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Digital Twins and Business Analytics: A Review of Predictive Modelling for Strategic Planning and Risk

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Abstract
This review examines the integration of digital twins with business analytics and predictive modeling to enhance strategic planning and risk management under deep uncertainty. Digital twins which are virtual representations mirroring physical assets through bidirectional IoT data flows, ML-driven simulations, and hybrid physics-data models, enable real-time anomaly detection, scenario forecasting, and prescriptive optimisation across manufacturing, supply chains, healthcare, and finance. Addressing core research questions, findings reveal their efficacy in embedding predictive frameworks for "what-if" analyses and DMDU paradigms (monitor-adapt over predict-act), yielding cost savings via prototyping efficiencies, PHM, and resilient decision-making amid nonlinear risks. Despite transformative benefits like shorter design cycles and proactive interventions, challenges persist: high deployment costs, legacy integration barriers, data standardisation gaps, cybersecurity vulnerabilities, and AI opacity. Future research must prioritise interoperable ontologies, edge-cloud architectures, and empirical validations to realise self-evolving twins, fostering agile enterprises in volatile contexts.

1. Introduction

1.1.Background

Digital Twin (DT) is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin. In the simplest words, a digital twin is a ‘digital’ ‘twin’ of an existing physical entity. The elementary components without which a DT cannot exist: 1. Physical Asset (could be either a product or a product lifecycle) 2. Digital Asset (the virtual component) 3. Information flow between the physical and digital asset (this could be 1-way or 2-way/bijective). Digital Twin aims to combine the best of all worlds, namely, twinning, simulation, real-time monitoring, analytics and optimisation (Sharma et al., 2022).

A digital twin, according to Kritzinger et al, is a digital representation of a physical entity with a fully integrated and automated bi-directional data flow to the physical entity. The modelling of a twin entity, as a key component of the digital twin, must meet the high-fidelity criteria of the digital twin, ensuring high accuracy and real-time performance to accurately represent the true state of the physical entity. The digital twin can sense, diagnose and predict the state of physical entities in real time, regulate the behaviour of physical entities through collaboration and optimisation decision-making between twins, realise self-evolution through self-learning across relevant digital models, and achieve the autonomous intelligent evolution of total twin networks. (Wu et al., 2021).

Digital Twins are basically classifiable into three characteristics: (1) Physical reality, (2) Virtual representation and (3) Linking of (1) and (2) to exchange information (VanDerHorn and Mahadevan, 2021). The connection between (1) and (2), the interconnection (3), represents the communication link through which the real system can and should communicate with its Digital Twins and exchange data. This exchange occurs in both directions: From the real system to the Digital Twin, as well as from the Digital Twin to the real system. There is also information fusion, where data from both systems are combined, eliminating duplication and redundancy (VanDerHorn & Mahadevan, 2021). (Metzger, 2023). Business analytics can be defined as the process of collecting data, processing this data and gain insights from the data (Gupta, 2021). Business analytics is also defined as the science of discovering insights from data to support timely decision-making (Delen and Ram, 2018). Camm et al. (2020) consider that business analytics is “the scientific process of transforming data into clues for making better decisions”. For Muñoz-Hernandez et al. (2016) business analytics allows the efficient use of all the information available to organizations, to obtain a competitive advantage. Business analytics uses statistical analysis, predictive modeling, data mining and other techniques to employ information and develop a competitive advantage in its favor (Evans and Lindner, 2012; Medina, 2012).

This standard also specifies that a DT (Digital Twin) assists with detecting anomalies in manufacturing processes to achieve functional objectives such as real-time control, predictive maintenance, in-process adaptation, Big Data analytics, and machine learning. Real-time machine learning capacity is what differentiates a DT from a simulator or a real-time monitoring tool. Analytics is essential, as one of the cardinal uses of a DT is to be able to reliably and accurately output how a physical asset would behave in conditions which have not arisen yet, using the real-time data it is receiving – in other words – for ‘testing’ the physical asset in an unforeseen situation. The other cardinal use of ML (Machine Learning) in DT is to predict an impending problem which needs attention while revealing the imperfections in the system (anomaly detection [Celebi & Aydin, 2016]). (Sharma et al., 2022).

Data-driven models are widely utilized in the field of data analytics (Adrian et al., 2018). However, their significance becomes particularly evident inside digital twin systems, where they play a critical role in updating virtual models by incorporating real-time data. Data analytics techniques, including anomaly detection, regression analysis, and machine learning, are employed in the realm of monitoring and process optimization (Rajendran & Asokan, 2021; Baalbergen et al., 2020). The implementation of predictive maintenance is contingent upon the utilization of data analytics and machine learning techniques. Real-time data interpretation employs many data analytics approaches, such as signal processing, computer vision, and machine learning (Dihan et al., 2024).

Analytics is essential, as one of the cardinal uses of a DT (Digital Twin) is to be able to reliably and accurately output how a physical asset would behave in conditions which have not arisen yet, using the real-time data it is receiving – in other words – for ‘testing’ the physical asset in an unforeseen situation. The other cardinal use of ML (Machine Learning) in DT is to predict an impending problem that needs attention while revealing the imperfections in the system (through anomaly detection [Celebi & Aydin, 2016]). Machine learning supports predictions and feedback, as well as to identify effective mitigation strategies, in exceptional circumstances. This requires a joint optimisation feature for the sub-components of the DT. The ‘self-evolving’ nature of DTs, where a DT can improve itself from the true results of its predictions, can only be implemented using machine learning. Machine learning can also help in creating resilient DTs. With continual learning a ML model gets updated with the incoming data stream. Although potentially prone to catastrophic forgetting, recent research methods and results have started to address this problem (Kirkpatrick et al., 2017). This could aid in implementing the 'self-evolving' property of DT.

1.2. Problem Context

Human beings have cognitive limits that introduce error into judgments and decisions. Organizations by virtue of their structuring and the broader environments in which they operate tend to introduce their own peculiar decision challenges. Organizational decision makers work with and through others. Unlike many clinical psychologists and accountants, managers practice solo. They are not only responsible for their own decisions, but managers often are also accountable for the decisions others make, responsibilities associated with gaps in both information and understanding that create uncertainty and concern with control. Organizational decisions often have lots of stakeholders, inside and outside the organization, prompting a tendency for managers to avoid information that is less available or to work around those who make a decision more complicated. Organizational decision makers can face highly dynamic situations. Missing information and interpreting data are common in dynamic environments, making it difficult to determine appropriate courses of action. In contrast, an accountant is likely to know what information is needed to close the books and where to find it. Furthermore, organizational decision makers often face a diverse array of decisions made concurrently, rather than similar decisions over and over, and consequently there are fewer frameworks, checklists, and decision supports to guide organizational decisions than in professions such as nursing, medicine, engineering, or accountancy. Managers typically prefer to focus on concrete evidence and distance themselves from information that raises doubt. Instead, it's better to manage uncertainty or even try to reduce it by gathering facts and reflecting on information, rather than assuming uncertainty away. There is no shortcut to a thoughtful start to the decision process, regardless of urgency or the resources poured into a problem. Uncertainty can be technical or procedural in that the decision maker lacks understanding of how to make something happen (no clear cause-effect connections), for example, how to go about building a patient information database that serves the needs of physician services, the billing department, and medical researchers. Uncertainty may be political (ambiguous goals and tenuous relationships) in that no clear course of action is known that all key stakeholders will accept, as in the case of a police department seeking better community relations. Uncertainty can be due to environmental change, which may vary from somewhat predictable to totally unpredictable. Environmental change can involve physical, economic, technological, and broader social forces, sometimes exemplified in combination, as by the multi-faceted nature of climate change. "Knowns" refer to domain knowledge available to decision makers. They can be technical, where the situation is well understood, like how to post an internal position. Or knowns can be political, where interests and differences among parties are well-established, as in some labour-management disputes. In either case, use of domain knowledge can improve the quality of the decision. In contrast, in 'unknowns', problems with much critical information do not exist and must be created, as in the case of responses to hacking or exploring business opportunities in an emerging market. Unknowns are addressed through learning by doing and experimentation. Reliance on easily available information means being swayed by the salient opinion of the sponsor, a manager's own experiences, or the intuitions of the folks in the room, without attention to other sources of relevant information. The aim of evidence-based practice (EBP) is systematic use of the best available information from multiple sources in order to improve decision outcomes. The bias of easily available information can be reduced by searching for different kinds of relevant evidence, and then appraising how good it is (its reliability, validity, consistency, and relevance) in helping make the decision. All decisions ignore some evidence, but the point is to pay attention to evidence more systematically so that available quality evidence is used. Implications: Organisational decisions have better odds of success if the six de-biasing processes are used. These processes are synergistic and work well together. In combination they help organisational decision makers do something humans often find tough to do: confront and manage incomplete information, ambiguity, and uncertainty. Scenarios are specific representations of the future to facilitate thinking about the possible consequences of different events or courses of action within a systematic foresight exercise. For example, the Intergovernmental Panel on Climate Change (IPCC) defined a scenario as a 'plausible and often simplified description of how the future may develop, based on a coherent and internally consistent set of assumptions about driving forces and key relationships'. The literature generally splits scenarios into three broad categories, depending on their nature and purpose and on the degree of complexity and uncertainty involved. Predictive scenarios use knowledge about the past to derive probabilistic estimates of alternative future conditions. Exploratory scenarios start from the present and explore the impacts of various drivers, trends, and interactions from now into the future. Normative scenarios start from a particular desired vision of the future and work their way backward to identify pathways for reaching this future. The term "forecast" is commonly used to describe a predictive exercise that identifies a most likely future, as in shorter-term contexts such as monthly market forecasts, whereas the term "projections" is often used to describe the results of scenarios without assigning probabilities to the different outcomes. For exploratory scenario studies, the selected set should be maximally diverse to maximize the span of potential futures considered (Wiebe et al., 2018)

1.3. Purpose of the Review

This literature review defines Digital Twins and introduces their concepts, then describes their areas of application, shows how they can be implemented, addresses the important issue of data management and finally presents their benefits and challenges. Accordingly, the goal of this paper is to provide an overview of the current state of research and industry as well as the current concept, applications and implementation strategies of Digital Twins. The research questions are what the current state of the art of literature on Digital Twins is, how Digital Twins can be used effectively in industry to optimise production processes and reduce costs, and what needs to be considered in their application. The first categorisation criterion is the ability of a Digital Twin to describe the past and present state of the physical twin ("descriptive Digital Twin"); the second to predict the state, function, behavior, and dynamics of the physical twin ("predictive Digital Twin"); and the third to enable driving the physical twin to or towards a desired future state ("prescriptive Digital Twin"). When considering Digital Twins, Negri et al. (2017) categorised Digital Twins into three complexities for application. Grieves (2014) additionally describes that the use case of Digital Twins includes and supports three of the most important and powerful tools of human knowledge. These are conceptualisation, comparison and collaboration (Grieves,2014). Digital Twins are used for different tasks in different industries (Psarommatis & May, 2022; Greif et al., 2020). According to VanDerHorn and Mahadevan (2021), four points are absolutely necessary in order to integrate a Digital Twin into a business: the specification of the exact, desired end result or outcome, the precise and comprehensive development of the solution (clear definition of the physical, real system as well as the exact levels of abstractions), the development and creation of the virtual model, and finally the establishment of the data links and connections necessary for the Digital Twins (VanDerHorn and Mahadevan, 2021). Digital Twins bring several benefits as well as opportunities, but there are also some disadvantages and challenges open to be faced (Metzger, 2023).

