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Digital Twin adoption in manufacturing systems

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Table of contents

Acronyms

ADT: Adaptive Digital Twin

AGV: Automated Guided Vehicle

AI: Artificial Intelligence

AR: Augmented Reality

ASC: Autonomous Sub-Component

CDT: Cognitive Digital Twin

CSC: Constrained Sub-Component

CPS: Cyber Physical Systems

DES: Discrete Event Simulation

DSC: Dynamic Sub-Component

DS: Digital Shadow

DST: Digital Sub-Twins

DTMU: Digital Twin Manufacturing Unit

DTP: Digital Twin Prototype

DT: Digital Twin

DTI: Digital Twin Instance

DTMC: Digital Twin Manufacturing Cell

FE: Functional Element

IaaS: Infrastructure as a Service

IoT: Internet of Things

KG: Knowledge Graph

OME: Observable Manufacturing Element

PaaS: Platform as a Service

SoS: System of System

UN SDGs: United Nations Sustainable Development Goals

VR: Virtual Reality

List of Figures

List of tables

Abstract

This thesis investigates the role of Digital Twins in enhancing manufacturing systems within the context of Industry 4.0. The study provides an overview of Industry 4.0 highlighting the importance of digital transformation in modern industrial practices. The research delves into the concept of Digital Twins, their applications, and the benefits they offer in terms of optimizing operations, improving efficiency, and driving innovation in manufacturing industries. Through a literature review, the study examines the challenges and enablers of Digital Twin adoption. The thesis aims to contribute to the ongoing discourse on digital transformation in the manufacturing sector, providing insights for companies seeking to leverage Digital Twins to enhance their operations and competitiveness.

Questa tesi indaga il ruolo dei Digital Twins nel miglioramento dei sistemi di produzione nel contesto dell'Industria 4.0. Lo studio fornisce una panoramica dell'Industria 4.0 evidenziando l'importanza della trasformazione digitale. La ricerca approfondisce il concetto dei Digital Twins, le sue applicazioni e i vantaggi che offre in termini di ottimizzazione delle operazioni, miglioramento dell'efficienza e spinta all'innovazione nelle aziende manifatturiere. Attraverso una revisione della letteratura, lo studio esamina le sfide e i fattori abilitanti dell'adozione del Digital Twin. La tesi si propone di contribuire al discorso in corso sulla trasformazione digitale nel settore manifatturiero, fornendo spunti per le aziende che cercano di sfruttare i Digital Twin per migliorare le loro operazioni e la loro competitività.

Keywords: Digital Twin, Industry 4.0, Manufacturing, IoT, Artificial Intelligence, Simulation, Optimization, Sustainability.

1 Introduction

Industry 4.0 has brought a revolution in the manufacturing industry. The term refers to the fourth industrial revolution that integrates digital and physical technologies into manufacturing systems. The objective of Industry 4.0 is to create smart connected factories through the employment of technologies such as Internet of Things (IoT), Cyber Physical Systems (CPS) and Artificial Intelligence (AI), that enable real-time collection, analysis, and communications among machines, products, and people.

The concept of Digital Twin (DT) has gained significant traction in recent years. It offers manufacturers the ability to create virtual representations of their physical assets, processes, and systems. DT technology leverages real-time data and advanced analytics to enable companies to gain valuable insights into the behavior and performance of their assets. This helps predict maintenance needs, optimize production processes, and even simulate different scenarios to improve decision-making. To have a better understanding of what DTs are and how they apply in the manufacturing sector, a literature review on relevant academic publications has been conducted.

The objective of this thesis is to investigate the adoption of DTs in manufacturing systems and the impacts that it may have on efficiency, productivity, and sustainability manufacturing processes. For this purpose, the thesis is structured as follows: first, the research methodology used for this thesis is presented, followed by an introduction to DT technology and its growing trend; then the focus shifts to the general functioning of DTs followed by their application in the manufacturing context based on the classification criteria used. The benefits and challenges of using Digital Twins are finally outlined and the conclusions are presented.

2 Research methodology

A Scopus search was conducted to analyse the use of DTs and the benefits derived from their use in manufacturing industries.

Four types of search were carried out, corresponding to different keywords (Figure 1).

As the aim of the thesis was to analyse the use of DTs in manufacturing companies, the keywords 'digital twin' and 'manufacturing' were used. Others were added depending on the objective.

For a general overview, the words 'industry' and 'ecosystem' were added.

In addition, the keywords 'barriers', 'concerns', 'challenges', 'requirements' and 'enablers' were used to analyse the barriers that may be encountered in the implementation of a DT and the basic requirements that a company should have in order to successfully exploit this new technology.

Finally, the keyword "sustainability" was introduced to assess whether DTs could bring benefits in terms of sustainability.

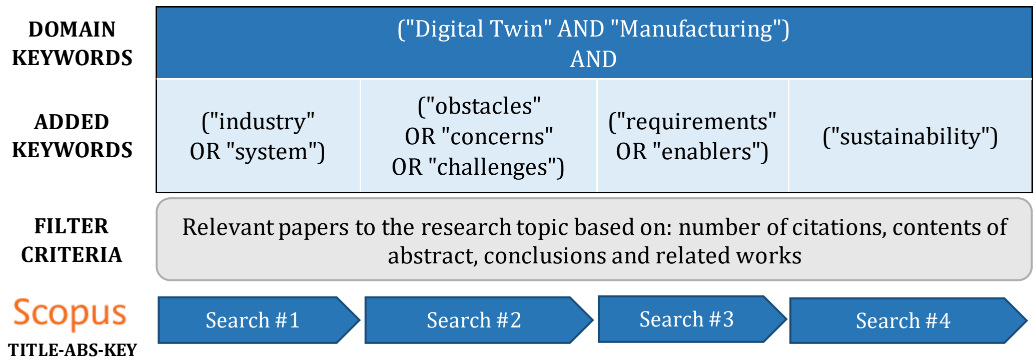

Figure 1: research methodology

Some papers were excluded immediately after reading the abstract, introduction and conclusion. Others were excluded after a more thorough reading. Finally, 94 documents were selected.

In order to give a general overview of the selected documents, Figure 2 illustrates the number of articles published per year. Looking only at the documents used for this thesis, we can see that from 2017 onwards the number of publications per year increases. Although this does not represent the totality of documents related to DTs in the literature, we can assume from this graph that this year marks a turning point where the concept of the Digital Twin has matured enough to be discussed more concretely.

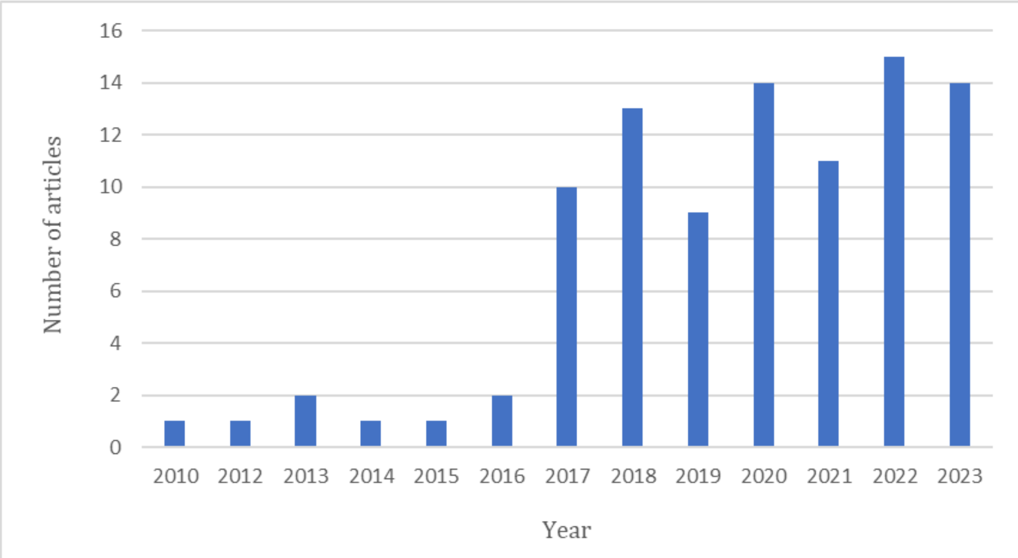

Figure 2: distribution of the reviewed publications per year

The type of articles selected are illustrated in Figure 3: the majority are journal articles, followed by web page, report and conference proceedings, and finally book sections.

