Strategic End of Life Management of Industrial Assets: A Literature Review and Conceptual Framework on the Role of Digital Twins

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Abstract: The end-of-life (EoL) management of industrial assets is a critical aspect of sustainable manufacturing and resource efficiency. As industries strive to minimize waste, reduce environmental impact, extend the useful life of assets, and support circular manufacturing objectives, there is an increasing demand for data-driven and forward-looking strategies to guide EoL decision-making. Traditionally, such decisions have relied on static assessments and reactive interventions, which often fail to account for real-time asset condition or long-term value. Digital Twin (DT) technology has emerged as a transformative enabler across asset lifecycles. While DTs are well-established in supporting middle-of-life (MoL) activities, such as condition monitoring and predictive maintenance, their strategic potential for informing EoL decisions remains underexplored. Current applications tend to focus on operational and tactical levels, lacking structured approaches to support higher-level strategic decisions such as EoL planning and asset lifecycle extension assessment. This paper addresses this gap through a structured literature review that maps existing DT-enabled indicators and technologies across operational, tactical, and strategic decision-making levels. A conceptual framework is then proposed to illustrate how DT-generated outputs, especially operational indicators like RUL, can evolve into actionable insights for EoL strategy formulation. The findings underscore the importance of reinterpreting current indicators and developing new value-centric metrics to support circular and sustainable asset lifecycle management. This study offers a foundation for repositioning DTs as not only diagnostic tools but also as strategic tools in EoL decision support.

Keywords: End-of-Life management, Digital Twin, Remaining useful life, Lifecycle extension, Manufacturing

1.Introduction

In contemporary industrial systems, the efficient management of industrial assets across their lifecycle has become essential for achieving sustainable manufacturing and resource efficiency (Zarte, Pechmann and Nunes, 2019). Within this context, end-of-life (EoL) asset management (AM) represents a critical, yet often underexploited, opportunity to reduce waste, extend asset usability, and align with circular manufacturing (CM) principles (Shafiee and Animah, 2017).
At the policy level, two key EU initiatives underscore the growing importance of EoL strategies. The European Green Deal (European Commission, 2019) promotes asset lifecycle extension and circularity, while the EU Circular Economy Action Plan (European Commission, 2020 - updated 2023) introduces sector-specific measures for reuse, recycling, and sustainable EoL treatment. These policies highlight the need for more strategic, data-informed approaches to asset retirement and repurposing.

Strategic EoL decisions - such as whether to refurbish, repurpose, or decommission an asset - have far-reaching implications for cost efficiency, availability, regulatory compliance, emissions, and material recovery (Shafiee and Animah, 2017). However, such decisions are inherently complex, requiring the integration of asset condition, performance trends, and stakeholder priorities - often in contexts where accurate, lifecycle-spanning information is lacking (Alquraidi and Awad, 2024; Meng *et al.*, 2020). Conventional AM approaches, often static and fragmented, struggle to support such multi-dimensional assessments (Meng *et al.*, 2020). Consequently, effective EoL decision-making increasingly demands technologies capable of combining real-time data with historical asset records. Within this perspective, EoL decisions are being re-envisioned as integral to asset management processes across operational, tactical, and strategic levels (Roda and Macchi, 2018).
In this context, Digital Twin (DT) technology has emerged as a promising solution. DTs create dynamic digital replicas of physical assets, continuously updated with real-time sensor data, historical records, and simulation outputs (Negri, Fumagalli and Macchi, 2017). This integration facilitates predictive analytics, condition monitoring, and scenario evaluation across the lifecycle, supporting operational decisions (Tao *et al.*, 2019). DTs are therefore suited for lifecycle management, offering

decision support from asset commissioning to decommissioning (Macchi *et al.*, 2018).

To date, however, most DT applications have been concentrated in the middle-of-life (MoL) phase, with a focus on operational and tactical maintenance decisions via indicators such as Remaining Useful Life (RUL) (Macchi *et al.*, 2018; Macchi, Roda and Toffoli, 2018; Errandonea, Beltrán and Arrizabalaga, 202). Their use in guiding strategic EoL decisions remains limited. This reveals a significant gap in the literature: while DTs are frequently employed to estimate operational indicators like RUL, they rarely address value-based indicators relevant at the EoL phase of the assets' lifecycle.

