



UNIVERSITY OF  
GLOUCESTERSHIRE

This is a peer-reviewed, final published version of the following document and is licensed under Creative Commons: Attribution 4.0 license:

**Wynn, Martin G ORCID: 0000-0001-7619-6079 and Irizar, Jose (2023) Digital Twin Applications in Manufacturing Industry: A Case Study from a German Multi-National. Future Internet, 15 (9). art 282. doi:10.3390/fi15090282**

Official URL: <https://www.mdpi.com/1999-5903/15/9/282>

DOI: <http://dx.doi.org/10.3390/fi15090282>

EPrint URI: <https://eprints.glos.ac.uk/id/eprint/13058>

#### **Disclaimer**

The University of Gloucestershire has obtained warranties from all depositors as to their title in the material deposited and as to their right to deposit such material.

The University of Gloucestershire makes no representation or warranties of commercial utility, title, or fitness for a particular purpose or any other warranty, express or implied in respect of any material deposited.

The University of Gloucestershire makes no representation that the use of the materials will not infringe any patent, copyright, trademark or other property or proprietary rights.

The University of Gloucestershire accepts no liability for any infringement of intellectual property rights in any material deposited but will remove such material from public view pending investigation in the event of an allegation of any such infringement.

PLEASE SCROLL DOWN FOR TEXT.



## Article

# Digital Twin Applications in Manufacturing Industry: A Case Study from a German Multi-National

Martin Wynn \* and Jose Irizar

The Business School, University of Gloucestershire, Cheltenham GL50 2RH, UK; jirizar1@glos.ac.uk

\* Correspondence: mwynn@glos.ac.uk

**Abstract:** This article examines how digital twins have been used in a multi-national corporation, what technologies have been used, what benefits have been delivered, and the significance of people- and process-related issues in achieving successful implementation. A qualitative, inductive research method is used, based on interviews provided by key personnel involved in three digital twin projects. The article concludes that digital twin projects are likely to involve incremental rather than disruptive change, and that successful implementation is usually underpinned by ensuring technology, people, and process change factors are progressed in a balanced and integrated fashion. Building upon existing frameworks, three “properties” are identified as being of particular value in digital twin projects—workforce adaptability, technology manageability, and process agility—and a related set of steps and actions is put forward as a template and point of reference for future digital twin implementations. The combination of assessing digital properties and following a set of key actions represents a novel approach to digital twin project planning, and overall the findings are a contribution to the developing theory around digital twins and digitalization, in general, and are also of relevance to professionals embarking on DT projects.

**Keywords:** digital twin; data analytics; digital thread; workforce adaptability; technology manageability; process agility; template; action list



**Citation:** Wynn, M.; Irizar, J. Digital Twin Applications in Manufacturing Industry: A Case Study from a German Multi-National. *Future Internet* **2023**, *15*, 282. <https://doi.org/10.3390/fi15090282>

Academic Editors: Paolo Bellavista, Giuseppe Di Modica and Fernando Cucchiatti

Received: 31 July 2023

Revised: 19 August 2023

Accepted: 19 August 2023

Published: 22 August 2023



**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

A recent discussion in the business and academic press on the Metaverse and what it may mean for different industries [1] has highlighted the current role and future potential of a digital twin (DT), which is likely to be featured as a main component in Metaverse environments in the future. The existing literature notes a range of potential benefits that DT projects can deliver, including efficiency gains [2], waste reduction [3], and improved decision-making [4], and DTs are also considered integral to smart manufacturing environments and Industry 4.0 [5]. De Giacomo et al. [6] (p. 1), for example, referring to DTs, note “they bridge the virtual and real world with the goal to model, understand, predict, and optimise their corresponding real assets. Such powerful features can be exploited in order to optimise the manufacturing process”. However, there are relatively few documented case studies of successful DT projects, and there are not clear guidelines on how to approach and implement such projects either. In this context, VanDerHorn and Mahadevan [7] (p. 10) note “this has raised questions regarding the technology’s ability to provide tangible improvements over existing processes”. This contributes to filling this gap in the literature by studying how three DT projects were initiated, implemented, and managed in a multi-national German enterprise, using the first-hand accounts of the senior managers involved in these projects.

Understanding these dynamics is of increasing significance and value, as DT projects are likely to extend into new functional areas, even before the advent of the Metaverse on any significant scale in industry. This study uses an inductive, qualitative research method and seeks to establish the role of human factors in delivering successful project outcomes,

what technologies were used in these projects, and how they were deployed to deliver cost efficiencies and process improvements. Based on research findings, three key digital properties and related actions are put forward as a template that can be used as a checklist in future DT projects.

The paper consists of six sections. Following this brief introduction, relevant literature is reviewed, and three research questions are set out. There follows a short section on the research methodology, providing an overview of the case study company and the interviewees. The results are reported in Section 4, in which the three research questions are addressed. Section 5 reflects upon some key issues emerging from the findings, and Section 6 provides a conclusion, pointing out limitations of the study and possible areas for future research in this field.

## 2. Relevant Literature

### 2.1. Concept Definition

One of the first documented examples of a DT was as a computer-aided design (CAD) object, which was an element in a product lifecycle management (PLM) process and its support systems [8]. This illustrates the fact that DT is a concept and not a specific technology. Parrott and Warshaw [9] (p. 3) assert that “a digital twin can be defined, fundamentally, as an evolving digital profile of the historical and current behavior of a physical object or process that helps optimise business performance”, and Grieves and Vickers [8] (p. 92) suggest that a DT “is based on the idea that a digital informational construct about a physical system could be created as an entity on its own”. VanDerHorn and Mahadevan [7] reviewed 46 digital twin definitions evident in the extant literature and suggested that DT can be defined as “a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems” (p. 2). Johnson [10] (para. 2) observes “digital twinning is the process of creating a highly realistic model of a device, system, process or product to use for development, testing and validation”.

The two-way exchange of information between the virtual and physical systems is a key aspect of a DT that differentiates it from most other technology concepts. A decade ago, Grieves [11] set out the three main components of a DT: products in the physical space, products in the virtual space, and the connections of data and information that unify both spaces. More recently, Trauer et al. [12] (p. 761) similarly noted that “a digital twin is a virtual dynamic representation of a physical system, which is connected to it over the entire lifecycle for bidirectional data exchange”.

Some authors also distinguish different types of DT projects. Essex [13] (para. 8), for example, identifies three types: first, pre-built twins that “come complete with products they represent or in generic form in business software”; second, commercial—off the shelf—twins that can “be started from templates”; and third, “custom twins” that are “custom developed from scratch”. Essex notes “custom twins are the easiest to modify but take the most time and skill”, whilst “pre-built twins are the opposite” and “templates occupy the middle ground, are widely available, but rarely match the completeness of product digital twins”. In a similar vein, VanDerHorn and Mahadevan [7] (p. 10) conclude “several approaches can be considered: build a Digital Twin using existing commercial tools, construct a Digital Twin from commercial components, or a hybrid approach”.

There are many areas of business in which DTs are being applied, but it is in manufacturing, and particularly in product design and development, that DTs are in greatest use. A DT can connect with different data flows, thus reflecting how a product can be better designed, manufactured, operated, and maintained. The insights gained on how the product changes in different conditions can contribute to innovation in any of the stages of product development [14]. De Giacomo et al. [6] (p. 1) affirm that “the DT can evaluate the production decisions, access the product performance, command and reconfigure machines remotely, handle the troubleshoot equipment remotely and connect systems/processes to improve monitoring and optimise their control”, and that “DTs can also be applied for

process control, process monitoring, predictive maintenance, operator training, product development, decision support, real-time analytics and behavior simulation”.

