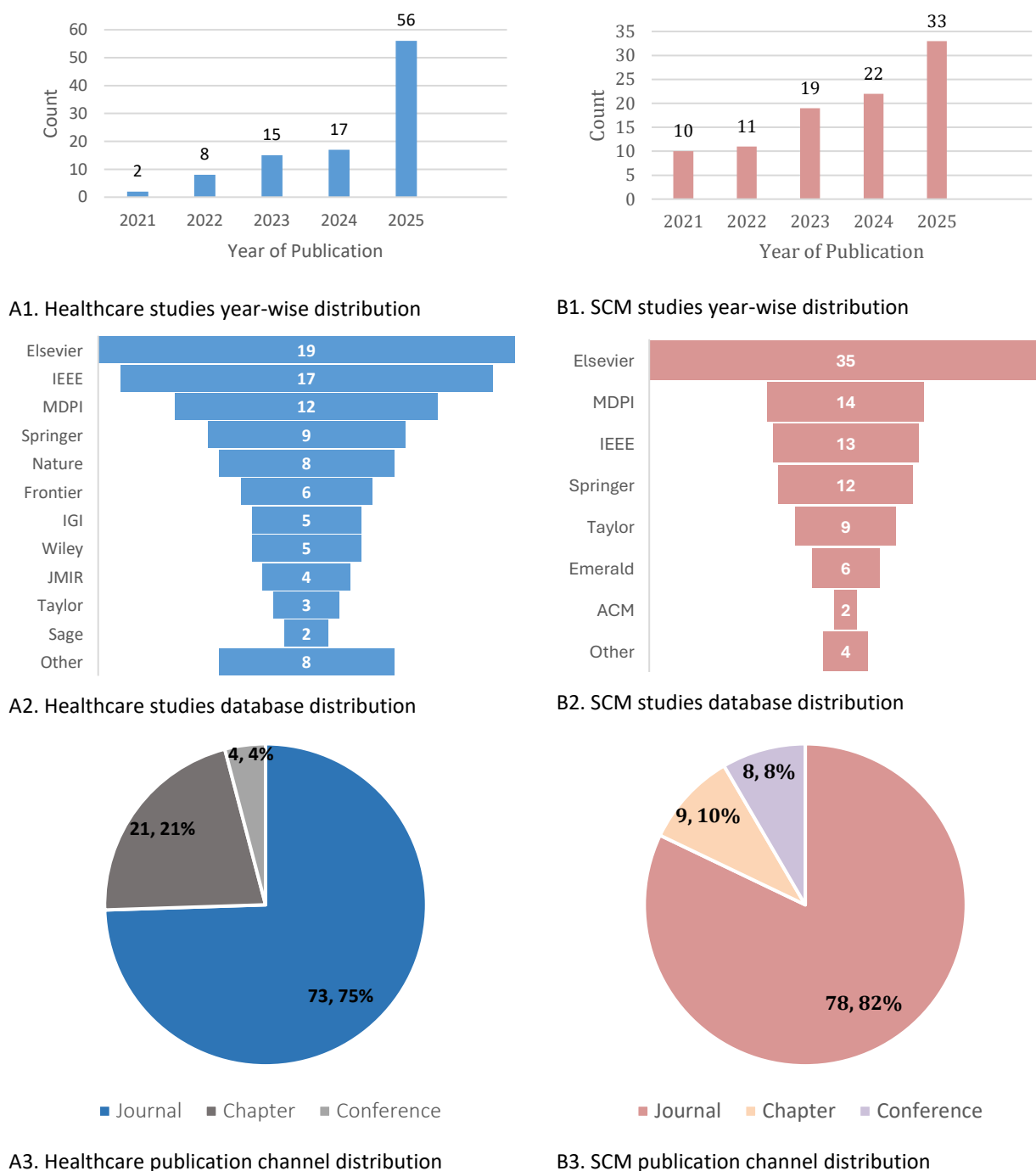


Fig. 3. Demographics of articles selected for this paper

4.2 Geographical Distribution of Reviewed Studies

The geographical distribution of the reviewed studies, as summarized in Table 3, reveals that DT research in both SCM and healthcare is a truly global endeavor, encompassing 30 and 29 countries, respectively. Despite this widespread international reach, the research is heavily concentrated in specific regional hubs, primarily across Asia and Europe. Notably, India emerges as the most prolific contributor in both domains, leading with 14 studies in SCM and 17 in healthcare. China and the United Kingdom also demonstrate robust, cross-disciplinary engagement, consistently ranking among the top contributors in both fields. However, distinct regional specializations are evident. European nations, particularly Germany and Italy, show a stronger inclination toward SCM and industrial applications, reflecting their robust manufacturing bases.

Table 3

Geographical distribution of reviewed healthcare studies

Healthcare studies			SCM studies		
Geographic location	Number of studies	Studies	Geographic location	Number of studies	Studies
India	17	[13, 85–100]	Germany	15	[11, 36, 101–113]
China	11	[114–124]	India	14	[69, 125–137]
USA	11	[138–148]	China	13	[29, 33, 149–159]
Italy	10	[9, 16, 160–167]	United Kingdom	10	[35, 168–176]
United Kingdom	9	[14, 177–184]	France	4	[185–188]
Australia	4	[189–192]	Italy	4	[30, 32, 193, 194]
France	4	[195–198]	Sweden	4	[199–202]
Greece	3	[10, 203, 204]	USA	4	[26, 28, 205, 206]
Bangladesh	2	[207, 208]	Finland	2	[99, 209]
Brazil	2	[210, 211]	Greece	2	[212, 213]
Canada	2	[214, 215]	Norway	2	[216, 217]
Mexico	2	[218, 219]	Switzerland	2	[220, 221]
Netherlands	2	[222, 223]	Taiwan	2	[34, 224]
Norway	2	[225, 226]			
Turkey	2	[239, 240]			
		Belgium [241], Denmark [242], Egypt [243], Germany [244], Ireland [245], New Zealand [246], Pakistan [247], Poland [248], Portugal [249], Qatar [250], Romania [251], Saudi Arabia [252], South Korea [253], Thailand [254]			
1 study			1 study		Canada [7], Denmark [227], Indonesia [27], Iran [228], Jordan [229], Malaysia [230], Netherlands [231], New Zealand [37], Pakistan [232], Poland [31], Portugal [233], Qatar [234], Saudi Arabia [235], Singapore [12], Slovenia [236], South Korea [237], Spain [238]

Conversely, North America, led by the United States, exhibits a significantly higher concentration of healthcare-focused DT research compared to SCM, highlighting a regional prioritization of medical and clinical innovations. Meanwhile, emerging economies across Asia are rapidly expanding their footprint in both sectors, driven by aggressive digitalization initiatives in smart manufacturing and digital health infrastructures. Ultimately, while the foundational technologies of DTs are universal, geographical distribution underscores that regional industrial strengths, healthcare priorities, and national digital strategies heavily dictate the specific application domains of DT research worldwide.

4.3 Functional Architecture of Digital Twins

Across the reviewed articles, a common architectural pattern emerges in how DTs are conceptualized, implemented, and integrated into industrial and logistics environments. While terminology and modeling depth vary, most studies describe DT systems as comprising three interlinked layers: physical, virtual, and data and integration layers. Importantly, the depth and sophistication of each layer differ from paper to paper, reflecting both the maturity of the underlying

application area and the scale of the SCM problem being modeled. Most notably, the field remains anchored in simulation-centric approaches. Many selected studies engaged a virtual or simulation layer, demonstrating that DTs are most frequently used to model system behavior, experiment with operational alternatives, or forecast performance outcomes. Similarly, many selected studies incorporated live or historical data inputs, typically through IoT sensor streams, ERP data, or manufacturing execution systems. This strong methodological skew confirms that data-connected modeling is now the dominant pattern in DT-enabled SCM research. However, fewer than half of the studies explicitly described a mirrored physical entity—be it a machine, workstation, or asset cluster. Around a third of the papers implemented the full synergy of all three layers, forming complete cyber-physical ecosystems capable of sensing, predicting, and acting in a closed loop. At the opposite extreme, a noticeable minority of papers used the DTs label to describe data-driven dashboards or simulation-only planning environments, without establishing a persistent connection to physical systems. These findings align with ongoing debates in the field regarding terminology and maturity: the term “digital twin” is increasingly applied to systems that offer partial twinning capabilities, particularly virtual and data-integration functions, even when they do not yet support full bidirectional synchronization.

5. Digital Twins in Healthcare

DT technology is revolutionizing healthcare by creating virtual replicas of patients, organs, and healthcare systems. Figure 4 synthesizes the findings of Section 5 by conceptualizing DT-enabled healthcare as a layered socio-technical decision system. The figure illustrates how integrated digital health technologies underpin DT cores that support decision-making across operational, tactical, and strategic levels, ultimately generating clinical, operational, and economic value. Stakeholder involvement and cross-cutting challenges moderate value realization across all layers.



Fig. 4. Layered socio-technical decision system of DT-enabled healthcare

5.1 Applications

The reviewed literature demonstrates that DT applications in healthcare span a wide spectrum of clinical, operational, and strategic functions. Table A2 – Appendix A summarizes the key uses under each application, and the papers focused on each category. At the clinical level, DTs are primarily employed for patient monitoring [87, 160], personalized medicine [118, 254], disease prediction [164, 243], treatment optimization [210, 211], rehabilitation [218, 239], and surgical planning [197, 208]. These applications leverage real-time physiological data, medical imaging, Electronic Health Records (EHRs), and AI-driven analytics to support individualized care and improve patient outcomes [123, 203]. At the organizational level, DTs facilitate hospital operations [92, 247], workflow optimization [246, 255], resource allocation [97, 219], equipment management [88, 179], and emergency preparedness through simulation and predictive analytics [119, 252]. Emerging applications extend beyond clinical environments into medical education [114, 250], medical device prototyping [145], public health planning [9, 165], and healthcare system management [191, 195]. Across these domains, a common pattern emerges: DTs transform healthcare decision-making from reactive and episodic processes toward predictive, preventive, and personalized models [90, 163, 196]. Rather than serving merely as virtual representations of patients or healthcare assets, DTs increasingly function as integrated decision-support systems that combine real-time monitoring, simulation, and forecasting capabilities [98, 253]. This evolution highlights the growing role of DTs in supporting clinical decision-making, hospital management, resource optimization, and population-level healthcare planning.

5.2 Stakeholders

Healthcare DT ecosystems involve a diverse group of stakeholders whose roles expand as DT implementations progress from patient-level applications to organizational and system-wide deployments. Table A3 – Appendix A summarizes the main stakeholders, their roles, and impacts. Patients, clinicians, and healthcare providers remain the primary beneficiaries and users of DT-enabled decision support, particularly in personalized medicine, disease management, and continuous monitoring contexts [85, 160, 246]. At the organizational level, healthcare administrators and managers utilize DT insights to optimize resource allocation, workflow efficiency, and service delivery [145]. Technology providers contribute by developing AI, IoT, cloud, and analytics infrastructures that enable DT functionality, while insurers increasingly explore DT-generated insights for risk assessment and healthcare planning [249, 256]. Regulatory agencies and governing institutions play a critical role in establishing standards for privacy, security, ethical compliance, and clinical validation [142]. Across all stakeholder groups, successful DT implementation depends on balancing innovation with trust, accountability, interoperability, and data governance [89, 240]. As DTs evolve from isolated clinical tools into integrated healthcare platforms, stakeholder alignment becomes increasingly important, particularly regarding data sharing, decision authority, ethical oversight, and patient safety [147, 192].

5.3 Technological Integration

DT-enabled healthcare systems depend on integrating multiple digital technologies to create continuously synchronized, data-rich environments that support real-time, predictive, and adaptive decision-making. Across the reviewed literature, six interdependent technology layers consistently underpin healthcare-DT implementations: IoT/Internet of Medical Things (IoMT), AI and ML, EHRs, telemedicine platforms, cloud computing and big data analytics, and blockchain-based security mechanisms. Table 4 summarizes these technologies and their principal application areas.

Table 4

Technological integration supporting DT applications in healthcare

Application area	Key benefits	Technologies involved
Patient monitoring & chronic care [121, 239, 243, 251, 252]	Continuous monitoring; early anomaly detection; personalized interventions	IoT/IoMT, AI/ML, cloud computing, EHR integration
Predictive diagnostics [192, 214, 219, 252, 257]	Improved diagnostic accuracy; early disease detection	AI/ML, advanced imaging, big data analytics
Telemedicine & remote care [86, 248, 250]	Increased accessibility; remote decision support	Telehealth platforms, IoT, AI, cloud computing
Hospital operations & workflow optimization [239, 251]	Resource optimization; reduced delays; operational efficiency	IoT sensors, AI analytics, cloud/edge computing
Secure data sharing & governance [86, 207, 251]	Data privacy; interoperability; regulatory compliance	Blockchain, decentralized identity
Training, simulation & visualization [142, 250–252]	Enhanced learning; improved interpretability	Extended reality, DT platforms, AI

Across these layers, IoT/IoMT provides the continuous physiological and environmental data required for DT synchronization, while AI and ML transform these heterogeneous data streams into predictive and decision-support insights for diagnosis, treatment planning, and patient monitoring [219, 239, 252]. EHR integration complements real-time sensing with longitudinal clinical information, enabling DTs to incorporate medical histories, laboratory results, imaging, and treatment records into patient-specific models [99, 214]. Telemedicine and digital health interfaces extend these capabilities beyond institutional settings, supporting remote supervision, consultation, and patient engagement [86, 248]. Cloud and edge infrastructures provide the computational capacity required for continuous model updating and large-scale analytics, whereas blockchain-based mechanisms address secure data exchange, identity management, transparency, and cross-institutional trust [207, 251]. The reviewed evidence therefore shows that healthcare-DTs derive their decision-support capability not from any single technology, but from the integration of sensing, clinical data, analytics, computing, and governance mechanisms within a unified socio-technical architecture.