1.4. Research Questions

Q1. What predictive models are integrated into digital twin frameworks?

Q2. How do digital twins support strategic planning across industries?
Q3. How do digital twins contribute to risk management?
Q4. What challenges and limitations exist in current research and adoption?

2. Literature Review

2.1. Evolution and Architecture of Digital Twins

Digital Twins were first introduced in early 2000s by Michael Grieves in a course presentation for product lifecycle management (Grieves, 2014). In 2011, implementing DT was considered a complex procedure, which required many developments in different technologies (Tuegel et al., 2011). Despite being coined in 2003, the first description to use of Digital Twin was years later by NASA in Technology Roadmaps (Shafto et al., 2012), where a twin was used to mirror conditions in space and to perform tests for flight preparation (another example of such hardware twin was the Airbus Iron Bird). Having dawned with the aerospace industry, the DT methodology extended to the manufacturing industry around 2012. So what took the concept nearly a decade to be implemented? Digital Twins are virtual copies of products, processes or services which encompass all the above qualities (Schleich et al., 2017). Grieves and Vickers (2017) define the Digital Twin (DT) as 'a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its Digital Twin". In the simplest words, a digital twin is a 'digital' 'twin' of an existing physical entity. DT was first introduced by Grieves (2015) with components of three components: the digital (virtual part), the real physical product, and the connection between them. However, other authors, such as Tao et al. (2018), have extended this concept to have five components, by including data and service as a part of DT. As conceptually sound the above definitions are, reaching consensus on a DT definition requires specifying the fundamental requirements for a DT. With the advancements in the technologies on which DT depends (such as machine learning, big data and cybersecurity), these requirements have changed over time. With the advancements in technologies like cloud computing, IoT and big data, many domains have seen major developments, such as Industry 4.0 (Lu, 2017). It was because of the Industry 4.0, the storage of all data in digital format, and sensors being in-built into the industrial spaces, that digital twin implementations became possible, rejuvenating the concept. Continuing the debate on whether DT should be the product or the product lifecycle, Schleich et al. (2017) propose a DT reference model for production systems for geometrical product specification (GPS), where they pitch the idea to represent the DT as an abstract form of the physical product, mentioning clearly that DT is the entire product lifecycle and not just the product. The diverse applications of DT such as simulation, real-time monitoring, testing, analytics, prototyping, end-to-end visibility (Ivanov et al., 2019) can be broadly classified as sub-systems of DT (for example, a DT can be used for testing during prototyping, for real-time monitoring and evaluation, or for both).

Cloud services are playing an increasingly important role in the way that businesses and organizations collect, store, and manage data. One of the key benefits of cloud services is that they allow organizations to collect and store large amounts of data from a wide range of sources, including sensors, devices, and applications, in a centralized location. This data can then be easily accessed and analyzed by different departments or teams, enabling faster and more informed decision-making. In addition to data collection and storage, cloud services also offer powerful tools for data association, fusion, sorting, and coordination. By fusing data from different sources, organizations can gain insights into the performance of individual machines, as well as broader trends across their entire production line. Cloud services also offer powerful tools for data processing and analysis, which are critical for digital twin technology. With the ability to process large volumes of data in real time, cloud services enable organizations to quickly identify patterns and anomalies in the data and use this information to optimize their operations (Dihan et al., 2024).

The IoDT engine is created through the convergence of various emerging technologies including IoT, AI, semantic communication, and blockchain. The IoT is the underlying technology of IoDT, which offers the sensing/networking/computing infrastructures and capacities to PEs. The pervasive IoT sensors carry out real-time data collection from things and the environment and feed it to the IoDT engine. The cloud-edge computing paradigm provisions massive feasible computing power to enable massive data analysis, data storage, and modeling. A digital twin can be deployed within a cloud or an edge server. A synchronized private link can be established for real-time data transmission between the digital twin and its PE or other twins. Because of the bidirectional connection between PEs and their digital twins, the IoDT engine feeds the PEs' private data to support the modeling, creation, maintenance, and updating of the digital representatives along with the virtual assets. The IoDT engine is created through the convergence of various emerging technologies including IoT, AI, semantic communication, and blockchain (Wang et al., 2023).

This paper conducts a comprehensive review of the existing work on digital twins from four perspectives: data, model, network and application, and strives to gain a better understanding of the development of the field from the physical to the virtual and back to the physical. It presents a systematic representation of the whole process starting from the digital twin data, through the model and twin network and finally up to the application. Shao & Helu (2020) synthesized the different views on digital twins in the existing literature to sort out the development needs of standardization frameworks. Autiosalo et al. (2019) summarized the basic characteristics of digital twins in existing research and reviewed how to classify digital twins based on these characteristics. Mihai et al. (2022) described how enabling technologies can be used to enable digital twin services, using real-world examples, and emphasized the significance of enabling technologies for the functioning of digital twin services. Wu et al. (2021) defined a digital twin network (DTN) as a many-to-many mapping network comprised of numerous digital twins (DTs), in which physical entities and virtual counterparts can communicate with each other and cooperate to perform complex tasks. In this chapter, we summarize the work on the implementation of physical–virtual state synchronization, both in terms of state synchronization and state correction, as well as twin deployment within twin networks and computational offloading. Twin deployment requires the dynamic placement of twin entities depending on the mobility of physical entities, computing resources at the network edge, and low-latency requirements between physical entities and their twins. Considering the limited processing resources of the edge cloud and the social relationships between IoT devices, Chukhno et al. (2020) proposed an optimal solution to the network-edge placement problem of socially connected IoT digital twins. (Wu et al., 2021)

2.2. Predictive Modelling Approaches in Digital Twins

When coupled with Artificial Intelligence (AI), DTs enable data-driven experimentation, precise diagnostic support, and predictive modeling without posing direct risks to patients. This enables not only personalized treatment plans but also sophisticated predictive medicine, allowing for early intervention and proactive management of health conditions before critical deterioration. By modeling the progression of recovery, DTs facilitate the simulation of robotic rehabilitation protocols and the optimization of individual outcomes. The transformative potential of DTs in healthcare lies in their ability to enable highly personalized and proactive medicine. By integrating continuous data from various sources, DTs promise to provide detailed insights that facilitate treatment adaptation, performance optimization, and prevention of adverse events. AI is a critical tool that allows for the integration of diverse patient data from symptoms to laboratory results, helping to produce increasingly accurate diagnoses and prognoses, thereby enabling clinicians to compare current findings with medical evidence and prescribe personalized treatments. The integration of DTs with IoT and AI further refines predictive analytics, enabling early detection of impending health issues and automated alerts for care teams (Kadari et al., 2023; Klimo et al., 2023) . AI-supported Digital Twins (DTs) have emerged as a compelling avenue for advancing healthcare solutions. By creating tailored virtual environments, DTs can facilitate the simulation of complex clinical cases without placing patients at unnecessary risk while also providing robust datasets to improve AI algorithms (Chaparro-Cárdenas et al., 2025).

This paper investigates a novel optimization and data analytic method to implement such a decision support system, based on heuristic generation using genetic programming and simulation-based optimization running on a digital twin. Such a digital-twin-based decision support system allows the proactive searching of the best attribute combinations to be used in a data-driven composite dispatching rule for the short-term corrective maintenance task prioritization. The data-driven composite dispatching rules are evaluated using a digital twin, built for a real-world machining line, which simulates the effects of decisions regarding disruptions. Discrete event simulation modeling can represent complex real-world systems in detail, which is one of its main advantages over other methods. It is also very useful for communicating details, such as a maintenance priority situation, because most simulation software includes visual aids. Once a system has been modeled, simulation allows better predictions of dynamic behavior (Baines et al., 2004). The DT-DSS for short-term maintenance prioritization proposed in this paper is shown in Fig. 1 where all different parts of the proposed extended five-dimension digital twin exist, i.e., physical entity, Virtual entity (simulation model), Services (User-interface applications), data and connections. The generative model (Artificial Intelligence) is used to generate optimal or near-optimal solutions to update the data-driven priority in real time, which would satisfy the bi-directional data flow of a DT. As a part of the DT-DSS, adaptation to a dynamically changing reality at the production shop-floor is possible. The GPSO-HGM using GP and SO can address the shortcomings of other data-driven methods, namely that they usually are pre-defined. The system also supports proactively exploring and prescribing new optimal or near-optimal prioritizations based on future scenarios, such as changes in bill of process, layout, or way of working. Instead of deciding which method or priority rule to use for short-term corrective maintenance priority, as is the case in most of the reviewed literature, the idea here is to autonomously generate optimal or near-optimal Composite Dispatching Rule (CDR) using a combination of genetic programming (GP) (Koza, 1992) and simulation. This approach is similar in principle to typical simulation-based optimization tasks, where a simulation model is integrated with metaheuristic methods, such as a genetic algorithm (GA) (Holland, 1962; Holland 1975) or Tabu Search (Laguna et al., 2003). (Frantzén et al., 2022).