## 2.2. Technology and Data Aspects

A DT can take several forms and usually utilises a combination of existing technologies, which differ from project to project. These include the following:

**Corporate Information Systems:** DTs will often use corporate data, particularly that relating to manufacturing products, and this is usually located in some of the core business information systems. Typically, these may be an Enterprise Resource Planning (ERP) system such as Oracle or SAP, and other software packages with product-related data—PLM and Manufacturing Execution System (MES) applications, for example.

**Digital Thread:** The digital thread is particularly relevant to shop floor product development and manufacturing DTs. It provides the linkage and connectivity between systems and technologies that provide the data required by the DT. Dontha [15] (para. 14) notes that the digital thread “provides a communication framework to help facilitate an integrated and connected data flow of the product’s data throughout its lifecycle. Digital thread enables accessing, transforming, integrating, and analyzing data from various different systems in the entirety of the product life cycle”.

**Internet of Things:** Essex [13] (para. 9) says of DT: “its implementation is intertwined with another relatively new technology—IoT”, which is now widely deployed across many aspects of business operations [16]. A DT will use IoT generated data via a range of devices, monitors, and controllers for data collection within the physical and virtual environments.

**Edge processing:** This refers to the processing of data near its point of collection (on the “edge”) via IoT devices. This avoids delays and overheads that may be incurred by moving data to the cloud or elsewhere for onward processing. This also reduces possible network bottlenecks that have limited the viability of DT projects hitherto.

**Data Analytics/Artificial Intelligence:** Many DT projects rely on data analytics to analyse and organise data to support DT operation and output. Advanced business intelligence tools like Power BI are often used for DT reporting and analysis purposes, and artificial intelligence (AI) applications may be developed to enhance system and product prediction, simulation, and visualization functions.

**Workflow/3-D Modelling:** Many DTs use 2D or 3D computer-aided design images, although this is not always the case. Three-dimensional modelling technologies create virtual world images, products, and other objects. Workflow products are often linked with, and/or contain, 3D modelling capabilities.

**Extended Reality:** Extended reality headsets and glasses provide users with virtual reality parallels of the physical world. virtual reality (VR), augmented reality (AR), and mixed reality (MR) technologies can be used individually or in combination with DTs.

Most DT projects will involve implementing a combination of these technologies to construct the DT (Figure 1). Interoperability issues between technologies in the production environment are commonplace, and here a number of solutions are being developed, notably the asset administration shell (AAS). The AAS model for digital twins is promoted within Industry 4.0 and “encompasses the interpretation of the digital representation of any production-related asset”, so that “materials and products, devices and machines but also software and digital services have a respective digital version” [17] (p. 160). It “describes the technological features of an asset” and “was created to present data and information in a structured and semantically defined format, allowing for interoperability” [18] (p. 2533). Some data from corporate information systems will usually be required to provide the basis for developing the simulation, and AAS can be used to support data exchange between manufacturing software applications [19]. Effective data management underpins DT applications, so data management technologies are of particular relevance. VanDerHorn and Mahadevan [7] (p. 9) highlight the importance of “connecting data and models that existed in previously independent silos, with the aim of increasing the efficiency and speed at which asset information can be kept current and exchanged between these silos”.

Baldwin [20] similarly emphasises the need for a digital thread in some DT projects to allow businesses to centralise their data into one standardised hub, providing all manufacturing elements with access to the same data.

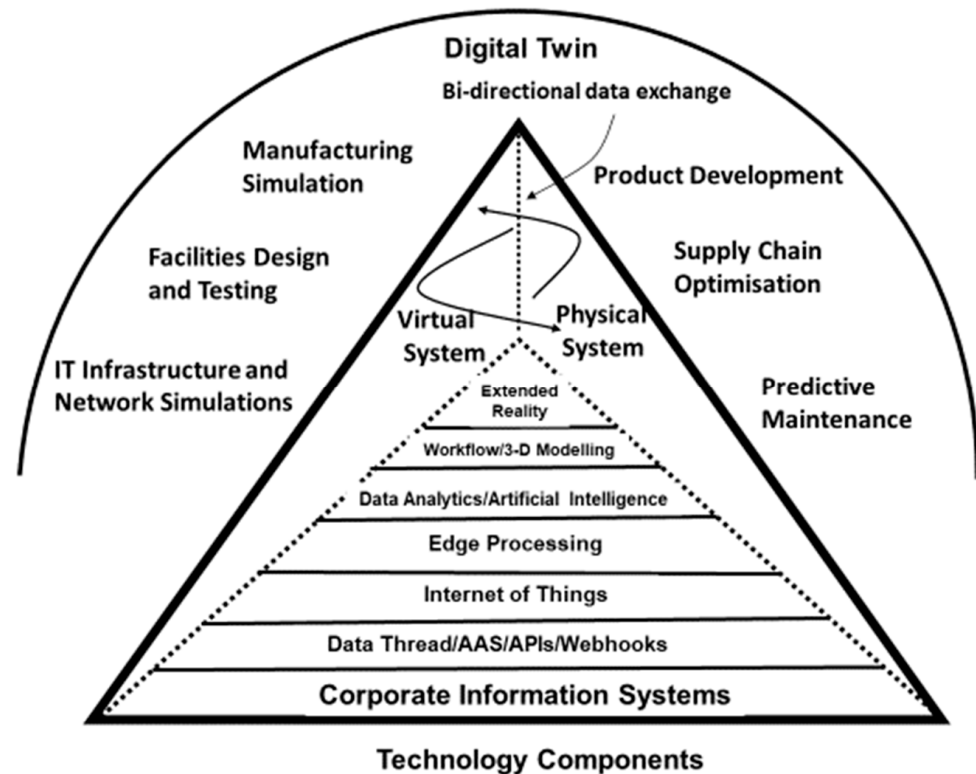


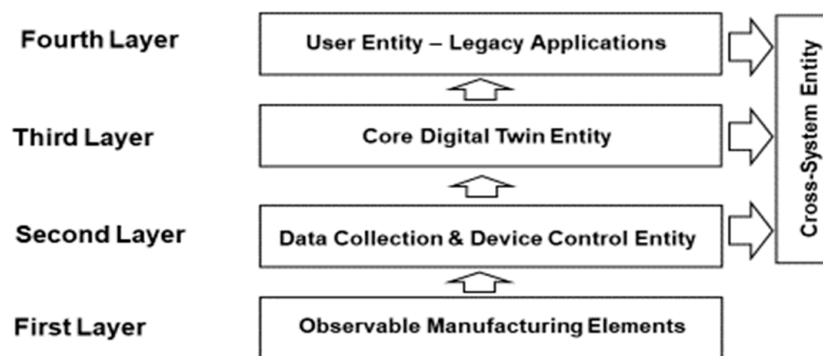
Figure 1. Digital Twin technology components and application areas.

Whilst the data thread sets out the required links, application program interfaces (APIs) are often used in conjunction with an AAS to provide the physical connections between systems and technologies. Webhooks are another technology component that supports the digital thread. A key difference between the webhooks and APIs is that the latter need to be asked to pull or modify data, whereas the former automatically sends data in response to a specific event, without any request from other software. Essex [21] (para. 4) notes “the data link, often but not necessarily two-way, is what differentiates digital twins from similar concepts. This link makes it possible for users to investigate the state of the object or process by querying the data, and for actions communicated through the digital twin to take effect in its physical counterpart”.