5.4 Decision-Making Levels

DTs support healthcare decision-making across three levels: clinical (operational), hospital management (tactical), and health policy (strategic). Table 5 summarizes the distribution of the reviewed studies and the principal decision-support functions identified at each level. While this section examines how DTs support decisions across these levels, Section 5.5 separately evaluates the value generated through these capabilities.

5.4.1 Strategic Decision-Making

This category represents the dominant decision-making level, accounting for 51% of the selected studies, reflecting the maturity of DTs in supporting long-term healthcare transformation, governance, and system-wide planning. Unlike operational and tactical applications, strategic DTs extend beyond individual clinical settings to inform policy development, infrastructure planning, regulatory compliance, and population-level healthcare management. At this level, DTs have been conceptualized as mechanisms for transforming traditional EHRs into dynamic, continuously evolving platforms capable of supporting precision medicine and public health interventions [177]. National-level integration strategies, including interoperable infrastructures, governance frameworks, clinician training, and ethical safeguards, have similarly been proposed as essential prerequisites for large-scale DT adoption within healthcare systems [165].

Table 5
Distribution of DT applications across decision-making levels in healthcare

Decision level	Key enhancements by DTs	Study	Number of studies
Strategic decision-making (health policy)	Population-level immunization program management; value-based healthcare transformation frameworks; public health surveillance and epidemic response (e.g., COVID-19); national healthcare system integration roadmaps; smart healthy city planning and resource distribution; policy scenario simulation and systemic risk assessment; ethical governance frameworks for data privacy and informed consent; cross-border health data interoperability standards; methodological frameworks for DT implementation	[9, 10, 13, 14, 64, 89, 93, 94, 97–99, 115, 117, 120, 121, 123, 124, 140–142, 144, 146–148, 161, 162, 165, 166, 177–179, 184, 191, 195, 196, 198, 207, 210, 211, 215, 219, 222, 225, 240, 242, 244, 246, 249, 250, 255]	50
Operational decision-making (clinical)	Real-time patient monitoring (vitals, respiration, SpO ₂ via wearables/Wi-Fi CSI); personalized treatment simulation for cancer/radiotherapy; mental health intervention delivery; surgical planning/rehearsal with 3D anatomical models; chronic disease management (diabetes, cardiovascular); predictive diagnostics using multimodal imaging/AI; rehabilitation support via exoskeleton control; drug efficacy prediction (e.g., amiodarone in AF); biological age assessment for risk stratification	[85, 87, 90, 95, 96, 114, 118, 119, 122, 138, 139, 145, 160, 163, 164, 167, 180–182, 189, 190, 192, 197, 203, 204, 208, 214, 218, 223, 239, 241, 243, 248, 252–254]	36
Tactical decision-making (hospital management)	Real-time facility monitoring (HVAC, IAQ, oxygen tanks); predictive maintenance of medical equipment/MRI machines; emergency department workflow optimization with biometric authentication; bed/resource allocation using formal models/ SMT solvers; digital replication of entire hospital environments for operational continuity; vaccination storage temperature management; trauma coordination ecosystems; workflow automation with blockchain integration; infrastructure performance optimization	[16, 86, 88, 91, 92, 100, 116, 143, 183, 226, 247, 251]	12

Strategic public health applications further illustrate the broader decision-making role of DTs. These include vaccine cold-chain monitoring, disease surveillance, population health management, and smart healthy city initiatives integrating hospitals, community health centers, and urban infrastructures into unified planning environments [14, 210]. DTs have also been employed to simulate alternative policy scenarios, evaluate systemic risks, and assess the long-term effects of healthcare interventions, thereby supporting evidence-based policymaking and resource allocation [182, 249]. Furthermore, virtual patient representations integrating diverse biological and clinical datasets have enabled population-level disease modeling, precision medicine, and insurance risk stratification [211, 219]. Collectively, these studies demonstrate that strategic DTs increasingly function as governance and policy-support infrastructures, enabling healthcare systems to move beyond isolated clinical applications toward coordinated, evidence-based decision-making at organizational and national scales.

5.4.2 Operational Decision-Making

The clinical (operational level) decision layer appears in 37% of the selected studies, making it the second most prevalent decision layer in healthcare-DT research. At this level, DTs primarily support real-time, patient-specific clinical decision-making, with a strong focus on continuous monitoring, personalized treatment simulation, and chronic disease management. Clinical DTs function as

continuously updated virtual counterparts of individual patients by integrating heterogeneous data streams, including medical imaging, physiological signals, and wearable sensor data [118]. Through the integration of AI and ML techniques, DTs enable predictive risk assessment and early intervention, thereby enhancing patient safety and clinical outcomes [118]. Their value at the operational level lies in translating complex, high-frequency clinical data into actionable insights that support diagnosis, treatment selection, and therapy adjustment in near real time [190]. In oncology, for example, DTs combined with AI have been shown to overcome limitations of conventional treatment planning by enabling individualized and adaptive therapeutic decisions [190]. Operational DT applications span continuous physiological monitoring, chronic disease management, oncology, and cardiovascular care, illustrating their role in supporting patient-specific decisions across diverse clinical contexts [139, 181, 253].

5.4.3 Tactical Decision-Making

Hospital management (tactical level) appears in 12% of the selected studies and is primarily concerned with mid-term operational efficiency, encompassing equipment maintenance, resource allocation, and workflow optimization. At this level, DTs shift focuses from individual patients to healthcare facilities and organizational processes, enabling administrators to manage resources under dynamic and uncertain conditions. Hospital-level DTs support real-time monitoring and predictive optimization of infrastructure, staffing, and clinical workflows, leading to improved patient flow and reduced operational costs [88, 100]. Continuous performance supervision of both clinical and non-clinical operations has been demonstrated through a DT framework piloted in a Shanghai hospital, integrating multi-source data to enable real-time operational control [116]. DT-enabled scenario simulation allows hospital managers to assess the operational impact of changes in facility layout, staffing policies, or resource allocation, supporting evidence-based tactical planning and productivity improvement [100].

5.5 Business Value

DT technologies generate value by translating data-driven decision capabilities into measurable clinical, operational, and organizational outcomes. While Section 5.4 examined how DTs support decision-making across different organizational levels, this section focuses on the value created through those capabilities, including improvements in patient outcomes, operational efficiency, resource utilization, resilience, and long-term healthcare sustainability. Table 6 summarizes the principal value dimensions identified in the reviewed literature.

5.5.1 Research and Innovation

Research and innovation are the dominant value dimension, accounting for 49% of the selected studies and reflecting the innovative maturity of DTs in healthcare. Most contributions emphasize methodological foundations, conceptual frameworks, and validation protocols, rather than large-scale deployed applications that deliver measurable economic returns. DTs are primarily positioned as experimental and exploratory decision-support environments that enable the safe simulation of diseases, therapies, medical devices, and system-level interventions prior to real-world implementation [142]. Framework-driven contributions dominate this stream. The DECIDE-Twin framework has been developed to guide DT design and implementation for clinical decision-making through a systematic scoping review, addressing issues of transparency, usability, and clinical relevance [144]. Ethical and user-centric development practices have been formalized through the ETHICA methodology, which advocates iterative stakeholder engagement throughout the DT lifecycle [242]. A meta-review synthesizing 25 literature reviews has identified three dominant DT application

domains, personalized medicine, operational efficiency, and medical research, while exposing persistent gaps in scalability, interoperability, and clinical validation [215].

Table 6
DT business value in healthcare

Business value	Key enhancements by DTs	Study	Number of studies
Research & innovation	Reference architectures and conceptual frameworks for cyber-physical healthcare; VVUQ protocols and AI/ML algorithms; multimodal data integration techniques; DT brain modeling approaches; medical imaging in anatomical replication; cross-sectoral adoption analysis using TOE framework; ethical guidelines development and technology readiness assessment; policy/implementation roadmaps for national healthcare systems	[9, 10, 13, 64, 89, 93, 94, 97–99, 115, 117, 119–121, 123, 124, 140–142, 144, 146–148, 161, 162, 164–167, 177–179, 184, 191, 195, 196, 198, 207, 214, 215, 218, 222, 225, 240, 242, 244, 250]	48
Hospital management	Fast-track service; real-time facility monitoring; bed allocation optimization; trauma coordination ecosystems; vaccination coverage monitoring against official calendars; urban healthcare resource planning; surgical planning/rehearsal with IoRT integration; telerehabilitation infrastructure	[14, 16, 85, 86, 92, 100, 114, 116, 122, 143, 145, 180, 183, 197, 208, 226, 239, 246–249, 251, 255]	23
Clinical management	Personalized treatment optimization; real-time physiological monitoring enabling early intervention; predictive modeling of treatment response; mental health intervention delivery with sensor-driven CBT; biological age assessment for risk stratification; chronic disease management	[87, 90, 95, 96, 118, 138, 139, 160, 163, 181, 189, 190, 192, 203, 204, 223, 241, 243, 252–254]	21
Economic management	Vaccine dose wastage reduction; predictive maintenance; operational efficiency gains in diabetes management; workflow automation; catastrophic case forecasting; equipment lifecycle management	[88, 91, 182, 210, 211, 219]	6

Methodological rigor has been emphasized as a prerequisite for clinical translation. VVUQ protocols have been positioned as non-negotiable safeguards for DT deployment in high-stakes domains such as cardiology and oncology [147]. Concurrently, conceptual imprecision within the literature, where non-conforming implementations are mislabeled as DTs despite lacking modeling fidelity or bidirectional synchronization, has been systematically documented, prompting calls for terminological discipline and methodological clarity prior to scaling [240]. Strategic visions for transforming static EHRs into dynamic, population-scale platforms for precision medicine and public health intervention further illustrate the research-centric orientation of current DT value creation [177].

5.5.2 Hospital Management

Hospital management constitutes 24% of the selected studies, with value creation concentrated in workflow optimization, resource allocation, and facility-level decision support. DTs enable real-time operational visibility across clinical and non-clinical processes, supporting coordination, throughput optimization, and infrastructure intelligence. Comprehensive DT frameworks integrating multi-source data have demonstrated continuous control of hospital operations, advancing digitization and automation across clinical workflows [116].

Operational decision-making has been improved through formal modeling approaches that transform patient admission streams into dynamic bed allocation optimization problems under

resource constraints [226]. Facility-level intelligence has been enhanced through continuous monitoring of HVAC systems, indoor air quality, pulsed-light decontamination processes, and MRI interference from radio frequencies, enabling proactive infrastructure management [183]. Patient flow efficiency has been improved through biometric authentication-enabled fast-track services in emergency departments, achieving success rates exceeding 80% [85]. Beyond hospital boundaries, DT-enabled healthcare delivery has been extended to urban and regional scales. A three-tier hierarchical DT architecture integrating individual residences, community health centers, and city-wide infrastructure has been proposed to support strategic health planning within smart healthy city ecosystems [14]. These studies demonstrate that DTs create value by enhancing tactical decision-making capacity, particularly in environments characterized by congestion, resource scarcity, and operational complexity.

5.5.3 Clinical Management

Clinical management appears in 21% of the reviewed studies, representing the most empirically substantiated value stream in DT healthcare research. DTs enable personalized, predictive, and adaptive clinical decision-making by integrating heterogeneous data from EHRs, wearable devices, medical imaging, and real-time monitoring systems [90, 95]. Mental health outcomes have also improved. Wearable sensor-integrated DTs delivering cognitive behavioral therapy interventions have produced significant reductions in depressive (−5.61) and anxiety (−5.21) symptom scores [203].

Quantifiable clinical improvements have been reported across multiple disease domains. A commercial DT program for Type 2 diabetes has demonstrated a mean HbA1c reduction of 1.8%, with 89% of participants achieving glycemic targets below 7% after one year [96]. In oncology, Bayesian-calibrated DTs have generated radiotherapy regimens that increased median time to progression by six days or reduced radiation dose by 16.7% while preserving tumor control in high-grade glioma patients [139]. Cardiovascular DT applications have enabled the prediction of amiodarone therapeutic efficacy in atrial fibrillation patients, with significantly lower recurrence rates observed among patients classified as responsive (20.8% versus 45.1%; HR 0.37, $p = 0.046$) [253].

5.5.4 Economic Management

Finally, explicit cost-reduction outcomes are reported in 6% of the selected studies, highlighting a notable gap in economic evaluation in DT healthcare research. Where cost-related value is identified, savings are primarily generated through operational efficiency, waste reduction, and risk mitigation, rather than direct reductions in clinical treatment expenditures. Operational cost efficiencies have been achieved through optimized workflow analysis and resource allocation, reducing overhead and improving utilization rates [182]. Administrative automation has further reduced human error and processing time, contributing to shorter waiting times and improved service efficiency [91]. Indirect cost savings have been demonstrated in public health logistics, where DT-based monitoring of vaccine storage temperatures and immunization coverage has reduced dose wastage [210], supported by simulation-based validation of resilient cold-chain management protocols [211].

Predictive maintenance of medical equipment has minimized downtime and optimized maintenance resource allocation through the integration of IoT sensing and AI [88]. At the system level, forecasting of catastrophic case incidence within health insurance portfolios has supported improved risk stratification and resource provisioning through DT-enabled digital shadow implementations [219]. Despite these advances, the limited proportion of cost-focused studies underscores the need for rigorous cost-benefit and value-based care analyses in future DT research.

5.6 Challenges and Limitations of Digital Twin Applications in Healthcare

Despite their significant potential, DT applications in healthcare face several interconnected challenges that intensify as systems scale from individual patients to enterprise-wide and cross-institutional deployments. Table A4 – Appendix A summarizes the key challenges. Data-related issues remain among the most significant barriers [210, 258], including interoperability limitations, fragmented information systems, inconsistent data quality, and the integration of heterogeneous clinical datasets [141, 146, 177]. Equally important are concerns surrounding privacy, cybersecurity, and regulatory compliance, as healthcare-DTs rely on highly sensitive patient information subject to strict governance requirements [141, 178, 192]. Model validation and clinical reliability present additional challenges, given the need to demonstrate safety, accuracy, and effectiveness before DT-generated recommendations can influence patient care [166, 196, 259]. Organizational barriers include limited digital readiness [99, 241], difficulties with workflow integration [141, 243], and resistance to adopting AI-supported decision-making processes [123, 141]. At broader system levels, ethical concerns surrounding informed consent [146, 241], data ownership [117, 196], algorithmic bias [141, 184], and equitable access [165, 166] become increasingly prominent. Consequently, healthcare-DT adoption requires not only technological advancement but also robust governance frameworks, interdisciplinary collaboration, and transparent validation mechanisms capable of balancing innovation with patient safety, accountability, and societal trust [196, 259].