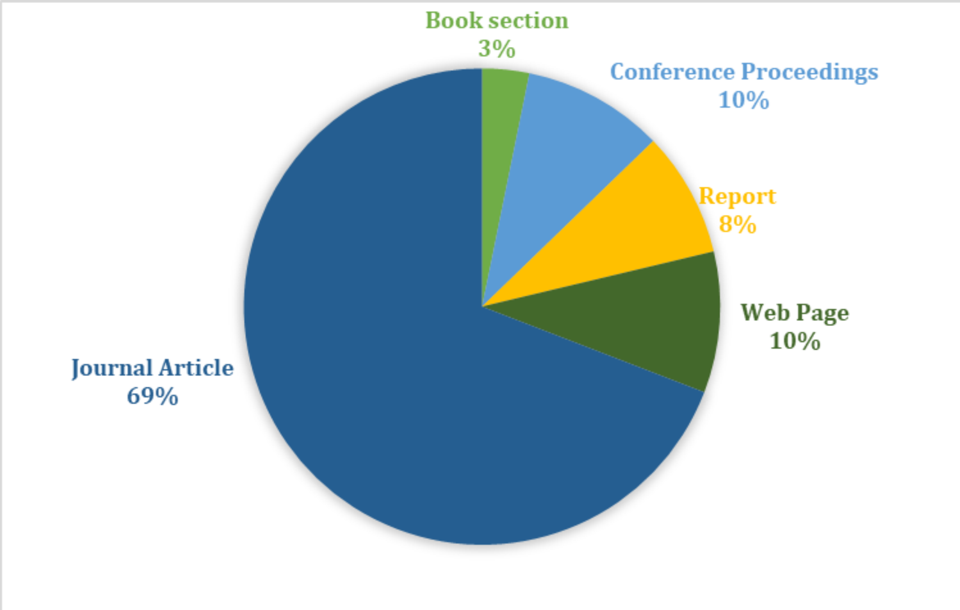

Figure 3: distribution of the reviewed publication per type of document

After introducing DT technology, section 5.1 presents how the documents dealing with the focus of this thesis (the use of DTs in the context of manufacturing industries) have been classified.

3 Introduction to DT technology

3.1 DTs and Industry 4.0

The now familiar and established term “Industry 4.0” first appeared in Germany in 2011, in a newspaper article about the German government's high-tech strategy [1].

The term refers to the 4th Industrial Revolution, which is seen as an extension of the first three industrial revolutions. While these are seen as the result of mechanisation and the introduction of electricity and information technology, the 4th Industrial Revolution has been ushered by Internet of Things (IoT) and Cyber Physical Systems (CPS) [2].

The first industrial revolution began in England in 1780, and then spread to the rest of Europe and the United States; the mechanised production was born with it, thanks to a new energy source, coal, and the introduction of the steam engine. Around 1870 the Second Industrial revolution began; new inventions like the electric light, the internal combustion engine, and the first cinema set, were accompanied by a new way of producing: the mass production. Then, in the second half of the 20th century, we start talking about the Third Industrial Revolution where traditional industrial technologies are being abandoned and replaced by digital and computer technologies which allowed manufacturing automation.

In recent years, we have finally been able to take another step forward. With Industry 4.0, the digital and physical worlds are converging, thanks to the emergence of digital manufacturing, network communications, computer and automation technologies (Figure 4) [1].

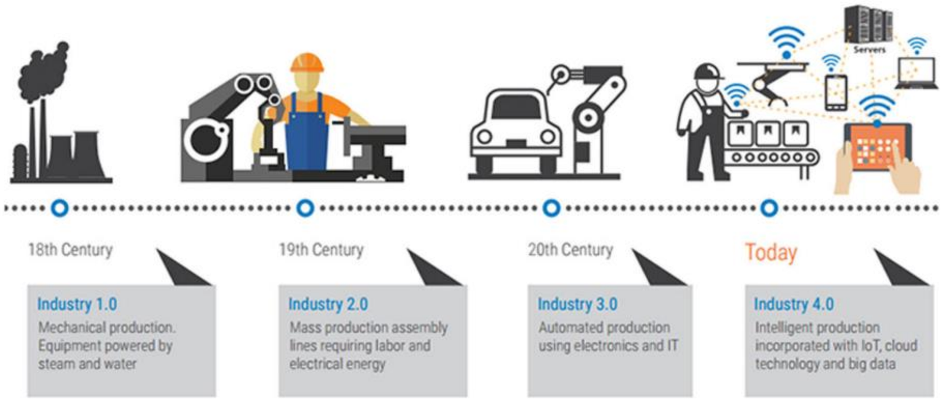

Figure 4: the four Industrial Revolutions [1]

The ongoing fourth industrial revolution is made possible by modern advanced technologies such as autonomous robots, IoT, Augmented Reality (AR), Artificial Intelligence (AI), and Digital Twins (DTs) [1].

DTs and Industry 4.0 are closely linked as DTs play a vital role in fulfilling various requirements of Industry 4.0. They are virtual representations of physical objects, processes, factories, supply networks, and manufacturing lines; they enable real-time monitoring, predictive maintenance, and data-driven decision-making, all of which are essential components of Industry 4.0. Furthermore, they provide intelligence to networked machines on the shop floor, allowing them to organize and execute production efficiently, which aligns with the goals of Industry 4.0 [3].

On the other hand, DTs make use of the fundamentals of Industry 4.0: technologies such as Big Data, simulation, the Internet of Things and the cloud are just some of the components required for DTs to operate effectively and provide new functionality to the business organisation [4].

In summary, DTs and Industry 4.0 are connected through their shared focus on utilizing advanced technologies, data analytics, and virtual representations to enhance industrial processes, increase efficiency, and promote innovation in manufacturing and production.

As will be discussed in more detail below, the integration of the Digital Twin emerges as a technologically complex process. However, the steady increase in investments in the context of digitisation attests to the willingness of companies to undergo a significant transformation. In a report published by Statista [5], we can observe not only the substantial investments being made in digital transformation but also how these are not limited to a single sector (Figure 5).

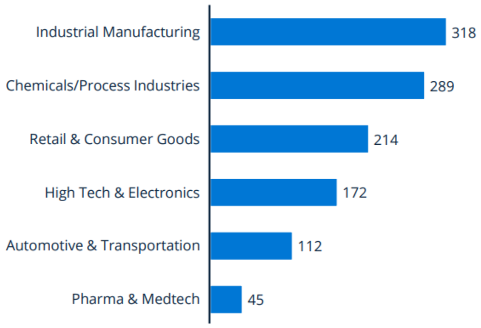

Figure 5 : Annual investments in digital factory transformation 2022 in billion US$ (Statista, 2023)

3.2 The history of DT

Using a general definition, we can say that DTs are a virtual replica of an object, a production line, a manufacturing process, or a supply chain, that utilises real-time data to predict the future performance of a machine, a process, etc. [5].

Although the concept of DTs has gained traction in recent years, its origins can be traced back several years [6]:

Since 1970, the use of simulation and reflective objects has been discussed. NASA utilised a mirrored replica of inaccessible systems to carry out simulations and find solutions to problems. After an oxygen tank exploded in the Apollo 13 mission, various simulations were conducted on a replica of the original tank to find a solution to communicate to the astronauts in space.

In 1991, David Gelernter introduced the concept of a DT in his book "Mirror Worlds": a software was capable of reproducing the physical world based on specific inputs [7].

In 2002, Michael Grieves introduced the first DT model, known as the "Mirrored Space Model". As can be seen from Figure 6, this model included [6]:

- A physical space containing the physical object.
- A virtual space containing the digital replica of the physical object.

The convergence between the physical and digital worlds was ensured by a flow of data from the physical space to the virtual space and a flow of information in the opposite direction.

