Chapter 2:

Digital Twin Capabilities: From Decision Support to Organizational Value

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Abstract

Digital Twin (DT) technology offers an advanced information infrastructure capable of supporting decision-making processes by integrating digital representations of physical systems with real-time data, analytics, prediction, and simulation capabilities. However, the existing literature largely focuses on the technical architectures and sectoral applications of DT; the mechanisms by which technological capabilities are transformed into decision support capacity and organizational value are not sufficiently explained. This study develops a conceptual model to address this gap by examining digital twin-based decision support from a Management Information Systems (MIS) perspective. Design Science Research (DSR) provides the design logic for the model development process, while Task–Technology Fit (TTF) is used as the theoretical perspective explaining the fit between digital twin capabilities and the requirements of decision tasks. Based on an integrative synthesis of the literature, Information Quality, Real-Time Visibility, Predictive Capability, and Simulation Capability are conceptualized as four analytically synthesized DT capability dimensions relevant to decision support. The proposed model suggests that these capabilities can support Decision Quality through Decision Support Capability, initiating a cascading value-creation process that extends through Organizational Agility to Organizational Performance. The study thus presents an integrated MIS framework in which organizational value emerges through a value-creation process that transforms technological capabilities into usable decision support aligned with decision-task requirements and subsequently into organizational outcomes.

Keywords: digital twin, decision support, management information systems, task-technology fit, design science research

1. Introduction

To accelerate digital transformation, businesses must collect the large volumes of heterogeneous data generated by physical systems, operations, and business processes and convert them into meaningful information for decision-making. In complex systems where real-time data flow is critical, information infrastructures that go beyond typical information systems' static reporting and monitoring functions are required. In this context, the Digital Twin (DT) has emerged as a technological method that maintains the data link between a physical thing, process, or system and its digital representation. While the breadth and application methods of the DT concept differ, the literature regards the connection between physical and digital aspects, data sharing, and modeling capability as fundamental qualities (Fuller et al., 2020; Tao et al., 2019; VanDerHorn & Mahadevan, 2021).

The evolution of the digital twin has expanded into diverse application areas, driven by advancements in technologies such as the Internet of Things (IoT), artificial intelligence, advanced analytics, and cyber-physical systems. These developments have broadened DT from a digital representation of a physical system into an infrastructure integrating real-time data use, modeling, analysis, prediction, and simulation (Dihan et al., 2024; Huang et al., 2021; Minerva et al., 2020). Accordingly, the organizational relevance of DT also derives from the potential to use the resulting information in operational and managerial processes.

One important consequence of this development is the growing research interest in the relationship between Digital Twin and Decision Support Systems (DSS). DT-based decision support approaches can combine up-to-date data from physical systems with analytical models, simulations, and predictive assessments, enabling decision-makers to evaluate current conditions and examine possible alternatives. For example, Zhou et al. (2021) combined digital twinning and analytics within a decision support system designed to support resilient port operations, while Meierhofer et al. (2021) examined the role of DT characteristics in developing decision support services in industrial ecosystems. From a

decision support perspective, these studies position DT as an infrastructure that integrates data provision with multiple information-processing and analytical functions.

Nevertheless, a substantial portion of the existing literature focuses on DT applications in specific sectors, their architectures, or their technical characteristics. Studies conducted in areas such as manufacturing, construction, healthcare, and urban systems have demonstrated that DT can be applied to a wide variety of problems (Caprari et al., 2022; Corral-Acero et al., 2020; Sacks et al., 2020). However, beyond this application literature, there is still a need for an integrative information systems perspective that explains which functions the different capabilities of the digital twin assume in the decision support process and through what mechanisms these functions are linked to organizational outcomes. In other words, while there is a significant amount of information in the literature regarding the question of How can the digital twin be implemented? the question of Which capabilities of the digital twin are transformed into decision support capabilities, and how do these capabilities support the organizational value creation process? requires a more holistic conceptualization.

This gap necessitates approaching the digital twin from an information systems (IS) perspective. According to the IS literature, the ability to create information, analyze it, and assist decision-making processes is a critical challenge for businesses dealing with uncertainty and complexity. Studies on analytical information processing capacities show that processing various data sources and transforming them into analytical outputs might help with decision-making processes (Naseer et al., 2021). Similarly, the literature on the application of artificial intelligence (AI) in business demonstrates that AI skills can be linked to many organizational activities such as information generation, process improvement, and decision support (Enholm et al., 2022). From this standpoint, the study conceptualizes the digital twin as an information systems capability through which diverse information-processing resources can be brought into decision-making processes. This conceptual perspective is developed

through a synthesis of the existing literature and does not represent an established classification.

The integration of AI and advanced analytics into DT broadens the reach of this information processing capability. Studies on the integration of AI into DT contexts show that machine learning and other artificial intelligence approaches can be utilized to predict, analyze, and model system behavior (Dai et al., 2025; Kreuzer et al., 2024). However, these technological advances do not guarantee higher-quality organizational decisions. Their decision-support value depends on how the information and analytical outputs generated by DT are incorporated into decision processes. The proposed model therefore incorporates decision support capability and decision quality as intermediary mechanisms between technology and organizational outcomes.

As a result, this study creates a conceptual model to describe the connection between digital twin capabilities and organizational outcomes. The model aims to explain how a digital twin's information and analytical capabilities, which are addressed under the headings of Information Quality, Real-Time Visibility, Predictive Capability, and Simulation Capability, can be linked to decision quality via decision support capability, which can then be linked to organizational agility and, finally, to organizational performance. By combining the digital twin, DSS, and information systems literatures, the framework traces organizational value through the transformation of technological capabilities into decision-making processes.