As a first step towards overcoming this gap, this paper investigates how DTs can be repositioned to support EoL AM beyond traditional maintenance functions. Specifically, it examines how existing operational indicators (e.g., RUL) and the DT's technological infrastructure can be leveraged to inform high-level EoL strategies. Through a structured literature review and conceptual analysis, the study proposes a conceptual framework illustrating how DT-enabled information can flow across operational, tactical, and strategic level - positioning DTs as comprehensive tools for lifecycle intelligence and EoL value realization.

In detail, the paper is structured as follows. Section 2 provides the research methodology. Section 3 presents the results of the literature review on DTs for EoL decision support (3.1) and the conceptual DT information flow framework for EoL decision-making (3.2). Last, section 4 presents the discussion and conclusions.

2.Research methodology

While this paper specifically focuses on the strategic application of DTs in EoL asset management, it builds upon broader literature exploring the convergence of Circular Economy (CE) and Industry 4.0 (I4.0). Several systematic reviews have examined how digital technologies, including DTs, enable CE transitions in manufacturing. For example, Cagno et al. (2021) review digital tools supporting CE implementation, while Rosa et al. (2020) assess the integration of I4.0 paradigms with CE principles across product lifecycles. Similarly, Tavera Romero et al. (2021) propose a conceptual framework linking enabling technologies to circular practices, and Kristoffersen et al. (2020) emphasize data-driven strategies for smart CM.

However, these studies mainly address general or operational aspects, leaving a gap in understanding how DTs can inform strategic-level asset EoL decisions. The present research builds on these foundations by focusing on how existing DT-generated indicators can be repurposed to support long-term, value-driven planning aligned with CM goals.

To investigate the role of DTs in EoL AM, a structured literature review (LR) was conducted using the Scopus database. Given the limited number of studies explicitly addressing industrial assets at EoL (despite a broader body of research on product-level EoL), the review focused on identifying DT-computed indicators with the potential to enhance strategic EoL decision-making.

Therefore, the following keywords were used to compose the research string:
("digital twin*") AND ("remaining useful life" OR "RUL" OR "remaining life" OR "remaining * value" OR "residual life" OR "residual value") AND ("asset*" OR "machine*" OR "equipment*" OR "component") AND ("manufacturing" OR "production").

As a result, 55 papers were identified and carefully screened, leading to a final selection of 20 papers for in-depth analysis.

3.Digital Twins for End-of-Life Asset Management

3.1 Literature Review on Digital Twins for End-of-Life decision support

To initially characterize the technological focus of the DT-based support, the asset types addressed in each selected contribution were categorized and grouped. As shown in Figure 1 (some papers cover more than one category), most papers concentrate on components (rolling bearings), machineries, and equipment (including industrial robots and CNC machines). In contrast, more complex physical assets such as casting machines and aerospace engines appear less frequently.

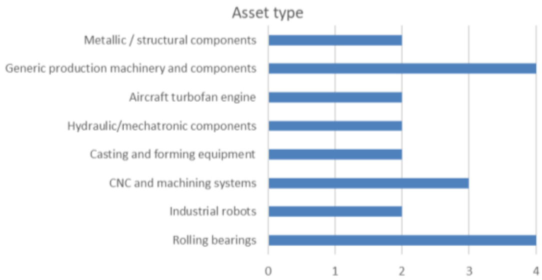

Figure 1: Asset type distribution

Further analysis focused on how DTs contribute to the generation of decision-relevant information for stakeholders involved in EoL strategies. Each paper was examined along three key dimensions: (i) decision-making level targeted (operational, tactical, strategic), (ii) types of indicators computed, and (iii) key enabling technologies. Before that, an overview of DT-supported tasks/activities is provided.

Digital Twins (DTs) are increasingly central to predictive and prescriptive maintenance, as they integrate real-time sensing, simulation, and data analytics in a unified system (e.g., Beliakova, Beliakov and Topolsky, 2024). Unlike traditional approaches that rely on either physics-based models or data-intensive machine learning (ML), DTs combine both, enabling accurate RUL predictions even in data-scarce contexts (e.g., Cattaneo and Macchi, 2019). Maintaining a bi-directional connection with physical assets, DTs offer real-time insights and long-term planning capabilities (e.g., Mao et al., 2023). Unlike static models or standalone ML tools, DTs offer lifecycle-wide insights into failure risks, costs, and sustainability(e.g., Werner, Zimmermann and Lentes, 2019; Beliakova, Beliakov and Topolsky, 2024). Moreover, when integrated into enterprise systems, DTs support multi-level decision-making, extending their impact beyond maintenance into strategic AM and alignment with CM goals (Paramatmuni and Cogswell, 2023). In this sense, DTs are not just diagnostic tools, but essential platforms for lifecycle-aware, value-driven AM.