6. Digital Twins in Supply Chain Management

DT technology has emerged as a foundational capability for transforming contemporary supply chains, extending from shop-floor assets and warehouse systems to transportation fleets and multi-tier production–distribution networks [28]. Figure 5 synthesizes the DT literature in SCM by mapping key application domains, business value dimensions, stakeholder groups, and cross-cutting challenges. The figure illustrates how DT-enabled SCM evolves from operational optimization toward enterprise coordination and network-level decision support, while remaining constrained by interoperability, governance, and collaboration barriers.

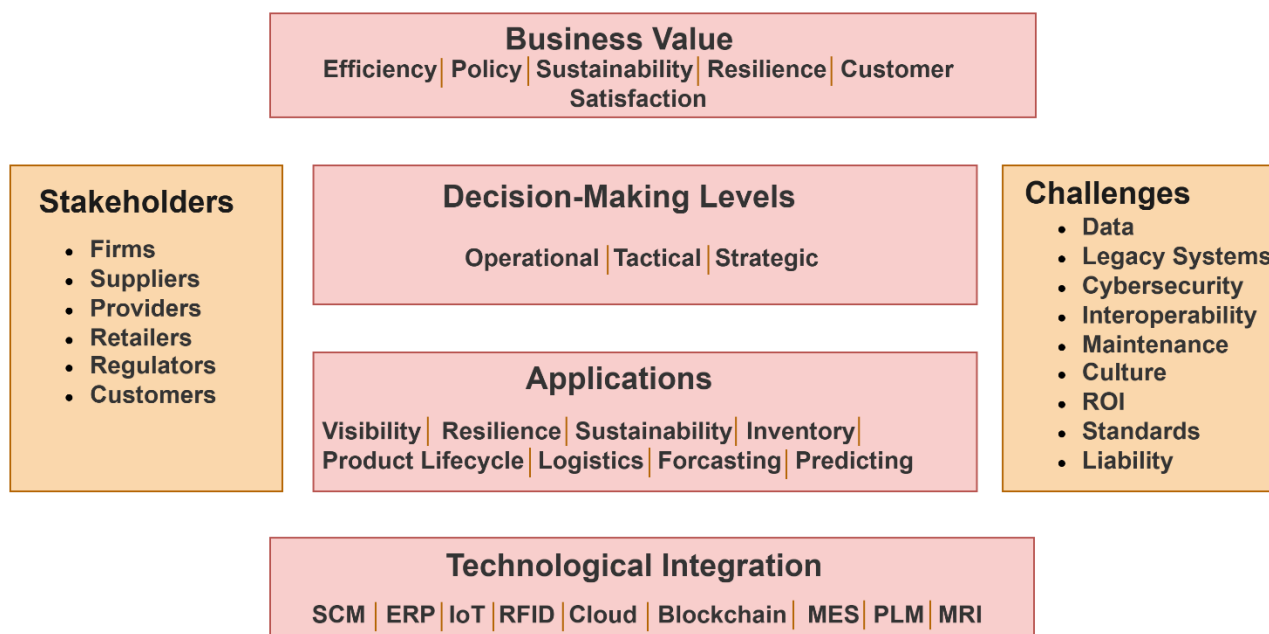


Fig. 5. Layered socio-technical decision system of DT-enabled SCM

6.1 Applications

The literature demonstrates that DT applications in SCM have evolved from asset-level monitoring toward integrated decision-support systems spanning entire supply networks. Table B2 – Appendix B summarizes the key applications. Core applications include visibility and traceability [69, 235], inventory and production synchronization [105, 149], logistics and transportation management [153, 200], demand forecasting [131, 231], predictive maintenance [126, 234], resilience planning [52, 134], sustainability management [27, 158], and product lifecycle integration [176, 201]. Through continuous synchronization of physical and digital operations, DTs enable organizations to monitor performance in real time, evaluate alternative scenarios, anticipate disruptions, and optimize resource allocation. Increasingly, DTs support not only operational control but also tactical planning and strategic network design [29, 216]. The reviewed studies indicate a clear shift from isolated engineering applications to ecosystem-level coordination, in which DTs facilitate collaboration among suppliers, manufacturers, logistics providers, and customers. Across these application areas, a common objective emerges, transforming SCM from reactive and schedule-driven operations into predictive, adaptive, and resilience-oriented systems that support data-driven decision-making under uncertainty.

6.2 Stakeholders

DT deployment in SCM involves a progressively expanding stakeholder ecosystem. Table B3 – Appendix B summarizes the main stakeholders, their role, and their impacts. Engineering teams, operations personnel, and technical specialists responsible for asset monitoring, process optimization, and system integration typically drive early implementations [105, 185]. As DTs become embedded within organizational planning processes, additional stakeholders emerge, including production managers, logistics coordinators, supply chain planners, enterprise architects, and senior executives who rely on DT-generated insights for decision-making [131, 201]. At the network level, stakeholders extend beyond individual firms to include suppliers, distributors, logistics providers, technology vendors, platform operators, regulators, and customers [26, 129]. Unlike in healthcare, where privacy regulations often constrain collaboration, SCM DTs increasingly rely on cross-organizational data sharing and coordinated decision-making across multiple supply chain partners [220, 221]. Consequently, stakeholder alignment, trust, governance mechanisms, and shared standards become critical success factors [136, 227]. As DT ecosystems continue to mature, value creation increasingly shifts from technical implementation toward collaborative governance, capability development, and effective coordination among diverse stakeholders operating across organizational boundaries [136, 187, 232].

6.3 Technological Integration

Effective DT deployment in SCM requires the integration of multiple complementary technologies to form an interoperable, intelligent decision-support ecosystem [2]. Across the reviewed literature, DT implementations consistently combine IoT sensing, AI, blockchain, ERP systems, and cloud computing infrastructures [130, 136]. These technologies and applications are depicted in Table 7.

Over 90% of studies incorporate IoT-enabled data collection, reflecting its foundational role in capturing real-time operational signals. More than 60% explicitly integrate enterprise platforms such as ERP or MES, while nearly half employ hybrid simulation or AI-enabled analytical engines to support scenario experimentation and foresight. This distribution aligns closely with decision layers: real-time sensing underpins operational DTs, enterprise integration supports tactical coordination, and advanced modeling enables strategic planning and resilience analysis [30, 37]. Transforming granular operational data into actionable managerial insight through structured data–information–knowledge

architectures has been identified as a critical enabler of DT-driven decision intelligence [36]. Enterprise-level integration, observed in approximately two-thirds of SCM studies, marks a transition from isolated technical models toward embedded, organization-wide decision infrastructures.

Table 7

Summary of DT benefits and technologies in SCM

Application area	Key benefits	Technologies involved
Supply chain visibility & traceability [26, 31]	Tracking the movement and status of products throughout the supply chain; enhancing transparency	RFID-based systems; IoT sensors; blockchain
Resilience, disruption modeling, and risk management [36, 37, 106]	Ability to evaluate stress scenarios; simulation of disruptions; identification of robust network configurations	Scenario engines; stochastic simulation; multi-tier modelling; DIKW or decision-layered logic; risk mapping tools
Sustainability & efficiency [30, 31]	Waste reduction; reverse logistics optimization; tracking and valorizing recovered materials; emissions visibility	Reverse-flow modelling; lifecycle data capture; IoT-enabled tracking; circularity databases; twin-enabled environmental calculators
Inventory management & production synchronization [26, 28]	Better stock-to-capacity alignment; reduction of buffer stock; minimization of bottlenecks; dynamic matching of supply to demand	Embedded shopfloor IoT; MES/ERP linkages; discrete-event and agent-based modelling; predictive work allocation dashboards
Product lifecycle & engineering design integration [32, 34]	Continuity from product design → production → service; lower redesign cost; improved maintainability and manufacturability	CAD/PLM integration, hybrid modelling; engineering–MES linkages; digital product passports; parametric simulation
Logistics & transportation systems [30, 35, 175, 260] [104]	Real-time routing and load balancing; fleet coordination; reduction in dwell times and spoilage; improved order fulfilment accuracy	IoT sensors (location, environmental, RFID); fleet telematics; WMS/ERP integration; simulation engines for route optimization
Demand forecasting & planning [36, 37]	Improved alignment of production to market signals; ability to rehearse planning scenarios; better replenishment and scheduling under uncertainty	Forecasting engines; ML; scenario simulation; ERP-linked planning modules; integrated digital-physical sandboxes
Predictive maintenance & asset reliability [27, 34]	Reduction in unplanned downtime; increased asset life; smoother production cycles; lower maintenance expenditure	Condition monitoring sensors; vibration and wear sensing; prognostics modelling; IIoT platforms; analytics for degradation prediction

Together, these technologies form a layered decision infrastructure in which IoT and IIoT provide real-time operational signals, simulation and AI/ML transform those signals into predictive and prescriptive insights, and ERP/MES'S integration embeds DT outputs within organizational planning and coordination processes [34, 37, 260]. Blockchain contributes trust, traceability, and cross-organizational coordination in multi-actor supply chains, while cloud infrastructures provide the scalability required for distributed simulation, analytics, and collaboration [151, 186, 205]. The reviewed evidence therefore indicates that SCM-DT maturity is increasingly associated with the integration of sensing, analytical, enterprise, and governance technologies, enabling progression from isolated operational twins toward organization- and network-level decision-support systems [11, 236].

6.4 Decision-Making Levels

DTs enhance decision-making across all levels of SCM by enabling data-driven insight, predictive reasoning, and scenario-based evaluation. While DTs initially entered the SCM domain as tools for real-time operational control, their role has rapidly expanded to include tactical coordination and

strategic system design. This multi-level impact positions DTs not merely as analytical tools, but as emerging organizational infrastructures capable of orchestrating decisions across processes, actors, and time horizons. Table 8 summarizes how DTs support decision-making at the strategic, tactical, and operational levels, along with the dominant research focus identified in the reviewed literature.

Table 8

Distribution of DT applications across decision-making levels in SCM

Decision-making level	Key enhancements by DTs	Study	Number of studies
Strategic (Long-term vision, network design, sustainability, resilience)	Long-term capacity planning; strategic decision-making; resilience and sustainability; system architecture design; sustainability integration; policy and ecosystem modeling	[7, 11, 27, 36, 37, 52, 69, 102–104, 106, 107, 109–111, 113, 125, 128–132, 134, 135, 150, 151, 153, 154, 156–159, 169–171, 173–176, 185, 186, 188, 193, 194, 199–202, 205, 206, 209, 212, 213, 216, 217, 230, 232, 233, 235, 238, 261]	61
Tactical (Medium-term planning and coordination)	Demand forecasting and planning; resource sizing & inventory allocation; supply chain coordination; risk management and disruption response; inventory and production planning	[12, 26, 30, 35, 101, 108, 112, 136, 137, 152, 168, 172, 187, 220, 221, 224, 227–229, 236]	20
Operational (Day-to-day execution and control)	Real-time monitoring and control; process optimization and logistics execution; adaptive routing & bottleneck mitigation; inventory management; predictive maintenance	[28, 29, 31–34, 105, 126, 127, 149, 155, 231, 234, 237]	14

6.4.1 Strategic Level

The strategic level refers to long-term vision and system design, including framework development, ecosystem architecture, sustainability integration, and cross-sector transformation [157]. Strategic applications dominate the SCM-DTs literature, accounting for 64% of studies and reflecting the technology's relatively early stage of organizational maturity. Rather than supporting routine execution, most DT research focuses on defining how DTs should be architected, governed, and embedded within supply networks [171]. At this level, DTs enable long-term capacity planning and network configuration, allowing organizations to evaluate future demand scenarios, infrastructure investments, and sourcing strategies [194]. They also support high-level strategic decisions such as supply chain redesign, outsourcing, and vertical or horizontal integration [233]. Strategic DTs also enable decision-makers to stress-test alternative supply chain configurations under disruption and sustainability scenarios, supporting long-horizon choices concerning network resilience and future supply chain design [37, 216, 238].

6.4.2 Tactical Level

The tactical level focuses on medium-term planning over weeks or months, encompassing inventory policies, supplier selection, production planning, and disruption mitigation [26]. Tactical applications account for 21% of the reviewed studies, indicating a growing recognition of DTs as tools for resilience planning and coordinated resource allocation. At this level, DTs enhance demand forecasting and production planning by integrating real-time data with predictive analytics, improving alignment between supply and demand [224]. They also facilitate supply chain coordination, enabling synchronized decision-making across manufacturers, suppliers, and logistics providers [101]. Risk management is a central theme, with DTs supporting scenario planning and

early-warning mechanisms for supply shortages, transportation disruptions, and demand shocks [35, 187]. Tactical DTs also function as controlled experimentation environments in which managers can evaluate alternative layouts, scheduling policies, capacity configurations, routing, and replenishment decisions before implementation [26, 108, 172]. This scenario-based capability supports more systematic medium-term planning under variable demand and operational uncertainty.

6.4.3 Operational Level

The operational level refers to day-to-day execution, including real-time monitoring, shop-floor control, warehouse automation, and machine scheduling [28]. Despite the strong conceptual promise of DTs for real-time control, operational applications account for only 15% of studies, revealing a notable execution gap between theoretical potential and deployed practice. Operational DTs primarily enable real-time monitoring and control, improving responsiveness and execution efficiency across production and logistics processes [105]. Operational DTs support bottleneck detection, dynamic throughput balancing, human-machine adaptation, predictive maintenance, and reverse-logistics control by continuously synchronizing physical operations with their virtual counterparts [28, 31, 34].