2. Literature Review

2.1. The Conceptual Foundations of Digital Twin

Although the DT literature initially developed around the idea of representing a physical asset, process, or system in a digital environment, the scope of the concept has expanded considerably over time. Recent literature has expanded this view, describing DT as a structure that connects physical-system data with digital models for monitoring, analysis, and management (Barricelli et al., 2019; Fuller et al., 2020; VanDerHorn

& Mahadevan, 2021). Nevertheless, there is still no complete conceptual consensus in the literature regarding the definition, scope, and technical characteristics of DT. In their higher-level review synthesizing systematic literature reviews across different domains, Wooley et al. (2026) show that DT research varies considerably in terms of sectors, application purposes, and technologies employed. This diversity points to a multidimensional view of DT that integrates data, modeling, and system-integration elements.

The expanding scope of DT is also associated with the prominence of different technical and information-processing characteristics depending on the intended use. Barricelli et al. (2019) demonstrate that the concept has been approached differently across disciplines. Similarly, Boje et al. (2020) discuss the requirements for developing a semantic construction digital twin approach, while Sacks et al. (2020) relate the DT concept to construction information systems and emphasize the importance of integrating data and information sources. These studies indicate that the role of DT is not limited to representing a physical system in a digital environment; linking this representation with different information sources and systems broadens the scope of DT applications.

From this perspective, DT architectures depend on sustained data exchange and technical connections between physical systems and their digital representations. Minerva et al. (2020) examine DTs for IoT by reviewing technological specifications, sample projects, and architectural models; their perspective sees sensor connectivity within communication infrastructure and data processing components as critical components in the operation of such a technology architecture with a corresponding digital representation. Botín-Sanabria et al. (2022) provide a broader account of the evolution of DT technology throughout multiple application domains as well as a description of certain technical and application issues encountered. When this literature is considered holistically, it is possible to conclude that DT's data generation potential includes collecting raw data from physical systems and developing more context around these systems by associating incoming data with digital models and other information sources to develop meaning. The

information-infrastructure character of DT therefore encompasses both the technological connection between data collection and processing and the digital representation of physical-system states.

Recent studies reveal that as DT has become increasingly institutionalized across several industries, it has grown beyond its original application in engineering. Bae et al. (2025) conduct a thorough analysis of DT technology, applications, and challenges across several industries and sectors, demonstrating significant disparities in application approaches. Hasan and Crawford (2025) discuss the progression of digital twin technology from research-oriented development toward broader adoption in real-world business settings. These findings suggest that considering DT as a technical solution limited to a single sector may be overly restrictive. This stage is also where the conceptual interpretation used in this work from an information systems perspective comes into play: DT may be considered as a digital infrastructure that allows data acquired from physical systems to be used in various information-processing activities.

Another direction in the evolution of DT is the combination of digital representations with more complex analytical and cognitive processes. Bacnak et al. (2026) thoroughly investigate the Cognitive Digital Twin method and review studies aimed at broadening the DT concept to include cognitive skills. This development reflects a broader trend in DT research to build analytical and inferential capacities rather than just portraying the current state of a physical system. Adding cognitive or AI-enabled capabilities to DT does not, however, turn it into a decision-making system. Such advances may instead expand its capacity to generate information and analytical outputs for decision processes. Maintaining the conceptual separation between DT and decision support systems is thus critical.

For the purposes of this study, the significance of DT is precisely that distinction. DT is positioned not as an autonomous decision-making mechanism but as an information infrastructure that allows continuously updated data about a physical system to be linked with digital models and

used for monitoring, analysis, modeling, and, when appropriate, scenario evaluation. This positioning allows the study to examine the information and analytical inputs that DT can contribute to decision-making processes without associating its technical qualities with decision support capability. As a result, DT's increasing position as an information infrastructure serves as the foundation for the link between digital twins and decision support systems, which is explored in the next section.

2.2. Digital Twins and Decision Support

The importance of digital twins for decision support lies not simply in representing a physical system in a digital environment but in their ability to transform that representation into information that can be used in decision-making processes. Therefore, the relationship between DT and DSS should be considered within a broader framework than the technical integration of two technologies. From a decision support perspective, the central issue is how data obtained from physical systems are processed according to the requirements of a decision problem, how relevant information is selected, and how this information is transformed into outputs that enable decision-makers to evaluate alternatives. The view that information collection and processing activities in decision-intensive processes are interdependent with the decision itself also supports this relationship (Voorberg et al., 2021).

Applications reported in the literature show that DT can be incorporated into decision support processes at different levels. In urban facility management, manufacturing, energy, supply chains, and other complex systems, DT has been used to integrate data from physical systems, assess current conditions, and analyze possible intervention options (Bujari et al., 2021; Ghanbari & Nissinen, 2025; Li et al., 2024). A common feature of these studies is that across these applications, DT primarily functions as an information and analytical environment that provides a more comprehensive representation of the decision problem while leaving decision authority with the decision-maker. The role of DT in decision support should therefore be evaluated less in terms of its

individual technical components and more in terms of how these components connect to the decision-making process.

The scope of this relationship is expanding as analytical and learning-based methods are incorporated into DT architectures. Methods such as artificial intelligence, machine learning, optimization, and reinforcement learning can enable DT to move beyond reflecting the current state of a system and support decision-making by evaluating the potential consequences of different conditions or interventions (Mo et al., 2025; Orlova, 2025). Similarly, interconnected digital twins can contribute to shared situational awareness among different actors and support decision coordination (Schink et al., 2026). DT-based decision support can therefore extend beyond operational decisions concerning a single asset and provide greater capacity for coordination and evaluation in more complex and interconnected systems.