As AM decision-making spans from immediate operational responses to long-term strategic planning (Roda and Macchi, 2018), DTs offer context-aware support across all levels, turning data into insights and foresights (Grieves and Vickers, 2016; Tao *et al.*, 2019). Understanding these decision levels - operational, tactical, and strategic - is therefore essential to evaluate how DT-indicators and technologies contribute to asset lifecycle optimization, particularly at the EoL phase. Each level differs indeed in terms of decision horizon, data requirements, and stakeholder involvement (Roda and Macchi, 2018):

- Operational level decisions involve real- or short-term actions such as fault detection and predictive maintenance, typically handled by operators or control systems.
- Tactical level decisions involve mid-term planning activities such as scheduling and resource allocation, usually managed by planners.
- Strategic level decisions involve long-term planning, capital investment, sustainability, and lifecycle extension strategies (e.g., replacement, refurbishment, reuse). Although DTs have the potential to support such high-level decisions, there is limited evidence of their systematic application at this level (e.g., Zacharaki *et al.*, 2021).

While DTs support these levels to varying degrees, current implementations primarily target the operational and tactical levels (e.g., Lu and Li, 2023; Alrabghi, 2025), especially for MoL tasks like condition monitoring and predictive maintenance (e.g., Wu and Li, 2021; Arena et al., 2022). Indicators like RUL, Health Index (HI), and other operative-oriented indicators (e.g., wear depth) (Mayr *et al.*, 2024) are used to provide insights into the state of health of the asset or its components:

- RUL: predicts the time before failure or threshold crossing, enabling just-in-time maintenance (Cattaneo and Macchi, 2019; Xu *et al.*, 2025).
- HI: a composite score representing the general condition of a system, often used for prioritizing maintenance (Sundaram and Zeid, 2021).

These indicators are valuable for short/mid-term decisions but insufficient for strategic-level EoL planning, which demands multi-dimensional insights such as economic residual value, environmental impact, and remanufacturing feasibility of the asset. Only a limited number of studies, such as Paramatmuni and Cogswell (2023), address these higher-level considerations. This reveals a critical gap in the literature: although DTs already incorporate a wide array of enabling technologies and systems, their application remains narrowly focused on operational and tactical levels. As shown in Table 1 (the full table with references is presented in Appendix A), DTs enabling technologies and systems exist and are, in principle, capable of supporting high-level EoL strategies - if coherently integrated and strategically applied.

Table 1: Enabling technologies of Digital Twins

Digital Twin enabling technologies and systems	Role in EOL decision-making support
IoT and sensor systems	Provides real-time operational data for degradation tracking and RUL prediction
Database	Store structured and unstructured lifecycle data, and historical and simulation records
Data analytics	Extracts patterns and trends from sensor data for anomaly detection and health assessment
AI-based analytics	Enable prediction and support uncertainty quantification via learning-based models
Simulation	Simulates physical behaviour under operational stress and failure modes
Cloud / Edge computing	Supports scalable, low-latency data processing and centralized decision-making
Asset passports	Provide traceability, component history, recyclability, and material properties
ERP/MES /SCP enterprise system	Links DTs with business planning, production scheduling, and supply chain operations
Decision Support Systems	Synthesizes data into actionable insights for higher-level strategic planning

These insights set the stage for developing a more integrated approach to EoL decision-making.

2.2 Conceptual Information Flow Framework for End-of-Life Decisions Enabled by Digital Twins

Building on the technological foundations outlined above, this section presents a conceptual framework for elevating DT-generated information across decision-making levels. By illustrating how operational indicators (e.g., RUL, HI) can be reinterpreted through enabling technologies and systems, the framework supports the strategic alignment of EoL decisions. These technologies indeed have the potential to (Kritzinger *et al.*, 2018; Tao *et al.*, 2019):

- Aggregate and contextualize real-time IoT sensor data and historical data
- Simulate asset performance under EoL scenarios
- Facilitate multi-stakeholder decision-making
- Support multi-criteria optimization (e.g., economic, environmental, regulatory) relevant to strategic planning.