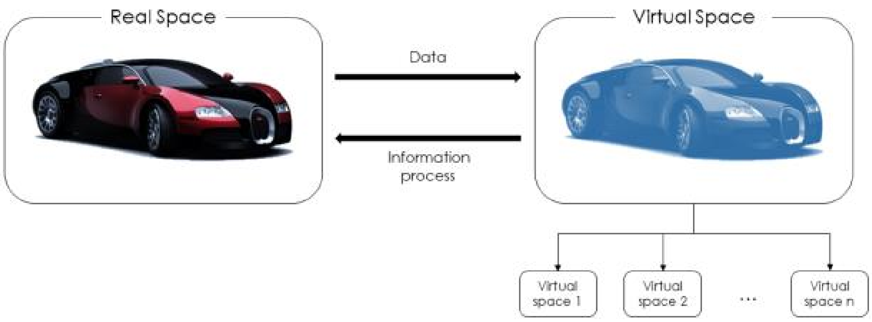

Figure 6: the Mirrored Space Model of Micheal Grieves [6]

In 2006, Grieves' model was renamed into "Information Mirroring Model"; this highlighted the possibility of representing a single physical reality in multiple virtual models to explore different alternatives.

Although the concept of a DT already began to emerge, due to the inadequate technologies available, it was not possible to implement it until 2010 (Figure 7).

In this year NASA published the technological roadmap where, for the first time ever, the term "Digital Twin" was coined. Here, it was described as:

"An integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or

system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin" [7].

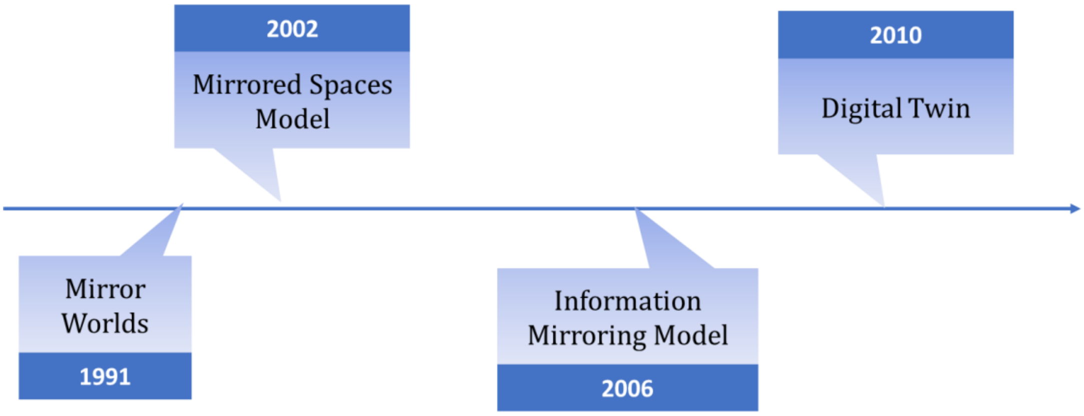

Figure 7: DT's timeline [7]

3.3 Digital Twin trends

Although, as mentioned above, the concept of DT first appeared in 2010, it is only in recent years that it has begun to spread and become increasingly popular.

In 2019, Gartner placed it fourth in its ranking of the 'Top 10 strategic technology trends for 2019", ahead of autonomous things, augmented analytics, and AI-driven development, followed by empowered edge, immersive experiences, blockchain, and smart spaces [8].

The growing interest in this new technology is evident; indeed, Google Trends shows us how online searches for 'Digital Twins' increased almost linearly in the last 5 years, peaking in November 2022 and September 2023 (Figure 8) [9].

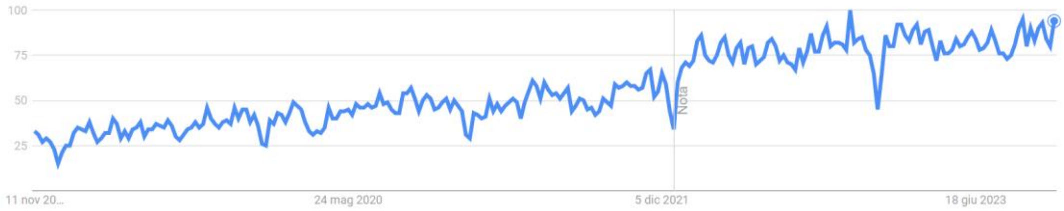

Figure 8: Interest in the search term 'Digital Twins' in the last 5 years [9]

As we can see from Figure 9, the rise in popularity of DTs has been followed by an increase in their use on almost every continent. North America leads the way, followed by Europe, Asia, Latin America, the Middle East and Africa. The highest growth rate is seen in the top 3, while Latin America and MEA show significantly lower growth [10].

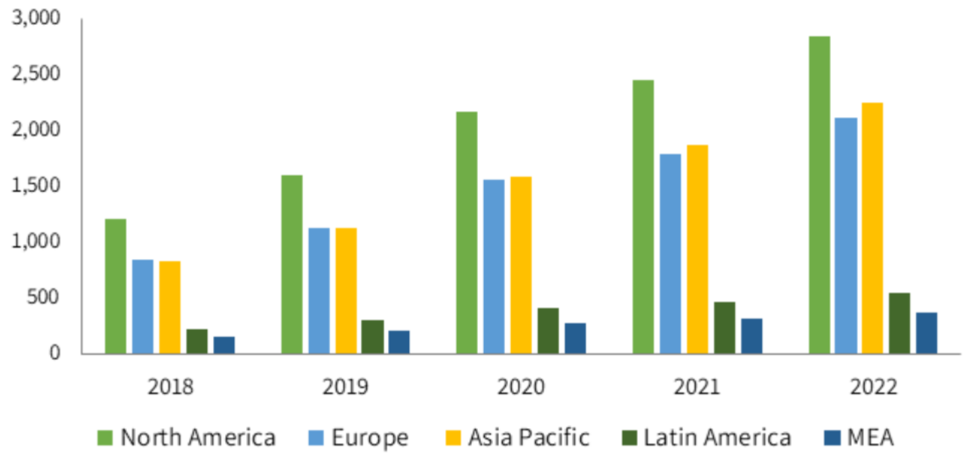

Figure 9: DT market size, by region (USD Million) [10]

Manufacturing industry accounted for over 22% of the global DT market share in 2020, followed by the automotive industry with over 18% (Figure 10) [11].

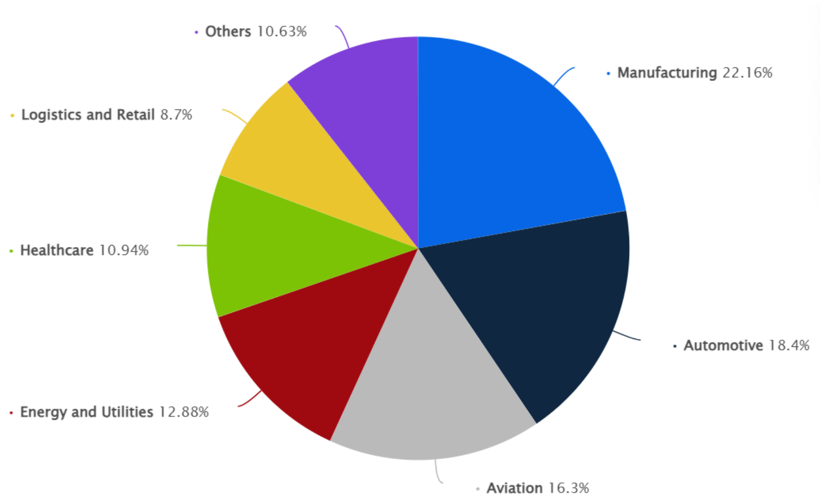

Figure 10: global DT market share in 2020 [11]

Looking ahead to 2025, Statista [12] predicts that the market value will soar. It will be the manufacturing sector, which as mentioned above already holds the leadership in terms of market share, that will have the highest growth rate (Figure 11).