However, more data and more advanced analytical capabilities alone do not necessarily translate into higher-quality decision support. The ability of the decision-maker to identify what information is needed, understand the analytical results generated, and translate them into action is also crucial for the effectiveness of decision support. Studies on the importance of features such as interpretability, justifiability, and actionability in decision support show that it is not sufficient for analytical outputs to be merely technically correct (Coussement & Benoit, 2021). In this respect, the high-volume, real-time data generation capacity of decision support only creates value when this data is transformed into meaningful information relevant to the decision problem.

Nevertheless, the existing literature mostly examines the contribution of DT to decision support through specific applications or technological mechanisms. Some studies focus on data integration and real-time system visibility, while others concentrate on analytical mechanisms such as simulation, artificial intelligence, learning, or optimization. Although these studies reveal the contribution of DT to decision-making processes from different perspectives, there are a limited number of studies that explain, from a holistic information systems

perspective, the mechanisms through which the technological capabilities of DT are transformed into decision support capacity. The more important gap, therefore, concerns a systematic explanation of the capabilities and information-processing mechanisms through which DT generates decision support.

This study addresses the gap by framing the relationship between DT and DSS as a transformation process through which technological capabilities are translated into decision-support capabilities. The elements identified across these literature streams—data, visibility, analytics, prediction, and simulation—serve as empirical and conceptual inputs for the framework rather than as an established taxonomy of DT capabilities. Accordingly, the conceptualization of digital twin capabilities developed in the next section is positioned as a structure grounded in the existing literature but systematically organized in this study from a management information systems (MIS) perspective.

2.3. AI, Analytics, and the Expansion of Decision Support

The development of digital twins for decision support is increasingly associated with their integration with artificial intelligence, data analytics, simulation, and optimization techniques. However, incorporating AI into a digital twin architecture does not, in itself, imply an advanced decision support capability. What matters is the type of analytical outputs into which these technologies transform the data generated or integrated by the digital twin and how these outputs can be used in decision-making processes. Accordingly, AI and analytical techniques are treated as mechanisms that extend the information-processing and decision-support potential of DT rather than as defining components of DT itself.

The literature on information systems indicates that the organizational worth of artificial intelligence cannot be solely defined by its technological efficacy. Enholm et al. (2022) associate the establishment of commercial value through AI applications with not just technological

capabilities but also organizational processes and contextual usage. Applied to digital twins, this perspective shifts attention from predictive accuracy and technical functionality toward the conversion of DT-generated data into actionable insights for decision-making.

Studies on the integration of models, data, and AI, along with discussions on digital twins, also support this development. Wu et al. (2020) claim that when models, data, and artificial intelligence are combined for battery digital twins, this combination can jointly support analytical functions and intelligent management processes. He and Bai (2021) point out the importance of synchronizing data, modeling, simulation capability, and analytics in their investigation of digital twins in sustainable smart manufacturing. Within this setting, AI can extend the virtual representation by enabling more sophisticated analytical techniques in addition to automating analytical tasks.

A relevant distinction is that between predictive analytics and prescriptive decision support. Wissuchek and Zschech (2025) review prescriptive analytics systems from an information systems perspective, emphasizing the analytical processes involved in evaluating potential courses of action. This distinction is particularly relevant to digital twins. Predictive outputs indicate what may occur, whereas prescriptive analytics connects such outputs with the assessment of possible courses of action.

One application of this development is the integration of physics-based digital twins with simulation and optimization. Keshvarinia et al. (2025) demonstrate how a simulation-enhanced digital model can represent current system conditions while also providing a platform for evaluating alternative decision strategies through data-driven optimization. Similarly, Lian and Zhang (2025) integrate digital twins with a multi-criteria decision-making approach for a comprehensive assessment of many choice factors concurrently in the context of predictive maintenance. These applications illustrate how digital twin outputs can inform the evaluation of decision alternatives.

Integrating artificial intelligence into digital twins can extend their adaptive and learning capabilities. Mo et al. (2025) present a self-adaptive decision-making framework for industrial robots, whereas Orlova (2025) looks into reinforcement learning-based decision support within a digital twin management system. These studies demonstrate the integration of learning mechanisms with dynamic digital twin systems. These learning functions can inform decisions without necessarily transferring decision authority to the technology.

The literature suggests that artificial intelligence, analytics, simulation, and optimization can improve digital twins for use in decision-making processes. The common theme in these studies is that these technologies lack inherent decision support capabilities; instead, they permit the study of data generated by the digital twin, enable future predictions, and evaluate alternatives. The following section uses this distinction to clarify the theoretical positioning of the proposed framework.

2.4. Research Gap and Theoretical Positioning

A comprehensive review of the literature points to three key research gaps in explaining the relationship between digital twins and decision support systems. The first gap is conceptual. Despite the rapid expansion of the digital twin literature, there is no complete consensus on the definition, architecture, scope, and evolving functions of the concept. Wooley et al. (2026) reveal the conceptual and application-related diversity in digital twin research by comparing systematic reviews conducted in different sectors. Bacnak et al. (2026), on the other hand, consider the emergence of the cognitive digital twin approach as an indicator of the expanding scope of digital twins with more advanced analytical and cognitive functions. This situation necessitates clarifying not only "what a digital twin is" but also "what functions it can provide" in terms of organizational information and decision-making processes.