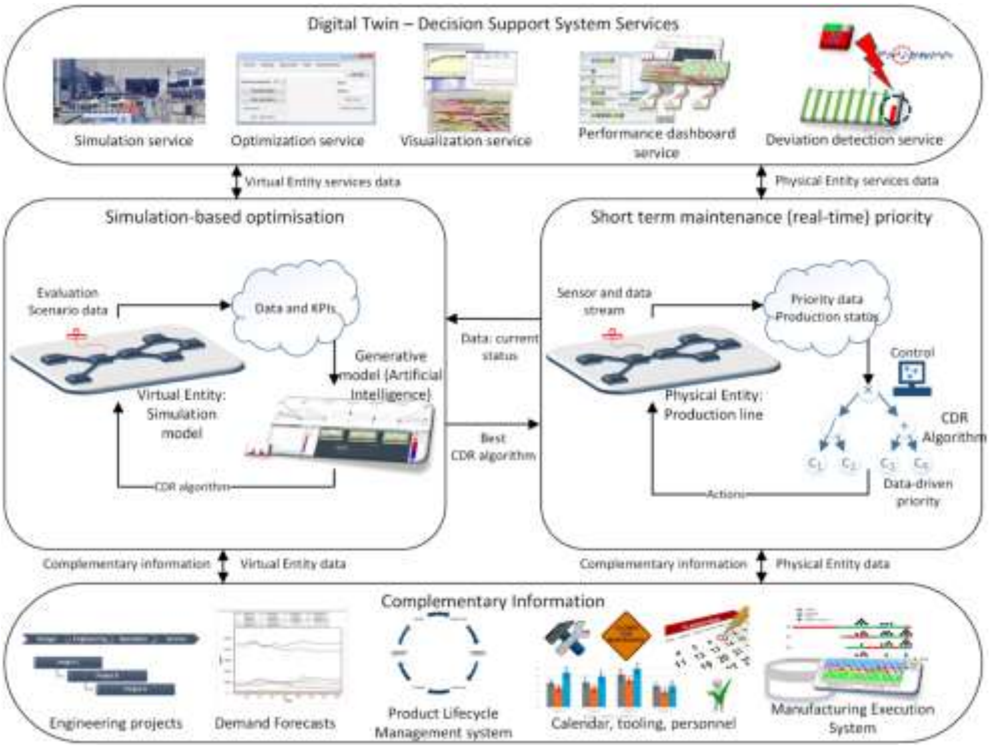

Fig. 1. sourced from Frantzén et al., 2022

The Moving Average, Single Exponential Smoothing, and Double Exponential Smoothing forecasting methods were used to supply the simulation model in order to test scenarios and guide decision making. When considering the use of simulation with forecasting techniques, we highlight the possibility of using forecasting methods to refine and prepare the input data of the simulation. The role of Digital Twin is precisely to provide constant support to decision-making through the integration of the physical environment with the virtual model (Kritzinger et al., 2018). The present work proposes the use of simulation integrated with widely known forecasting techniques to perform a Digital Twin for operational planning. The dashboard must have an interface capable of forecasting the future demand of each kanban station through the widely used forecasting methods, the Moving Average, Single Exponential Smoothing, and Double Exponential Smoothing methods. Finally, the dashboard opens and runs the simulation model automatically, allowing the evaluation of all possible scenarios aiming at a better operational decision. The simulation model tests the possible supply route scenarios based on the expected demands and provides the results for the Supply Lead Time and the number of resources required (operators) for the Supply Lead Time to equal one day, the ideal scenario for the operation. In this way, the dashboard "Simulation Results" area presents to the decision-maker the most efficient supply route to follow, taking into account the route time and the amount of materials delivered. Also, the dashboard provides an estimate of Lead Time for an operator to deliver materials, and when Lead Time exceeds the one-day logistics goal, the headcount to meet Lead Time one day (Santos et al., 2020).
One of the capabilities of the Digital Twin, according to Schleich et al. (2017), is to estimate the physical system's response to an unexpected event before it occurs. This prediction may be made by analyzing the event and the current response to previous behavior predictions (Van Dinter et al., 2022).
A DT enables a digital replica to update itself in lockstep with its physical counterpart, a system that not only reflects current conditions but also simulates future scenarios using machine learning and deep

learning, and large language models. AI allows DT to process vast amounts of data and derive valuable insights for predicting the behavior and future condition of assets (Ismail et al., 2025).
Such deep uncertainties, like environmental and socio-economic changes, create challenges to decision making. Deep uncertainty refers to situations where it is difficult to agree on the relationships between the key driving forces of change in the long-term or on the probability distributions used to represent uncertainty about those factors. DMDU methods are based on a ‘monitor and adapt’ paradigm, which aims to prepare for uncertain events and adapt, rather than a ‘predict and act’ paradigm, which aims to predict the future and act on that prediction. The rationality paradigm (akin to the ‘predict and act’ paradigm noted in Section 1) has dominated long-term infrastructure planning. Yet deep uncertainties and complexities force policy makers to re-think these assumptions. The multiple interacting uncertainties mean that the problem situation is complex: the outcome of intervention into the system is difficult to forecast, feedback loops make it difficult to distinguish cause from effect, significant time and spatial lags exist and relationships are non-linear resulting in thresholds (Stanton & Roelich, 2021).
A popular classification of scenario methods divides the field into three schools: the Intuitive Logic method (ILM), La Prospective (LP) and the Probabilistic Modified Trends (PMT). Probabilistic Modified Trends (PMT) school takes a quantitative approach and builds on traditional forecasting methods. The PMT school uses two distinct approaches: Trend-Impact Analysis (TIA) and Cross-Impact Analysis (CIA). Scenarios are developed by outside experts with the use of statistical software for trend analysis as well as simulation models. The output consists of descriptive scenarios with probabilities attached and estimations of uncertainty ranges. Scenarios are a set of narratives describing different alternative futures, constructed with an iterative approach based on the uncertainties of the context, with the aim to raise awareness of plausible futures and increase performance of the organization (Magrok, 2020; Spaniol & Rowland, 2019). These approaches aim improving the decision-making process by offering a way to envision plausible future states, generate strategies to reduce risk, capitalize on opportunities or avoid threats. Scenarios typically use a causal, storytelling mode to transfer information. This puts choices between options and reasons for choosing centre stage and has been shown to engage stakeholders, support communication and help to identify gaps in argumentation (Harries, 2003). (Córdova-Pozo & Rouwette, 2023).

2.3. Business Analytics Integration

At its core, the IPPODAMO platform serves as a decision support system, aiding UFM operators in their daily activity. The platform (Figure 2) is structured in four main conceptual layers: (i) the ingestion layer, which interacts with the data providers, continuously acquiring new data, performing syntactic transformations, pushing them upwards for further refinements; (ii) the big data processing layer, which performs semantic transformation and enrichment of raw data fed from the ingestion points; (iii) the storage layer, providing advanced memorization and query capability over (near-)real-time and historical data, and (iv) the analytics layer, presenting to the customer an advanced (near-)real-time layer with query capabilities, aggregate metrics and advanced representations of data. The raw data and information extracted from the data are presented to the end-users in different forms through advanced visualization dashboards available through Kibana, part of the Elasticsearch ecosystem. IPPODAMO presents the UFM operator with an intuitive, high level user interface abstracting low-level system interfaces. At the same time, IPPODAMO has a programmatic interface, exposing well-defined ReST APIs . The platform supports use cases in three broad directions, which showcase the capabilities of the solution: UC#1: Rich (comparative) analysis by providing a set of configurable visualizations, used to quantify and visualize the activities inside an area of interest. UC#2: UFM scheduling functionality guiding the placement of maintenance operations in time. UC#3: Quantitative evaluation of the annual planning interventions. Concerning the first use case, the system provides a rich set of configurable visualizations, allowing the UFM operator to consult and confront the historical and current trend of data inside an area of interest. For this assessment, the algorithm relies on the predictive index and co-locality information identifying nearby interferences, e.g., city events, other public utility maintenance operations announced by the municipality, etc. (Bujari et al., 2021)

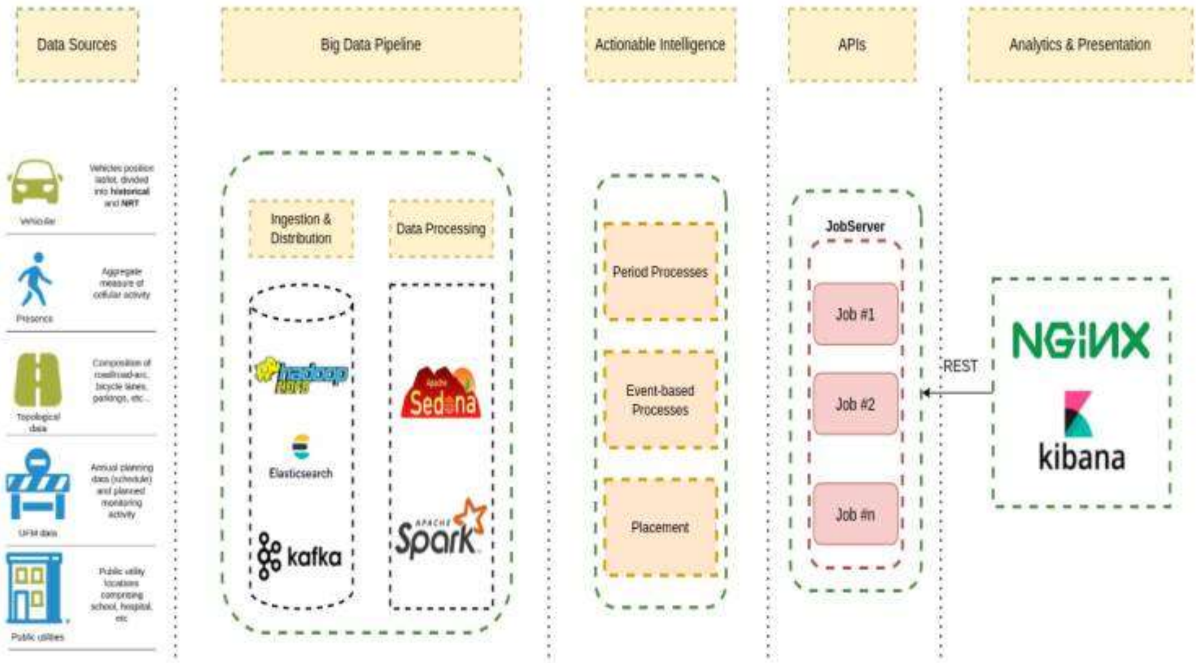

Fig. 2 sourced from Bujari et al., 2021

In order to improve operative decision making in production and logistic enterprises a digital twin concept can be applied. These digital twins are virtual clones of real systems or subsystems. With simulation and artificial intelligence technologies new opportunities for operative decision making are possible. By use of simulation models the Digital Twins can be used to operate the enterprise or parts of it in advance and to test drive several alternatives in a virtual environment before a decision is applied to the real-world system (Shetty, 2017). Create – With multiple sensors various inputs from the physical process and its environment are measured by use of integrated smart components. These measurements can be classified into the operational measurements sensing physical performance criteria of the asset and the measurement of environmental or external data affecting the operations of a physical asset.