6.5 Business Value

DTs generate substantial business value in SCM by enhancing efficiency, resilience, sustainability, and, more recently, customer-oriented performance. While early adoption concentrated primarily on operational performance improvements, the reviewed literature demonstrates a clear expansion of value creation toward planning quality, strategic foresight, risk preparedness, and lifecycle-aware decision-making, as depicted in Table 9.

Table 9
DT business value in SCM

Business value	Key enhancements by DTs	Study	Number of studies
Efficiency	Operational optimization; cost reduction and cycle time improvement; productivity gains; resource utilization and waste reduction	[28, 30, 32–34, 101, 105, 112, 126–128, 134, 137, 149, 153, 155, 159, 172, 185, 187, 209, 217, 220, 221, 224, 227, 229, 231, 233, 234, 237]	31
Strategic & policy value	Adoption frameworks, scenario planning and system redesign; implementation and governance challenges; technology adoption strategies and policy recommendations	[7, 11, 27, 36, 69, 104, 107, 113, 125, 129, 130, 135, 151, 154, 156, 157, 169, 170, 176, 193, 194, 199, 200, 202, 205, 213, 230, 235, 261]	29
Sustainability	Environmental impact reduction; carbon footprint, eco-design, and circular economy; energy efficiency and resource conservation	[31, 35, 37, 102, 109, 110, 132, 136, 150, 158, 171, 174, 186, 201, 212, 216, 232, 236]	18
Resilience	Disruption response and supply continuity; risk mitigation and recovery from shocks/pandemics/crises	[12, 26, 52, 103, 106, 111, 152, 168, 173, 175, 188, 206, 228, 238]	14
Customer satisfaction	End-customer experience and demand responsiveness; product personalization and customization; service quality and food safety	[29, 108, 131]	3

This progression points to a shift in how firms perceive the potential of DTs, from tools that “tune the system” to platforms that actively shape the evolution of SCM. Early DT deployments deliver

tangible gains in operational efficiency and reliability through real-time synchronization. Subsequent work demonstrates improved planning quality and decision-making enabled by simulation and scenario analysis. The most recent studies position DTs at the center of systemic transformation, resilience engineering, and environmental stewardship.

6.5.1 Efficiency

Efficiency represents the primary operational value of DTs, accounting for 33% of reviewed studies. The dominant focus is on immediate and quantifiable performance gains, including cost reductions (reported up to 30%), cycle-time compression (15–25%), and improved resource utilization, particularly in warehousing, production synchronization, and logistics optimization. DTs enhance operational efficiency by improving SCM visibility and enabling accurate, data-driven decision-making [137]. Real-time monitoring, predictive analytics, and adaptive control mechanisms streamline workflows and reduce bottlenecks [234]. Cost reduction benefits are consistently reported, with one study documenting an 18.7% reduction through advanced optimization supported by DT-based modeling [155]. Empirical studies demonstrate accelerated throughput, smoother material flows, and reduced waiting or setup times through feedback-driven synchronization [101, 185, 209]. These effects are observed both on the production floor [153, 229] and in warehouse environments [30]. In several cases, efficiency gains are amplified when design knowledge and process constraints are explicitly embedded into operational DT models [32].

6.5.2 Strategic and Policy Value

Strategic and policy-oriented contributions represent 30% of the corpus, underscoring the technology's conceptual and developmental maturity stage. Rather than reporting direct performance metrics, these studies focus on frameworks, architectures, governance considerations, and implementation pathways [7, 125]. DTs provide strategic guidance for adoption by identifying critical enablers such as IoT, AI, cloud computing, and enterprise integration, while also addressing ethical, legal, and regulatory considerations [235]. Several reviews and conceptual studies highlight opportunities for future development, particularly in extreme-event logistics and crisis management contexts [157]. A central theme in this domain is the role of twin-enabled simulation as a decision environment. DTs allow organizations to experiment with alternative schedules, sourcing strategies, and resource configurations without incurring real-world risk. Scenario analysis increasingly replaces intuition-based planning with model-supported reasoning [36, 156]. Other studies report reduced planning uncertainty and improved responsiveness in volatile environments where traditional heuristics fail [129, 193].

6.5.3 Sustainability

Sustainability accounts for 19% of studies, reflecting a rapidly expanding research stream. DTs are increasingly applied to environmental performance improvement, particularly in food and agri-supply chains (waste reduction), construction (life-cycle assessment integration), and circular economy contexts such as remanufacturing and industrial symbiosis [171, 186]. DTs contribute to sustainability by optimizing resource use and reducing environmental impact [109]. Enhanced planning and monitoring capabilities enable improved resource efficiency and waste reduction [132]. Several authors demonstrate how digitally mapped material and energy flows reveal inefficiencies that remain invisible through physical inspection alone [35]. Real-time monitoring and traceability across multiple process stages and, in some cases, across organizational boundaries, support coordinated sustainability actions. Importantly, the literature frames visibility not as an endpoint but as an enabler of higher-order value creation, particularly in strategic planning and policy alignment

[35]. DTs integrated with advanced environmental modeling have also been shown to reduce carbon emissions and improve overall environmental performance [174].

6.5.4 Resilience

Resilience-related value represents 15% of studies, reflecting a marked increase in attention following COVID-19 and subsequent geopolitical disruptions. This body of work focuses on stress-testing supply chains, activating alternative suppliers, and supporting recovery strategies [228, 238]. DTs enhance resilience by enabling organizations to anticipate disruptions through real-time insight and predictive analytics [12, 188]. They support proactive risk management, adaptive reconfiguration, and continuity planning in uncertain environments [173]. Beyond execution efficiency, DTs contribute to system stability, particularly through predictive maintenance and early degradation detection [102, 168]. Several studies report improved machine uptime and reduced maintenance costs, with these benefits propagating system-wide to improve logistics reliability, scheduling stability, and customer service performance [173, 188].

6.5.5 Customer Satisfaction

Customer satisfaction remains significantly underexplored, accounting for only 3% of the studies. Most DT applications prioritize internal operational optimization rather than directly targeting customer-facing outcomes, revealing a notable research and practice gap [131]. Where addressed, DTs are shown to improve service levels by enhancing visibility, demand forecasting accuracy, and inventory coordination, leading to more reliable delivery performance [108]. Improved demand responsiveness and reduced stockouts contribute indirectly to customer satisfaction [29]. Given DTs' potential for personalization and real-time adaptation, this domain represents a promising avenue for future research.

6.6 Challenges and Limitations of Digital Twin Applications in SCM

Although DTs offer substantial benefits for SCM, their implementation remains constrained by a combination of technical, organizational, financial, and inter-organizational challenges. Table B4 – Appendix B summarizes the key challenges. At the operational level, organizations frequently encounter difficulties integrating legacy systems [29, 262], ensuring data quality [28, 36], maintaining cybersecurity [237, 263], and justifying the significant investments required for sensing [7, 32], connectivity [69, 101], and computational infrastructure [27, 110]. As DTs expand to enterprise-wide applications, interoperability between ERP, MES, Warehouse Management Systems (WMS), and planning systems becomes increasingly complex, while organizational readiness, analytical capabilities, and managerial trust influence adoption success [30, 36]. At the network level, the most significant challenges relate to collaboration, governance, and data sharing among independent supply chain partners [212, 216]. Concerns regarding data ownership, competitive sensitivity, cybersecurity risks, and the absence of common standards often hinder ecosystem-level DT development [237, 263, 264]. Furthermore, balancing efficiency, resilience, sustainability, and regulatory compliance remains an ongoing challenge [31, 107, 170]. These barriers demonstrate that DT maturity depends not only on technological capabilities but also on organizational learning, stakeholder alignment, governance structures, and the ability to coordinate decision-making across increasingly interconnected supply networks [107, 170].

7. Comparison of DT-Enabled Decision Environments (SCM vs. Healthcare)

The purpose of the comparison is not to contrast an industry with a business function, but to examine how DTs operate within two distinct socio-technical decision environments. Throughout this

section, SCM is conceptualized as a coordination-intensive decision environment, whereas healthcare is conceptualized as a personalization-intensive decision environment. This contrast provides a useful lens for understanding how domain characteristics influence DT adoption, governance, value realization, and decision-support capabilities. Figure 6 synthesizes the comparative role of DTs in healthcare and SCM from a decision-making perspective. While both domains share a common technological backbone, they diverge markedly in decision objectives, maturity across decision levels, automation tolerance, and governance constraints. The figure highlights how SCM-DTs evolve toward autonomous, network-level decision orchestration, whereas healthcare-DTs prioritize safety-critical, human-centered clinical support.

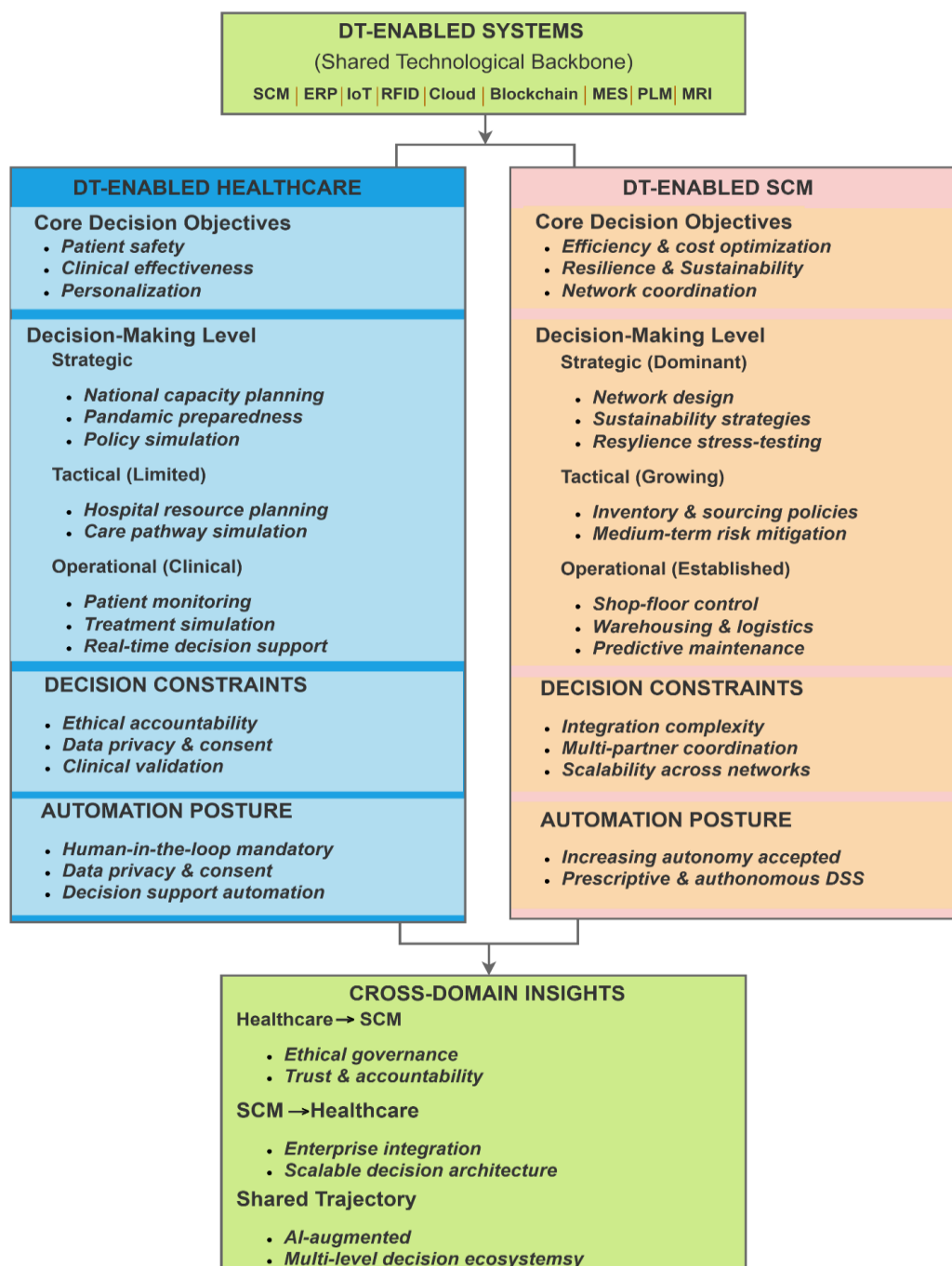


Fig. 6. Decision-centric comparison of DT applications across coordination-intensive and personalization-intensive decision environments

The comparative synthesis indicates that the observed differences between the two decision environments can be interpreted through four interrelated explanatory mechanisms. First, decision focus and system representation reflects what DTs primarily represent and the decisions they are expected to support: SCM twins predominantly model assets, processes, flows, and interorganizational networks to facilitate coordination and optimization [106, 194], whereas healthcare twins increasingly focus on individual patients, clinical pathways, and population-health systems to support personalized and clinically effective decisions [177, 190]. Second, data-governance coupling captures how increasing integration generates different forms of complexity. In SCM, scaling primarily intensifies interoperability, information-sharing, and interorganizational coordination requirements, whereas healthcare integration additionally amplifies privacy, consent, regulatory, and ethical obligations [165, 197]. Third, decision criticality and delegation tolerance influence how far DT-supported decisions can progress toward automation. SCM applications increasingly use DT-generated recommendations as prescriptive inputs for performance-oriented decisions, while safety-critical healthcare decisions retain stronger requirements for professional judgment, validation, accountability, and human oversight [36, 118]. Finally, value-realization logic differs because SCM value is more readily expressed through measurable efficiency, cost, resilience, and sustainability outcomes [106, 194], whereas healthcare value is predominantly reflected in patient safety, personalization, clinical effectiveness, and broader societal outcomes, for which conventional financial returns are less explicit [177, 190]. The following subsections examine how these mechanisms, identified through cross-environment synthesis, manifest across the principal comparative dimensions.