The second gap is mechanistic. As discussed in Section 2.2, studies across application domains have examined the use of digital twins for decision support. Li et al. (2024), Yin et al. (2025), Liang et al. (2025), and Keshvarinia et al. (2025) integrate digital twins with analytical, simulation, optimization, or decision-making approaches in different decision problems. However, these studies mostly focus on solving specific application problems. Therefore, the common mechanisms through which the technological capabilities provided by digital twins are transformed into decision support capacity have not yet been sufficiently explained within a comparable MIS framework across applications.

The third gap lies in the perspective of information systems and organizational values. While a significant portion of digital twin research develops along the axes of engineering, manufacturing, modeling, simulation, and technical architecture, the literature on decision support systems focuses on information use, analytical capabilities, decision tasks, and user requirements. Onwujekwe and Weistroffer (2025) demonstrate that decision support systems are increasingly integrated with artificial intelligence and machine learning (ML), and this development strengthens the trend toward intelligent decision support systems. However, a clear theoretical framework is needed to understand how this advanced decision support approach can be integrated with the continuously updated physical-digital representations of digital twins and how this integration affects organizational decision-making capacity.

The study responds to these gaps by conceptualizing the digital twin as an information infrastructure capable of extending the information-generation and information-processing capacity of decision support processes, while decision authority remains outside the technology itself. From this perspective, the central question is not whether a digital twin makes decisions but how the technological capabilities provided by a digital twin are transformed into decision support capabilities and through which mechanisms this transformation occurs.

Accordingly, the relationship between digital twins and decision support capability is conceptualized through the integrated effect of multiple functional dimensions derived from the literature. The full scope and conceptual justification of these dimensions are discussed in detail in Section 3. Thus, no predetermined taxonomy of DT capabilities is assumed at this stage; instead, the underlying problem to be addressed through the literature synthesis in the following section is established.

Theoretically, the study draws on two complementary perspectives. Design Science Research (DSR) makes it possible to approach the research problem as one of developing a conceptual solution by integrating knowledge and relationships that are dispersed across the existing literature. Task–Technology Fit (TTF), meanwhile, is used to explain the role of alignment between the technological capabilities provided by digital twins and the requirements of decision tasks in enabling these capabilities to create value in decision-making processes. In this way, the study moves away from the assumption that the mere presence of technology generates performance and develops a framework in which technological capabilities can be transformed into decision-support capabilities through their fit with decision-task requirements.

The study is conceptual in scope: it integrates relationships dispersed across the DT and decision-support literatures to develop a conceptual model and associated design knowledge, without undertaking empirical hypothesis testing or measurement-model development.

3. Theoretical Foundation and Conceptual Model Development

3.1. Theoretical Foundation: Design Science Research and Task–Technology Fit

The conceptual framework of this study complementarily utilizes DSR and TTF approaches to explain how digital twin-based decision support can be structured. DSR provides the design rationale for

developing a conceptual model for the problem identified in the literature, while TTF provides the theoretical perspective explaining under what conditions digital twin capabilities become meaningful for decision support. Therefore, the two approaches perform different but complementary functions in the model.

DSR provides an approach to information systems research that centers on the development of useful artifacts, models, or methods in response to identified problems (Hevner et al., 2004). Peffers et al. (2007) structure this process into six stages: problem identification and motivation, definition of the objectives for a solution, design and development, demonstration, evaluation, and communication. In this study, these stages are not applied as a complete empirical DSR process but are used as a design logic guiding the development of the conceptual model. At the problem identification stage, the fragmented treatment of the relationships among technological capabilities, decision support, and organizational outcomes in the digital twin literature is identified as the central problem. The objective of the solution is to develop an explanatory decision support framework that integrates these relationships. At the design and development stage, the literature synthesis is used to construct the following structure: Digital Twin Capabilities → Decision Support Capability → Decision Quality → Organizational Agility → Organizational Performance. The components of the model and the relationships among them are conceptually justified through comparison with the existing literature; however, the study does not claim to conduct an empirical demonstration or evaluation of the artifact. Accordingly, the demonstration and evaluation stages defined by Peffers et al. (2007) are considered beyond the scope of the present study and remain to be addressed through future empirical testing of the proposed model. The communication stage is addressed through the presentation of the conceptual model and its implications in this study.

The TTF perspective addresses a different issue within the model. According to Goodhue and Thompson (1995), technological characteristics alone are insufficient to explain the contribution of technology to performance; the fit between these characteristics and the

requirements of the task must also be considered. In this study, "task" refers to the information and analytical requirements of a decision task; "technology" refers to the technological and analytical capabilities provided by the digital twin; and "fit" refers to the extent to which these capabilities meet the requirements of the relevant decision task.

The study's conceptual structure explicitly highlights this alignment. Decision tasks requiring reliable and usable information are associated with information quality; tasks requiring a timely understanding of the current state of the system with real-time visibility; tasks requiring the assessment of future conditions with predictive capability; and tasks requiring the comparison of the potential consequences of alternative interventions with simulation capabilities. Fit therefore represents the degree of alignment between the requirements of a particular decision task and the relevant technological capability; it is not treated as a separate DT capability. Consequently, the same DT capability is not expected to provide the same level of decision support across different decision tasks.

Task–technology fit and decision support capability do not represent the same conceptual construct. Fit explains the alignment between the requirements of a decision task and the technological capabilities of the digital twin. Decision Support Capability, by contrast, is conceptualized in the literature synthesis of this study as a higher-order mechanism that explains how these technological capabilities can be used to support decision functions such as understanding the current situation, assessing predictions, and comparing alternatives. Thus, the role of TTF in this study is not to derive decision support capability directly as a component of the theory but to explain why the transition from digital twin capabilities to decision support capability depends on task–technology alignment.