For instance, although RUL traditionally signals the timing of maintenance interventions, it could also be leveraged (e.g., leveraging simulation models, cloud/edge infrastructure, and ERP/MES integration) to inform value-based asset indicators such as residual functionality, cost-benefit trade-offs, or material recovery. Similarly, material and electronic asset passports can enhance traceability and support recyclability assessments aligned with CM objectives. Hence, they have the potential of being repositioned to guide EoL strategic decisions, such as lifecycle extension strategies (Cagno *et al.*, 2021; Wynn and Jones, 2022).

This transition requires addressing two main gaps:

- First, a deeper exploration is needed on how operational indicators (e.g., RUL, HI) can be systematically interpreted and integrated across decision levels. This would enable strategic decision-makers to benefit from the high-resolution data already being collected to generate foresight into long-term asset viability.
- Second, there is a need to design and implement new indicators that reflect asset value beyond functional life. These indicators, once validated and integrated into DTs, can provide strategic insights necessary to align AM with CM principles and sustainability targets.

By leveraging existing technological enablers and introducing such metrics, DTs can evolve into full-spectrum tools for EoL AM. To support this shift, the following conceptual framework illustrates how existing DT-generated outputs can evolve from operational and tactical insights into strategic decision support. This addresses not a technological void, but a methodological one: the lack of structured approaches to elevate operational data into high-level EoL strategies. To deepen this understanding, a mapping of the DT-enabling technologies and systems has been performed across the operational, tactical, and strategic levels. While many of them span more than one level, as shown in Figure 2, each exhibits specific functionalities relevant to the flow of information toward strategic decision-making:

- IoT and sensor systems: at the operational level, sensors provide real-time condition data for computing indicators like RUL and HI, as shown by Erpalov, Khoroshevskii and Gadolina (2024). Aggregated and contextualized over time, this data forms the basis for higher-level insights.
- Database technologies: serving all decision-making levels, databases store, organize, and retrieve the large volume of heterogeneous data generated by DT systems. As seen in Wang et al. (2022), databases support the structured storage of real-time and historical sensor data at the edge and in the cloud, ensuring consistency and accessibility. Strategically, well-structured databases enable longitudinal analysis, integration of EoL indicators, and asset lifecycle traceability, thus forming a critical foundation for lifecycle intelligence and strategic planning.
- Data analytics: at operational and tactical levels, traditional statistical and signal-based analytics are often used to preprocess sensor data, detect trends, and compute condition-based indicators. These methods enable early anomaly detection and prepare data for higher-level modelling, such as in the proposal of Arena et al. (2022).
- AI-based data analytics: applied at operational and tactical levels, ML and hybrid AI models are used for time-series prediction. These models not only forecast failures but also help structure patterns (e.g., Lu and Li (2023)) that can be generalized for risk evaluation and trend analysis, pushing data into the tactical decision layer.
- Simulation: mainly applied at tactical and strategic levels (e.g., Fanelli et al., 2022), simulation tools enable scenario testing that can support EoL planning.
- Cloud/Edge computing: at all levels, facilitates cross-level data availability and computational scalability. For example, Wang et al. (2022) use edge computing in intelligent water conservancy systems to continuously collect and process sensor data locally, enabling dynamic DT model updates. This supports not only timely fault detection and operational decisions but also long-term safety assessments and optimization of maintenance cycles, thereby contributing to strategic-level AM and lifecycle planning.
- Asset passports (Material/Electronic): while still emerging in implementation, asset passports offer critical value across all decision-making levels. At the operational level, they support real-time traceability and component identification. At the tactical level, they help in planning maintenance or refurbishment by providing component history and specifications. Strategically, they enable assessments of recyclability, residual value, and remanufacturing potential, aligning AM with circular economy goals (Paramatmuni and Cogswell, 2023).
- Enterprise systems (ERP/MES/SCP): integration with enterprise systems, as proposed by Alrabghi (2025), allows DT outputs to align with business and asset investment strategies, extending their relevance into strategic planning.
- Decision Support Systems (DSS): while not widely implemented in the reviewed papers, some contributions (e.g., Werner, Zimmermann and Lentes, 2019) highlight the potential of DSS to synthesize tactical insights into dashboards or interfaces that guide strategic-level decisions.