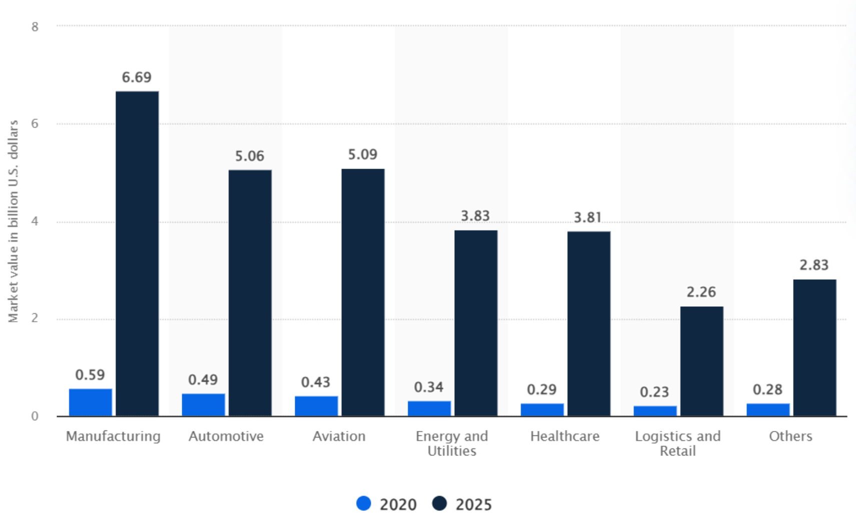

Figure 11: global DT market size in the year 2020 and 2025, by industry (in billion U.S dollars) [12]

To summarize, the interest and utilization of DTs is expected to increase significantly. The manufacturing industry, which has already adopted DT on a wide scale, will lead the charge in specializing in this new technology more quickly than other industries. It's not surprising that the most developed countries will invest heavily in the development of DT.

4 Digital Twin technology: definition and classification in literature

4.1 Definitions of Digital Twin

Nowadays, many definitions of a DT can be found in literature; Barricelli, Casiraghi, e Fogli (2019) has grouped them together, and essentially, they can be summarized in Table 1, where it has been also specified the sector in which the author has applied the definition.

Table 1 : Definitions of DT in literature

Key points	*#*	*Definition*	*Sector*
Integrated system	[13]	Integrated multi-physics, multiscale, and probabilistic simulation composed of physical product, virtual product, data, services and connection between them	Aerospace
	[14]	An ultra-realistic integrated multi-physics, multiscale, probabilistic simulation of a system	Aerospace
	[15]	A systematic approach consisting of sensing, storage, synchronization, synthesis and service	Manufacturing
Clone, counterpart	[16]	Computerised clones of physical assets	Manufacturing
	[17]	The virtual and computerised counterpart of a physical system	Manufacturing
Simulation, test, prediction	[18]	A safe environment in which you can test the impact of potential change on the performance of a system	Healthcare
	[19]	Virtual model of physical objects to simulate their behaviours	Manufacturing
Virtual, mirror, replica	[20]	A virtual representation of the system	Aerospace
	[21]	Digital mirror of the physical world	Manufacturing
	[22]	A cyber copy of a physical system	Manufacturing
	[23]	A virtual model of physical object	Manufacturing

Both of the first two definitions, formulated by authors who have applied them to the aerospace sector, highlight several key aspects of its capabilities and characteristics [13], [14]:

- Integration: DT technology integrates multiple aspects of a complex product, including its physical and virtual components, as well as the data linking them.
- Simulation: DT technology uses advanced simulation techniques to create a virtual model of a complex product that accurately reflects its real-life behaviour.
- Multi-physical and multi-scale: DT technology can simulate a wide range of physical phenomena and scales, allowing complex products to be modelled with high accuracy.
- Probabilistic: DT technology incorporates probabilistic modelling techniques to account for uncertainties and variations in the behaviour of complex products.

On the other hand, Lee, Lapira and Balgheri (2013) [15] extend the context of the DT. They emphasise the incorporation of data-driven analytical algorithms and physical knowledge to simulate and monitor the health of a manufacturing machine throughout its operating life.

Both definitions [16] and [17] refer to DTs in the context of manufacturing, highlighting their virtual nature. However, while in the former the focus is on the fact that the DT constitutes an exact duplication, thanks to the use of the term 'clone', in the latter, with the use of the term 'counterpart', a parallel existence is implied, emphasising the DT as an entity corresponding to the physical system.

Definitions [18] and [19] of DT focus on the purpose and usefulness of this technology in the areas of testing and simulation. The difference between the two definitions is subtle. In definition 8, the DT is viewed as a tool for simulating hypothetical situations or "what if" scenarios. On the other hand, Definition 9 defines it as a tool that anticipates the behavior of the corresponding physical object.

In relation to the final section of the table, while all definitions agree on the virtual representation of physical systems or objects, each author introduces a distinct nuance. Definition [20] has a broad emphasis on the virtual representation of the system. Definition [21] highlights the reflection of the physical world through the concept of a digital mirror. Definition [22] emphasises the cybernetic nature and duplication of the system. Finally, Definition [23] focuses on virtual models of physical objects. These differences highlight the conceptual richness and interpretative aspects of the DT.

The diversity of definitions proposed to describe a DT reflects its versatility and the breadth of possible applications. It is clear that there is no single universally accepted definition, but rather a set of perspectives that fit specific contexts and objectives.

4.2 DTs classification in literature

After introducing the concept of DT and providing various definitions, it might be interesting to analyse how they have been classified in the literature before presenting the classification criteria for this thesis.

Various documents present distinct classification criteria based on their respective objectives. To offer a comprehensive and diverse outlook on these criteria, we have collected a range of them.

Grieves M. and Vickers J. (2016) [24] categorized the different types of DTs on the base of its creation time in relation to its physical counterpart, identifying two types of DTs: **Digital Twin Prototype** (DTP) and **Digital Twin Instance** (DTI). The first one is created before the physical object, allowing for aesthetic and functional tweaks to be made before the production begins, while the latter is created after its physical twin has been produced and remains "attached" to it throughout its lifecycle.

Kritzinger et al. (2018) [25] identified three types of DT based on the level of integration between the physical and digital object. The differences among these types are determined by the data exchange that takes place (or not) between the physical and digital world (Figure 12):

1. **Digital Model**: in a digital model, there is no exchange of data between the physical product and its DT. Data from the physical product is used to construct the digital product, but if the physical product were to change, the DT would not automatically change.
2. **Digital Shadow**: in this case there is a one-way exchange of data so that a change in the physical object would result in a corresponding change in the digital one.

3. **Digital Twin**: in this case a two-way flow of data takes place. Whereby any change, whether occurring in digital or physical space, would be reflected in the corresponding physical/digital object.

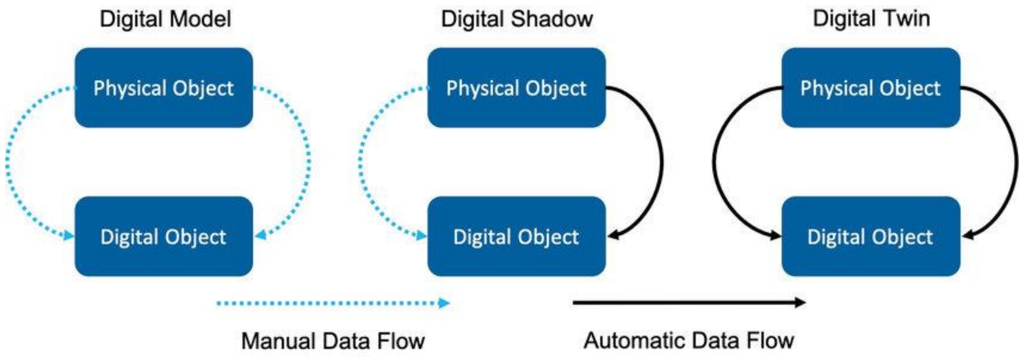

Figure 12: integration level of DTs [25]

Another type of classification that has been found in literature is relative to the intended use of a DT, so that the following types can be identified [26]:

- **Product Digital Twins**: it is used to represent a physical product in virtual space. The DT of a product makes it possible to simulate different conditions, see how the product reacts and then make changes to the design until the ideal one is achieved.
- **Production Digital Twin**: this type of twin makes it possible to assess the functioning of an entire production process. By simulating production, they can reveal possible inefficiencies in the production line (such as bottlenecks) before they manifest themselves in the physical world. By combining the DT of machinery (DT of a product) with that of production, we can also predict when maintenance will be required.
- **Performance Digital Twin**: these twins are able to harness the data produced by smart assets and products, then aggregate, analyse and enable informed decision making.