DSR and TTF are therefore employed together, but at different analytical levels. DSR provides the design logic underlying the development of the proposed conceptual model, whereas TTF contributes to the theoretical explanation of the Digital Twin Capabilities → Decision Support Capability relationship within the model. The

resulting framework therefore specifies a gradual value-creation mechanism beginning with task-aligned technological capabilities and extending through decision support to organizational outcomes.

3.2. Digital Twin Capabilities: Information Quality, Real-Time Visibility, Predictive and Simulation Capabilities

The decision-support value of digital twins extends beyond the digital representation of physical systems. Their significance lies in the ability of this representation to bring together different data and model sources and create an information and analytical environment that can be used in decision-making processes. However, there is no single, widely accepted dimensional structure of digital twin capabilities in the literature. Therefore, in this study, information quality, real-time visibility, predictive capability, and simulation capability are used as an analytical synthesis of DT characteristics that have been addressed in different ways in the literature, viewed from a decision support perspective. These dimensions represent analytical components of the proposed conceptual model and are not intended as a standardized classification of DT capabilities.

Information Quality. The first dimension relates to integrating data from different sources to create a usable information base for decision-making processes. Malaibari et al. (2024) address the digital twin from a data management perspective, emphasizing the importance of data collection, integration, and management in DT structures. Ouedraogo et al. (2025) relate DT data management to the processes of data collection, processing, storage, integration, and sharing, while Alcaraz et al. (2025) focus on secure data sharing between different digital twin communities. Based on these findings, information quality is considered in this study as an analytical dimension representing the ability to transform data in the DT environment into usable and meaningful information for decision-making purposes.

Real-Time Visibility. The second dimension is the ability to monitor the current state of the physical system in real-time. Alonso et al. (2024) demonstrate that integrating IoT, big data, and other data sources with digital twin architecture can improve the flow of information between physical and digital environments. From a broader perspective, Yang et al. (2026) argue that digital twins are evolving into decision infrastructures that support continuous data exchange between physical and digital environments. In this context, real-time visibility combines high-frequency data generation with the decision-maker's ability to obtain an up-to-date view of system conditions at the time a decision is made.

Predictive Capability. The third dimension concerns the ability to generate predictions about future conditions based on the current state of the system. Weingram et al. (2025) examine the integration of digital twins with machine learning and scientific applications, demonstrating how DTs are expanding through data-driven learning and modeling functions. Abbasgholizadeh Rahimi et al. (2025), meanwhile, examine an AI-enabled digital twin approach in the context of clinical decision-making and show how AI-supported DT structures can be integrated with predictive and decision-making processes. In this study, artificial intelligence is not treated as an independent DT capability but as an analytical mechanism that can enable prediction. Predictive capability, therefore, refers to the ability to generate predictions about future system states or possible outcomes.

Simulation Capability. The fourth dimension refers to the ability to examine alternative conditions and interventions in a digital environment before they are implemented in the physical system. Madni et al. (2019) show that digital twins can enable the modeling of physical system behavior and the examination of different conditions within a model-based systems engineering context. Rasheed et al. (2020) emphasize the importance of modeling for analyzing system behavior, while Walton et al. (2024) associate a DT approach that integrates virtual, physical, and prescriptive analytical components with adaptive real-time decision-making. Similarly, dos Santos et al. (2022) systematically examine the use of discrete-event and agent-based simulation approaches for decision

support in the digital twin context, highlighting the role of simulation in evaluating alternative system behavior s. Within this framework, simulation capability is defined as the capacity to evaluate the potential consequences of alternative conditions or interventions in a digital environment before their physical implementation.

These four dimensions represent complementary technological capabilities that can be associated with different decision-task requirements from a TTF perspective. Decision tasks requiring reliable and usable information are associated with information quality; those requiring a timely understanding of the current situation with real-time visibility; those requiring the assessment of future conditions with predictive capability; and those requiring the comparison of the consequences of alternative interventions with simulation capabilities. Here, fit refers to the extent to which the relevant DT capability can meet the information and analytical requirements of a particular decision task. From a TTF perspective, these capabilities become relevant to decision support when they are meaningfully aligned with the information and analytical requirements of the decision task. This transformation is addressed in the following section through the concept of decision support capability.

3.3. Decision Support Capability

To explain the contribution of digital twins to decision-making processes, it is necessary to conceptually distinguish between the technical and analytical capabilities of a digital twin and the use of these capabilities in decision-making problems. Information Quality, Real-Time Visibility, Predictive Capability, and Simulation Capability can provide important information and analytical resources for decision-making; however, the presence of these capabilities alone does not mean that decision support has been achieved. As discussed in the preceding sections from a TTF perspective, the value of technological capabilities for decision support depends on their fit with the information and analytical requirements of the decision task. In this study, Decision Support Capability is conceptualized as an integrative mechanism through which DT-based

information and analytical resources become usable for specific decision tasks; it is conceptually distinct from task–technology fit itself.

The fundamental challenge for decision support systems is to transform data and analytical outputs into insights relevant to the decision-maker. Phillips-Wren et al. (2021) discuss the role of data and analytics in generating more profound insights and decision support by integrating the relationships between business intelligence, analytics, and decision support systems. In the DT context, this places emphasis on the usability of operational data and analytical outputs for specific decision problems.