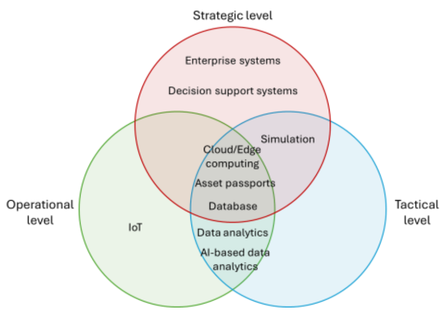

Figure 2: Mapping of Digital Twin enabling technologies across decision-making levels

A practical illustration of this progression is provided by Paramatmuni and Cogswell (2023): real-time sensor data feeds AI models to estimate RUL (operational); aggregated Digital Thread insights guide maintenance scheduling (tactical); and material passports, combined with simulation, support lifecycle extension strategies (strategic). Generalizing from this, Figure 3 outlines how the information flow unfolds with the support of the DT:

- Operational level: real-time and historical data are used to monitor asset degradation and calculate indicators such as RUL and HI. These inform daily decisions around fault detection and maintenance.
- Tactical level: aggregated operational insights are used for planning and resource coordination, enabling proactive and cost-effective AM strategies.
- Strategic level: tactical insights are integrated with lifecycle, economic, and regulatory data to inform EoL decisions. Here, residual value indicators must extend beyond technical condition to reflect feasibility, compliance, and stakeholder priorities (Shafiee and Animah, 2017). When enriched with residual asset value indicators and viewed through an EoL lens, properly integrated DTs have the potential to support a cross-level, data-driven approach that connects operational insights with strategic, long-term value realization.

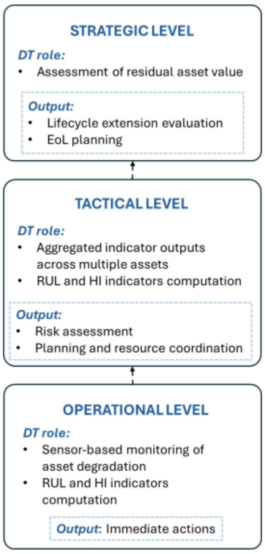

Figure 3: Information Flow Framework for End-of-Life decisions enabled by Digital Twins

Overall, DT can therefore operationalize this conceptual framework by collecting, organizing, integrating, and contextualizing the diverse data streams needed for value-based EoL assessments. Indeed, DTs can help ensure that strategic evaluations remain compliant and goal-oriented, thanks to their multiple supporting functionalities and subsequent abilities. Amongst them, it is worth remarking: i) the continuous monitoring and historical data retention, ii) the ability to simulate EoL scenarios that can support feasibility analysis, and iii) the ability to embed regulatory constraints and stakeholder priorities into decision support models.

In this context, RUL emerges not merely as a failure prediction metric, but as a foundational input for value-based lifecycle planning - especially when coupled with DT infrastructure capable of scaling it into a strategic signal. This positions DTs as pivotal tools in bridging the gap between operational data and high-level EoL AM.

4. Discussion and Conclusions

4.1 Contribution to knowledge

This study has examined the current state of DT applications in industrial AM, with a focus on their evolving role in EoL decision-making. The literature review reveals a predominant focus on operational and tactical uses of DTs, particularly for maintenance optimization, while strategic-level integration remains limited. Nonetheless, the enabling DT technologies and systems have the potential to support decision-making across all levels when paired with appropriate data transformation and contextualization strategies. A key contribution of this study is the conceptual framework outlining how information generated at the operational and tactical levels, such as RUL and HI, can be aggregated and reinterpreted to inform long-term, value-based decisions. By building on this foundation, the introduction of new value-based indicators can enable more comprehensive EoL planning and strategy selection aligned with sustainability and CM goals.

4.2 Managerial implications

For practitioners, the study offers a methodological perspective into how existing DT infrastructures can be leveraged for long-term asset planning:

- Technology repurposing: it illustrates that technologies already in use for MoL purposes can be strategically integrated to support EoL decisions without requiring new technological investments.
- Indicator integration: the proposed approach encourages reframing operational indicators (e.g., RUL) through a strategic lens, promoting continuity in decision support across lifecycle stages.

The findings suggest that organizations should extend DT use cases beyond short-term operational tasks by embedding strategic objectives - such as refurbishment, reuse, and remanufacturing - into AM. This requires coordinated data flows across operational, tactical, and strategic levels to ensure that condition-based insights support long-term value creation aligned with cost-efficiency, sustainability, and circularity goals.

Finally, adopting value-based indicators that incorporate economic, environmental, regulatory, and criticality dimensions can enhance EoL decision-making, improve asset recovery, and strengthen sustainability performance.