7.1 Decision-Making Orientation and Core Objectives

A central distinction between healthcare and SCM lies in the purpose for which DT-enabled decisions are made. In SCM, DTs are predominantly oriented toward performance optimization, cost reduction, resilience enhancement, and sustainability improvement. Decision-making is framed in economic and operational terms, emphasizing efficiency, throughput, and network robustness [106, 194]. By contrast, healthcare-DTs prioritize clinical effectiveness, patient safety, and individualized care, where decisions carry direct ethical and human consequences [177, 190]. This divergence shapes how DT outputs are interpreted and acted upon. In SCM, DT-generated recommendations are increasingly accepted as prescriptive inputs that may autonomously reconfigure schedules, routes, or inventory policies [36]. In healthcare, DTs predominantly function as decision-support systems, augmenting rather than replacing clinical judgment because decisions directly affect patient safety and remain subject to professional and medico-legal accountability [118, 197]. This contrast indicates that the focus of the decision and the criticality of its consequences shape the extent of permissible decision delegation. Thus, automation tolerance emerges as an important differentiator between the two decision environments, with SCM allowing greater scope for automated coordination and healthcare requiring stronger human oversight and professional accountability.

7.2 Decision-Making Logic Across Domains

While SCM and healthcare rely on similar DT technological foundations, including IoT-enabled sensing, AI-driven analytics, simulation engines, and cloud platforms, the review reveals fundamentally different decision-making logics across the two domains. In SCM, DTs primarily function as coordination and optimization mechanisms that support visibility, scenario planning, disruption response, resource synchronization, and sustainability management. Decision quality is

therefore evaluated largely through operational efficiency, resilience, cost reduction, and network performance outcomes [106, 194].

In contrast, healthcare-DTs primarily function as personalization and clinical decision-support mechanisms. Applications focus on patient monitoring, disease prediction, treatment optimization, hospital resource management, and population-health planning. Consequently, decision quality is assessed through patient outcomes, safety, clinical effectiveness, and ethical compliance rather than purely economic performance [177, 190].

The comparative evidence suggests that these contrasting decision logics arise primarily from differences in decision focus and value-realization objectives. SCM-DTs typically represent interconnected assets, processes, and flows whose performance depends on coordination across multiple organizational actors; therefore, their decision logic evolves toward orchestration, where value is created by synchronizing activities and optimizing system-level performance [106, 194]. Healthcare-DTs, conversely, increasingly represent patient-specific states and clinical trajectories, making personalization and context-sensitive intervention the dominant decision logic [177, 190]. The comparison thus suggests that orchestration and personalization are not simply sector-specific application patterns, but distinct pathways through which the object represented by the DT and the value sought from it shape how digital intelligence is translated into decisions.

7.3 Distribution Across Decision-Making Levels

The review reveals notable differences in the distribution of DTs across operational, tactical, and strategic decision-making levels in SCM and healthcare. In SCM, DT research exhibits a top-heavy distribution, with strategic applications accounting for 64% of studies, followed by tactical (21%) and operational applications (15%). Strategic DTs are commonly used for network design, resilience planning, sustainability initiatives, and long-term capacity management [37, 133]. Tactical implementations increasingly support inventory policies, sourcing decisions, and disruption mitigation, while operational deployments focus on predictive maintenance, warehouse coordination, and production synchronization [26, 28, 30]. Healthcare exhibits a similarly strategy-oriented distribution, although less pronounced than SCM. Strategic decision-making represents the largest category (51%), encompassing population-health planning, policy support, governance frameworks, methodological standardization, and healthcare-system transformation [165, 249]. Operational clinical applications account for 37% and support patient monitoring, treatment simulation, and personalized interventions [96, 118], while tactical applications represent 12% and primarily address hospital resource management and workflow optimization.

The distributions reveal convergence as well as divergence between the two decision environments. Strategic applications constitute the largest category in both SCM and healthcare, indicating that DT research increasingly extends beyond immediate operational support toward broader planning and system-level decision-making. However, healthcare exhibits a substantially larger operational share, reflecting the continuing importance of patient-specific monitoring, simulation, and treatment support, whereas SCM shows stronger concentration at the strategic and tactical levels, consistent with its emphasis on network design, resilience planning, resource coordination, and long-term optimization. The comparative finding is therefore not an operational-versus-strategic divide, but a difference in the relative distribution of DT-supported decisions and the forms of decision support emphasized within each environment.

7.4 Adoption Maturity and Translational Gaps

The comparative analysis indicates that DT adoption is substantially more mature in SCM than in healthcare. SCM benefits from structured operational data, established enterprise systems (e.g., ERP,

MES, and WMS), and clear economic incentives that support large-scale deployment and measurable returns on investment [110, 236]. Consequently, DTs increasingly serve as embedded organizational infrastructures that support planning, execution, and performance optimization across supply networks.

Healthcare-DTs remain at an earlier stage of maturity. Although many studies demonstrate promising capabilities in patient monitoring, treatment simulation, and personalized medicine, most applications remain confined to pilot projects, simulation environments, or proof-of-concept implementations [190, 253]. The transition from technical feasibility to routine clinical adoption is constrained by validation requirements, fragmented data ecosystems, regulatory obligations, and the need for clinician trust. Moreover, relatively few studies explicitly quantify economic outcomes or system-wide efficiency gains, highlighting a persistent translational gap between DT potential and healthcare practice. These findings suggest that SCM currently leads in deployment maturity and organizational integration, whereas healthcare remains focused on demonstrating clinical value and establishing the governance foundations required for broader adoption.

The comparative evidence suggests that these maturity differences arise not simply from different rates of technological adoption, but from the conditions required to translate DT capabilities into scalable practice. In SCM, deployment can often progress incrementally from asset- and process-level applications toward enterprise and network integration, with interoperability and cross-organizational coordination representing the principal scaling challenges [7, 194]. In healthcare, technological integration is more tightly coupled with clinical validation, data protection, ethical oversight, professional accountability, and institutional approval, increasing the requirements that must be satisfied before experimental DT capabilities can be translated into routine practice [165, 197]. The resulting maturity gap should therefore not be interpreted solely as slower technological development in healthcare; it also reflects a more demanding translational environment in which technical readiness must advance alongside clinical, organizational, and governance readiness.

7.5 Data Characteristics and Decision Reliability

Differences in data characteristics further explain the divergent decision-making roles of DTs. SCM data is typically continuous, structured, and process-oriented, capturing machine states, inventory levels, transportation flows, and environmental conditions [16]. These properties support forecasting accuracy, scenario experimentation, and automated optimization. Healthcare data is inherently heterogeneous, sparse, and privacy-sensitive, combining medical imaging, EHRs, genomics, wearable data, and clinician notes. This complexity increases modeling uncertainty and raises the stakes of erroneous decisions, necessitating higher levels of validation, explainability, and human oversight [148, 197]. Consequently, healthcare-DTs demand greater semantic fidelity and trustworthiness before their outputs can influence clinical decisions. The comparative evidence therefore suggests that data characteristics shape not only analytical capability but also decision reliability: comparatively structured SCM data primarily enable DTs to reduce operational uncertainty, whereas heterogeneous and privacy-sensitive healthcare data couple decision support more closely with validation, explainability, and human oversight [16, 148, 197].

7.6 Regulatory and Governance Constraints

Regulatory environments strongly condition DT-enabled decision-making. SCM operates under general data protection, trade compliance, and industry standards, allowing relatively flexible experimentation and cross-firm data integration [37]. Healthcare-DTs, however, must comply with stringent regulatory frameworks governing patient safety, informed consent, and data protection

(e.g., GDPR, HIPAA), which significantly slow innovation but reinforce accountability [165, 197]. This regulatory asymmetry explains why SCM-DTs have progressed toward interorganizational and network-level decision ecosystems, while healthcare-DTs remain largely confined within institutional boundaries.

The comparative evidence therefore suggests that governance requirements do not merely constrain DT adoption; they shape the boundaries within which DT-enabled decisions can be integrated, delegated, and scaled. In SCM, comparatively flexible governance conditions facilitate experimentation and cross-organizational integration, although governance complexity increases as DTs expand toward network-level ecosystems [37]. In healthcare, governance is more tightly coupled with decision criticality because the use of patient data and DT-generated recommendations carries direct implications for safety, privacy, consent, and professional accountability [165, 197]. This coupling helps explain why comparable technological capabilities can produce different scaling trajectories across the two decision environments.

7.7 Stakeholder Configuration and Decision Authority

Stakeholder involvement expands differently across the two domains. In SCM, DT adoption follows a concentric expansion pattern: asset-level twins led by engineers, firm-level twins governed by cross-functional managers, and network-level twins dependent on interorganizational coalitions and platform intermediaries [31, 35]. Decision authority progressively shifts from local operators to distributed governance mechanisms. Healthcare exhibits earlier constraints on stakeholder expansion due to privacy, liability, and ethical considerations. Clinical decision authority remains tightly coupled to licensed professionals, limiting automation and cross-institutional decision delegation [118].

The comparative evidence therefore indicates that stakeholder expansion affects decision authority differently across the two environments. In SCM, scaling DTs from assets to networks progressively distributes decision authority across firms, functional units, and platform actors, making coordination and shared governance increasingly important [31, 35]. In healthcare, stakeholder expansion does not produce an equivalent transfer of decision authority because clinical responsibility remains anchored to licensed professionals even as patients, technology providers, regulators, and institutions become more involved [118]. Thus, increasing stakeholder complexity leads primarily to distributed coordination in SCM but to intensified accountability and oversight in healthcare. This distinction helps explain why greater DT integration can support broader decision delegation in SCM while requiring stronger human and institutional safeguards in healthcare.

7.8 Value–Complexity Trade-Off Across Domains

Synthesizing the preceding comparative findings reveals a value–complexity relationship, summarized conceptually in Table 10. In SCM, increasing DT integration and scale generate additional technological and interorganizational complexity, but the associated value is comparatively visible through measurable improvements in efficiency, resilience, resource utilization, and sustainability. Healthcare-DTs also generate substantial value, particularly through patient safety, personalization, clinical effectiveness, and population-health support [177]; however, realizing this value requires the simultaneous management of heterogeneous data, clinical validation, privacy, ethical oversight, and professional accountability. The comparison therefore suggests that value realization and implementation complexity are more tightly coupled in healthcare, whereas SCM provides comparatively clearer pathways for translating increasing integration into measurable organizational and network-level outcomes.

Table 10

Value–complexity trade-off matrix for DT applications in healthcare and SCM

Dimension	Healthcare-DTs	SCM-DTs
Primary value objective	Patient safety; personalized treatment; clinical decision accuracy	Efficiency optimization; cost reduction; resilience; sustainability
Value realization horizon	Long-term; outcome-driven (clinical effectiveness, quality of care)	Short- to medium-term, performance-driven (ROI, throughput, service levels)
System complexity	Heterogeneous data; semantic richness; ethical constraints increase integration and implementation complexity	Multi-process integration and large-scale coordination increase system complexity
Data characteristics	Heterogeneous; privacy-sensitive data requiring strong semantic consistency and low error tolerance	Predominantly structured, sensor-driven; continuous data supporting iterative refinement
Regulatory burden	Extensive requirements for patient safety; data protection; clinical validation	Requirements primarily related to data protection; trade compliance, and operational standards
Scalability complexity	Increases sharply with scale due to governance and privacy constraints	Increases gradually; enabled by standardized enterprise systems
Automation tolerance	Human oversight retained due to clinical accountability and decision risk	Greater scope for automated decision support as integration and system maturity increase
Stakeholder alignment difficulty	Involves clinicians; patients; regulators; and institutions with diverse accountability requirements	Distributed across firms; suppliers; logistics partners
Position in value–complexity space	Substantial societal and clinical value accompanied by extensive implementation demands	Measurable organizational and network value accompanied primarily by integration and coordination demands
Dominant risk types	Ethical; safety; accountability risk	Operational; coordination; cybersecurity risk

The value–complexity analysis further indicates two contrasting DT evolution pathways emerging from the comparative synthesis. SCM follows an orchestration pathway, in which increasing integration extends DT-supported coordination from individual assets and processes toward organizational and network-level decisions. Value is progressively realized through synchronization, efficiency, resilience, sustainability, and system-level optimization [106, 194]. Healthcare follows a personalization pathway, in which increasing integration enables progressively richer patient-specific modeling, clinical decision support, precision medicine, and population-health applications [177, 190]. However, expansion along this pathway simultaneously increases requirements for data governance, clinical validation, ethical oversight, and professional accountability [165, 197]. These pathways represent a comparative conceptual finding rather than empirically validated developmental trajectories: they synthesize how differences in decision focus, governance coupling, decision authority, and value realization are associated with distinct patterns of DT development across the reviewed literature. Accordingly, the value–complexity perspective should be understood as a conceptual explanation of these patterns that requires future empirical validation.

7.9 Cross-Domain Learning and Transferable Insights

The comparative analysis identifies reciprocal learning opportunities between the two decision environments. Healthcare can draw from SCM’s experience with enterprise integration, modular architectures, scenario-based planning, and progressively scaled coordination to improve DT interoperability and translation from isolated applications toward organizational and system-level decision support [106, 194]. However, these practices require adaptation to healthcare-specific requirements for clinical validation, privacy, professional accountability, and patient safety [165, 197]. Conversely, SCM can draw from healthcare’s stronger emphasis on human oversight, validation,

transparency, and accountability as DT-enabled decisions become increasingly AI-supported and extend across organizational networks [118, 197]. The comparison further indicates that technological capability alone does not determine DT maturity: both environments continue to face challenges in translating increasingly sophisticated DT architectures into integrated decision systems spanning multiple decision levels. Cross-domain learning should therefore focus not on replicating applications, but on adapting complementary decision practices, with SCM providing insights into scalable orchestration and healthcare into responsible decision augmentation. Combining these strengths offers a pathway toward DT ecosystems that balance integration and scalability with governance appropriate to the criticality and consequences of the decisions being supported.

8. Discussion

This study provides a comparative synthesis of DT applications across two contrasting socio-technical decision environments: the coordination-intensive SCM environment and the personalization-intensive healthcare environment. The findings reveal how differences in decision logic, governance structures, stakeholder complexity, and organizational objectives shape DT adoption pathways, decision-making roles, value realization, and persistent challenges. This section interprets the implications of the findings for theory, practice, and future research on DT-enabled decision systems.