This transformation is primarily important for assessing the current situation and understanding the decision problem. The digital twin's ability to integrate different data sources and make the system state visible can contribute to a more comprehensive assessment of the decision-making environment by the decision-maker. West et al. (2021) demonstrate the potential of digital twins to support decision-making processes, while Gálvez del Postigo Gallego et al. (2025) systematically examine decision support within digital twins. In this respect, DT capabilities can support the necessary knowledge base for understanding the current conditions of the decision problem.

Another function of decision support is the evaluation of alternatives. Decision-makers must be able to assess alternative courses of action and their potential consequences in addition to understanding the current system state. At this point, the modeling and simulation capabilities of DT become relevant to decision support. Carlin et al. (2024) propose an interactive framework that incorporates decision-making requirements into digital twin design, while Mayer et al. (2025) approach the selection of different DT applications as a decision problem involving value and effort criteria. These studies support the importance of relating technological capabilities to decision requirements.

Similarly, predictive and analytical outputs can be used at more advanced stages of the decision-making process. However, generating a prediction about the future and using that prediction to evaluate possible actions do not represent the same functions. Monek and Fischer (2025)

propose the Expert Twin approach, in which a fuzzy-based decision-making module is integrated into a digital twin, while Walton et al. (2024) develop a DT approach that integrates physical and virtual components with prescriptive analytical elements to support adaptive, real-time decision-making. These examples demonstrate how analytical outputs generated by DT can be integrated with the evaluation of alternatives and action-oriented decision support.

Decision Support Capability is therefore conceptualized as a higher-order mechanism rather than as either a single DT characteristic or an established multidimensional scale. This conceptualization also distinguishes decision support from autonomous decision-making. The model retains decision authority with the decision-maker and focuses on technology's role in strengthening information processing and alternative evaluation.

Accordingly, the Digital Twin Capabilities → Decision Support Capability transition is a conceptual relationship derived from this literature synthesis rather than a causal relationship specified directly by TTF. TTF provides the theoretical rationale for this transition through the fit between technological capabilities and the requirements of the decision task. "Decision Support Capability," distinct from this fit, refers to the extent to which appropriate DT capabilities can be put to use in decision activities. In this way, the model moves from the question of "what capabilities does a digital twin possess?" to the question of "how are these capabilities transformed into usable decision support for specific decision tasks?"

3.4. Decision Quality and Organizational Agility

To explain the transformation of digital twin-based decision support into organizational value, it is necessary to consider the intermediary mechanisms between technological capabilities and organizational outcomes. This transformation is examined through the relationships among decision support capability, decision quality, and organizational agility. The model locates the organizational value of DT in

the use of information and analytical capabilities within decision processes, potentially improving decision quality and organizational responsiveness.

In this chain, Decision Support Capability represents an intermediate mechanism through which task-aligned digital twin capabilities can become usable in decision-making processes and potentially contribute to decision quality. In the DSS literature, decision quality extends beyond the quality of system-generated information to include the decision-maker's evaluation and use of that information in the relevant task. Indeed, Davern et al. (2008) show that human decisions can be susceptible to systematic errors and biases and that decision support can play a role in identifying and improving these problems in the decision-making process. Similarly, Raghunathan (1999) reveals that an increase in information quality does not automatically improve decision quality in every case; this relationship can vary depending on the decision-maker's qualifications. This distinction is important for digital twin-based decision support because large volumes of data, real-time visibility, or advanced analytical outputs do not, by themselves, imply high-quality decisions. In this study, Decision Quality is conceptualized as a construct reflecting the quality of the decision resulting from the evaluation of information relevant to the decision problem and the comparison of appropriate alternatives. Walton et al. (2024) show that a digital twin approach integrating physical and virtual components with prescriptive analytical elements can support adaptive real-time decision-making. The contribution of DT's analytical capacity to decision quality therefore depends on both the technical quality of its outputs and their relevance to the decision problem, possible actions, and subsequent decision process.

Organizational agility provides the next organizational-level link in this value-creation mechanism. In the information systems literature, Lu and Ramamurthy (2011) associate organizational agility with an organization's capacity to capitalize on opportunities and adapt its operations in response to changing conditions and identify positive relationships between IT capability and organizational agility. From this perspective, organizational agility emerges through the effective

deployment of technological resources within organizational processes rather than from technology use alone.

More recent literature on digitalization also supports this relationship. Ciampi et al. (2022) systematically review the literature on digitalization and organizational agility, showing that the relationships between IT (Information Technology) capabilities and big data analytics capabilities, on the one hand, and organizational agility, on the other, constitute an important area of research. This finding similarly cautions against treating digital twin capabilities as technological characteristics that directly generate organizational agility.

The proposed conceptual model advances a relationship between decision quality and organizational agility for future empirical examination. Accordingly, the Decision Quality → Organizational Agility link is advanced here as a conceptual proposition derived from the literature synthesis rather than as a previously established empirical relationship: when DT capabilities are used in alignment with the requirements of decision tasks, they can support decision-making capability; this capability can help decision-makers evaluate current conditions and alternatives more effectively; and decisions based on more relevant and up-to-date information may, in turn, support the organization's capacity to respond appropriately and in a timely manner to changing conditions. Organizational agility thus occupies a higher organizational level in the model and may emerge through improvements in decision support and decision quality.

This interpretation also recognizes the importance of organizational context. Galera-Zarco and Moretti (2025) show that the transformation of digital twin capabilities into organizational and innovation-related outcomes depends on the organizational context. Accordingly, value creation in the proposed model is conceptualized as a gradual transformation mechanism: Digital Twin Capabilities → Decision Support Capability → Decision Quality → Organizational Agility. Organizational performance is considered the subsequent and indirect outcome of this transformation chain.