4.3 Limitations and future work

Several limitations of this study must be acknowledged. First, this study is based on a scientific literature review, hence, it misses the industrial stakeholders' perspective. Second, the review highlights the theoretical potential of DT at the strategic level, yet few studies provide either academic or real-world implementations or validated case studies of DTs supporting EoL strategies for industrial assets. This restricts the generalizability of the proposed framework.

As future research directions, an in-depth analysis and validation of value-based EoL indicators at the strategic level is needed. The analysis should include input from industrial stakeholders regarding which dimensions of value (economic, environmental, and asset criticality) are most relevant in practice, as well as examine how different stakeholder needs influence the types of DT-supported information required for EoL decision-making. Coupled with this insight, the technology infrastructure – hosting the DT systems for lifecycle management – is also worth investigation, including related technological concepts such as the Digital Threads. The conceptual framework, provided in this work, aims to be a starting point, to be used to inform future research steps. Overall, future contributions should explore a broader theorization of the integration of DT systems with CM metrics and regulatory compliance frameworks.

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Appendix A. FIRST APPENDIX

Enabling DT technology	**Role in EOL decision-making support**
IoT and sensor systems (Aivaliotis et al., 2019; Aivaliotis, Georgoulias and Chryssolouris, 2019; Cattaneo and Macchi, 2019; Werner, Zimmermann and Lentes, 2019; Guo et al., 2021; Sundaram and Zeid, 2021; Wu and Li, 2021; Arena et al., 2022; Wang et al., 2022; Lu and Li, 2023; Mao et al., 2023; Beliakova, Beliakov and Topolsky, 2024; Erpalov, Khoroshevskii and Gadolina, 2024; Yang et al., 2024; Alrabghi, 2025; Xu et al., 2025)	Provides real-time operational data for degradation tracking and RUL prediction
Database (Lu and Li, 2023; Paramatmuni and Cogswell, 2023; Beliakova, Beliakov and Topolsky, 2024; Erpalov, Khoroshevskii and Gadolina, 2024; Yang et al., 2024)	Store structured and unstructured lifecycle data, and historical and simulation records
Data analytics (Aivaliotis et al., 2019; Aivaliotis, Georgoulias and Chryssolouris, 2019; Cattaneo and Macchi, 2019; Werner, Zimmermann and Lentes, 2019; Guo et al., 2021; Sundaram and Zeid, 2021; Arena et al., 2022; Fanelli et al., 2022; Hassan, Svadling and Björsell, 2023; Lu and Li, 2023; Mao et al., 2023; Beliakova, Beliakov and Topolsky, 2024; Erpalov, Khoroshevskii and Gadolina, 2024; Mayr et al., 2024; Yang et al., 2024; Alrabghi, 2025; Xu et al., 2025)	Extracts patterns and trends from sensor data for anomaly detection and health assessment
AI-based analytics (ML, DL, hybrid models) (Werner, Zimmermann and Lentes, 2019; Guo et al., 2021; Wu and Li, 2021; Arena et al., 2022; Fanelli et al., 2022; Wang et al., 2022; Lu and Li, 2023; Mao et al., 2023; Paramatmuni and Cogswell, 2023; Beliakova, Beliakov and Topolsky, 2024; Xu et al., 2025)	Enable prediction and supports uncertainty quantification via learning-based models
Simulation (Aivaliotis et al., 2019; Aivaliotis, Georgoulias and Chryssolouris, 2019; Cattaneo and Macchi, 2019; Werner, Zimmermann and Lentes, 2019; Arena et al., 2022; Fanelli et al., 2022; Lu and Li, 2023; Paramatmuni and Cogswell, 2023; Erpalov, Khoroshevskii and Gadolina, 2024; Yang et al., 2024; Alrabghi, 2025; Xu et al., 2025)	Simulates physical behavior under operational stress and failure modes

Cloud / Edge computing (Cattaneo and Macchi, 2019; Wu and Li, 2021; Wang et al., 2022)	Supports scalable, low-latency data processing and centralized decision-making
Asset passports (e.g., material, electronic) (Mao et al., 2023; Paramatmuni and Cogswell, 2023; Beliakova, Beliakov and Topolsky, 2024)	Provide traceability, component history, recyclability, and material properties
ERP/MES/SCP enterprise system (Alrabghi, 2025)	Links DTs with business planning, production scheduling, and supply chain operations
Decision Support Systems (Werner, Zimmermann and Lentes, 2019)	Synthesizes data into actionable insights for higher-level strategic planning