According to Tao et al. (2019) from a hierarchical perspective – i.e the level of involvement within the company - DT can be divided into three different levels (Figure 13) [27]:

- **Unit level:** this level refers to the smallest participant in the production process. It can be a material, a component or a piece of equipment.
- **System level**: multiple DTs at the level of units exchanging data form a DT at the system level. At the system level we can have a production line, a department or an entire factory.
- **System of Systems** (SoS) level: several DTs at the level of units exchanging data form a DT at the system level. This could be a production line, a department or an entire factory. Sometimes a complex product can be represented by such DTs, which can also evaluate and improve the interaction between multiple components.

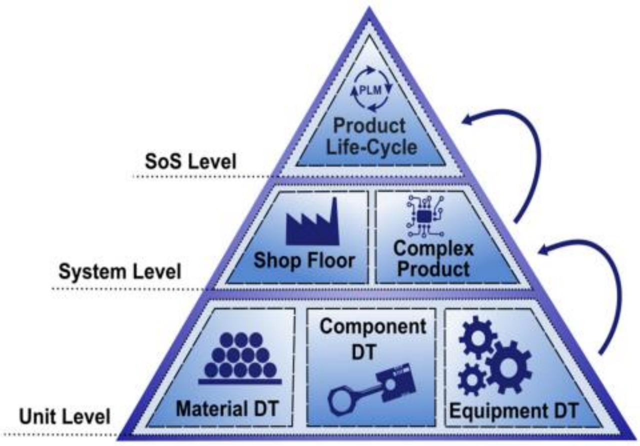

Figure 13: classification of DT at hierarchical leve [27]

Madni et al. (2019) identifies four levels of virtual representation based on the sophistication level [28]:

- **Pre-Digital Twin**: it is built before a product is prototyped to help guide design decisions and identify problems early on.
- **Digital Twin**: it represents the DT as we have introduced it so far.
- **Adaptive Digital Twin**: it can support real-time planning and decision-making during operations, maintenance, and support by acquiring the preferences of the operator or user.
- **Intelligent Digital Twin**: in addition to all the characteristics of the previous levels, this type of DT also has learning capabilities.

Other rwo classification criteria are the ones identified by Yu et al. (2022) and Enders et al. (2019). The first one classified the DTs on the base of their application scale: nano (molecular level), **Micro** (single operation or part), **Meso** (collection of operations) and **Macro** (community, local area) [29]. The second one instead divided the DTs depending on the purposes: **simulation**, **monitoring** and **control** [30].

5 DTs in manufacturing

5.1 The proposed classification framework

After having reviewed various DTs classification criteria in the literature, this thesis will adopt a specific criterion that will be used throughout the following sections.

Looking at the documents related to the adoption of DTs in manufacturing companies, this being the focus area of the thesis, it is possible to make an initial distinction between three main categories of approaches (Figure 14).

The first category includes documents that provide an overview of the general operation of DTs, focusing on explaining the basic principles and their overall functioning.

The second identified category includes documents presenting specific DT frameworks designed for particular purposes within manufacturing companies. These documents focus on the structure and application of DT models.

Finally, the third category includes documents that do not deal directly with the development or application of DTs, but rather provide guidelines regarding the enabling factors, challenges and opportunities of using a DT within manufacturing frameworks.

Figure 14: first classification of the literature

For the documents presenting a general overview no further classification has been adopted.

For the second type of documents, those presenting a DT model, a further categorisation criterion was introduced. In particular, the purpose for which the presented DT was developed was considered. More specifically, we have identified 6 different functions:

- **Monitor and improve the production process**: use the DT to monitor and optimise the production process, allowing more efficient management and early identification of potential improvements.
- **Design the layout in an optimised way**: use the DT for optimised layout design of equipment and resources, improving spatial and operational efficiency.
- **Enhance sustainability**: employ the DT to monitor and optimise resource utilisation, reducing environmental impact and promoting sustainable production practices.
- **Handle flexibility of the production system**: Leverage the DT to quickly and efficiently adapt the production system to changes in demand or other changes, ensuring greater flexibility.
- **Collaboration with other DTs**: use the DT as a platform for collaboration between different Digital Transformation systems, facilitating the exchange of data and information to optimise interconnected processes.
- **Cognitive DT**: to offer enhanced predictive analysis, decision-making and optimisation capabilities thanks to its cognitive functionalities.

Moreover, for each function, it has been identified that DTs can offer different services:

- **DT Services:** this refers to what the DT does to fulfil its purpose. On the base of the analysis of the documents found in literature we have identified that a DT can perform real-time monitoring, support decision-making, predict potential failures, and conduct optimization analysis.
    - **Real time state monitoring**: the DT allows real-time monitoring of a system or object, providing immediate data on its current status. This allows constant and up-to-date observation of the operating conditions.
    - **Decision-making support**: the DT provides detailed and contextual information to support decision-making. It helps to make informed decisions based on the data and simulations generated by the digital model.
    - **Failure analysis and prediction**: by analysing historical and real-time data, DT is able to identify potential faults and predict future problems. This functionality allows preventive intervention to avoid malfunctions.
    - **Analysis for optimization**: the DT allows in-depth analysis of processes and operations, facilitating the identification of areas where efficiency can be optimised, costs reduced, or overall performance improved.

To summarize, the documents presenting a DT framework has been divided on the base of the DT purpose. And for each document has been identified the DT service and the scope (Figure 15).

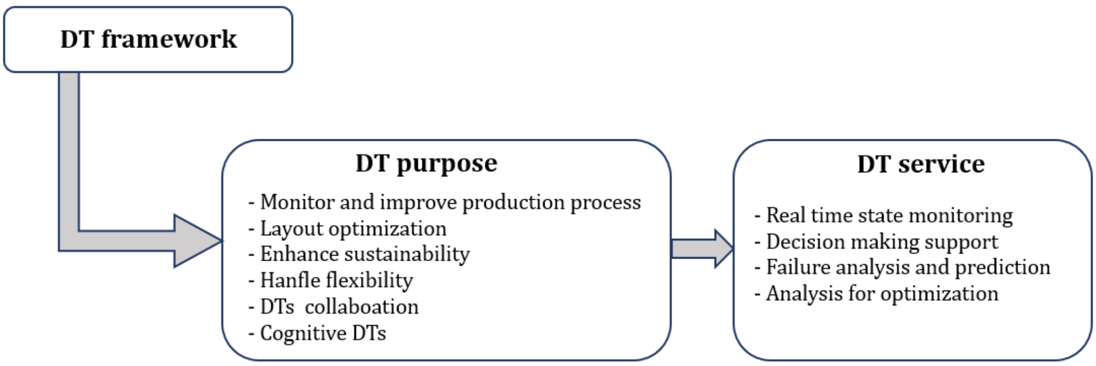

Figure 15: sub-classification of the literature for documents presenting a DT framework

The documents that fall under the third classification criterion (enablers, challenges and opportunities) were subclassified. The enabling factors were further divided based on their dependence on specific technologies, adherence to processes, essential employee skills, or a well-defined corporate culture. This approach helped in gaining a more detailed understanding of the factors that contribute to organizational success. The challenges are divided in 3 building blocks: engineering related challenges, organizational challenges and data related challenges. Instead, for the opportunities no further classification has been adopted.

Table 2 summarizes all the classifications that have just been listed. On the left we can see the first classification (general overview, DT frameworks and enablers, opportunities, and challenges); the second column shows the subclassification (for example for the documents showing a DT framework this column illustrates every function DT can have, like monitor and improve production process); the third block of the table shows instead the transversal classification (for example, for a specific DT function, it is illustrated the service that DT offer).