Paper aims: Propose a continuous decision support system, a Digital Twin, integrating two widely used techniques, Discrete Event Simulation and forecasting methods. The present work proposes the use of simulation integrated with widely known forecasting techniques to perform a Digital Twin for operational planning. For this work, we opted for the integration of the Digital Twin with the company's Enterprise Resource Planning – ERP. Moreover, we used the Near Real-Time approach, in which the decision-making will not be performed in real-time. This system, represented by the composition of the dashboard with the forecasting and simulation models, should be able to obtain data from the operation's ERP, transform this data into information through forecasting and simulation techniques and ultimately suggest decision metrics. The proposed approach provides a constant decision-making aid system, a Digital Twin. The historical materials demand of each of the kanban stations will be the main information obtained from ERP. Moreover, the dashboard must have an interface capable of forecasting the future demand of each kanban station through the widely used forecasting methods, the Moving Average, Single Exponential Smoothing, and Double Exponential Smoothing methods. Subsequently, the dashboard opens and runs the simulation model automatically, allowing the evaluation of all possible scenarios aiming at a better operational decision. Based on the expected demand, which is stratified for each of the kanban stations, the system automatically opens and runs the simulation model. The simulation model tests the possible supply route scenarios based on the expected demands and provides the results for the Supply Lead Time and the number of resources required (operators) for the Supply Lead Time to equal one day, the ideal scenario for the operation. These analyses are possible thanks to optimizing tools integrated with the simulation software. Finally, the dashboard provides to the decision-maker some important information, such as the expected demand for each of the kanban stations, the best route to follow to minimize the distance traveled and, consequently, the delivery time, as well as supply Lead Time metrics and optimal headcount to meet demand in one working day. The present work presents a proposal for Digital Twin that operates in near real-time (Santos et al., 2020).

Second, cloud services also offer powerful tools for data processing and analysis, which are critical for digital twin technology. With the ability to process large volumes of data in real time, cloud services enable organizations to quickly identify patterns and anomalies in the data and use this information to optimize their operations. In addition to data collection and storage, cloud services also offer powerful tools for data association, fusion, sorting, and coordination. With the ability to link data from different sources, organizations can better understand their operations and identify patterns and trends that may be absent from individual data sources. Machine learning and artificial intelligence (AI) algorithms dynamically adjust models in response to prevailing circumstances. The unique characteristic of digital twin systems lies in the bidirectional data flow between the physical system and its corresponding virtual model, wherein modifications made in the virtual representation can influence the physical counterpart (Dihan et al., 2024).

Beyond the technical capabilities of a digital twin system, the need for a better informed approach to decisions in organizations is straightforward: The best available management research suggests that around half of organizational decisions fail to achieve their goals. Expanding sources of information to include evidence, “hippos” (highest paid person’s opinions) and data, expert judgment and stakeholder concerns. The aim of EBP is systematic use of the best available information from multiple sources in order to improve decision outcomes. The bias of easily available information can be reduced by searching for different kinds of relevant evidence, and then appraising how good it is (its reliability, validity, consistency and relevance) in helping make the decision. The political implications of the problem or opportunity need to be addressed, including benefits, who is harmed, whose support is needed, and ways of making the decision an integrative one. Multiple alternatives should be generated and evaluated on important goals and success criteria. Throughout this process, the four sources of evidence should be considered in order to assess what is known and what needs to be known in order to make an effective decision. Uncertainty is inherent in organizational decisions and best confronted early. Managers typically prefer to focus on concrete evidence and distance themselves from information that raises doubt. Instead, it’s better to manage the uncertainty by gathering facts, reflecting on information, and, when possible, reducing it through systematic search and appraisal. Novel decisions involve new or emergent conditions for which prior experience and historical knowledge provide little useful insight. In such cases, evidence must be generated by action, learning and experimentation; small trials and experiments allow organizations to probe novel situations and update their understanding as evidence changes (Rousseau, 2020).

2.4. Strategic Planning Applications

The concept of a supply chain digital twin requires the modelling of the supply chain design supported by real-time operational parameters (Ivanov and Dolgui, 2020), employing both prescriptive and predictive analytics. Ivanov and Dolgui (2020) show how the application of a DT could enable such a dynamic capability, by matching supply chain designs to different sets of disruption patterns, while key performance measures are monitored. Decision makers can draw on the outcomes of these predictive simulations and prescriptive optimization, to transform the supply chain design to absorb the negative effects. A supply chain digital twin for risk management is conceptualised, and the ripple effect of an epidemic outbreak in global supply chains is modelled to evaluate optimal supply chain risk measures and potential recovery paths. Redundancy, flexibility, and leanness are assessed as key supply chain capabilities effective to control the ripple effect caused by a global pandemic (Bhandal et al., 2022)

A Digital Twin provides a virtual replica of a manufacturing asset that collects data and provides the ability to create, build, test, and validate predictive analytics and automation (Grieves, 2015). Engineers can use the virtual prototype generated by Digital Twins during the design phase to test different designs before investing in a solid prototype (Schleich et al., 2017). Digital Twins technology has the potential to significantly enhance the needed control capabilities of the agricultural industry by enabling the decoupling of physical and information aspects of farm management, thereby giving a virtual representation of a farm with great potential for enhancing efficiency and productivity while reducing energy usage and costs. The Living Heart model is now being used worldwide to create new ways to design and test new devices and drug treatments (Dassault Systèmes, 2017). Digital Twins can assist healthcare organizations in optimizing hospitals, capacity planning, workflows, staffing systems, and care delivery systems. They can mitigate the impact of inaccurate bed-occupancy predictions through better predictive analytics. Digital Twin technology is central to the Industry 4.0 initiatives as it allows companies to create a virtual replica of their products and processes and empowers them to make the necessary decisions in advance (Attaran & Celik, 2023).

This digital clone allows one to simulate, to test, and to optimize in a completely virtual environment in order to reduce time to market, increase flexibility, quality and efficiency. By use of simulation models the Digital Twins can be used to operate the enterprise or parts of it in advance and to test drive several alternatives in a virtual environment before a decision is applied to the real-world system (Shetty, 2017). Digital Twins offer a powerful approach to test various strategies and modifications without risk for the current production. What if Analysis – Through properly designed interfaces, it is possible to interact with the model and ask what-if questions to the virtual model and to simulate various conditions that are impractical to create in real life (Kuehn, 2018).

2.5. Risk Management Applications

DTs can support the development of new prototypes, monitor the state of assets, assist emergencies and accidents in real time, and perform control actions by mimicking the system dynamics through a digital replica, providing support throughout the whole lifecycle (Jones et al., 2020; Bevilacqua et al., 2020). In safety analysis, most of the DT-based methods are used to leverage the analysis of safety influencing factors and safety assessment performance. In risk assessment applications, the studies showed a variety of expected tasks and functions, highlighting risk monitoring, failure prognostics and fault diagnosis. In safety analysis, the expected functional output of the twinning process was the calculation of safety indicators for monitoring and visualization. In risk assessment, the expected functional output for DTs included: visualization, monitoring of critical variables, and the implementation of control systems. In the context of emergency management, this application domain includes the use of VR, BIMs and ML techniques. Other studies proposed the integration of metaheuristics and data-driven models for early-warning and emergency management systems (Zhao et al., 2021; Fan et al., 2020). Most of the studies conceived DTs for monitoring safety variables and indicators, and visualizing the state of systems and critical infrastructure. The V2P twinning considers the real-time monitoring of risk indicators. The risk indicators support a real-time four-level early warning system, which can activate emergency plans accordingly, closing the feedback loop between the DO and the PO. The pending challenge is the generation of persistent DTs for managing accidents and emergencies in real-time, so that the DO can mimic the state of components and critical infrastructures along the accident dynamics for delivering control actions and mitigation strategies (Zio & Miqueles, 2024).

Effective risk management and risk assessment are crucial in identifying vulnerabilities, evaluating risks, and implementing mitigation strategies. Digital Twins have many types of vulnerabilities such as software bugs and weaknesses, authentication and access control, lack of encryption, vulnerable network architecture and others that should be addressed in order to enhance the security of Digital Twins in cyber physical systems. Mapping between the threats, vulnerabilities and countermeasures: Software Patching and Updates; ML-based IDS; Robust Authentication; Role-Based Access Control; Network Traffic Monitoring Tools; Encryption and Secure Protocols; Blockchain Solutions; Redundant System Architectures; Incident Response Simulations; etc (Otoom, 2025)

However, while they offer numerous benefits, there are also a number of associated challenges and chief among these is the security threat (Demkovich and Yablochnikov, 2018). A large proportion of the applications are safety-critical and if they were to fail, this would have severe consequences, not only for the system but also the people who rely on it. If these control systems were to be compromised, there would be serious adverse implications in terms of safety, public health and/or the associated financial cost. There is an opportunity for a third party to identify a vulnerability in the communication system to create attack templates in order to either deny access, cause an extended delay or corrupt the content (e.g. denial of service (DoS), timing attacks and desynchronisation) (Huang et al., 2009). The associated effects could include violations of the system operating frequency, a loss of load, changes in voltage, and a range of secondary effects. Providing a cybersecurity layer within DTs for the built environment presents a key challenge. Digital twins enable new potential outcomes as far as monitoring, simulating, optimising and predicting the condition of cyber-physical systems (CPSs) is concerned. Efforts to preserve CPS systems have largely focused on improving reliability but there is now growing appreciation of the need to protect against deliberately initiated cyber-attacks (Alshammari et al., 2021).