### 2.3. Relevant Theory and Models

There are a number of implementation frameworks in the existing literature, some of which are specific to implementing certain types of DTs, or DTs for specific purposes. For instance, Zhang et al. [22] and Guo et al. [23] proposed frameworks to optimise factory layout designs. Friederich et al. [24] focused on developing a framework to improve the simulation functionality of a DT using machine learning and process mining techniques. Loaza et al. [25] (p. 12) developed a “small-scale digital twin implementation framework”, in which they identified Resources (“labour, capital and materials”), Technology, and Digital Transformation (“enabling digital processes such as simulation, diagnostics, prognostics”) as the “high-level requirements” for DT projects. Schweigert-Recksiek et al. [26], in their case study of a DT in technical product development, suggest five key dimensions for DT projects, based on earlier work by Kreimeyer et al. [27]. These are people, process, data, product, and tools. The International Organization for Standardization (ISO) detailed requirements for a DT framework [28] in which it partitions a DT into four layers defined by standards (Figure 2). The lowest layer describes the observable manufacturing

elements—the items that need to be modeled in the DT. The second layer is the device communication entity which “collates all the state changes of the observable manufacturing elements, and sends control programs to those elements when adjustments become necessary” (para. 2). The third layer is the digital twin entity, which reads the data collated by the device communication entity and uses the information to update its models. The fourth layer contains user entities. These are applications that use the digital twins to enhance manufacturing efficiency. They are “legacy applications such as ERP and PLM, and new applications that make processes work more quickly” (para. 3). The ISO 23247 framework is based on the Internet of Things and also includes a “cross system entity”, linking shop floor devices, the digital twin, and main applications in the fourth “user entity” layer.



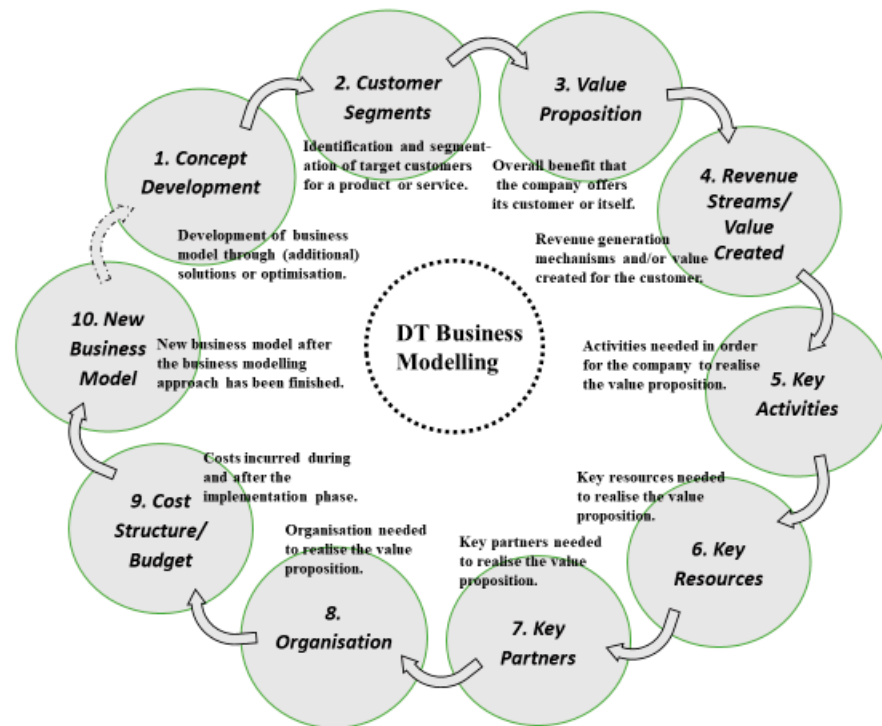
**Figure 2.** ISO digital twin framework for manufacturing. Based on [28] (Figure 1).

The three change dimensions of technology, process, and people have been used as a framework to analyse IT projects [29,30] and develop IT strategy [31] in the digital era. This is somewhat similar to the approach adopted by Loaiza et al. [25] (p. 12) and, in particular, the framework put forward by Schweigert-Recksiek et al. [26] for implementing DT projects. Their framework includes process and people change dimensions, plus data and tools (which can be viewed as part of the technology dimension), and the product itself—the focus of the DT simulation. The significance of the people change dimension is emphasised by Schweigert-Recksiek et al. [26] (p. 384), who note “current barriers between departments have to be considered as the usage of a twin also changes the significance of certain tasks or even departments of the product development process”. In terms of process change, the authors note “many of the processes in a company will change with the introduction of a twin, as for example some simulations will be conducted automatically instead of a simulation assignment being handed over from one department to the other”. They also note that “the generation and usage of data, especially from the use phase of products, has to be altered in many places to enable the implementation of a Digital Twin” (p. 385).

More recently, Trauer et al. [32] put forward a “business modelling approach” for digital twin projects, which is a 10-step guide to implementing a DT and transitioning to new processes (Figure 3). In a similar vein, VanDerHorn and Mahadevan [7], in their analysis of DT implementation, identify a number of key challenges, including terminology, standardization, organizational culture, technology maturity, and automation. As regards automation, the authors note “a prominent targeted outcome in many digital twin implementations is to reduce the manual effort through automation of data exchange and analysis”, but that “there is still a strong reliance on human-in-the-loop as part of current solutions” (p. 9).

In this context, Actor Network Theory (ANT) is of relevance. ANT is a social technical theory that has been employed in a number of studies of digital technology implementation [33,34]. It recognises both human and non-human actors in networks that aim to achieve a set goal with both contributing equally. The theory maintains that for any actor to act, others must act, highlighting their interdependence [35]. In the context of DT projects, De Giacomo et al. [6] (p. 1) concluded that “a single manufacturing process may include

hundreds of different actors (humans, equipment, organizations), together with their digital twins”, and that “at any moment in time, in order to provide resilience, manufacturing process should be able to automatically adapt to new conditions, considering new actors (with lower cost and low probability of breaking) for the fulfilment of the manufacturing goals. This task cannot be performed manually when actors span multiple organizations possibly separated from both the geographical and organizational points of view”.



**Figure 3.** Digital Twin Business Modelling Framework. Source: based on Trauer et al. [32], Figure 2, p. 125.

In the wider context of digitalisation, Bonnet and Westerman [36] identified five main key change factors: the digital platform, customer experience, operations, employee experience, and the business model. Other authors have tried to identify key success factors or “pillars” for successful digital transformation. Lang [37], for example, suggests four internal pillars for successful transformation: empower employees, transform products, optimise operations, and engage customers. Furr et al. [38] similarly identified four pillars: IT uplift, digitising operations, digital marketing, and initiating new ventures. Newman [39] pointed to six pillars that underpin successful digital transformation: experiences, people, change, innovation, leadership, and culture.

This research builds on these theoretical foundations and practical guidelines, focusing on the interplay of technology, process, and people dimensions. The overall aim is to get a picture of the key issues relating to these three dimensions of change that underpin successful DT project outcomes. More specifically, the following research questions (RQs) are addressed:

- RQ1. What was the significance of people factors in the digital twin projects?
- RQ2. What technologies were deployed in the digital twin projects and have there been technology integration issues?
- RQ3. What have been the impacts of digital twin projects in terms of process change and benefits delivery?

### 3. Research Method

The overall aim of this research is to examine the nature of DT projects in the manufacturing industry, focusing on technologies deployed, benefits delivery, and the significance of people-related factors. The study adopts a qualitative, inductive approach

using a literature review, and interviews with three industry professionals with relevant knowledge and experience. The literature review provided “a means of gaining an initial impression” [40] (p. 97) of pertinent issues. Relevant publications and web sources were reviewed to establish the depth and breadth of current literature relating to the subject area. Internet surveys were conducted using Google as the search engine with appropriate search strings from May to July 2023. This allowed the identification of a set of key issues and the development of research questions.

A case study was the main applied methodology “to develop sharper and more insightful questions about the topic” [41] (p. 13). The validity of generalizing from case studies has been discussed extensively in the literature with differing views [42,43]. Here, the features of the three projects studied in the case study company are examined and assessed to develop a template for DT project implementation, which builds upon concepts and models in the recent literature. As this framework is grounded in empirical inquiries in a manufacturing environment, it is put forward as a valid framework—for subsequent development and amendment—for DT projects in similar business contexts.