<table>
<tr><td rowspan="2">OVER VIEW</td><td colspan="12">References</td></tr>
<tr><td colspan="12">[31], [32], [33], [34], [35] [36], [37],</td></tr>
<tr><td rowspan="9">DT FRAMEWORKS</td><td rowspan="2">Function</td><td colspan="12">DT services</td></tr>
<tr><td colspan="3">Real time state monitoring</td><td colspan="3">Decision making support</td><td colspan="3">Failure analysis and prediction</td><td colspan="3">Analysis for optimization</td></tr>
<tr><td>Monitor and improve production process</td><td colspan="3"></td><td colspan="3">[38], [39], [40], [41], [42], [43]</td><td colspan="3"></td><td colspan="3">[44], [45], [46], [47], [48], [49], [50]</td></tr>
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<tr><td>DTs collaboration</td><td colspan="3">[62]</td><td colspan="3"></td><td colspan="3">[63], [64]</td><td colspan="3"></td></tr>
<tr><td>Cognitive DTs</td><td colspan="3">[65], [66], [67]</td><td colspan="3">[68], [67], [69]</td><td colspan="3">[66]</td><td colspan="3">[65], [68], [66]</td></tr>
<tr><td>Enhance Sustainability</td><td colspan="3"></td><td colspan="3">[70], [71], [72]</td><td colspan="3">[72], [73]</td><td colspan="3">[73], [74], [75], [76]</td></tr>
<tr><td rowspan="8">ENABLERS, OPPORTUNITIES & CHALLENGES</td><td rowspan="2"></td><td colspan="12">Category</td></tr>
<tr><td colspan="3">Systems and Technologies</td><td colspan="3">Process</td><td colspan="3">People and competences</td><td colspan="3">Culture and strategy</td></tr>
<tr><td>Enablers</td><td colspan="3">[77], [78], [79], [80]</td><td colspan="3">[77]</td><td colspan="3">[77], [81]</td><td colspan="3">[77]</td></tr>
<tr><td>Opportunities</td><td colspan="12">[82], [83], [84], [85], [86], [87]</td></tr>
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<tr><td rowspan="2">Challenges</td><td colspan="4">Engineering</td><td colspan="4">Organizational</td><td colspan="4">Data</td></tr>
<tr><td colspan="4">[88], [89], [90], [91], [92], [93]</td><td colspan="4">[89], [90], [92], [93]</td><td colspan="4">[89], [90], [91], [93]</td></tr>
</table>

Table 2: classification criteria

5.2 General overview

This section is dedicated to understanding how a DT works, i.e. how the interaction between the physical world and the real world takes place.

As previously mentioned in subsection 3.2, Michael Grieves provided the initial representation of how a DT operates in 2014. He depicted it as a connection between physical and virtual space [31].

Stark et al. (2017) [32] characterises the DT as the combination of an asset's Digital Master model, its individual Digital Shadow and an intelligent linking of the two. It involves the digital shadow being created through operation and condition data, process data, etc., generated by the individual product or production system (Figure 16).

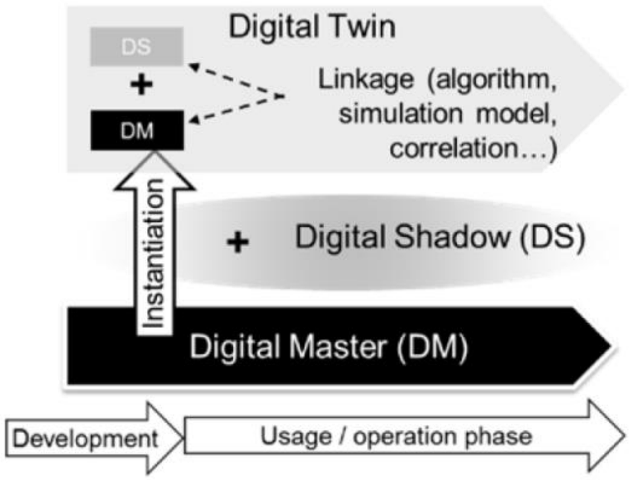

Figure 16: Stark's DT characterization [32]

Another proposition is made by Tao et al. (2018). Their five-dimension DT model includes the following components (Figure 17) [33]:

- **Physical entity** (PE): the actual physical equipment being monitored.
- **Virtual entity** (VE): the DT or virtual model of the equipment.
- **Sensor system** (Ss): the system of sensors used to collect data from the equipment.

- **DT data** (DD): the data collected from both the physical and virtual aspects of the equipment, as well as their fusion.
- **Connection model** (CN): the bidirectional connections between the PE, VE, Ss, and DD to facilitate data exchange and analysis.

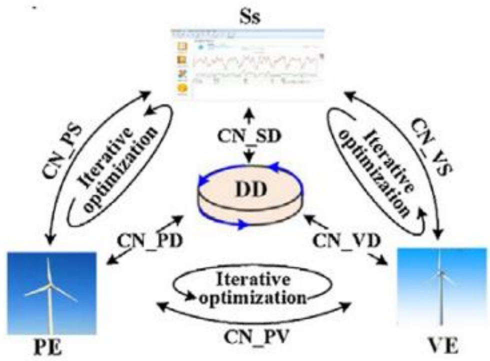

Figure 17: Five dimension DT model [33]

Similarly, Redelinghuys et al. (2019) [34] propose a six layers DT to illustrate the data information flow (Figure 18). The first two layers contain the physical twin: the first one includes all the physical devices, while the second one the local controllers which provide some functionalities to the DT. Layer 3 contains the data which reflect the details of the physical twin. Layer 4 acts as gateway between layer 3 and 5, selecting only the data that need to be transmitted. Layer 5 contains the database servers that act as repositories of the information transmitted by the gateway in layer 4. Finally, Layer 6 represents the intelligence of DT: here is where emulation and simulation take place.

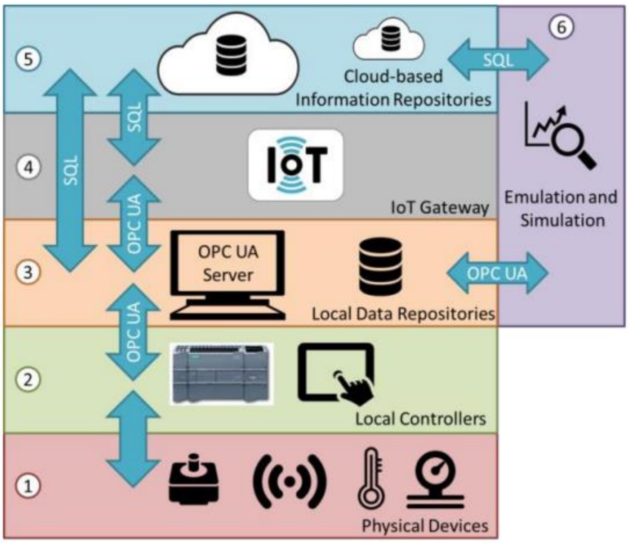

Figure 18 : Redelinghuys' six layers DT architecture [34]

Boje et al. (2020) [35] have defined DT architecture consisting of three distinct layers, comprised of a variety of components and technologies. The physical layer represents tangible entities and reflects the product life cycle stage. The network layer links the physical and virtual domains and enables the data and information exchange. The computing layer is comprised of the virtual entities that replicate their physical counterparts with data-driven and physics-based models, as well as services and users. Key DT components such as information structures, models, software technologies, hardware technologies, etc. play a paramount role across these layers [35].

If we compare the frameworks illustrated above, we can see that the application areas of Digital Twins are many. The frameworks illustrated by Stark [32] is used within cyber physical system for testing during ongoing operations to ensure error-management real-time performance and analysis. The DT in [33] is employed to monitor work conditions of products difficult to accede, with lots of components that may fall (for example wind turbine). The focus of [34] is instead the exchange of data and information between a remote simulation and a manufacturing cell. Finally [35] illustrated a construction DT whose benefit, in the built environment, is the accrual of knowledge about the physical world delivering improved lifecycle costs and bult asset resilience.

According to a report by Deloitte [36] , the process can be defined as sensors gathering data about the machines, production line and environment, which is transmitted to the DT for analysis. Any deviation from the ideal are flagged, and the production process is changed. Communication interfaces are used, and a number of security measures including firewalls, encryption and device certificates are needed. The key components of this process are also explained (Figure 19): Sensors to gather data; Data that must be compared against company records to find the discrepancies; Data must be transmitted to the DT where the digital and physical worlds are overlaid; Data received by the DT, so that it can be modeled; Actuators that can then adjust the process as needed.