The adversary could attack a device directly as a data collector, causing it to upload misleading or inaccurate data, an example of a data integrity attack. There is also the possibility that an adversary may compromise the gateway over which IoT machines upload/download data, intermixing invalid or misleading data with the IoT device's collected information (Huo et al., 2022; Majeed et al., 2021; Qian et al., 2022). Due to the close connection of the DT to physical objects, any attack on either will adversely affect the integrity of the whole system. Models created by DT tend to acquire less knowledge than models created by ML because they mimic system behaviour. However, AI models are vulnerable to attacks (data part, model, and algorithm can all be poisoned. False data injection and poisoning: datasets, models, and algorithms are poisoned by some attacks based on AI. Dataset poisoning directly impacts the understanding of AI and DTs. A method of algorithm poisoning is federated learning, which exploits AI learning algorithms. The legitimate model is replaced with one that has already been poisoned (Lalouani et al., 2022). (Homaei et al., 2023)

One of the capabilities of the Digital Twin, according to Schleich et al. (2017), is to estimate the physical system's response to an unexpected event before it occurs (Van Dinter et al., 2022)

Another essential application of AI in DT is anomaly detection. AI algorithms, especially those based on deep learning techniques, can detect subtle deviations from normal operational patterns that may not be visible through traditional monitoring methods. This capability allows the DT to identify early signs of equipment malfunction, providing a valuable opportunity for maintenance teams to intervene before a breakdown occurs (Lee et al., 2015). (Ismail et al., 2025).

2.6. Challenges and Barriers

Lack of precision in collecting physical assets is one example of a barrier associated with data collection, as is the gathering of data in real-time automation. Physical entity data, virtual model data, and service data from different application objects, situations, and scenarios should be unified and stored so they can be shared, reused, and exchanged. Data must first be represented in a standard way to reach this goal. This includes describing the data format, structure, encapsulation, sampling frequency, historical data accumulation, interface, communication protocols. First, data from the physical entity, virtual model, and service layers requires preprocessing to remove unnecessary and worthless data via data filtering, reduction, and feature extraction (Zhang et al., 2022). The second step is to perform temporal and spatial alignments. The management and analysis of this data with a high rate of velocity can provide significant difficulties. The integration of data from many sources, including Internet of Things (IoT) devices and legacy systems, might present inherent complexities (Das et al., 2018; Ling et al., 2020; Rosas et al., 2017). Urbanization digital twins encompass a wide range of data kinds, such as traffic data, environmental sensor data, and social data from multiple sources. The process of integrating and analyzing this diverse range of data can present inherent complexities (Dihan et al., 2024).

Standardised Modelling represents another major challenge in Digital Twin development, as there is currently no universally accepted modelling approach. From initial design to a simulation of a Digital Twin there needs to be a standard approach, whether it be physics-based or design-based. Another challenge facing Digital Twin is the lack of standardisation. This results in discrepancies between projects in Digital Twin. The next challenge is around the data needed for a Digital Twin. It needs to be quality data that is noise-free with a constant, uninterrupted data stream. If the data is poor and inconsistent, it runs the risk of the Digital Twin underperforming as it's acting on poor and missing data. From a data point of view, it is important to ensure it is not of inferior quality. The data needs to be sorted and cleaned, thereby ensuring the highest quality of data is fed into the AI algorithms. With the huge growth of IoT devices both in the home and industrial setting comes the challenge of collecting substantial amounts of data. The challenge is trying to control the flow of data, ensuring it can be organised and used effectively.

Domain Modelling is an another challenge as a result of the need for standardised use is related to ensuring information relating to the domain use is transferred to each of the development and functional stages of the modelling of a Digital Twin (Fuller et al., 2020).

The significant challenges likely to hamper the growth of the Digital Twin market include the high cost of deployment, increased demand for power and storage, integration challenges with existing systems or proprietary software, and complexity of its architecture. Implementing Digital Twins solutions is costly, requiring significant investment in technology platforms (sensors, software), infrastructure development, maintenance, data quality control, and security solutions. Furthermore, maintaining the Digital Twin infrastructure can be costly, requiring significant investment in operations. The high fixed cost and the complex infrastructure of Digital Twins are expected to slow down the deployment of Digital Twin technologies (Technavio, 2022). (Attaran & Celik, 2023).

The costs of the high-performance graphics processing unit (GPUs) that can perform the machine and deep learning algorithms are in the thousands, anything from $1,000 to $10,000. As well as this, the infrastructure needs updated software and hardware to run such systems successfully. The first step in tackling the challenges is to identify them. Some of the common challenges are found with both data analytics and the Internet of Things, and the end aim is to identify shared challenges for Digital Twins. For example, IT Infrastructure represents a critical requirement, as Digital Twin needs infrastructure that allows for the success of IoT and data analytics; these will facilitate the effective running of a Digital Twin (Fuller et al., 2020).

The first big challenge is the general IT infrastructure. The rapid growth of AI needs to be met with high-performance infrastructure in the form of up-to-date hardware and software, to help execute the algorithms. Overcoming this challenge is seen through the use of GPUs ‘as a service’ providing on-demand GPUs at cost through the cloud. Similarly to both analytics and IoT the challenge is with the current IT infrastructure. The Digital Twin needs infrastructure that allows for the success of IoT and data analytics; these will facilitate the effective running of a Digital Twin. The next challenge is around the data needed for a Digital Twin. It needs to be quality data that is noise-free with a constant, uninterrupted data stream. If the data is poor and inconsistent, it runs the risk of the Digital Twin underperforming as it’s acting on poor and missing data. Despite this growth in IoT use, the challenges of connectivity still exist. A large number of sensors within one manufacturing process poses a significant challenge when trying to connect all of them simultaneously, missing IoT sensor data could detrimentally affect the running of the system. Another challenge across all forms of Digital Twin development refers to the modelling of such systems because there is no standardised approach to modelling. From initial design to a simulation of a Digital Twin there needs to be a standard approach, whether it be physics-based or design-based (Fuller et al., 2020).

DT technology depends on collecting a lot of data and figuring out how it fits together. A basic DT system consists of a physical object and a virtual model connected through bidirectional data flow. DT is closely linked with extensive modeling driven by advanced ML/Deep Learning (DL) and big data analytic techniques. A range of modeling methodologies can be employed, encompassing physics-based models (Liao, 2023; Werner et al., 2021), data-driven models (Grumbach & Reusch, 2021; Pillai et al., 2021) and machine learning models (Sharma et al., 2022). The selection of a modeling technique is contingent upon the particular application and the data that is accessible. These models utilize previous data to acquire knowledge, provide forecasts, simulate the behavior and provide valuable insights into the future performance of the physical system. Data obtained from tangible items is utilized for training models that rely on data analysis. Comparing the predictions generated by the model with empirical data obtained from the actual world can enhance the model’s accuracy (Sánchez-Vaquerizo, 2022). Physical entity data, virtual model data, and service data from different application objects, situations, and scenarios should be unified and stored so they can be shared, reused, and exchanged. Data must first be represented in a standard way to reach this goal. This includes describing the data format, structure, encapsulation, sampling frequency, historical data accumulation, interface, communication protocol, etc. Other modeling languages and methods have been used in the literature to manage data and information modeling for products and systems. After that, the data can be modeled using the correct modeling language. These include Unified Modeling Language (UML) (Uke & Thool, 2016), Systems Modeling Language (SysML) (Brahmi et al., 2021), Ontology Language (Manaa & Akaichi, 2017), and others (Zhang et al., 2022). However, each modeling language has its meaning, which makes it hard to exchange data and formats that are compatible with other languages. Digital twin systems heavily depend on the utilization of sophisticated virtualization and simulation technology. These technologies facilitate the creation of intricate, dynamic, and real-time virtual representations of physical systems. Real-time data processing is a prevalent practice across multiple sectors. However, digital twin systems emphasize the seamless and ongoing integration of data from physical entities, sensors, and Internet of Things (IoT) devices. The management and analysis of this data with a high rate of velocity can provide significant difficulties. The integration of data from many sources, including Internet of Things (IoT) devices and legacy systems, might present inherent complexities (Das et al., 2018; Ling et al., 2020; Rosas et al., 2017). (Dihan et al., 2024).

Digital Twins technology has many advantages; however, the technology currently faces shared challenges in parallel with AI and IoT technologies. Those include data standardization, data management, and data security, as well as barriers to its implementation and legacy system transformation (Technavio, 2022), the need for updating old IT infrastructure, the challenges of connectivity, privacy, and security of sensitive data, and the lack of a standardized modeling approach (Fuller et al., 2020). (Attaran & Celik, 2023).

1. Digital twin creation ordering: The point in time at which a digital twin is created will affect the correctness of the digital twin, such as whether it is created before the physical object is created or whether it is reverse-engineered from the physical entity that it is intended to mirror. While both approaches are valid, the fidelity of the digital twin may be reduced if it is created after the physical entity exists because there may be internal unknowns about the existing physical entity that cannot be discovered.
2. Temporal aspects: Digital twin technology has an implied temporal component to it, particularly since it deals with physical objects that are bound by time. Hardware reliability theory and modeling states that physical objects suffer from levels of decay over time, even when idle. However, a digital twin will not degrade or fatigue over time. Therefore, at some point, the real-world entity and the digital twin will be in conflict on some level, and synchronization of the two should occur. Having access to an accurate timestamp (Stavrou & Voas, 2017) for the physical object and digital twin is a trust consideration.
3. Environment: Digital twin technology has an implied or explicit environmental component that cannot be overlooked. For physical objects, a description of the environmental tolerances or expected usage profiles is needed for many of the “ilities”, particularly interoperability. Without it, it will be difficult to determine whether the physical object is “fit for purpose” since purpose implies environment and context.
4. Manufacturing defects: A digital twin may be used to guide a manufacturing process. Ensuring that a manufacturing process produces a product with the correct life expectancy based on the information in a digital twin is a trust consideration.