8.1 Theoretical Implications

This study advances DT literature by reframing DTs not merely as technical artifacts, but as decision-enabling socio-technical systems that mediate between physical operations and digital intelligence. By comparing two contrasting socio-technical decision environments represented by SCM and healthcare, the paper extends theoretical understanding in several important ways. First, the findings contribute to emerging theories of digital transformation and cyber-physical decision ecosystems by demonstrating that the value of DTs is contingent on how effectively they connect decision layers, operational, tactical, and strategic, rather than on technical sophistication alone. The comparative analysis shows that DT maturity is best understood as an organizational capability that evolves alongside governance structures, data practices, and stakeholder trust, rather than as a linear technology adoption process.

Second, the study enriches decision-making theory in digital contexts by illustrating how domain constraints shape the delegation of authority between humans and models. SCM environments increasingly tolerate prescriptive and semi-autonomous decision logic, while healthcare-DTs remain embedded within human-in-the-loop frameworks due to ethical, clinical, and regulatory imperatives [193]. This contrast suggests the need for domain-sensitive theories of algorithmic decision authority that account for risk asymmetry, accountability, and societal impact. Third, the findings open new theoretical pathways in data governance and interoperability research [37] [265]. The analysis demonstrates that interoperability challenges are not purely technical but deeply institutional, shaped by incentives, power relations, and regulatory regimes. By highlighting how similar technologies yield divergent outcomes across domains, the study supports a socio-technical view of DTs in which data, models, and organizational norms co-evolve.

Fourth, the findings suggest that DTs should be understood as domain-specific decision architectures rather than generic cyber-physical systems. Although healthcare and SCM share similar technological foundations, they organize DT capabilities around different decision objectives, governance requirements, and stakeholder structures. Consequently, DT success depends not only on technological sophistication but also on the alignment between decision context, organizational complexity, and value realization. This perspective extends existing DT research by positioning DTs

as socio-technical mechanisms for managing uncertainty and coordinating decisions across multiple organizational levels. Finally, by explicitly comparing two contrasting decision environments at different maturity levels, the paper contributes to theory development on cross-domain knowledge transfer, showing how lessons from one context (e.g., SCM's integration maturity or healthcare's ethical governance) can inform DT design and evaluation in others. These theoretical contributions should be interpreted as conceptual propositions derived from the comparative synthesis of secondary literature rather than as empirically validated relationships, providing a basis for subsequent testing across organizational and sectoral settings.

8.2 Practical Implications

The findings provide several practical implications for managers, technology developers, and policymakers involved in DT initiatives. First, organizations should recognize that DT implementation is not solely a technological undertaking but a socio-technical transformation requiring alignment among data infrastructures, decision processes, governance mechanisms, and stakeholder capabilities. Across both SCM and healthcare, successful DT adoption depends on integrating technological readiness with organizational learning, trust, and decision-making practices.

For SCM managers, the review demonstrates that the greatest value from DTs emerges when implementations move beyond isolated asset monitoring toward integrated planning and coordination platforms. Organizations should therefore prioritize interoperability between DTs and enterprise systems such as ERP, MES, WMS, and forecasting platforms. Such integration enables DTs to support not only operational optimization but also tactical planning, resilience management, and long-term network design. Managers should also invest in data governance and cross-organizational collaboration mechanisms, as future DT value increasingly depends on information sharing across supply network partners rather than on optimization within individual facilities.

For healthcare practitioners and administrators, this review highlights the importance of balancing innovation with clinical safety and regulatory compliance. While DTs offer significant opportunities for personalized medicine, patient monitoring, and hospital resource optimization, their adoption requires rigorous validation, explainable analytics, and strong clinician engagement. Healthcare organizations should prioritize trust-building mechanisms, transparent model validation procedures, and interoperability standards that facilitate secure integration across clinical systems while preserving patient privacy and autonomy.

For technology developers, the paper emphasizes the need to design DT platforms that are scalable, interoperable, and explainable. Future DT systems should support integration across heterogeneous data sources while providing decision transparency suitable for both operational and high-stakes decision environments. Particular attention should be given to cybersecurity, privacy-preserving analytics, and human-centered interfaces that facilitate effective interaction between users and DT-generated recommendations [30, 117].

From an implementation perspective, organizations should approach DT adoption as a phased organizational transformation rather than a standalone technology project. First, managers should establish robust data governance mechanisms that define data ownership, quality standards, cybersecurity responsibilities, and accountability for AI-assisted decisions, as governance deficiencies remain a major barrier to scalable DT deployment [14, 37]. Second, investment in interoperability should precede large-scale DT implementation by ensuring that enterprise systems, IoT infrastructures, and analytical platforms exchange standardized, high-quality data across organizational boundaries [7, 262]. Third, organizations should strengthen organizational readiness through multidisciplinary implementation teams, employee capability development, and executive sponsorship to improve trust in DT-supported decisions and facilitate organizational change [26,

227]. Finally, governance frameworks should evolve alongside technical capabilities to ensure that increasing levels of automation remain transparent, explainable, and aligned with organizational objectives, ethical principles, and regulatory requirements [9, 69].

8.3 Future Directions

Despite rapid progress in DT research, several important opportunities remain for future investigation. First, more empirical studies are needed to evaluate DT performance in real-world operational environments. Much of the existing literature remains conceptual, simulation-based, or limited to pilot implementations, particularly in healthcare. Longitudinal case studies and large-scale deployments would provide stronger evidence regarding organizational impact, decision quality, and value realization.

Second, future research should examine how DTs operate across interconnected decision levels. Existing studies typically focus on operational, tactical, or strategic applications in isolation, yet relatively little is known about how information generated at one level influences decisions at other levels. Investigating these interactions would improve understanding of DTs as integrated decision-support architectures rather than isolated analytical tools.

Third, cross-organizational and ecosystem-level DTs represent a promising but underexplored research frontier. While SCM is beginning to develop network-level twins connecting suppliers, manufacturers, logistics providers, and customers, similar developments remain rare in healthcare due to governance and privacy constraints. Future studies should explore mechanisms for secure data sharing, collaborative governance, and distributed decision-making across organizational boundaries.

Fourth, greater attention should be devoted to governance, accountability, and ethical considerations. As DTs increasingly incorporate AI-driven analytics and autonomous decision capabilities, questions surrounding transparency, explainability, responsibility, and decision ownership become increasingly important. Future research should develop frameworks that clarify accountability structures and support trustworthy human–AI collaboration within DT environments.

Fifth, further work is needed to refine and empirically validate the value–complexity perspective proposed in this study. Comparative investigations across additional sectors, including manufacturing, energy, construction, transportation, and smart cities, would help determine whether the patterns observed between SCM and healthcare generalize to other complex socio-technical systems. Such research could contribute to the development of a broader theory explaining how DT value evolves as organizational, technological, and governance complexity increase.

Finally, future studies should explore the convergence of DTs, AI governance, sustainability objectives, and human oversight mechanisms. As DTs evolve toward increasingly autonomous decision-support ecosystems, understanding how efficiency, resilience, ethical responsibility, and societal impact can be balanced will become one of the central challenges for both researchers and practitioners.

8.4 Limitations

Despite its comprehensive synthesis, this study has several limitations. First, as a systematic literature review, it relies on published academic sources, potentially excluding relevant industry reports, proprietary implementations, or unpublished case studies. This may introduce publication bias toward well-documented or successful deployments. Second, the literature search was intentionally restricted to studies published between 2021 and 2025 to capture the most recent developments in DT-enabled decision-making and reflect the rapid evolution of AI, IoT, and data-driven technologies. While this improves the contemporary relevance of the findings, it also excludes

earlier foundational studies that contributed to the conceptual and technological development of DTs. Consequently, the findings should be interpreted as representative of the contemporary decision-centric DT literature rather than of the field's complete historical evolution, and their generalizability to earlier phases of DT development is therefore limited.

Third, variation in terminology, methodological rigor, and reporting practices across technical and managerial studies complicated classification and comparison, particularly when identifying decision-making levels. Fourth, the analysis focuses on two contrasting decision environments, SCM and healthcare, selected for their differing maturity and decision contexts. While this enhances analytical depth, it limits generalizability to other industries. Fifth, the findings are time-sensitive given the rapid evolution of DT technologies, AI integration, and regulatory frameworks. Finally, the study is based on secondary data and does not include empirical validation through case studies or interviews. Future mixed-method research could strengthen and operationalize the conceptual insights proposed here.

9. Conclusion

DTs are rapidly evolving from digital representations of physical assets into intelligent socio-technical systems that support data-driven decision-making. However, existing research has largely examined DT applications within individual domains, providing a limited understanding of how they create value across different decision environments. To address this gap, this study conducted an SLR of 193 publications (98 healthcare and 95 SCM studies) and developed a decision-centric comparative framework for analyzing DT applications, technological integration, decision-making levels, business value, stakeholder involvement, and implementation challenges.

The findings indicate that although SCM and healthcare share a common technological foundation based on IoT, AI, simulation, and cloud technologies, they embody fundamentally different decision logics. SCM represents a coordination-intensive decision environment in which DTs primarily support optimization, resilience, sustainability, and organizational scalability. Healthcare, by contrast, represents a personalization-intensive decision environment where DTs emphasize patient-specific decision support, clinical safety, and ethical accountability under stronger regulatory constraints. Consequently, differences in governance, stakeholder complexity, and data characteristics shape distinct adoption trajectories and value realization mechanisms.

The principal contribution of this study is the development of a decision-centric comparative framework and a value–complexity perspective that explains how DT-generated value may evolve alongside technological, organizational, and governance complexity. The analysis suggests two conceptual DT evolution pathways: an orchestration pathway in SCM that enables increasingly integrated organizational coordination, and a personalization pathway in healthcare that enables richer patient-centered decision support while simultaneously increasing governance demands. Future research should validate these findings through empirical implementations, investigate DT integration across operational, tactical, and strategic decision levels, and examine governance, explainability, accountability, and human oversight as DT ecosystems become increasingly AI-enabled.

Appendix A

Table A1
Selected studies focused on healthcare and DTs integration

#	Study	Focus/ domain	Key findings
1	[207]	Healthcare-DT with blockchain	Proposed structured, patient-centered data model for HDT
2	[250]	DT-XR in immersive healthcare	Enables 3D patient models for telemedicine and training
3	[85]	Emergency care with DT & biometrics	Reduced ER stay; 80% success in treating anonymous patients
4	[160]	Medical DTs with 6G/IoT for disability care	Uses MQTT-CSI for real-time, unobtrusive health monitoring
5	[161]	DT applications & barriers in healthcare	Identify opportunities in precision medicine, trials, operations
6	[86]	Blockchain + DT in smart hospitals	Enhances security, interoperability, and predictive patient care
7	[138]	Cardiovascular DT applications	Enables multiscale modeling from cells to healthcare systems
8	[249]	Rare diseases, DT, EU policy	Empowers patients via decentralized identity & GDPR alignment
9	[87]	DT for anxiety detection in smart offices	Quantum-CNN model achieves >96% precision in anomaly detection
10	[244]	DT in patient journey transformation	Enables personalized, predictive care; raises data ownership issues
11	[177]	DT for precision medicine & public health	Transforms EHRs into dynamic tools for personalized care
12	[239]	DT for human activity recognition	Improves accuracy via edge-based ANN and multi-sensor fusion
13	[178]	DT ethics, validation, and regulation	Highlights need for standards and multidisciplinary collaboration
14	[162]	Digital Human Twins (DHTs)	Enables precision therapy, surgery, and medical education
15	[218]	AI-augmented DTs in rehab	Supports safety, predictive modeling for movement rehabilitation
16	[139]	DT for glioma radiotherapy	Personalized regimens boost tumor control or reduce dose
17	[88]	DT in hospital ops & equipment	Forecasts failures, optimizes resources, improves patient outcomes
18	[10]	DT in precision medicine & public health	Integrates multi-omics data for tailored treatments
19	[189]	DT in cardiovascular disease	Industry and academia advancing CVD simulation models
20	[114]	DT-Metaverse for VRMT	Enhance training, rehab, telemedicine; needs cybersecurity
21	[9]	Cross-sector DT adoption (industry vs healthcare)	Healthcare DTs lag but benefit from industrial spillovers
22	[208]	DT-IoRT in smart surgery	Enables bidirectional data flow for robotic-assisted surgery
23	[163]	Mechanistic DTs in precision medicine	Supports dynamic decisions via biological simulations
24	[210]	DT for immunization services	Improves vaccine temp control, coverage tracking, planning
25	[211]	DT for immunization services and vaccine monitoring	Reduces wastage; tracks coverage and cold-chain temps via UML/SimPy