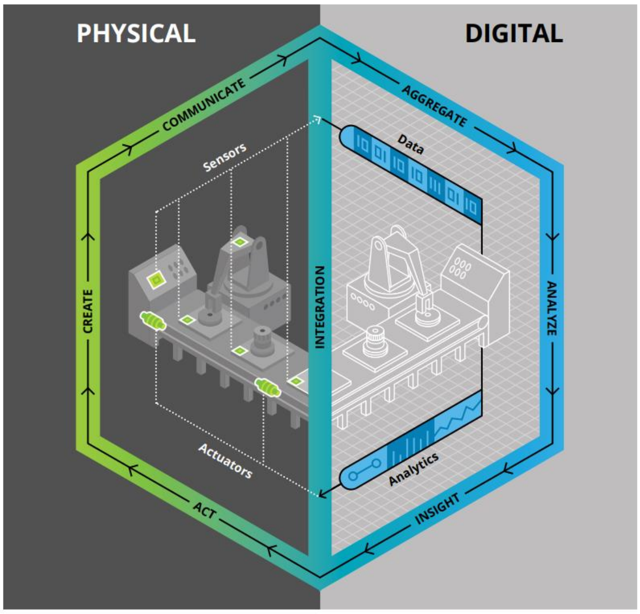

Figure 19: DT of a manufacturing process [36]

Shifting the focus on how the DT works, Colin J. Parris [37] identifies three phases: see, think, do (Figure 20).

In the **seeing phase**, the DT collects data to give a warning when a certain threshold is reached and then predicts the nature of the problem. The model, like the one in question, can update itself to represent the exact conditions of the physical product, second by second. In the second phase (**thinking phase**), the DT provides options for the user to pursue. To do this, the DT runs simulations looking at historical data, real-time data, cost and revenue forecasts. Each proposed option is accompanied by an explanation of the risks involved and the confidence level. Finally, in the **dew stage** the option selected by the operator is executed. If the one proposed it is a manual operation that must be done by an operator, then the operator himself is informed of the conditions required for the operation [37].

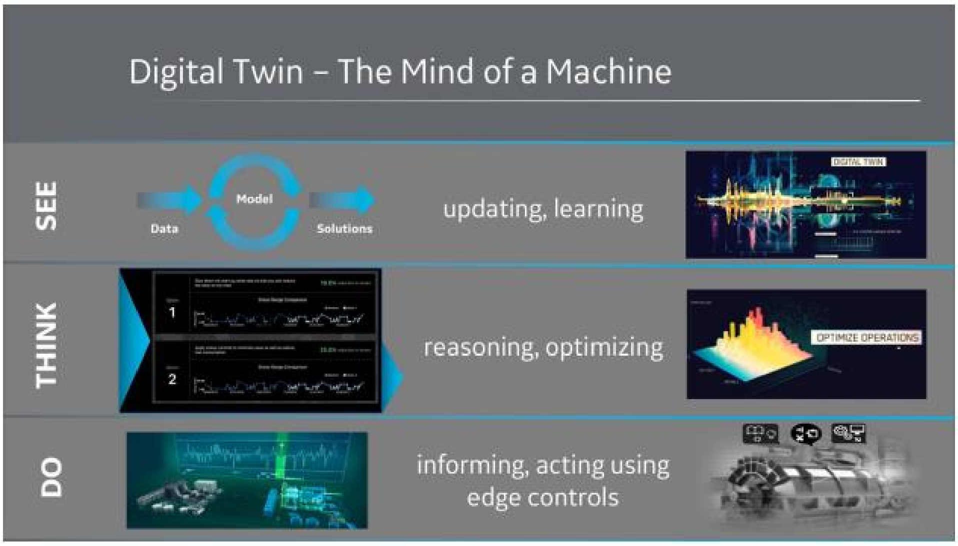

Figure 20 : the lifecycle of a DT [37]

5.3 DTs developed frameworks in literature

The aim of this section is to present some DT frameworks - i.e. a conceptual and technical structure designed to create and manage a digital twin - in the context of manufacturing companies, focusing on specific DT functions.

Before examining the different frameworks found in literature, it is important to understand how a company can implement DTs that enable a virtual representation of physical assets, systems, processes, products, services, or people.

Qamsane et al. (2021) identifies the following steps [44]:

- **Planning**: it involves determining if there is a need to enhance some aspect of the manufacturing ecosystem and if that need could be addressed through the application of a DT solution.
- **Requirements and Analysis:** it involves studying and analysing the requirements for the DT design and development activities.

- **Design**: it defines a design of a DT solution based on the recommended alternative that will meet functional, data, and interaction requirements.
- **Development:** it aims to transform the output design stage into a complete working DT solution that can address the manufacturing needs established in the planning stage.

Similarly, Deloitte [36] identifies 6 steps (Figure 21). The first one is to **imagine all the possibilities**: create a list of all the potential scenarios where it can be applied.

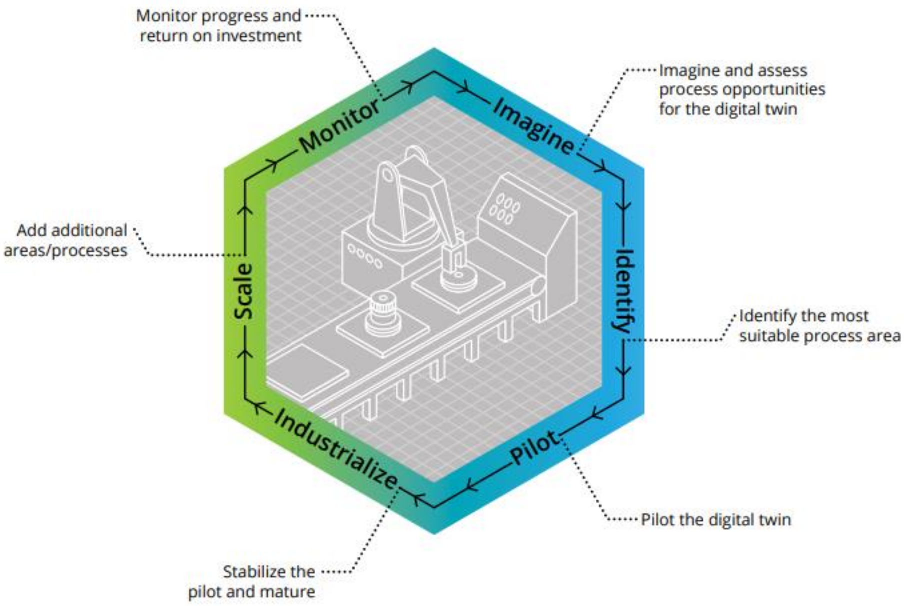

Figure 21 : the process to follow to get started with a DT [36]

Once the list is prepared, it is crucial to **identify** the pilot product or process that can provide the most value and where the implementation of DT is likely to succeed. Through iterative and agile cycles, we can start with the **pilot** and improve step by step. The next step is **industrialisation**: establishing a standardised and structured approach to the development and implementation of DTs. To **scale** the twin, the next step is to identify additional processes or products that are related to the pilot project.

As with any project, it is important to **monitor** if it is working properly once it has been completed.

Now we can go deep into the pilot phase (using the terminology of Deloitte article) or the design phase (using the Qamsane's terminology). We will show different DTs frameworks accordingly to the classification criteria used in 5.1; so we have divided the different subsection on the base of our classification criteria, which is based on DT's functions: monitoring and improving production processes, layout design, flexibility management, collaboration between DTs, and cognitive DTs.

5.3.1 Monitor and improve production process

As shown in section 5.1, DT could be used to monitor and improve production processes by providing decision support and optimisation analysis.

Analysis for optimization

In the context of implementing DTs to improve manufacturing processes, we will focus on two key aspects: (1) optimising the product development process and (2) using DTs for zero-defect manufacturing. DTs for product development process optimisation provide a virtual approach to design and validation, reducing the reliance on expensive physical prototypes and enabling faster and more efficient iterations[45]. At the same time, DTs for variation management play a key role in ensuring the consistency and accuracy of geometric specifications, helping to reduce unwanted variation in final products [46].