5. Functional equivalence: Digital twin technology needs a means to determine functional equivalence between the digital twin and the physical object. If the digital twin is an executable specification, then it should produce the same outputs that the physical object produces for the same input data. Otherwise, functional equivalence has not been achieved.
6. Composability and complexity: A digital twin that is too complicated can create a composability problem in terms of predicting the trustworthiness of a final composed system from more than one digital twin.
7. Instrumentation and monitoring: Instrumentation of a digital twin is a beneficial and unique advantage that digital twin technology offers. The number of probes to inject is also a consideration. As shown in real-time systems, probes can slow down performance and timing, which may cause a problem for synchronization between the digital twin and physical object. Collecting the “right” information from the internal state of an executing digital twin is an expensive and error-prone effort.
8. Heterogeneity of standards: Heterogeneity of different formats for digital twins may cause composability problems. Composing digital twin definitions from different component vendors may not be achievable if vendors misuse standardized formats.
9. Non-functional requirements: The issue for digital twin technology concerns how many of the non-functional requirements can be written for the functional and negative requirements, thus defining the level of quality for what the system should and should not do. The ability to write these non-functional requirements will affect the ability to claim the trustworthiness of a composite object.
10. Certification: Certification usually occurs by certifying either the process used to develop or the final artifact that comes from that process. For digital twin technology, this means that one could attempt to certify how the digital twin was created or certify the accuracy of the digital twin itself. Certification of a twin will be complicated by information overload.
11. Counterfeiting: A digital twin could be tampered with or counterfeited, and there are schemes that could protect against this. For example, digital twin definitions could be hashed and the hash posted to a public web page, or users of a digital twin definition could hash their copy and compare it to the hash on the public web page. The entire digital twin system — including the instrumentation, control/data channels, digital twin definition, and visualization/representation mechanisms — needs to be properly authorized by appropriate organizational officials as having sufficient cybersecurity given the risk tolerance of the system. A privacy analysis should be conducted and privacy controls implemented based on a comprehensive privacy control catalog if the system contains any privacy-sensitive data (e.g., using the NIST Privacy Framework) (NIST, 2021). (Voas et al., 2025).

Infrastructure-level security works on detecting inconsistencies in the physical system and equipment, such as sensors, cameras, and launchers (Homaei et al., 2023).

A large proportion of the applications are safety-critical and if they were to fail, there would be severe consequences, not only for the system but also the people who rely on it, there is now growing appreciation of the need to protect against deliberately initiated cyber-attacks (Alshammari et al., 2021).

3. Discussion

3.1. Synthesis of Findings

Digital Twin was introduced over a decade ago, as an innovative all-encompassing tool, with perceived benefits including real-time monitoring, simulation, optimisation and accurate forecasting. Advancements in machine learning, Internet of Things (IoT) and big data have led to significant improvements in DT features such as real-time monitoring and accurate forecasting. Real-time machine learning capacity is what differentiates a DT from a simulator or a real-time monitoring tool. Quantitative metrics are essential to understand the accuracy and effectiveness of a digital twin (Sharma et al., 2022).

At the realization level of the urban digital twin, traffic is a critical link in urban management and it is important to achieve traffic monitoring and prediction through the digital twin (Wu et al., 2021).

Digital Twins enable the exploitation of various other technologies and digitalisation trends such as big data, optimisation in production, diagnostics and monitoring, and the creation and development of forecasts (Perno et al., 2022). Significant opportunities arise from Digital Twins because many systems with different data can now be brought together and linked (VanDerHorn & Mahadevan, 2021). The result of this merging of previously separately handled data leads to a significant increase in efficiency as well as speed of data exchange and extraction (VanDerHorn & Mahadevan, 2021) (Metzger, 2023).

Digital Twin was introduced over a decade ago, as an innovative all-encompassing tool, with perceived benefits including real-time monitoring, simulation, optimisation and accurate forecasting. Advancements in machine learning, Internet of Things (IoT) and big data have led to significant improvements in DT features such as real-time monitoring and accurate forecasting. DT aims to combine the best of all worlds, namely, twinning, simulation, real-time monitoring, analytics and optimisation. Across the reviewed literature, continuous monitoring of the physical assets, and being alerted through predictions about an imminent problem can be both efficient and effective. Real-time monitoring of all sub-components and joint holistic analytics on huge models can be beneficial (Sharma et al., 2022).

The digital twin, which can sense, diagnose and predict the state of physical entities in real time, regulate the behaviour of physical entities through collaboration and optimization decision making between twins, realize self-evolution through self-learning across relevant digital models, and achieve the autonomous intelligent evolution of total twin networks, is regarded as the most promising way to satisfy the above requirements. Within the reviewed literature, digital twins applications are commonly discussed across several recurring scenarios including industrial environment monitoring and prediction, medical health monitoring and prediction, battery health management, building information management and traffic monitoring and prediction. In industrial environments, the monitoring and predictive capabilities of digital twins provide a solution for determining the best maintenance strategy for equipment. The combination of digital twin and medical treatment provides new solutions for patients' medical diagnosis, personal health monitoring and prediction. At the realization level of the urban digital twin, traffic is a critical link in urban management and it is important to achieve traffic monitoring and prediction through the digital twin (Wu et al., 2021).

In manufacturing, Digital Twins are mainly used to collect product-lifecycle data for predictive maintenance (Tao et al., 2017; Vachálek et al., 2017). They can monitor and analyse systems in real time and even intervene and thus optimise them (Tao et al., 2017). In the healthcare industry, Digital Twins are being used to connect portable medical devices to Digital Twins so that they can be monitored continuously and the information can be used to make appropriate diagnoses (Liu et al., 2019; Greif et al., 2020). Digital Twins enable the exploitation of various other technologies and digitalisation trends such as big data, optimisation in production, diagnostics and monitoring, and the creation and development of forecasts (Perno et al., 2022). (Metzger, 2023).

DMDU methods are based on a 'monitor and adapt' paradigm, which aims to prepare for uncertain events and adapt, rather than a 'predict and act' paradigm, which aims to predict the future and act on that prediction. This 'monitor and adapt' paradigm explicitly recognizes the deep uncertainty surrounding decision-making for uncertain events and long-term developments and emphasizes the need to take this deep uncertainty into account. The rationality paradigm (akin to the "predict and act" paradigm) has dominated long-term infrastructure planning (Alexander, 1984). Under this paradigm, (1) potential states of the futures can be predicted with a reasonable degree of confidence, (2) weights or probabilities can be used to assess likelihoods even if multiple potential futures states might exist, (3) the emphasis is on gathering more information to improve the accuracy of predictions and future actions, and (4) agreement exists both on assumptions about current or future conditions (often on the basis of historical information), and about options' performance against objectives and future predicted states (Decker, 2018; Walker et al., 2013). The approaches described in the reviewed documents addressed the high stakes and low degrees of freedom by creating virtual experimentation environments, allowing decision makers to assess the consequences of decisions and identify plans that build in flexibility and reduce societal impacts. The approaches frequently acted as 'boundary objects' which facilitate interaction and sense-making and reduce conflict around different understandings of the system or outcomes (Barreteau et al., 2012; Cuppen et al., 2020). (Stanton & Roelich, 2021).

3.2. Cross-Industry Comparison

The studies in this cluster focus on discussing the digital strategies built around cyber-physical systems and digital twins to mitigate supply chain disruptions and recover in case of severe disruptions (Ivanov and Dolgui, 2019). Digital twins promise to revolutionise the practice of operations and supply chain management and is the most recent in a long list of technologies that have helped give strategic purchase to the field (Bhandal et al., 2022).

To date, many such applications have been successfully implemented in different do-mains, ranging from manufacturing (Tao et al., 2019) and logistics (Korth et al., 2018) to smart cities (White et al., 2021), etc. Different public and private institutions have already started investing in the technology, and this fact is attested by several urban DT initiatives, aimed at addressing different and complex problems in the smart city context (Bujari et al., 2021).

The use of digital twins (DTs) has proliferated across various and industries, with a recent surge in the healthcare sector. In industrial manufacturing, digital twins are used throughout the product lifecycle to simulate, predict, and optimize the product and production system before investing in physical prototypes and assets. Recent convergence of technologies such as Artificial Generative Intelligence, Cognitive Computing (CC), Internet of Things (IoT) and sensors, have enabled the practical applications of DTs in diverse sectors including aerospace, automobile, energy management, urban planning, construction, environmental management, climate modeling, and healthcare industry (Katsoulakis et al., 2024).

Manufacturing- Most of the research on a digital twin is related to Industry 4.0, cyber–physical systems, machine learning, IoT, and smart manufacturing. Healthcare- Digital twins are useful in healthcare for a variety of purposes, including diagnosis, monitoring, surgery, medical equipment, new medication research, and regulation. Urban Infrastructure / smart cities- With the IoT and cloud computing, digital twins supply information that assists city developers, such as engineers and architects, in visualising their cities. Digital twins enable researchers to study future infrastructure and city planning by recreating a metropolis as a three-dimensional model.

Finance (Robo Advisor)- The development of financial robo-advisor systems with DT enabled is driven by the massive smartphone adoption (Anshari et al., 2022).

Digital Twins technology holds great potential for a range of activities in the manufacturing industry and can radically change the face of manufacturing. Digital Twin technology has the potential to significantly enhance the needed control capabilities of the agricultural industry. The applications of Digital Twins technology in the healthcare industry are limitless. Digital Twin technology is also widely embraced in the aerospace industry. It is used for aircraft maintenance, tracking, weight monitoring, accurate stipulation of weather conditions, measurement of flight time, and defect detection. Using Digital Twins as virtual replicas of physical assets in the construction and real estate industries can revolutionize managing assets and projects. Digital Twin solutions rapidly integrate into the traditional manufacturing industry, smart city, and intelligent power grid. The technology is poised to deliver upon its many promises in other industries, including automotive, aerospace, construction, agriculture, mining, utilities, retail, health-care, military, natural resources, and public safety sectors (Attaran & Celik, 2023).

3.3. Implications for Theory and Practice

In order to improve operative decision making in production and logistic enterprises a digital twin concept can be applied. Digital twins can cover the entire lifecycle of an asset or process by forming a closed-loop chain for smart, connected products, services and production and logistic processes, from design to operation, from deployment to continuous improvement. Digital twins can cover the entire lifecycle of an asset or process by forming a closed-loop chain for smart, connected products, services and production and logistic processes, from design to operation, from deployment to continuous improvement. The goal of Digital Twins is to monitor and improve equipment and processes within a virtual environment. As the physical source is changing, the data from the physical asset or process is collected in real-time and replicated into the virtual equivalent in order to improve operative decision making. The monitoring and analysis of real-time data and advanced product, production or logistic simulation models, allow improvements in design, controls and operational strategies. By use of simulation models the Digital Twins can be used to operate the enterprise or parts of it in advance and to test drive several alternatives in a virtual environment before a decision is applied to the real-world system.