The literature review provided the basis for setting out the initial research questions, and these were used as the basis for the interview questionnaire which comprised 12 open questions in three main sections concerning technology deployed; people and processes; and strategy. These were followed by 13 summary statements with which the respondents to the questionnaire were asked to agree or disagree on a five-point Likert scale. The final section invited further comment or information of relevance. The questionnaire was emailed to the three respondents, with whom follow-up interviews were held within a three-week period. The completed questionnaires were used as the basis for discussion in the interviews, when additional annotated notes were added to the returned questionnaires.

This research is based on a multi-project case study analysis of three DT projects in three separate subsidiaries within a large multi-national group. The industry group manufactures a variety of products, including transmission parts and drive axles for passenger and commercial vehicles, suspension equipment for heavy trucks, as well as gearboxes for wind turbines. The group operates in over 30 countries around the globe, with total sales of more than €25 billion, and with over 100,000 employees in 2022. The group is headquartered in Germany and the USA. The company as a whole has embarked on in excess of ten DT projects in the last five years, which were briefly reviewed. Of these, three projects were selected as representative of the projects being undertaken across the company in the manufacturing subsidiaries. One aimed at providing the basic data platform and linkages for DT projects; another aimed to retrospectively recreate production runs from the past to help answer customer enquiries; and the third was a forward-looking simulation of production prior to product launch.

Selection of interviewees (Table 1) was done through the professional networks within the company of the authors. The interviewees “are chosen because they have particular features or characteristics which will enable detailed exploration and understanding of the central themes and puzzles which the researcher wishes to study” [44] (p. 78), and specific knowledge and experience of the three projects under study. Interviews can be structured, semi-structured, or unstructured [45]. Semi-structured interviews were seen as the best way of eliciting qualitative data with the highest possible level of knowledge being acquired in a flexible manner. Interviewees were able to give their perspectives on specific DT projects, including less obvious factors giving interviewees a “voice” in the study [46]. The subsequent data analysis entailed the summarizing and structuring of the data to address the research questions, develop discussion points, and build the template for DT project operation. Framework analysis [47] was used to classify selected literature quotations, questionnaire responses, and interview transcript material against each of the three research questions and to surface additional points for discussion. The interviews lasted in excess of one hour, and quotes in the Results and Discussion sections are taken from the questionnaire responses, notes added in the interviews, or from the interview recordings.



**Table 1.** Interviewee job roles and experience.

CODE	Job/Role	Experience/Background
P0	Global IT Verification & Validation Manager	25 years IT, software and configuration management experience; responsible for Digital Thread project implementation
P1	Chief Engineering Manager/Manufacturing Digital Twin Champion	30 years of experience in global advanced manufacturing engineering, vehicle design engineering, and value management.
P2	Data Analytics Director	30 years of management experience in the marine division; holds a PhD in engineering.

The profiles of the three cases are set out below:

**Project 0:** Digital thread development. The main objective of Project 0 was to create a “platform for the management of digital twin simulations”. It was essentially an infrastructure project to provide the data connectivity that is required by digital twin projects in the manufacturing divisions of the company. It centered on the development of a “digital thread”, a data-driven architecture that links together information generated from across the product lifecycle. This project thus provided the technology platform and data connectivity for other digital twin projects, including the two noted below.

**Project 1:** Post-event production simulation and replication. As part of the Industrial Technology Division’s strategy to “be a digital company by 2022”, one of the first projects, implemented with the support of third-party consultants in 2018–2020, focused on using DT technologies as part of a quality analysis platform, allowing simulations of past manufacturing runs of transmission systems. The system, which went “live” in 2019, has been used to support claims management and answer quality enquiries from customers, allowing rapid retrieval of simulation data, indicating what was done to produce specific parts. Within five working days of receiving a claim, data from a simulated run of the produced part can be presented to the customer for analysis and discussion.

**Project 2:** Pre-production simulation prior to product launch. The digital twin is “the basis for the planning, simulation and validation of manufacturing processes from an early planning phase to the virtual commissioning of the production line”. This project objective was to allow for the simulation of production equipment use before the new product is launched. The system indicates capacity and output potential from existing equipment, depending on production load, human resource availability, and other variables. It supports the future optimisation of machines and equipment usage.

## 4. Results

### 4.1. RQ1: What Was the Significance of People Factors in the Digital Twin Projects?

The main people-related factors that emerge from the three projects are as follows: the value of a committed senior level sponsor; the benefit of cross-departmental involvement; and the need for multi-skilled implementation teams. Project 0 was run by a steering committee comprising “corporate R & D together with all divisions”, reporting directly to the CEO, reflecting the cross-departmental significance of getting the digital thread infrastructure in place. In Project 1, the project was managed by the head of Data Analytics, who played a key role in instigating and driving through the project. In 2018, a new Data Analytics group was created, and this was seen as their flagship project. P1 noted that the support from his line manager, the chief financial officer (CFO), was also critical to the success of the project “it was easier with a convinced CFO. . . who provided the budget”. P1 noted that “people [are] more important—not new technology, [we] used existing technology which the company can offer—it is more difficult to win people”. P1 noted that there was a “lot of interaction between Research & Development and corporate Information Systems (IT)”. In Project 2, “project initiation was within the division—the VP operations was the sponsor”; however, “it is part of the overall corporate digital initiative”.

P2 indicated the significance of people-related factors, underscoring the importance of a network of actors and a strong and committed project sponsor.

All three projects used third-party expertise. In Project 0, “several third party and externals” were required “to cope with the required know how”. The project was “a pilot for one division”, and a “top down approach” was pursued. In Project 1, “the development of a quality analysis platform” was undertaken “together with external consultants”. P1 highlighted the required skillsets for the project: data scientist/analyst, machine learning engineer, solution architect, data engineer, engineer and software developer. In project 2 “the vendor DELMIA provided their experts who teamed up with the process experts of the company”. P2 added that “at the beginning several contractors were engaged until the team acquired the required know how. The project started as a use case or proof of concept”.

4.2. RQ2: What Technologies Were Deployed in Digital Twin Projects and Have There Been Technology Integration Issues?

The technologies used in the three digital twin projects were built around existing systems and applications (Table 2). Project 0 linked various data sources together, but central to this was a configuration management tool (PDTEc) which combines a simulation capability with data management and workflow. This allowed the development of the data thread for configuration management. PDTEc had previously been used in production as a computer-aided engineering (CAE) tool and is now being evaluated for wider deployment in other subsidiaries. Because of the nature of the project, no core information systems were used as a consistent data feed, but the project had to follow corporate policy for granting access, and security rules for encryption and other data aspects.

Table 2. Technologies used in the 3 DT projects.