3.5. Organizational Performance

At the final stage of the conceptual model, organizational performance represents the ultimate organizational outcome of the proposed value-creation process. Technological capabilities first need to become usable within decision-making processes and contribute to the organization's capacity to respond to changing conditions. Organizational performance is therefore positioned as a higher-level outcome that may emerge from the decision-related and organizational mechanisms developed in the preceding stages.

The proposed conceptual model suggests that the potential contribution of digital twin capabilities to organizational outcomes depends on how these capabilities are used within organizational processes. Galera Zarco and Moretti (2025) examine the role of digital twin capabilities in the implementation of digital service innovation, addressing the transformation of technological capabilities into organizational outcomes within an organizational context. The capacity of DT to provide data, visibility, analysis, or prediction does not itself constitute organizational performance; value depends on how these capabilities are utilized within organizational activities.

In the model, the link between organizational agility and organizational performance constitutes the final stage of this indirect value creation logic. Lu and Ramamurthy (2011), by examining the relationships between information technology capabilities, organizational agility, and firm performance within the same theoretical framework, demonstrate that agility is an important structure in understanding the transformation of information technologies into organizational outcomes. For the present model, this finding provides theoretical support for an indirect relationship in which enhanced responsiveness arising from decision support and decision quality may contribute to organizational performance. This relationship is also supported by the meta-analysis of Werder and Richter (2022), which provides an integrative assessment of the relationships between IT capability, organizational agility, and

performance and highlights the importance of agility in translating technological capabilities into organizational outcomes.

At this point, the business case for digital twin applications discussed by Bean et al. (2026) provides a complementary perspective. Particularly when digital twin technology is introduced into existing systems, the need to justify the investment in terms of value and resource requirements challenges the assumption that every DT implementation will automatically create organizational value. Thus, between technology implementation and performance outcomes lie factors such as the intended use, organizational requirements, and expected value. Digital twin investment therefore represents an organizational value-creation issue alongside its technical implementation requirements.

In this study, organizational performance is expanded to encompass multiple dimensions beyond a single operational indicator. The concept is used as a high-level structure encompassing outcomes such as improved operational activities, more efficient use of resources, more effective execution of processes, and the creation of broader organizational value. Because these dimensions are not empirically measured in the present study, they are treated as potential organizational outcomes of the proposed value-creation mechanism.

These outcomes remain proposed rather than empirically established; the model is intended to guide subsequent examination of the organizational conditions under which they may arise.

3.6. Integration of the Conceptual Model

The conceptual model developed in this study traces the organizational value of digital twin technology through the transformation of technological capabilities into organizational outcomes via decision-making processes. Digital Twin Capabilities form the starting point, while Organizational Performance represents the final outcome. Decision Support Capability, Decision Quality, and Organizational Agility connect these levels through the gradual value-creation mechanism presented in Figure 1.

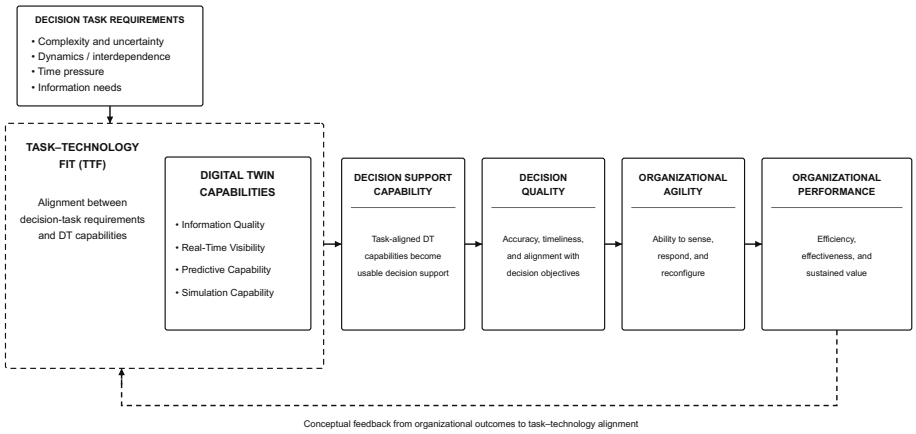


Figure 1. Conceptual Model
Source: Developed by the author based on the literature synthesis

In the first stage of the model, Information Quality, Real-Time Visibility, Predictive Capability, and Simulation Capability represent the information and analytical resources that a digital twin can provide for decision support. However, as explained in Section 3.1 from a TTF perspective, the presence of these capabilities alone does not constitute decision support. A technological capability must fit the information and analytical requirements of the decision task. Decision Support Capability is conceptually distinct from TTF fit and functions in the model as the integrative mechanism through which task-aligned technological capabilities become usable in decision-making.

In the second stage, decision quality represents a potential decision-related outcome of decision support capability. The availability of information, predictions, or simulation outputs provided by DT does not automatically lead to higher-quality decisions. These outputs need to be related to the decision problem and used in evaluating alternatives. Decision quality subsequently captures how this support is reflected in the evaluation of information and alternatives within the decision process.

In the third stage, organizational agility represents a potential organizational-level outcome of this improvement in decision-making processes. The IS literature has established a relationship between IT capability and organizational agility (Lu & Ramamurthy, 2011), while more recent research has examined the relationship of digitalization and digital

capabilities with agility (Ciampi et al., 2022). However, the Decision Quality → Organizational Agility link proposed in this study is not presented as a direct empirical finding of these studies but as a conceptual relationship derived from the literature synthesis. Specifically, the model proposes that decisions based on more timely and relevant information and a more comprehensive consideration of alternatives may support an organization's capacity to respond appropriately and promptly to changing conditions.