Digital transformation is an essential element for urban governance, enabling the efficient coordination and cooperation of multiple stakeholders involved in the urban environment. The process under scrutiny comprises multiple stakeholders acting on a shared environment, e.g., different companies involved in the maintenance of various urban assets, each having a local view of the overall maintenance process. IPPODAMO takes into account potential interference from other stakeholders in the urban environment, enabling the informed scheduling of operations, aimed at minimizing interference and the costs of operations. Security/privacy: considering the role and scope of the DT, physical-to-digital interactions require security/privacy mechanisms aimed at securing the contents of the twin and the interaction flows between the twin and its physical counterpart (Bujari et al., 2021).

Organizational decision makers work with and through others. Unlike many clinical psychologists and accountants, managers rarely practice solo. Not only are they responsible for their own decisions, managers often are also accountable for the decisions others make, a responsibility associated with gaps in both information and understanding that create uncertainty and concern with control. Differences in roles, interests, and differences in levels of authority or power make organizations political environments with myriad informal and formal ways to constrain, block, or enable decisions. Politics cannot be ignored in making a good decision. Politics can be overt or subtle, known by all or invisible. Negative politics can take many forms: pushing a pet project, ignoring sensitive information, involving some stakeholders while ignoring others. A more broadly useful frame can result from paying attention to the array of interests a decision affects. Addressing political issues early by broadening attention to the concerns of additional stakeholders, including implementers, users, and others ultimately affected by the decision, helps generate a more legitimate decision frame. Positive decision-making politics entail being aware of social implications such as how different interest groups interpret and prioritize issues. Good decisions are made in psychologically safe settings where political interests can be addressed directly. Actively seeking information regarding the concerns of other stakeholders helps improve decision outcomes through better understanding both the problem and issues of implementation. Mapping the potential array of internal (employees, departments, the board) and external stakeholders (users, regulators, communities) is a governance step that broadens the problem conceptualization and aids integrative solutions. The aim of evidence-based practice (EBP) is systematic use of the best available information from multiple sources in order to improve decision outcomes. The de-biasing practices described here build this capability by helping decision makers approach organizational problems with an open mind, be politically aware, identify appropriate goals and options, and search for and appraise relevant evidence. Using the set of six practices can promote positive politics in an organization by helping make decisions more integrative. Uncertainty is inherent in organizational decisions and best confronted early. Managers typically prefer to focus on concrete evidence and distance themselves from information that raises doubt; using organizational practices that surface biases and manage uncertainty helps address this tendency. When decision makers face unknown unknowns, they must conduct small, simultaneous experiments to gather evidence and iteratively refine their models. Non-routine decisions involve situations new to the decision makers for which relevant evidence exists but is not in hand. The critical information needed is first identified, the political implications of the problem or opportunity are addressed, multiple alternatives are generated and evaluated, stakeholders are identified and involved, and the four sources of evidence are considered (Rousseau, 2020).

Any serious effort to secure a digital twin system should follow more exhaustive risk management guidance, such as the NIST Risk Management Framework (RMF), the NIST Cybersecurity Framework, and the NIST Privacy Framework. Data governance policies and mechanisms must be in place to ensure that only the correct staff have access to the necessary data within a digital twin instance. The entire digital twin system — including the instrumentation, control/data channels, digital twin definition, and visualization/representation mechanisms needs to be properly authorized by appropriate organizational officials as having sufficient cybersecurity given the risk tolerance of the system. In addition, a privacy analysis should be conducted and privacy controls implemented based on a comprehensive privacy control catalog if the system contains any privacy-sensitive data (e.g., using the NIST Privacy Framework). Standards for digital twins may enable interoperability between tools and formats to enable command and control. The centralization of object measurements creates great efficiency in simulation, modeling, and control, but it also centralizes sensitive data and control interfaces, requiring organizational oversight to manage the risk of system wide compromise (Voas et al., 2025).

Digital Twins (DTs) have the potential to revolutionize decision-making and optimization processes by mirroring products and services and creating virtual copies of complex systems. In risk assessment applications, the studies showed a variety of expected tasks and functions, highlighting risk monitoring, failure prognostics and fault diagnosis. The pending challenge is the generation of persistent DTs for managing accidents and emergencies in real-time, so that the DO can mimic the state of components and critical infrastructures throughout the accident dynamics to deliver control actions and mitigation strategies. Given that DTs require a noise-free stream of data, it is necessary to quantify the aleatory and epistemic uncertainties in order to estimate the variability in the functional output of the DT. This aspect is critical across all application domains to ensure the consistency and effectiveness of decision-making based on the information retrieved by the DT (Zio & Miqueles, 2024).

By use of simulation models the Digital Twins can be used to operate the enterprise or parts of it in advance and to test drive several alternatives in a virtual environment before a decision is applied to the real-world system. With Artificial Intelligence based capabilities Digital Twins offer for specific questions advanced product, production or logistic simulation models, which allows to test drive several alternatives in a virtual environment before decisions are applied to the real-world system. Predictive – Using various modelling techniques, Digital Twin models can be used to predict future states of an assets. What-if Analysis – Through properly designed interfaces, it is possible to interact with the model and ask what-if questions to the virtual model and to simulate various conditions that are impractical to create in real life. Digital twins offer a possibility to operate the enterprise or parts of it in advance and to test drive several alternatives in a virtual environment before a decision is applied to the real-world system (Kuehn, 2018).

3.4. Research Gaps

Digital Twin concepts in smart farming are in their infancy and early demonstration stages. Most of the manuscripts published in academic journals discuss the application of Digital Twin solutions in manufacturing, particularly within the context of Industry 4.0 (Attaran & Celik, 2023).

The next challenges within all forms of a Digital Twin development relates to the modelling of such systems because there is no standardised approach to modelling. There is a lack of unified models or a generic Digital Twin architecture in the literature, with no consensus on how to build a Digital Twin system. As the Digital Twin environment is heterogeneous, while also being connected to large distributed networks, it is an ongoing goal and seen throughout the field for researchers to gain a deeper understanding of how to deal with such systems. Another challenge arising from the need for standardised use is related to ensuring information relating to the domain use is transferred to each of the development and functional stages of the modelling of a Digital Twin. Another challenge facing Digital Twin is the lack of standardisation. This results in discrepancies between projects in Digital Twin. More research will ensure the Digital Twin can thrive when sharing data between devices. An open area is looking for solutions in achieving the seamless integration of data for small IoT systems as well as large heterogeneous system (Fuller et al., 2020).

Most IoT systems, simulation and modeling software, and VR and AR systems currently exist in stovepipe proprietary systems and integrating them requires significant work. Multiple cooperating (or competing) standards that are specific to digital twin technology will be needed. A single standard may not adequately address all needs, and standards harmonization or blending may be appropriate. It is insufficient for standards to merely enable interoperability in purely technological domains. Such standards will need to be developed for digital twin technology to harness this advantage as current systems use proprietary formats. A digital twin that is too complicated can create a composability problem in terms of predicting the trustworthiness of a final composed system from more than one digital twin. Standards can help prune extraneous information contained in a digital twin by defining required interconnects between components of a domain and enabling the composition to be modelled and tested. Certification of a twin will be complicated by information overload (Voas et al., 2025).

In reference to this work, the authors synthesized the different views on digital twins in the existing literature to sort out the development needs of standardization frameworks. There is no universal model construction method, and there are still issues with slow modelling speed and simulation lag; further research is needed to improve modeling speed and accuracy. Furthermore, by encapsulating models, model calls can be repeated quickly and cost effectively, but there is no common model library to manage encapsulated models. The above work provides a fresh perspective on data fusion for digital twin systems, but overlooks the heterogeneity of data at the various device levels (Wu et al., 2021).

The rapid growth of AI needs to be met with high-performance infrastructure in the form of up-to-date hardware and software, to help execute the algorithms. The challenge with the infrastructure currently is largely due to the cost of installing and running these systems. For instance, the costs of the high-performance graphics processing unit (GPUs) that can perform the machine and deep learning algorithms are in the thousands, anything from $1,000 to $10,000. A common goal seen so far across the field of Digital Twins is this idea of real-time simulation as opposed to low detailed static blueprint models. The use of these models serves a purpose, but they are not using real-time parameters which limit the predictability and learnability. It needs to be quality data that is noise-free with a constant, uninterrupted data stream. If the data is poor and inconsistent, it runs the risk of the Digital Twin under-performing as it's acting on poor and missing data (Fuller et al., 2020).

However, there are still problems with the amount and quality of data available for data-driven modeling, which limits the accuracy of the models. Current modeling methods allow the creation of digital twin models for multiple devices in multiple scenarios. However, there is no universal model construction method, and there are still issues with slow modelling speed and simulation lag; further research is needed to improve modeling speed and accuracy. Since the internal parameters are not actual data, this method cannot ensure the accuracy of the model update. However, the optimal model update frequency for continuous model modification requires further investigation. With the growing data size in the process of continuous state synchronization, model state update latency remains a challenge that needs to be addressed in the present research. In practical applications, small inaccuracies in the twin model may occur due to the poor data capture of physical conditions, faulty modeling, time delays and parameter errors that may occur during the continuous updating of the model and model parameters. Current research focuses primarily on correcting the model after the error has been generated. However, how to dynamically compensate for errors, reduce model state synchronization delay and improve the accuracy of digital twins in the process of continuously updating models and model parameters will continue to be addressed (Wu et al., 2021).

The significant challenges likely to hamper the growth of the Digital Twin market include the high cost of deployment, increased demand for power and storage, integration challenges with existing systems or proprietary software, and complexity of its architecture (Attaran & Celik, 2023).