Technology/Project	Project 0	Project 1	Project 2
Extended Reality	NO	NO	NO
Workflow/3-D Modelling	YES (PDTEc)	YES (Knime/AAP)	YES
Data Analytics/Big Data	YES	YES (Power BI)	YES (Power BI)
Edge Processing	NO	YES	NO
Internet of Things	YES	YES	YES
Data Thread/APIs/Webhooks	YES	YES	YES
Corporate Information Systems	NO	YES (SAP/ Axalant PLM)	YES (Delmia/Siemens PTC/Axalant PLM)

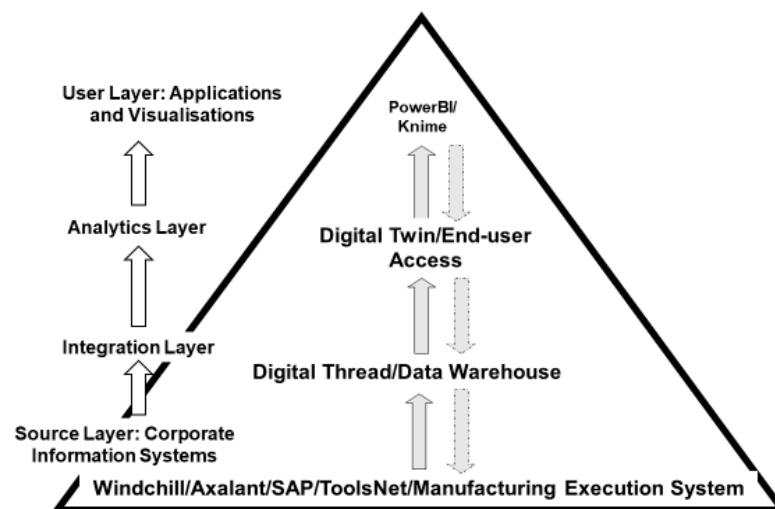
In Project 1, a data analytics tool (Power BI), workflow visualization software (Knime), a process management application (AAP), and an SQL database running on-premises were used to bring together data from various existing sources (Figure 4) to facilitate simulations of past production runs. These simulations—the digital twin—take past data relating to component manufacturing, product assembly, and product usage from the SAP ERP system. The DT combines this with test bench data to develop simulations of the manufacturing processes and allows end-user access to develop and configure different simulation scenarios. The system is located largely on-premises with some use of cloud technologies, but the entire system may be moved to the cloud in the near future. The data from the SAP system are retrieved every 15 min. As regards integration, P1 highlighted the use of APIs but also “quite a lot own development” to create “hybrid API access”.

In Project 2, the DT is based around the Delmia digital manufacturing software package, a capacity planning tool, which monitors and controls the “Advanced Manufacturing Execution Assets” of the company. It is linked with the Siemens PTC which is an open-source platform for monitoring and storing data from IoT and other devices. This allows

the simulation of production processes prior to the launch of a product. Integration has been problematic, P2 noting that “there is not much integration with other systems yet”, and there is “no data or interface to other systems but [we are] using data from the PLM system” and “the interface with PLM is manual, there is no interface available to see the release of product variation”. There are 9 databases feeding the system—but the “number of databases will be reduced”. The data from the digital twin “is stored in regional databases and it is accessed via Power BI”. P2 indicated, however, that technology integration issues, although evident, were not a significant problem. This contrasted with the other two interviewees, who viewed technology integration as a significant issue as yet unresolved (Table 3, Statement 7). Nevertheless, P2 noted that the “next step will be integration with the PLM system”.

**Table 3.** Questionnaire statements: interviewee responses.

Statement	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1. Human and non-human factors are of equal importance in determining the success of digital twin projects.		P1	P0		P2
2. Digital twin projects rely on a network of different actors from different functions acting together towards a common goal.				P0	P1 P2
3. Digital twin projects require a strong sponsor and champion to enroll an appropriate network to move the project forward.					P1 P2 P0
4. It is important for the digital twin project sponsor to clearly outline the project benefits and justify the costs.				P2	P1 P0
5. The project sponsor played a key role in enrolling the support and participation of other team members.				P2	P1 P0
6. Team members played out their different roles effectively to successfully deliver digital twin project(s).				P2 P0	P1
7. Integration of digital twins with other systems was a significant issue that has not been fully resolved.	P2			P1 P0	
8. IT strategy has played a key role in the selection and implementation of digital twin projects.	P2		P0	P1	
9. Our company has the necessary skills and competencies to successfully implement digital twin projects.			P0	P1 P2	
10. Digital twin projects have delivered significant benefits for our company.			P2	P0	P1
11. Digital twin projects have changed our processes and ways of working significantly.			P0	P2	P1
12. Digital twin projects have ushered in a significant change in the culture of our company.		P2	P0		P1
13. Digital twin projects have improved the quality of information in the functional areas where implemented.				P2 P0	P1



**Figure 4.** Project 1: Data sources and architecture layers (based on in-company project documentation).

#### 4.3. RQ3: What Have Been the Impacts of Digital Twin Projects in Terms of Process Change and Benefits Delivery?

The three respondents gave somewhat differing perspectives on process change resulting from the DT projects and associated benefits delivery. Project 0 was more of an infrastructure project to facilitate the launch of other DT projects. It started as a pilot “small scope to test the data for calibration and simulation”, and P0 conceded that the purpose of the project was “not clear to everyone at the beginning—it was a Development and Innovation (R&D) project”. However, P0 noted that the DT now provided the platform “for simulation of real assets—life cycle prediction, and estimation of rest of life and product reliability”.

P1 strongly agreed that clear benefits had been delivered and cited the example of how the DT simulation data have been made available for evaluation and discussion with customers. Prior to this, it was “a massive effort for our quality department to analyse the existing data”, using the process monitoring tools at their disposal, which were “missing information from other strategic systems like MES [manufacturing execution system] and SAP”. More specifically, P1 highlighted “quality savings” from the use of Power BI, the data analytics tool, for analyzing the DT simulated data. As regards process change and ways of working, P1 noted that “in many departments and areas, based on the digital twin, decisions are taken differently”, and that “cross-divisional solutions are now commonplace”.

Project 2 objectives included “improvement of productivity and quality by faster planning of complex products” and “enabling a high transparency of planning status” by “visualization of process steps, layouts and key figures” and “enabling a traceability of changes”. P2 noted that the DT project had been successful “in the sense that the accuracy [of machine and equipment capacity predictions] started with 75% and is currently at 90%”, and “there is a full business case and the project has a high ROI”. Indeed, one of the perceived benefits in all three projects, even if difficult to quantify, was an improvement in the quality of data in the functional areas impacted by the DT projects, all three respondents agreeing with this statement (Statement 13).

As regards the systems development and project management processes, these projects were based on an agile approach. P1 reported that Kanban (an agile methodology) was used in the project, whilst in Project 0 “scaled agile framework (SAFE) workstreams” were used. In project 2, P2 noted an “agile methodology was used—the entire approach is lean management and the project management approach is agile using agile-oriented tools such as JIRA to support project management and team progress”.

## 5. Discussion

The results outlined above raise some issues worthy of further discussion. Firstly, DT projects require consistent and accurate data, upon which simulations can be developed and operationalised. For this reason, DT projects will often go hand-in-hand with data analytics initiatives. The development of a digital thread and the use of webhooks and APIs to provide the necessary connectivity have parallels with the development of the data warehouse, data marts, and corporate data models in the 1990s [48]. For example, Dontha [15] (para. 15) notes “digital thread enables accessing, transforming, integrating, and analyzing data from various different systems [and] helps in delivering the right information at the right time and at the right place”, which resonates with the objectives of data warehouse projects of the past. Similarly, Dontha [15] (para. 12) adds “the very first step in digital thread as it relates to data management is identifying data sources, accessing the data, and organizing it in a way that various functions can harness that data”, which again is very similar to the objectives set out for developing corporate data models in a previous era. This highlights the lack of integration of core information systems, which bedevils many businesses. Perhaps this is inevitable in an advanced manufacturing environment when the main suppliers of company ERP systems do not contain the functionality for shop floor and MES requirements, and thus a series of add-on, supplementary systems and technologies are acquired. The vision of having one integrated package for everything, as put forward by the ERP vendors since the 1990s, has been put aside for a “best of breed” approach, using APIs, AASs, webhooks, and other technologies to create a data thread as a means of locating and extracting the data from various systems required for the DT. In this context, Essex [13] (para. 11) notes that “deriving value from digital twin technology . . . . requires mature data management processes and sophisticated systems integration, making digital twin development a complex, multi-year effort”.