Table A1
Continued

#	Study	Focus/ domain	Key findings
26	[164]	DT in radiology	Boosts diagnostic accuracy, therapy planning across modalities
27	[248]	DT for telerehabilitation	Enables immersive, remote exoskeleton control in VR
28	[203]	Data-driven digital therapeutics	Reduced depression/anxiety symptoms with wearable-AI intervention
29	[251]	DT in Metaverse & smart hospitals	Combines DT, AI, blockchain for immersive virtual care
30	[165]	DT in Italian precision medicine	Enables predictive, participatory care; needs governance
31	[166]	DT in oncology	Enhances decision-making; reduces costs; faces modeling challenges
32	[115]	DT Brain (DTB)	Simulates brain function for personalized neurotherapies
33	[116]	DT for smart hospital operations	Enables real-time control of clinical and non-clinical workflows
34	[179]	DT in healthcare transformation	Improves outcomes; challenges include data quality & ethics
35	[243]	DT + blockchain + federated learning	Ensures secure, privacy-preserving healthcare data processing
36	[253]	DT for amiodarone response in AF	Predicted drug efficacy; lowered AF recurrence by 54%
37	[180]	Real-time DT monitoring	Cut latency by 32%; 98% real-time prediction accuracy
38	[214]	AI-DT for prostate cancer	Enhance diagnosis/treatment; needs real-time data integration
39	[225]	DT security & trust in healthcare	Highlights privacy, safety, and operational conflicts
40	[140]	DT in IoMT & smart healthcare	Enables personalized care; addresses IoMT security gaps
41	[89]	DT architecture & use cases	Supports individualized therapy; limited by security & cost
42	[141]	DT for Health (DT4H)	Early stage; needs global R&D collaboration
43	[190]	DT-AI for endometrial cancer	Improves decision support; integrates heterogeneous data
44	[181]	Respiration DT using Wi-Fi CSI	Unobtrusive BPM estimation; 96.9% accuracy with fine tree classifier
45	[182]	DT for diabetes ops via SDM	SDM effective for simulating policy in vague environments
46	[242]	Human DT design methodology	Proposes ETHICA: ethical, user-centric, iterative HDT development framework
47	[117]	DT in clinical & hospital use	Cardiac DT exemplifies precision medicine potential
48	[142]	DT for treatment personalization	Addresses ineffective meds; needs multi-scale integration
49	[183]	Healthcare facilities management	Enables real-time HVAC, air quality, and MRI monitoring
50	[90]	Anxiety detection in academic settings	Detects behavioral irregularities; alerts caregivers via smart warnings
51	[247]	Blockchain + DT in smart hospitals	Enhances security, interoperability, and personalized patient care
52	[222]	Data integration for patient DTs	Multi-source data critical; standardization remains a hurdle
53	[14]	DTs in smart healthy cities	Multilevel DT improves urban health monitoring and equity

Table A1
Continued

#	Study	Focus/ domain	Key findings
54	[254]	Elderly DT with Gen AI	Delivers personalized feedback via GPT-4o and predictive LSTM models
55	[223]	Maternal cardiovascular DT	Dynamic DT supports preconception and pregnancy care
56	[118]	AI + 6G for injury response	Enables early injury classification via self-learning DT
57	[195]	AI-driven DTs in precision medicine	Improves diagnostics; lacks standardization and interoperability
58	[91]	Smart environments for health	Discusses smart home synergies
59	[92]	Oxygen tank monitoring via DT	Real-time sensor data prevents supply shortages
60	[191]	DTs for disease simulation & education	Enables risk-free trials, education, and digital biomarker use
61	[241]	Biological age in DTs	BA clocks stabilize health trajectories in DTs
62	[143]	DT-based Smart Medical Cyber-Physical System	Enhances hospital control, personalization, and long-term health management
63	[144]	AI-enabled DTs for clinical decision-making	Develops DECIDE-Twin framework to guide DT implementation in clinics
64	[93]	DT ethics and security	Stresses informed consent, bias reduction, and legal compliance
65	[16]	Ecosystems of healthcare DTs	Proposes DT-as-a-service for multi-asset health processes
66	[215]	DT applications and barriers	Identifies personalized medicine, ops, research; notes ethical gaps
67	[219]	Digital Shadow for insurers	Forecasts catastrophic COVID-19 cases using ML analytics
68	[94]	DT reference architecture	Outlines cyber-physical DT framework for personalized care
69	[145]	DT for critical care training	High usability; residents accept DT for ICU education
70	[146]	Medical DT policy framework	Defines 5 core DT components; merges AI + mechanistic models
71	[245]	Personal DT	Framework enables tailored care for cancer, diabetes, nutrition
72	[13]	DT in personalized medicine	Simulates disease; limited by privacy and interoperability
73	[184]	DT implementation challenges	Proposes lifecycle framework; stresses infrastructure and ethics
74	[147]	DT validation in precision medicine	VVUQ is essential for safety in cardiology and oncology
75	[95]	DT for chronic disease & surgery	Enable predictive diagnostics, rehab planning, remote monitoring
76	[96]	DT for type 2 diabetes	Reduced HbA1c by 1.8%; cut meds by 1.5 on average
77	[97]	DT in healthcare supply chains	Identifies TOE-based barriers to DT adoption
78	[98]	Hybrid DT with AI + physiology	Outperforms AI-only models in clinical prediction tasks
79	[119]	DT in oncology	Multimodal data improves treatment personalization in cancer
80	[226]	DT for hospital bed allocation	Solves short- and long-term ward planning via SMT
81	[255]	DT for urban health planning	Optimize resource use in cities via real-time feedback

Table A1
Continued

#	Study	Focus/ domain	Key findings
82	[252]	AI, blockchain, 5G in healthcare	Overview only; no DT-specific findings
83	[120]	DT in future medicine	DT enables precision diagnosis; validation and data gaps remain
84	[121]	DT for personalized treatment	Big Data + AI + IoT is vital for high-resolution DTs
85	[122]	DT for human-robot collaboration in care	Enables task rehearsal, low-latency sync, and traceable decision-making
86	[99]	DT innovation challenges	Needs cross-disciplinary collaboration and better data modeling
87	[167]	DT in neurology	Early-stage potential for brain disease management
88	[204]	DT in chronic & cancer care	Enables virtual surgery rehearsal and tailored therapies
89	[100]	DT in facilities management	Improves equipment uptime, layout planning, and patient experience
90	[196]	DT for clinical operations	Enhance prediction, personalization, training, and workflow efficiency
91	[198]	DT ethics in personalized medicine	Raise consent, bias, and discrimination concerns
92	[197]	DT in otorhinolaryngology (ORL)	DTs in ORL face several concerns including data privacy and security, data integration and interoperability, computational demands, model validation and accuracy, ethical and regulatory considerations, and cost and accessibility issues.
93	[123]	DT historical overview	Traces DT origins to aerospace; notes healthcare potential
94	[192]	Federated DT with model sharing	Preserves privacy via shared models, not raw data
95	[240]	DT research trends & gaps	Most studies conceptual; lacks implementation and validation
96	[148]	Hallmarks of healthcare DTs	Proposes 5 criteria; notes AI and metaverse opportunities
97	[246]	Digital health & value-based care	Supports outcomes-focused care
98	[124]	Medical imaging for DTs	High-res imaging vital; AI boosts DT clinical utility

Table A2
DT applications in healthcare

Application	Key enhancements by DT	Study	Number of studies
Digital patient models	Comprehensive virtual replicas integrating multi-omics, imaging, EHRs and real-time sensor data; dynamic bi-directional synchronization; personalized physiological simulations; "digitosome" integration for holistic health representation	[9, 10, 13, 64, 89, 93–95, 98, 99, 115, 117, 120, 121, 123, 140, 141, 146, 148, 161, 162, 165, 167, 177, 184, 190, 191, 195, 196, 198, 207, 215, 222, 225, 242, 244]	36
Workflow and resource optimization	Bed allocation algorithms using formal models/SMT solvers; vaccination coverage monitoring and temperature management; trauma coordination ecosystems; multimodal sensor integration for operational efficiency; urban healthcare resource planning, insurance sector catastrophic case forecasting	[14, 16, 91, 97, 210, 211, 219, 226, 240, 246, 255]	11

Table A2
Continued

Application	Key enhancements by DT	Study	Number of studies
Hospital operations	Real-time facility monitoring (HVAC, IAQ, oxygen tanks); predictive maintenance of medical equipment/MRI machines; emergency department workflow optimization with biometric authentication/face recognition; digital replication of entire hospital environments; infrastructure performance monitoring; smart hospital cyber-physical systems	[85, 86, 92, 100, 116, 143, 183, 247, 251]	9
Patient monitoring	Real-time physiological monitoring (vitals, respiration, SpO ₂); unobtrusive sensing via Wi-Fi CSI/wearables; continuous health tracking with AI-driven alerts; remote monitoring for elderly/vulnerable populations	[87, 90, 118, 160, 180, 181, 254]	7
Early disease detection and diagnostics	AI-enhanced predictive analytics from multimodal data; risk stratification before symptom onset; radiology applications across modalities; biomarker discovery; in silico hypothesis testing	[124, 144, 164, 178, 214, 241, 243]	7
Drug development and testing	In silico clinical trials with virtual patient cohorts; therapy simulation before administration, drug efficacy prediction (e.g., amiodarone in AF); toxicity optimization; target identification through mechanistic modeling	[119, 139, 142, 147, 163, 166, 252]	7
Chronic disease management	Personalized intervention protocols for diabetes, cancer survivorship, mental health; continuous adaptation of treatment plans, lifestyle integration (nutrition, activity, sleep); long-term trajectory forecasting	[96, 182, 192, 203, 204, 249]	6
Cardiovascular medicine	Virtual heart/atrium modeling for arrhythmia prediction; personalized treatment simulation (e.g., radiotherapy optimization); hemodynamic assessment; precision cardiology applications	[138, 189, 223, 253]	4
Rehabilitation programs	Telerehabilitation with exoskeleton control via VR; activity recognition for therapy adherence; personalized recovery trajectories; remote kinesiotherapy with safety prediction systems	[122, 218, 239, 248]	4
Medical training and education	Risk-free simulation environments for procedure practice; virtual anatomy/physiology models; critical care scenario training with EHR-based twins; immersive XR learning experiences	[114, 145, 250]	3
Surgical planning	Precision pre-operative simulation; 3D anatomical modeling for complex procedures; virtual rehearsal of interventions; custom implant design, augmented reality integration for intraoperative guidance	[197, 208]	2

Table A2
Continued

Application	Key enhancements by DT	Study	Number of studies
Medical device prototyping	Virtual testing of equipment performance; predictive maintenance frameworks; IoT sensor integration for device monitoring; simulation of device-patient interactions before physical deployment	[88, 179]	2
Governance & validation	Transparency, stakeholder engagement, and responsible implementation	[144, 242]	2
Population-level health intelligence	Smart healthy cities, precision medicine, and population-scale health planning	[14, 177]	2

Table A3
Key stakeholders in DT-enabled healthcare

Stakeholder	Role	Impact
Patients [85, 148, 160, 246]	Active participants in monitoring, data access, and shared decision-making	Empowerment, personalized care, improved outcomes, real-time and predictive health insights
Clinicians & healthcare providers [89, 142, 145, 240]	DTs for diagnosis, treatment, and patient management	Improved diagnostic accuracy and efficiency; challenges in data overload, digital literacy, and workflow integration
Healthcare administrators & managers [89, 142, 144]	DT implementation, change management, and staff training	Enhanced operational efficiency and resource allocation; resistance to change and high infrastructure investment
Technology providers & innovators [192, 246]	DT platforms, AI models, wearables, and infrastructure	Innovation and efficiency gains; challenges in interoperability, standardization, and competition
Insurers & payers [147, 219, 256]	Risk assessment, reimbursement, and population analytics	Improved actuarial accuracy and personalized insurance models; disruption of traditional reimbursement structures
Regulators & governing institutions [142, 249, 256, 259]	Governance, compliance, and ethical oversight	Protection of privacy and security; balancing innovation with regulatory control

Table A4
Key challenges in DT-enabled healthcare

Challenge	Impact	Proposed Solutions	Stakeholder impacted
Clinical / Asset-Level			
Data quality and fragmentation [141, 146, 177, 210, 258]	Reduced model accuracy and predictive reliability; limited cross-system integration	Standardized data collection; sensor calibration; longitudinal data integration	Clinicians, patients, engineers
Model interpretability and validation [166, 196, 259]	Limited clinical trust and adoption	Explainable AI; uncertainty visualization; clinician co-design	Clinicians, regulators
Cybersecurity and patient safety [86, 123, 141, 178, 192, 207, 243, 244, 247]	Risk of data breaches and clinical harm	Secure architectures; real-time monitoring, encryption	Patients, IT teams
Enterprise Level			
System interoperability [117, 141, 243]	Fragmented DT implementations	Open standards; middleware integration	Hospital management, IT teams

Table A4
Continued

Challenge	Impact	Proposed Solutions	Stakeholder impacted
Organizational readiness [99, 142, 241, 265]	Underutilization of DT insights	Training; decision-support alignment	Clinicians, managers
ROI uncertainty [123, 141, 244]	Slowed investment and scaling	Multi-criteria evaluation frameworks	Executives, policymakers
Network Level			
Privacy and regulatory compliance [165, 166, 184]	Constrained data sharing	Federated learning; privacy-preserving analytics	Regulators, patients
Ethics and data ownership [117, 141, 146, 148, 196, 241]	Limited ecosystem collaboration	Shared governance models; consent frameworks	Health systems, insurers
Trust, bias and equity risks [141, 165, 166, 177, 184]	Low adoption and underutilization; reinforcement of disparities	Training, explainable AI; workflow integration, bias audits; inclusive datasets	Clinicians, healthcare managers, public health bodies

Appendix B

Table B1
Selected studies focused on the integration of SCM and DTs

#	Study	Focus/ domain	Key findings
1	[234]	Predictive maintenance in wind farms	Fog-based DT reduces latency and computational cost
2	[230]	DTs in Industry 4.0 production	Proposes RL-enhanced framework for lean, agile production
3	[69]	DT challenges in supply chain integration	Prioritize implementation barriers using BWM and DEMATEL
4	[185]	DT in supply chain efficiency	Boosts productivity 25%, cuts cost up to 30%
5	[235]	Blockchain + DT in logistics	Enhances traceability, transparency, and predictive maintenance
6	[168]	DT for inventory & cash flow	Reduces cash conversion cycle during supply disruptions
7	[32]	DT in manufacturing retrofitting	Improves makespan via virtual commissioning methodology
8	[125]	DT in SCM	Enhances visibility, collaboration, risk mitigation, and efficiency
9	[30]	DTs for production & storage simulation	Generates realistic material flow data for greenfield supply chain modeling
10	[126]	DT for relay predictive maintenance	ML-enhanced DT predicts failures with high accuracy
11	[101]	Quantifying DSCT benefits	Presents method to measure DSCT impact on performance
12	[102]	Digitization in energy sector	Boosts efficiency, reduces costs >25%, extends plant life
13	[103]	Food SC resilience during pandemic	DSCT improves demand/inventory/transport resilience
14	[104]	Holistic digital supply chain twin	Proposes architecture for end-to-end multimodal SC simulation
15	[205]	DT + blockchain in metaverse CSC	Secures data, automates warranties/payments via smart contracts
16	[149]	Smart warehousing with DT & IoT	Automates inventory, improves accuracy via real-time sensing