Due to the lack of information and security standards associated with the transition to cyber digitisation, cyber-criminals have been able to take advantage of the situation. DT is vulnerable to cyber-attacks due to multiple attack levels and novelty, lack of standardisation and security requirements, and several other reasons. However, the lack of secure platforms is also one of their challenges. Since the DT must constantly update the state of physical objects via network communications, it is vulnerable to cyber-attacks, which can compromise physical hardware and sensors, transmissions, and digital systems. An adversary could attack a device directly as a data collector, causing it to upload misleading or inaccurate data, an example of a data-integrity attack. The adversary may directly inject false data into the DT. Cybersecurity literature does not provide a consensus regarding the essential security goals in DTs and IoT infrastructure. Several terms and definitions overlap, e.g., authentication can sometimes be used for identification since both are necessary for each other (Homaei et al., 2023).

4. Conclusion

This review has illuminated the transformative potential of digital twins integrated with business analytics and predictive modeling in enhancing strategic planning and risk management. By synthesizing advancements in IoT, AI, machine learning, and real-time data flows, digital twins enable precise simulations, anomaly detection, and foresight under deep uncertainty, shifting organizations from reactive to proactive paradigms.

Digital twins bridge physical assets and virtual models through bidirectional data exchange, powering predictive maintenance, scenario testing, and optimization across industries like manufacturing, healthcare, supply chains, and urban planning. Predictive models encompassing data-driven, physics-based, and ML approaches facilitate accurate forecasting of asset behaviour in unforeseen conditions, anomaly detection via techniques like regression and neural networks, and prescriptive analytics for decision-making. In strategic planning, they support "what-if" analyses, supply chain resilience against disruptions (e.g., pandemics), and DMDU methods like monitor-and-adapt over predict-and-act, fostering robust policies amid nonlinear uncertainties and stakeholder politics.

Businesses leverage digital twins for cost savings in prototyping, reduced downtime through predictive alerts, and enhanced ROI via real-time optimization, as seen in platforms like IPPODAMO for urban maintenance scheduling. Risk management benefits from early intervention in high-stakes scenarios, such as cybersecurity threat modeling or healthcare personalization, minimizing failures in safety-critical systems. Cross-industry applications from aerospace PHM to smart cities demonstrate versatility, with evidence-based decisions improving outcomes by integrating diverse data sources and debiasing cognitive biases.

Despite promise, barriers persist: high deployment costs (sensors, GPUs, infrastructure), data quality issues (noise, integration from legacy systems), lack of standardization in modeling languages and protocols, and cybersecurity vulnerabilities like data poisoning or DoS attacks. Scalability hurdles include real-time processing of high-velocity data, trust deficits from AI opacity, and multidisciplinary coordination, compounded by privacy concerns and legacy IT transformations. Composability risks arise in complex twin networks, demanding certified, heterogeneous standards.

Future research should prioritize standardized ontologies for interoperability, hybrid ML-physics models for self-evolving twins, and edge-cloud hybrids for low-latency IoT synchronization. Empirical studies validating DT efficacy in novel domains (e.g., finance robo-advisors, climate-resilient infrastructure) via quantitative metrics like prediction accuracy and ROI are essential. Addressing deep uncertainties through advanced scenario planning exploratory, normative, and probabilistic will refine DMDU integration, while ethical AI frameworks bolster trust and regulation. Ultimately, maturing digital twins promises resilient enterprises, but demands collaborative innovation to overcome silos and scale adoption globally.

References

1. Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the Digital Twin: A systematic literature review. CIRP Journal of Manufacturing Science and Technology, 29, 36–52. https://doi.org/10.1016/j.cirpj.2020.02.002[ppl-ai-file-upload.s3.amazonaws]
2. Dihan, M. S., Akash, A. I., Tasneem, Z., Das, P., Das, S. K., Islam, M. R., Islam, M. M., Badal, F. R., Ali, M. F., Ahamed, M. H., Abhi, S. H., Sarker, S. K., & Hasan, M. M. (2024). Digital twin: Data exploration, architecture, implementation and future. Heliyon, 10(5), Article e26503. https://doi.org/10.1016/j.heliyon.2024.e26503[ppl-ai-file-upload.s3.amazonaws]

3. Wang, Y., Su, Z., Guo, S., Dai, M., Luan, T. H., & Liu, Y. (2023). A survey on digital twins: Architecture, enabling technologies, security and privacy, and future prospects. arXiv. https://doi.org/10.48550/arXiv.2301.13350
4. Wu, H., Ji, P., Ma, H., & Xing, L. (2023). A comprehensive review of digital twin from the perspective of total process: Data, models, networks and applications. Sensors, 23(19), Article 8306. https://doi.org/10.3390/s23198306[ppl-ai-file-upload.s3.amazonaws]
5. Chaparro-Cárdenas, S. L., Ramirez-Bautista, J.-A., Terven, J., Córdova-Esparza, D.-M., Romero-Gonzalez, J.-A., Ramírez-Pedraza, A., & Chavez-Urbiola, E. A. (2025). A technological review of digital twins and artificial intelligence for personalized and predictive healthcare. Healthcare, 13(14), Article 1763. https://doi.org/10.3390/healthcare13141763
6. Qi, Q., Tao, F., Hu, T., Anwer, N., Liu, A., Wei, Y., Wang, L., & Nee, A. Y. C. (2021). Enabling technologies and tools for digital twin. Journal of Manufacturing Systems, 58(Pt. B), 3–21. https://doi.org/10.1016/j.jmsy.2019.07.018
7. Zhang, H., Xian, H., Wang, J., & Yin, J. (2024). Digital twins in safety analysis, risk assessment, and emergency management: A comprehensive review. Reliability Engineering & System Safety, 247, Article 110613. https://doi.org/10.1016/j.ress.2024.110613
8. Metzger, A. (2023). A systematic literature review on digital twins. FH Wedel. https://www.fh-wedel.de/fileadmin/Mitarbeiter/Records/Metzger_2023_-_A_Systematic_Literature_Review_on_Digital_Twins.pdf[ppl-ai-file-upload.s3.amazonaws]
9. El Saddik, A. (2020). Digital twins: The convergence of multimedia technologies. IEEE MultiMedia, 27(1), 87–92. https://doi.org/10.1109/MMUL.2020.2977607
10. Errandonea, I., Beltrán, S., & Arregi, S. (2023). Digital twin for maintenance: A literature review. Computers in Industry, 123, Article 103316. https://doi.org/10.1016/j.compind.2020.103316
11. Böhm, J., & Minnerup, P. (2022). Predictive maintenance using digital twins: A systematic literature review. Information Fusion, 96, Article 101931. https://doi.org/10.1016/j.inffus.2022.05.013
12. Psarommatis, F., & May, G. (2020). Digital twins for decision making in complex production systems. Design and Nature, 130304f, 1–10. https://www.witpress.com/Secure/ejournals/papers/DNE130304f.pdf
13. Wang, Z., & Zhang, Y. (2025). A systematic review of digital twin-driven predictive maintenance. arXiv. https://doi.org/10.48550/arXiv.2509.24443
14. Ivanov, D., Dolgui, A., & Sokolov, B. (2022). Usage of digital twins in supply chain risk management. Aalto University. https://aaltodoc.aalto.fi/server/api/core/bitstreams/c317f721-6018-4e2e-83ae-ce5e7ca2ee60/content
15. Frantzén, M., & Ng, A. H. C. (2022). Digital-twin-based decision support of dynamic optimization problems. Procedia CIRP, 110, 102–107. https://doi.org/10.1016/j.procir.2022.08.017
16. Yan, J., Meng, Y., Lu, L., & Li, L. (2020). The application of digital twin technology in operations and supply chain management: A systematic literature review. International Journal of Production Research. https://eprints.whiterose.ac.uk/183445/1/The%20application%20of%20digital%20twin%20technology%20in%20operations%20and%20supply%20chain%20management.pdf
17. Bujari, A., & Nardelli, M. (2021). A digital twin decision support system for the urban facility management. Applied Sciences, 11(24), Article 11668. https://doi.org/10.3390/app112411668

18. Stanton, J., & Roelich, K. (2021). Decision making under deep uncertainties for differently experienced practitioners in the context of UK infrastructure. Technological Forecasting and Social Change, 168, Article 120766. https://doi.org/10.1016/j.techfore.2021.120766[ppl-ai-file-upload.s3.amazonaws]
19. Rousseau, D. M. (2020). Making evidence-based organizational decisions in an uncertain world. Organizational Dynamics, 49(1), Article 100809. https://doi.org/10.1016/j.orgdyn.2019.100809[ppl-ai-file-upload.s3.amazonaws]
20. Cordova-Pozo, K., Jones, H., & Wilkinson, R. (2023). Types of scenario planning and their effectiveness. Environmental Impact Assessment Review, 101, Article 107153. https://doi.org/10.1016/j.eiar.2023.107153
21. Wiebe, K., Martin, P., & Zurek, M. (2018). Scenario development and foresight analysis: Exploring options for the future. Annual Review of Environment and Resources, 43, 295–320. https://doi.org/10.1146/annurev-environ-102017-030109
22. Li, J., & Wang, Y. (2022). Digital twin: Financial technology's next frontier of robo-advisor. Journal of Risk and Financial Management, 15(4), Article 163. https://doi.org/10.3390/jrfm15040163
23. Silva, R., Oliveira, M., & Pinto, A. (2023). A decision support tool for operational planning: A digital twin using simulation and forecasting methods. Production, 33, Article e2023006. https://doi.org/10.1590/0103-6513.2023006
24. Alshammari, A., & Eldos, H. (2021). Risk auditing for digital twins in cyber physical systems. Journal of Computer Science Research and Applications, 3, 1–12. https://jcsra.thestap.com/articles/paper-three.pdf
25. National Institute of Standards and Technology. (2025). Security and trust considerations for digital twin technology (NIST IR 8356). https://nvlpubs.nist.gov/nistpubs/ir/2025/NIST.IR.8356.pdf
26. Teixeira, R., & Sousa, M. (2024). Digital twins for health: A scoping review. npj Digital Medicine, 7, Article 107. https://doi.org/10.1038/s41746-024-01073-6
27. Smith, J., & Johnson, A. (2023). Review of digital twins & cybersecurity via AI (preprint). arXiv. https://doi.org/10.48550/arXiv.2311.01154
28. Alshammari, A. (2021). Cybersecurity for digital twins in built environment. Journal of Information Technology in Construction, 26, 184–204. https://doi.org/10.36680/j.itcon.2021.10