Secondly, the nature of innovation introduced by the DT projects constitutes incremental rather than disruptive change. As noted in Project 1, which focused on advanced use of data analytics “we are not reinventing the wheel, but connecting the dots”. Project 2 could be viewed as an advanced planning tool, applied in product development, having its origins in MRP, MRP2, and the load planning and forecasting modules evident in many ERP systems. The research findings provide some perspectives on existing frameworks and guidelines, but perhaps the most significant factor is that DT projects have very little that is new in terms of technology or business change. There were a number of key issues for project success that emerged from the project studies—a committed high level project sponsor, cross-functional teams, use of outside expertise, appropriate technology mix, the need for a sound data platform, the use of agile methodologies, and the value of a process change expert—but all these factors are of similar relevance in many other IT projects, big and small, digital era and pre-digital era. These projects harness and combine technologies to produce virtual simulations of physical reality, but project management issues and methodological considerations remain as in many other IT projects.

Thirdly, the cases highlight the absence of any common approach to DT projects, which limits the potential for developing models and frameworks that are applicable to a range of DT projects. Tonder et al. [49] (p. 112) recently concluded that “there is no universally accepted, robust conceptual framework that can assist businesses, practitioners and academics to understand the constructs of digitalisation, digital transformation and business model innovation”, and this would seem to apply to DT projects as much as to other digital technology implementations. The project management team in Project 1, for example, adopted a bottom-up perspective in developing the retrospective DT application (Figure 4). Data were collected from a range of corporate information systems, linking and aggregating it via digital thread and data warehouse technologies, which was then made available for the DT simulation. The output data from the DT were then used for further analysis using a range of analytics tools, including Power BI. The ISO model [28] (Figure 2), however, takes a different approach, focusing on shop floor production processes (level one), collecting data from them (level 2), building the simulation (level three), the

outputs from which are then used in a range of existing corporate systems (level four). The business modelling approach of Trauer et al. [32] (Figure 3) takes a different approach again but is essentially a progression of technology, process, and people factors (steps 5–8, 10 in Figure 3) with added actions to establish and verify a business case for the project (steps 1–4, 9). It reinforces conventional wisdom about the significance and interdependency of technology, people, and process issues in IT projects. In this context, the findings highlight the value of three interdependent digital “properties”—required for digitalization projects in general—which are of particular relevance to DT projects: workforce adaptability, technology manageability, and process agility. This builds upon the earlier work of Loaiza et al. [25] and Schweigert-Recksiek et al. [26] discussed above. More specifically, the projects studied here suggest a series of related smaller steps or actions that are needed to progress DT projects successfully (Figure 5).

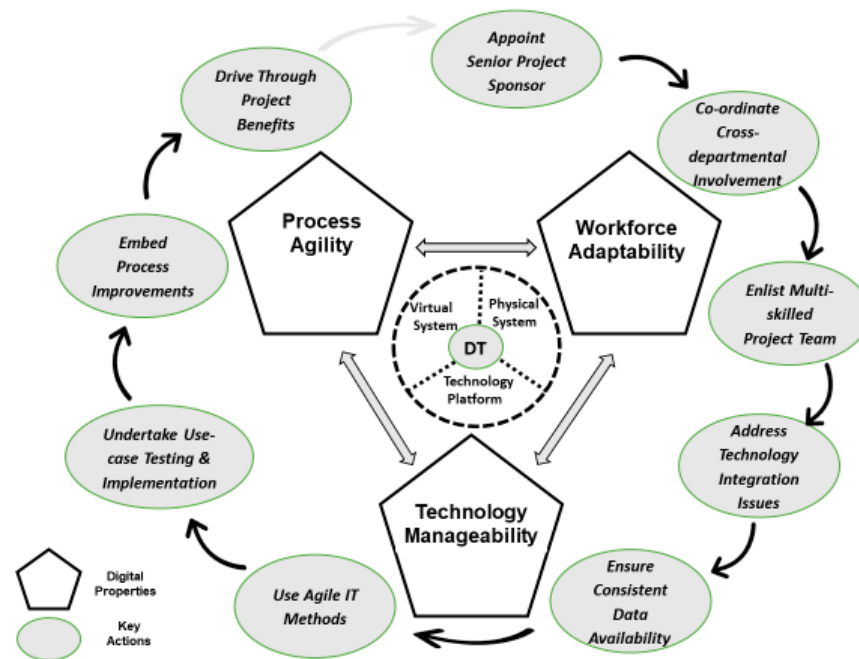


Figure 5. Template for digital twin project implementation.

There are several aspects to workforce adaptability that impact DT projects. All three projects evidenced the value of strong sponsorship and leadership from an appropriate senior manager—the CFO, the CEO, and the Vice-President of Operations in these projects. Coordinated cross-departmental involvement is also necessary, either as a project team or working party or via a more informal arrangement based around the use-case testing. Either way, committed and coordinated input from a range of functions will be required. A range of skillsets, some of them possibly new to the company (particularly in the IT area) will also be required, which may involve using third-party contract support in the short term.

Technology manageability implies that IT issues are adequately managed by the resources available and there is a sound and stable technology platform upon which to build. If the IT department is continually firefighting maintenance and other problems, it is unlikely to be successful in building a DT. Technology integration issues need to be addressed to provide the linkages and interfaces for sound and consistent data to populate the DT. This may involve the use of AASs, APIs, and webhooks, the development of a digital thread, and the use of a data warehouse as a staging post between feeder systems and the DT itself. The IT function, albeit possibly with third-party support, also needs the capabilities for use-case testing of the technology combinations involved in the DT project, and then to provide on-going support and maintenance.

Process agility assumes the use of agile, flexible project management methods in the conduct of the use cases, which will probably involve a multi-functional team drawn from several departments (IT and users). The company must have the agility and political will to embed process change in existing working practices, in which the commitment of the project sponsor will be a key influencing factor. Process change will be a major contributor to driving through overall project benefits, typically from overheads reduction, better information, and improved customer service (internal or external).

## 6. Conclusions

This article examined three DT projects implemented in a multi-national manufacturing company and identified some of the key issues underpinning successful project outcomes. This has allowed the development of a simple framework that can usefully act as a template for future DT projects, which will grow in number and areas of application, probably as a function of Metaverse developments in business environments within the coming decade.

There are clearly limitations to this study. It is based on just three interviews with the project leaders in three DT implementations. Their perspectives are inevitably subjective, although the interview findings have been verified informally with other staff members. The validity of generalizing about DT projects from such a small sample is also limited. The template, therefore, is put forward as a work in progress that can be tested and developed through the study of other DT projects. Further research could also progress the concept of digital “properties” required for successful digitalization, involving not only DT projects but other digital technologies as well. This contrasts somewhat with the concept of “pillars” for success put forward in some of the literature, and benefits from being organic in the sense that properties can evolve and develop with organizational and technological change. Technology integration in digital twins is another area where more research could profitably explore and develop the functions of AASs, APIs, webhooks, and other connectivity tools and frameworks.

VanDerHorn and Mahadevan [7] (p. 10) have observed that “the digital twin concept is clearly still evolving, as seen in the diversity of new industries and use cases that digital twins are being applied to. This continued concept evolution is also apparent in the lack of concrete examples demonstrating the clear benefits of digital twins in practice.” This article has attempted to help address this gap in the literature by providing some insights into an area that is only now starting to be researched in depth.