Table B1
Continued

#	Study	Focus/ domain	Key findings
17	[150]	DT in remanufacturing supply chains	Solves information asymmetry; enables dynamic data integration
18	[105]	DT in automotive SCM	Enhances visibility, real-time decisions, and resource use
19	[220]	DT in postharvest food supply	Predicts shelf life, reduces spoilage for fresh produce
20	[238]	DT for smallholder resilience	Simulates risks/policies across farm, SC, and environment
21	[35]	Urban farming decision support with DT	DT-ML optimizes aquaponics production and scales urban agriculture coordination
22	[31]	Waste sorting DT	Boosts recovery rates; enables real-time circular waste logistics decisions
23	[127]	DT for fruit storage	82% accuracy in predicting spoilage and shelf life
24	[33]	Shop-floor logistics–manufacturing synchronization	IIoT-DT enables synchronized planning, info sharing, and operations
25	[128]	DT in lean supply chains	Enhances info flow, JIT, waste reduction; gaps in sourcing
26	[169]	DT in food SCM	Proposes 5-step conceptual framework for DT implementation
27	[36]	Metaverse in SCM via DIKW model	Proposes 4-layer pyramid for immersive, intelligent supply chain decision support
28	[106]	Intelligent DT for SC resilience	Enables stress-testing, proactive adaptation, and learning
29	[11]	Formal models of SC DTs	Introduces cyber-physical SC framework with AI collaboration
30	[107]	DT in buyer-supplier relations	Mitigates principal-agent tensions in complex production
31	[129]	DT + blockchain in logistics	Boosts transparency, collaboration, and fraud prevention
32	[170]	DTs for SCM	Proposes architecture; identifies “addressability” as key gap
33	[212]	Cognitive DT for sustainability	Integrates business, data, and AI governance views
34	[199]	Supply chain visibility	Presents ABCDE framework for holistic visibility analysis
35	[186]	Sustainable DT in SCM	Proposes framework integrating IoT, cloud, blockchain
36	[130]	DT across industries	Most research in manufacturing; SCM focuses on visibility/resilience
37	[26]	DT for supply disruption response	DT-ML dynamically selects optimal mitigation strategies based on real-time state
38	[232]	DT cities for energy efficiency	Improves policy targeting and natural resource management
39	[237]	DT in auto supply chains	Reduces inventory/logistics costs via real-time optimization
40	[200]	Digital port twin	Requires situational awareness, analytics, multi-stakeholder interface
41	[12]	Multi-echelon S&P DT	Improves demand fulfillment and reduces makespan
42	[151]	Blockchain + DT in SCM	Enhances security, traceability, and efficiency in Industry 4.0
43	[216]	DT for industrial symbiosis	Identifies user needs from Norwegian wood industry
44	[224]	Data-driven supplier selection	Optimizes procurement; boosts performance by 6.5% via negotiation
45	[152]	Resilient mask SC during pandemic	DT enables rapid activation of backup suppliers/distributors
46	[187]	DT for inventory policies	Improves cost efficiency and customer satisfaction via simulation

Table B1
Continued

#	Study	Focus/ domain	Key findings
47	[193]	Agri-food SC DTs	Early-stage potential; addresses bottlenecks and planning
48	[201]	DT + LCA in wood construction	Enhances material traceability, circularity, and real-time LCA
49	[188]	DT for SCM efficiency & resilience	Enhances dual goals; gaps in crisis logistics remain
50	[108]	User acceptance of DT levels in SCM	Acceptance driven by usefulness, trust—not tech radicalness
51	[171]	Human-centric DTs in construction supply chains	Enhances real-time collaboration, sustainability, and bottleneck detection; challenges include interoperability and cybersecurity
52	[176]	DT in smart manufacturing & Industry 4.0	Supports integrated, flexible, collaborative manufacturing environments
53	[109]	DT for eco-design & circularity in auto	Digital shadow aids sustainability, reparability, and material tracking
54	[110]	DT in circular supply chains	Enables circular economy; lacks standardized implementation frameworks
55	[227]	Open SCM with DT in fashion	DT cuts design cost to 2% of total supply chain
56	[131]	DT in food SCM	Ensures safety, reduces waste, improves traceability via IoT
57	[202]	DT platform collaboration in manufacturing	Identifies 5 challenges, 4 strategies for successful co-creation
58	[29]	DT for manual assembly of custom products	Enables error reduction and monitoring in customized valve assembly lines
59	[236]	DT + agile SCM for sustainability	Reduces emissions, boosts efficiency, and enhances responsiveness
60	[213]	Blockchain-integrated DT in SCM	Improves data integrity, traceability, and security in supply chains
61	[132]	DT for sustainable SCM	Enables real-time monitoring and responsible resource use
62	[172]	DT for SCM visibility via GA	Enhances data-driven decisions, visibility, and operational optimization
63	[233]	Simulation-based DT in smart manufacturing	Optimizes job-shop configurations; integrates MaaS and AI
64	[153]	DigiPyramid DT for logistics	Improves reliability, visibility, and decision-making across org levels
65	[229]	DT + blockchain in public construction	Cuts dispute 30%, speeds payments 25% via smart contracts
66	[221]	Physics-based DT for postharvest produce	Quantifies cold chain optimizations; extends shelf life up to 73%
67	[173]	DT for resilient & sustainable FSC	Enhanced coordination is key for dual resilience-sustainability goals
68	[174]	DT's impact on MSC sustainability	DT boosts sustainability via resilience and performance mediation
69	[133]	DT in humanitarian SCM	Improves agility/resilience; stakeholder collaboration is key mediator
70	[134]	AI + DT in SCM	Enables demand forecasting, risk mitigation, forward-looking decisions
71	[111]	DT for SC viability amid disruptions	Enhances visibility, adaptability, velocity; gap in real-world use
72	[217]	DT in Industry 5.0 logistics	Supports smart, human-centric, sustainable logistics network design

Table B1
Continued

#	Study	Focus/ domain	Key findings
73	[261]	Stakeholder collaboration in DT ecosystems	Standardization (e.g., OPC UA) critical for ecosystem coherence
74	[135]	DT in smart cities & applications	Offers efficiency gains; limited by privacy and interoperability
75	[136]	DT + IoT to reduce food waste	Reimagines postharvest supply chain to cut 30% global waste
76	[209]	Business impact of DT in SCM	Reduces costs and boosts product availability; long-term ROI high
77	[34]	Low-cost DT for conventional machines	Economic DT framework enables real-time monitoring of legacy equipment
78	[154]	DT-driven smart supply chain	Enables real-time optimization; JD.com case shows pandemic agility
79	[112]	DT for air mobility networks	Optimizes aircraft redistribution; reduces wait times and ground time
80	[155]	Real-time DT for perishable SCM	Cuts inventory/production variance; avoids shortages in cake SC
81	[231]	DT in demand response (energy)	Enables real-time forecasting; still largely exploratory
82	[28]	Data-driven production line DT	Predicts system-level flow anomalies using machine substate analysis
83	[137]	Optimized DT using GA, ABM, MDP, SA	Achieves 86.5% resilience, 18.7% cost reduction, 93.2% efficiency
84	[156]	AR-assisted DT in industry	Enhances HMI, design, service; human-centric transformation key
85	[206]	DT, blockchain, AI for macro disruption	Tech duality: boosts resilience but raises energy/cyber risks
86	[37]	Energy DT in process industries	Reduces carbon footprint; enables renewable integration and efficiency
87	[27]	Sustainable and resilient supply chains	Identifies 5 research clusters; calls for real-world DT integration
88	[7]	DT implementation challenges in SCM	Proposes 3-layer framework; needs real-time sync and autonomy
89	[113]	DT in logistics (auto supplier case)	Identifies 5 use cases; highlights network/site-level applications
90	[194]	DT maturity model for SCM	Evaluates readiness; guides robust, scalable DT implementation
91	[175]	Cloud, platforms, and DT in SCM	Defines Digital Supply Chain Twin; enhances resilience potential
92	[157]	Info sharing in smart SCM	Digital maturity threshold shifts system to cooperative equilibrium
93	[158]	DT + blockchain in Industry 5.0 SCM	Drives sustainability; needs ethical, scalable integration strategies
94	[159]	Predictive maintenance via DT	Outperforms traditional methods; applicable across industrial sectors
95	[228]	DT for demand risk in distribution	Supports proactive/reactive risk response; ensures business continuity

Table B2
DT applications in SCM

Application	Description/ use	Study	Number of studies
Supply chain visibility & traceability	DTs to provide real-time data; predictive analytics, secure transaction records; tracking the movement and status of products	[7, 69, 107, 125, 129, 135, 151, 157, 170, 172, 193, 194, 199, 202, 205, 209, 213, 229, 235, 261]	20
Resilience & disruption management	Marks shift from efficiency to robustness; DTs used to evaluate contingencies, hedge against volatility, and simulate disruption trajectories; links tightly to uncertainty-aware planning	[11, 26, 52, 103, 106, 111, 130, 134, 152, 154, 169, 173, 175, 188, 206, 228, 238]	17
Sustainability & efficiency	DTs increasingly support ESG goals; model waste streams, track recovered materials, and assess environmental performance; expands in DT use from efficiency to environmental stewardship and resource ethics	[27, 35, 37, 102, 128, 132, 136, 137, 158, 171, 174, 185, 186, 212, 232, 236]	16
Inventory management & production synchronization	DTs support alignment between material availability, work-in-progress, and production capacity; move systems from static rules to adaptive flow decisions; integration across factory and warehouse systems is accelerating	[12, 28, 30, 32, 33, 101, 105, 149, 155, 168, 187, 230]	12
Product lifecycle integration	Extends DTs beyond operations toward design-production-service continuity; moves insights upstream to engineering and downstream to after-sales; early but conceptually important for long-term digital continuity	[29, 31, 109, 110, 150, 156, 176, 201, 216, 227, 233]	11
Logistics & transportation systems	Used for routing, warehouse coordination, vehicle allocation, and reverse flows; enable real-time orchestration and congestion/bottleneck mitigation; increasingly support circular loops	[104, 112, 113, 153, 200, 217, 221, 237]	8
Demand forecasting & scenario-based planning	DTs emerging as upstream decision tools; integrate forecasting, what-if scenarios, and tactical plan evaluation; value amplified in uncertain or perishable-product contexts; bridging analytics and execution	[36, 108, 131, 220, 224, 231]	6
Predictive maintenance & asset reliability	Traditional entry point; DTs track degradation, predict failure, and minimize downtime; increasingly connected to scheduling and resource planning; still focused on equipment-level intelligence but foundational for broader DT integration	[34, 126, 127, 159, 234]	5

Table B3
Key stakeholders in DT-enabled SCM

Stakeholder	Roles	Impact
Firms / manufacturers [32, 105, 185]	Implement DTs to optimize production processes, improve quality, and enhance supply chain performance	Cost savings; reduced energy consumption; improved productivity and flexibility
Suppliers [125, 131, 201]	Provide materials and components; integrate DTs for material utilization and quality control	Enhanced visibility and traceability; improved resource efficiency; reduced waste
Logistics providers [26, 129, 131]	Apply DTs for real-time tracking, routing optimization, and delivery coordination	Improved logistics efficiency; reduced bottlenecks; enhanced disruption resilience

Table B3

Continued

Stakeholder	Roles	Impact
Retailers [136, 220, 221, 227]	Use DT-enabled collaboration for inventory management and demand forecasting	Reduced stockouts; improved inventory turnover; enhanced customer service
Regulators [201, 206]	Ensure legal, ethical, and compliance oversight of DT deployment	Improved transparency, regulatory compliance, and fraud reduction
Customers [125, 129, 187]	Influence supply chain practices through demand signals and feedback	Improved product quality, faster delivery, more personalized services
Technology providers [28, 34, 103]	Develop DT platforms; support integration, analytics, and data management	Innovation acceleration; interoperability enablement; scalability support
Policymakers [136, 187, 232]	Promote DT adoption and sustainable supply chain practices	Strategic direction setting; resilience enhancement; sustainability promotion

Table B4

Key challenges in DT-enabled SCM

Challenge	Impact	Proposed Solutions	Stakeholder impacted
Asset & Facility Level			
Data interoperability & quality [7, 28, 32, 36]	Inaccurate or delayed asset mirroring; limited real-time visibility	IoT standardization; data preprocessing pipelines; edge computing	Engineers, operators, IT teams
Cybersecurity exposure [151, 188, 213, 237]	Operational disruptions; data breaches	Zero-trust architecture; blockchain	IT teams, cybersecurity units
Legacy system integration [29, 34, 209, 262]	High retrofit costs, incomplete sensing	Modular sensors; phased modernization	Manufacturers, SMEs
Investment & maintenance cost [27, 69, 101, 110]	Slowed adoption; limited scalability	ROI frameworks; incremental deployment	Firm management
Enterprise Level			
System interoperability [30, 36, 176]	Fragmented planning and execution	Middleware; open APIs	Planners, IT architects
Skills & simulation literacy [26, 37]	Underutilization of DT insights	Training programs; decision dashboards	Managers, planners
Cultural resistance [135, 216, 227]	Low trust in model-based decisions	Change management; participatory design	Senior management
ROI ambiguity [29, 132, 194]	Budgeting delays; ownership conflicts	Cross-functional KPIs	Executives
Network Level			
Data sharing & trust [35, 37, 216]	Incomplete system-level visibility	Incentive alignment; data governance	Suppliers, LSPs
Lack of standards [31, 107, 170, 202]	Poor model synchronization	Shared ontologies; industry standards	Platform providers
Systemic cybersecurity risk [237, 263, 264]	Cascading failures	Distributed security protocols	All partners
Regulatory & liability issues [36, 37, 150, 212]	Slowed collaboration	Regulatory sandboxes	Regulators, firms

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Conflicts of Interest

The authors declare no conflicts of interest.

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