In the final stage of the model, organizational performance represents the organizational value resulting from this transformation. Evidence that the translation of digital twin capabilities into organizational outcomes depends on context and on how these capabilities are used in organizational activities (Galera Zarco & Moretti, 2025) supports the argument that performance should not be treated as a direct consequence of technology. Similarly, the joint consideration of technological capabilities, organizational agility, and performance in the information systems literature highlights the importance of agility in the organizational value-creation process (Lu & Ramamurthy, 2011). Organizational performance represents the ultimate value outcome that may emerge through these decision-related and organizational mechanisms.

As illustrated in Figure 1, the model proposes a gradual value-creation mechanism that begins with digital twin capabilities and extends through decision support capabilities and decision quality to organizational agility and performance. This chain is not presented as a single causal model that has already been fully tested in the literature. The model is derived from the conceptual design logic of DSR and the task-technology fit perspective of TTF, integrating relationships addressed at different levels in the digital twin, decision support, and information systems literature. The conceptual contribution lies in integrating existing constructs into a framework that explains how DT capabilities can become decision-support capacity in appropriate tasks and how this transformation may extend to decision quality, organizational agility, and performance.

4. Research Agenda

The conceptual model developed in this study raises several questions for future research on digital twin-based decision support. The first research area concerns the conceptual and empirical validation of the Digital Twin Capabilities construct. The four dimensions are analytical constructs derived from the integration of functions identified across DT studies and have yet to be established as a standardized classification. Future research could examine whether these dimensions remain distinct across different sectors and decision contexts, how they interact with one another, and whether additional DT capabilities should be incorporated into the model. In particular, issues related to DT model validation, data reliability, and data management should be investigated as important conditions affecting the usability of these capabilities in decision-making processes (Bitencourt et al., 2025; Jeremiah et al., 2024).

The second research area concerns the empirical examination of the task–technology fit mechanism in DT-based decision support. The proposed model rejects the assumption that all DT capabilities create equal value across all decision tasks. Instead, it suggests that the fit between particular technological capabilities and the information and analytical requirements of a decision task is critical. Inyang and Taghikhah (2025), in their systematic review of digital twin-based decision support systems, show that DTs are used across different decision-making tasks and identify several research gaps in this area. For example, real-time visibility may be particularly important for time-sensitive operational tasks, whereas predictive capability may be more relevant when future conditions need to be assessed, and simulation capability may become more important when alternative interventions need to be compared. Future studies could compare different task types to test which DT capabilities provide a higher degree of fit under different decision conditions.

The third research area involves further developing the conceptual boundaries and measurement of decision support capability. Decision Support Capability is introduced in this study as an integrative mechanism

linking task–technology fit to the use of DT capabilities within decision processes; it is not an established component of TTF. Future studies could empirically examine functions associated with this capability, such as situation assessment, interpretation of analytical outputs, and comparison of alternatives. Moreover, the development of AI-enabled and increasingly cognitive DT structures raises an important research question concerning how the boundary between decision support and autonomous decision-making should be defined.

Finally, because the proposed Decision Support Capability → Decision Quality → Organizational Agility → Organizational Performance chain represents a set of conceptual propositions synthesized from different research streams, its causal structure requires empirical examination. Future studies could employ case studies, longitudinal research designs, and quantitative model testing to examine the organizational and environmental conditions under which these relationships emerge. In this way, digital twin research can move beyond describing what the technology is capable of doing toward explaining in which decision tasks, through which mechanisms, and under what conditions digital twins create organizational value.

5. Conclusion

The development of digital twin technology is moving beyond the digital representation of physical systems toward structures that integrate functions such as data integration, real-time monitoring, analytical assessment, prediction, and simulation within a common information environment. These technological advances alone, however, cannot account for the value of digital twins in organizational decision-making. Their contribution to decision support depends on how their capabilities are mobilized within the decision process.

Accordingly, based on the literature synthesis, this study proposes a gradual value-creation mechanism: Digital Twin Capabilities → Decision Support Capability → Decision Quality → Organizational Agility → Organizational Performance. Within this model, Information Quality,

Real-Time Visibility, Predictive Capability, and Simulation Capability are not treated as standardized DT dimensions but as an analytical synthesis of technological capabilities relevant to decision support. The TTF perspective explains why the value of these capabilities depends on their fit with the requirements of decision tasks, while decision support capability represents the conceptual mechanism developed in this study to explain how appropriate DT capabilities become functional in the decision-making process.

The relationships proposed in the model are not empirically validated causal relationships, but conceptual propositions derived from the integration of the existing literature. The main contribution of the study is therefore an MIS-based framework that traces the transformation of task-aligned technological capabilities into usable decision support and, through subsequent decision-related and organizational mechanisms, into organizational value.

Declarations

Ethics Committee Approval: This chapter does not fall within the scope of research requiring ethics committee approval, such as studies involving the collection of data from participants through surveys, interviews, focus groups, observations, experiments, or other qualitative and quantitative approaches; the experimental or scientific use of humans or animals (including materials/data); clinical studies conducted on humans; studies conducted on animals; or retrospective studies subject to personal data protection legislation. Therefore, ethics committee approval was not deemed necessary.

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Third-Party Materials and Permissions: Figure 1 was developed specifically for this chapter based on the literature synthesis and does not reproduce or adapt any third-party figure. The author confirms that no other third-party materials requiring permission have been used in the chapter.

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