**Author Contributions:** Conceptualization, J.I. and M.W.; methodology, J.I. and M.W.; validation, J.I. and M.W.; formal analysis, J.I. and M.W.; investigation, J.I.; data curation, J.I. and M.W.; writing—original draft preparation, M.W.; writing—review and editing, J.I. and M.W.; visualization, J.I. and M.W.; project administration, J.I. and M.W. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** All relevant research data are displayed within the article.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Deloitte. A Whole New World? Exploring the Metaverse and What It Could Mean for You. 2022. Available online: <https://www2.deloitte.com/content/dam/Deloitte/us/Documents/technology/us-ai-institute-what-is-the-metaverse-new.pdf> (accessed on 23 July 2023).
2. Lin, T.Y.; Shi, G.; Yang, C.; Zhang, Y.; Wang, J.; Jia, Z.; Guo, L.; Xiao, Y.; Wei, Z.; Lan, S. Efficient container virtualization-based digital twin simulation of smart industrial systems. *J. Clean. Prod.* **2021**, *281*, 124443. [[CrossRef](#)]
3. Singh, M.; Fuenmayor, E.; Hinchy, E.P.; Qiao, Y.; Murray, N.; Devine, D. Digital Twin: Origin to Future. *Appl. Syst. Innov.* **2021**, *4*, 36. [[CrossRef](#)]
4. Zhou, A.C.; Xu, J.; Miller-Hooks, E.; Zhou, W.; Chen, C.H.; Lee, L.H.; Chew, E.P.; Li, H. Analytics with digital-twinning: A decision support system for maintaining a resilient port. *Decis. Support. Syst.* **2021**, *143*, 113496. [[CrossRef](#)]

5. Jovanovic, V.; Kuzlu, M.; Cali, U.; Utku, D.H.; Catak, F.O.; Sarp, S.; Zohrabi, N. Digital Twin in Industry 4.0 and Beyond Applications. In *Digital Twin Driven Intelligent Systems and Emerging Metaverse*; Karaarslan, E., Aydin, Ö., Cali, Ü., Challenger, M., Eds.; Springer: Singapore, 2023; pp. 155–174. [[CrossRef](#)]
6. De Giacomo, G.; Favorito, M.; Leotta, F.; Mecella, M.; Silo, L. Digital twin composition in smart manufacturing via Markov decision Processes. *Comput. Ind.* **2023**, *149*, 103196. [[CrossRef](#)]
7. VanDerHorn, E.; Mahadevan, S. Digital Twin: Generalization, characterization and implementation. *Decis. Support. Syst.* **2021**, *145*, 113524. [[CrossRef](#)]
8. Grieves, M.; Vickers, J. Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In *Transdisciplinary Perspectives on Complex Systems*; Kahlen, F.J., Flumerfelt, S., Alves, A., Eds.; Springer: Berlin/Heidelberg, Germany, 2017; pp. 85–113. [[CrossRef](#)]
9. Parrott, A.; Warshaw, L. *Industry 4.0 and the Digital Twin: Manufacturing Meets Its Match*; Deloitte University Press, 2017; Available online: [https://www2.deloitte.com/content/dam/Deloitte/kr/Documents/insights/deloitte-newsletter/2017/26\\_201706/kr\\_insights\\_deloitte-newsletter-26\\_report\\_02\\_en.pdf](https://www2.deloitte.com/content/dam/Deloitte/kr/Documents/insights/deloitte-newsletter/2017/26_201706/kr_insights_deloitte-newsletter-26_report_02_en.pdf) (accessed on 17 July 2023).
10. Johnson, J. Digital Twinning Use Cases Strengthen with AR, VR. 2022. Available online: [https://www.techtarget.com/searchcio/tip/Digital-twinning-use-cases-strengthen-with-AR-VR?utm\\_campaign=20220323\\_ERU+Transmission+for+03%2F23%2F2022+%28UserUniverse%3A+354109%29&utm\\_medium=EM&utm\\_source=ERU&src=9403382&asrc=EM\\_ERU\\_212215417&utm\\_content=eru-rd2-rcpC](https://www.techtarget.com/searchcio/tip/Digital-twinning-use-cases-strengthen-with-AR-VR?utm_campaign=20220323_ERU+Transmission+for+03%2F23%2F2022+%28UserUniverse%3A+354109%29&utm_medium=EM&utm_source=ERU&src=9403382&asrc=EM_ERU_212215417&utm_content=eru-rd2-rcpC) (accessed on 23 March 2023).
11. Grieves, M. *Digital Twin: Manufacturing Excellence through Virtual Factory Replication*; Florida Institute of Technology: Melbourne, FL, USA, 2014.
12. Trauer, J.; Schweigert-Recksiek, S.; Engel, C.; Spreitzer, K.; Zimmermann, M. What Is a Digital Twin?—Definitions and Insights from an Industrial Case Study in Technical Product Development. In *Proceedings of the International Design Conference—Design 2020*, Online, 26–29 October 2020; Cambridge University Press: Cambridge, UK, 2020; pp. 757–766. [[CrossRef](#)]
13. Essex, D. Digital Twin Technology on Turbulent Climb to Stratosphere. 2020. Available online: [https://searcherp.techtarget.com/feature/Digital-twin-technology-on-turbulent-climb-to-stratosphere?track=NL-1815&ad=934555&src=934555&asrc=EM\\_NLN\\_129428578&utm\\_medium=EM&utm\\_source=NLN&utm\\_campaign=20200616\\_Sapphire%20Now%202020%20conference%20goes%20virtual.%20Also:%20implicit%20bias%20training%20and%20virtual%20recruiting%20strategies](https://searcherp.techtarget.com/feature/Digital-twin-technology-on-turbulent-climb-to-stratosphere?track=NL-1815&ad=934555&src=934555&asrc=EM_NLN_129428578&utm_medium=EM&utm_source=NLN&utm_campaign=20200616_Sapphire%20Now%202020%20conference%20goes%20virtual.%20Also:%20implicit%20bias%20training%20and%20virtual%20recruiting%20strategies) (accessed on 11 July 2023).
14. Felser, K. The Impact of Digital Technologies on IT Sourcing Strategies in the German Automotive Industry. In *Handbook of Research on Digital Transformation, Industry Use Cases, and the Impact of Disruptive Technologies*; Wynn, M., Ed.; IGI-Global: Hershey, PA, USA, 2022; pp. 383–408. [[CrossRef](#)]
15. Dontha, R. Data and Trending Technologies: Role of Data in Digital Thread. In *The Data Administration Newsletter*. 2018. Available online: <https://tdan.com/data-and-trending-technologies-role-of-data-in-digital-thread/24055> (accessed on 9 July 2023).
16. Kiran, M.B.; Wynn, M. The Internet of Things in the Corporate Environment. In *Handbook of Research on Digital Transformation, Industry Use Cases, and the Impact of Disruptive Technologies*; Wynn, M., Ed.; IGI-Global: Hershey, PA, USA, 2022; pp. 132–148. Available online: <https://eprints.glos.ac.uk/10497/> (accessed on 12 July 2023) ISBN 9781799877127.
17. Bader, S.R.; Maleshkova, M. The Semantic Asset Administration Shell. In *Semantic Systems—The Power of AI and Knowledge Graphs*; Acosta, M., Cudré-Mauroux, P., Maleshkova, M., Pellegrini, T., Sack, H., Sure-Vetter, Y., Eds.; SEMANTiCS 2019. Lecture Notes in Computer Science, 11702; Springer: Cham, Switzerland, 2019; pp. 159–174. [[CrossRef](#)]
18. Abdel-Aty, T.A.; Negri, E.; Galparoli, S. Asset Administration Shell in Manufacturing: Applications and Relationship with Digital Twin. *IFAC-PapersOnLine* **2022**, *55*, 2533–2538. Available online: <https://www.sciencedirect.com/science/article/pii/S240589632020997> (accessed on 14 August 2023). [[CrossRef](#)]
19. Ye, X.; Yu, M.; Song, W.S.; Hong, S.H. An Asset Administration Shell Method for Data Exchange between Manufacturing Software Applications. *IEEE Access* **2021**, *9*, 144171–144178. [[CrossRef](#)]
20. Baldwin, B. Digital Thread vs. Digital Twin: Which Do You Need Most? 2022. Available online: <https://vksapp.com/blog/digital-thread-vs-digital-twin> (accessed on 22 July 2023).
21. Essex, D. Digital Twin: What Is a Digital Twin and How Does It Work?; TechTarget. 2022. Available online: <https://www.techtarget.com/searcherp/definition/digital-twin> (accessed on 10 July 2023).
22. Zhang, Z.; Wang, X.; Wang, X.; Cui, F.; Cheng, H. A simulation-based approach for plant layout design and production planning. *J. Ambient Intell. Humaniz. Comput.* **2019**, *10*, 1217–1230. [[CrossRef](#)]
23. Guo, J.; Zhao, N.; Sun, L.; Zhang, S. Modular based flexible digital twin for factory design. *J. Ambient Intell. Humaniz. Comput.* **2019**, *10*, 1189–1200. [[CrossRef](#)]
24. Friederich, J.; Francis, D.P.; Lazarova-Molnar, S.; Mohamed, N. A framework for data-driven digital twins of smart manufacturing systems. *Comput. Ind.* **2022**, *136*, 103586. [[CrossRef](#)]
25. Loaiza, J.H.; Cloutier, R.J.; Lippert, K. Proposing a Small-Scale Digital Twin Implementation Framework for Manufacturing from a Systems Perspective. *Systems* **2023**, *11*, 41. [[CrossRef](#)]
26. Schweigert-Recksiek, S.; Trauer, J.; Engel, C.; Spreitzer, K.; Zimmermann, M. Conception of a Digital Twin in Mechanical Engineering—A Case Study in Technical Product Development. In *Proceedings of the International Design Conference—Design 2020*, Online, 26–29 October 2020; Cambridge University Press: Cambridge, UK, 2020; pp. 383–392. [[CrossRef](#)]



27. Kreimeyer, M.; Deubzer, F.; Herfeld, U.; Lindemann, U. Holistic integration of CAD and CAE: Analysis and combination of diverse current approaches. In Proceedings of the 9th International Research/Expert Conference Trends in the Development of Machinery and Associated Technology, Antalya, Turkey, 26–30 September 2005; pp. 1081–1084, ISBN 9958-617-28-5.
28. ISO. Digital Twin Framework for Manufacturing ISO 23247. 2023. Available online: <https://www.ap238.org/iso23247/> (accessed on 18 July 2023).
29. Irizar, J. Digital Technology Deployment in Multi-National Enterprises. In *Handbook of Research on Digital Transformation, Industry Use Cases, and the Impact of Disruptive Technologies*; Wynn, M., Ed.; IGI-Global: Hershey, PA, USA, 2022; pp. 18–33. [CrossRef]
30. Altundag, A. A New Model for the Digital Transformation of the Strategic Procurement Function: A Case Study from the Aviation Industry. In *Handbook of Research on Digital Transformation, Industry Use Cases, and the Impact of Disruptive Technologies*; Wynn, M., Ed.; IGI-Global: Hershey, PA, USA, 2022; pp. 92–116. [CrossRef]
31. Wynn, M. Conclusion: Digital Transformation and IT Strategy. In *Handbook of Research on Digital Transformation, Industry Use Cases, and the Impact of Disruptive Technologies*; Wynn, M., Ed.; IGI-Global: Hershey, PA, USA, 2022; pp. 409–421. Available online: <https://eprints.glos.ac.uk/10126/5/10126-Wynn-Conclusion.pdf> (accessed on 27 July 2023).
32. Trauer, J.; Mac, D.P.; Mörtl, M.; Zimmermann, M. A Digital Twin Business Modelling Approach. In Proceedings of the International Conference on Engineering Design, ICED23, Bordeaux, France, 24–28 July 2023; Available online: [https://www.cambridge.org/core/services/aop-cambridge-core/content/view/45218E723B02C7B579E9106913A4CFD2/S2732527X23000135a.pdf/digital\\_twin\\_business\\_modelling\\_approach.pdf](https://www.cambridge.org/core/services/aop-cambridge-core/content/view/45218E723B02C7B579E9106913A4CFD2/S2732527X23000135a.pdf/digital_twin_business_modelling_approach.pdf) (accessed on 27 July 2023).
33. Arif, S.; Sidek, S.; Abu Bakar, N. Actor-Network Theory as an Interpretative Tool to Understand the Use of Online Technologies: A Review. *Asian J. Inf. Technol.* **2017**, *16*, 61–68.
34. Iyamu, T.; Sekgwele, T. Information Systems and Actor-Network Theory Analysis. *Int. J. Actor-Netw. Theory Technol. Innov.* **2013**, *5*, 1–11. [CrossRef]
35. Cresswell, K.M.; Worth, A.; Sheikh, A. Actor-Network Theory and Its Role in Understanding the Implementation of Information Technology Developments in Healthcare. *BMC Med. Inform. Decis. Mak.* **2010**, *10*, 67. [CrossRef] [PubMed]
36. Bonnet, D.; Westerman, G. The New Elements of Digital Transformation. *MIT Sloan Manag. Rev.* 2021. Available online: <https://sloanreview.mit.edu/article/the-new-elements-of-digital-transformation/> (accessed on 27 July 2021).
37. Lang, V. Digitalization and Digital Transformation. In *Digital Fluency*; Lang, V., Ed.; Apress: Berkeley, CA, USA, 2021; pp. 1–50, ISBN 978-1-4842-6773-8. [CrossRef]
38. Furr, N.; Shipilov, A.; Rouillard, D.; Hemon-Laurens, A. The 4 Pillars of Successful Digital Transformations. 2022. Available online: <https://hbr.org/2022/01/the-4-pillars-of-successful-digital-transformations#:~:text=The%20framework%20outlines%20the%20four,most%20companies%20digital%20transformation%20journey> (accessed on 15 July 2023).
39. Newman, D. Understanding the Six Pillars of Digital Transformation Beyond Tech. *Forbes* **2018**. Available online: <https://www.forbes.com/sites/danielnewman/2018/05/21/understanding-the-six-pillars-of-digital-transformation-beyond-tech/> (accessed on 31 July 2023).
40. Bell, E.; Bryman, A.; Harley, B. *Business Research Methods*; Oxford University Press: Oxford, UK, 2018.
41. Yin, R.K. *Case Study Research and Applications: Design and Methods*, 6th ed.; Sage Publications: Thousand Oaks, CA, USA, 2018.
42. Gray, D. *Doing Research in the Business World*; SAGE Publications Ltd.: Thousand Oaks, CA, USA, 2016.
43. Flyvbjerg, B. Five Misunderstandings about Case-Study Research. *Qual. Inq.* **2006**, *12*, 219–245. [CrossRef]
44. Ritchie, J.; Lewis, J.; Elam, G. Designing and selecting samples. In *Qualitative Research Practice: A Guide for Social Science Students and Researchers*; Ritchie, J., Lewis, J., Eds.; Sage Publications: Thousand Oaks, CA, USA, 2003; pp. 77–108.
45. Saunders, M.; Lewis, P.; Thornhill, A. *Research Methods for Business Students*, 8th ed.; Pearson Education Limited: London, UK, 2018.
46. Lee, N.; Lings, I. *Doing Business Research: A Guide to Theory and Practice*; Sage Publications Ltd.: Thousand Oaks, CA, USA, 2008.
47. Mason, W.; Mirza, N.; Webb, C. *Using the Framework Method to Analyze Mixed-Methods Case Studies*; Sage Research Methods Cases, Part 2; Sage Publications: Thousand Oaks, CA, USA, 2018.
48. Wynn, M.; Brinkmann, D. Exploiting Business Intelligence for Strategic Knowledge Management: A German Healthcare Insurance Industry Case Study. *Int. J. Bus. Intell. Res.* **2016**, *7*, 11–24. Available online: <https://eprints.glos.ac.uk/3841/> (accessed on 23 July 2023). [CrossRef]
49. Tonder, C.; Schachtebeck, C.; Nieuwenhuizen, C.; Bossink, B. A framework for digital transformation and business model innovation. *Management* **2020**, *25*, 111–132. [CrossRef]

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.