The product development cycle has three key phases: product design, product validation and product manufacturing (Figure 22).

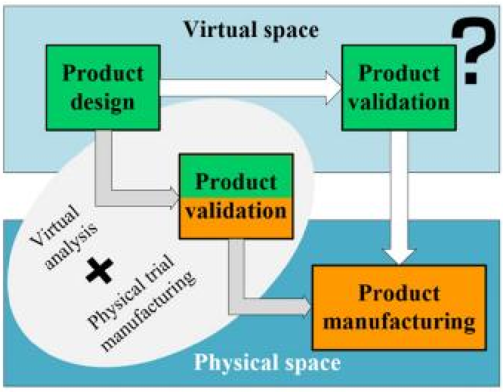

Figure 22: product development process [49]

For product design Ma et al. (2019) [49] presented a framework for digital twin augmented human-machine interaction during conceptual design phase. In the virtual world designers can interact with the virtual model via AR/VR technologies, which allow designers to "see", "touch" or "interact" with the model.

Xiang et al., (2019) [48] proposed a DT based technique to intelligently select green materials, to identify the most suitable material for a given design; their DT model can imitate and improve the qualities of materials that are potentially selected, in order to make a repetitive comparison between forecasted qualities of these materials and required properties.

Regarding product validation phase, this is still a significant challenge in terms of cost and time. Traditionally, this phase involves the use of physical prototypes to assess the feasibility of the previously designed product [47].

Huang et al. (2022) [47] proposed a framework where a virtual replica of the manufacturing system is created, allowing for the development of a virtual prototype, which exactly reproduces the physical prototype by replicating the operations that would have been performed in the physical world; in the virtual space, the validation phase of the prototype can be detailed, and if the virtual prototype passes successfully this phase it is considered ready for production, otherwise an iterative process is begun in which the design is optimised, and re-tested in the virtual world.

While each framework addresses different aspects of product development, they can be complementary. For instance, the virtual prototype created in the validation phase by Huang et al. (2022) [47] can benefit from the use of green materials selected in the design phase using the DT model proposed by Xiang et al. (2019) [48]. Even if each framework addresses specific aspects of product development, collectively providing a more holistic understanding and optimization opportunities there may be challenges in integrating DT frameworks seamlessly, particularly if they rely on different technologies, data formats, or modeling approaches. Contradictions may arise if the results or recommendations from one DT framework conflict with those from another. For example, the selection of certain materials in the design phase may lead to unforeseen issues during virtual validation, necessitating iterative refinement.

While DTs have revolutionized the product development space and focused largely on the design, validation, and manufacturing phases, there is yet another area critical to consider — variation management or geometry assurance during the manufacturing phase. Now the information available through the DTs for product development from design and validation can be integrated with DTs for variation management, by re-purposing the simulation model used for the validation phase, to 'see' the geometric variations of the part in real-time as it proceeds through the assembly process. [46].

With this aim Figure 23 represents a DT framework for geometry assurance.

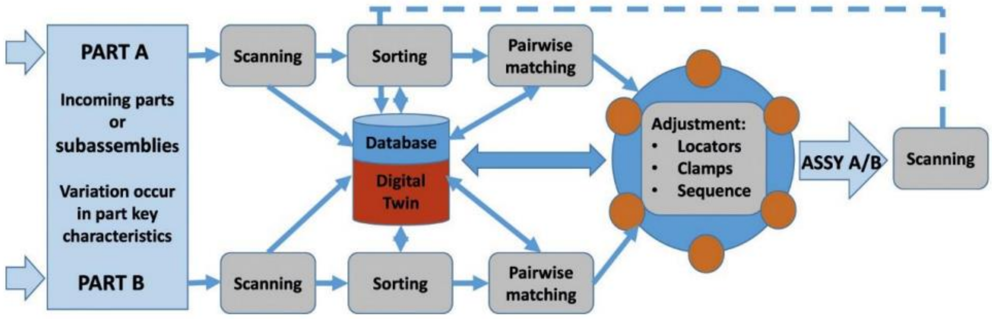

Figure 23: DT framework for geometry assurance [47]

Two parts A and B are scanned, and the data collected is entered into the simulation model. The data is sorted by class to achieve a pairwise match that minimizes assembly variation. In addition, the deviation from the standard can be reduced by careful analysis of how to adjust the weld points (locating schemes) and by defining the optimal welding sequence to follow [47].

Decision making support through real-time state monitoring

In this section we will explore the potential of DTs in real-time monitoring to support operational decisions and improve the performance of production processes. In particular, we will look at how the integration of a DT into a production cell can enable improved autonomy, how real-time data acquisition can identify and mitigate bottlenecks within a manufacturing system, and how the use of real-time location information can optimise production logistics. We will explore how these aspects, supported by an effective implementation of the DT, can contribute significantly to the dynamics and efficiency of manufacturing operations.

By integrating a DT into a manufacturing cell, we can examine how this virtual entity interacts with the production process in real time, capturing detailed data and providing a constant flow of information. To this end, we can define the DT Manufacturing Cell (DTMC) as "*a minimum implementation unit for industrial* *enterprises to put intelligent manufacturing into practice*” [38].

Thanks to its structure, which consists of five different types of spaces, the cell is capable of independent decision-making and proposing improvements [39]. More precisely, the layers that make up this entity are as follows (Figure 24) [40]:

- **Physical space**: thanks to sensors the status of the physical process, such as WIP, can be monitored in real time.
- **Virtual space**: here is where all the data collected in the physical space come together. Thanks to them, and thanks to DTs of the physical elements involved in the production process, it is possible to carry out a simulation in virtual space, which makes it possible to predict and, if necessary, improve.
- **Data space**: before entering the virtual space, data on WIP, machine status and other process elements are transported here to be pre-processed.
- **Knowledge space**: a dynamic knowledge base in this area enables improvement decisions to be made.
- **Social space**: it integrates various service systems like CRM and ERP, bridging the gap between DTMC supply and customer demand.

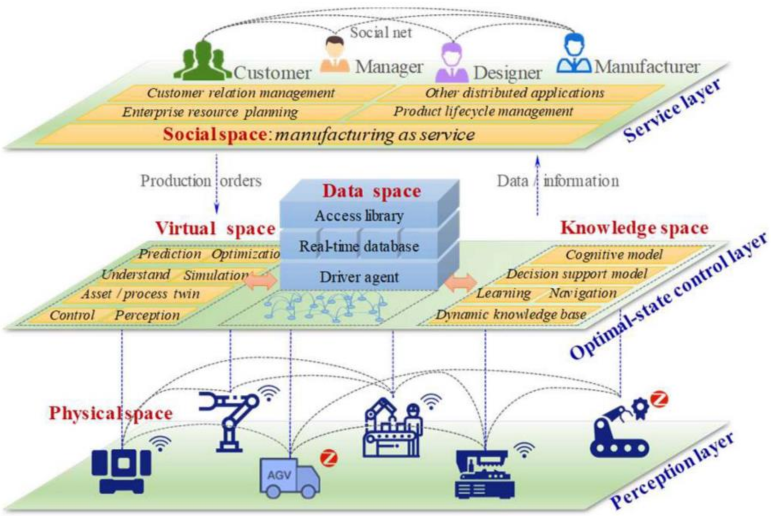

Figure 24: DT Manufacturing Cell [40]

Within an intelligent production cell, multiple improvements can be made without the need for human intervention. An example is the diagnosis and improvement of bottleneck throughput: Mahesh *et al. (2023*) [42] proposed a framework (Figure 25) in which, in line with what has been said above, data relating to an Observable Manufacturing Element (OME) - such as a machine, a process or an entire physical system - is collected and pre-processed. Processing means [42]:

- Cleaning: handling missing instances and standardisation.
- Integration of different types of data from the physical space.
- Transformation of data.

After collecting event logs and timings, a dynamic map of resource dependencies and interactions is created. The resulting information is then used by the DT to replicate the OME. The utilisation rate is determined by monitoring individual resources using asset monitoring. Finally, prescriptive analytics identifies the busiest resources and targets them for DT improvement opportunities.

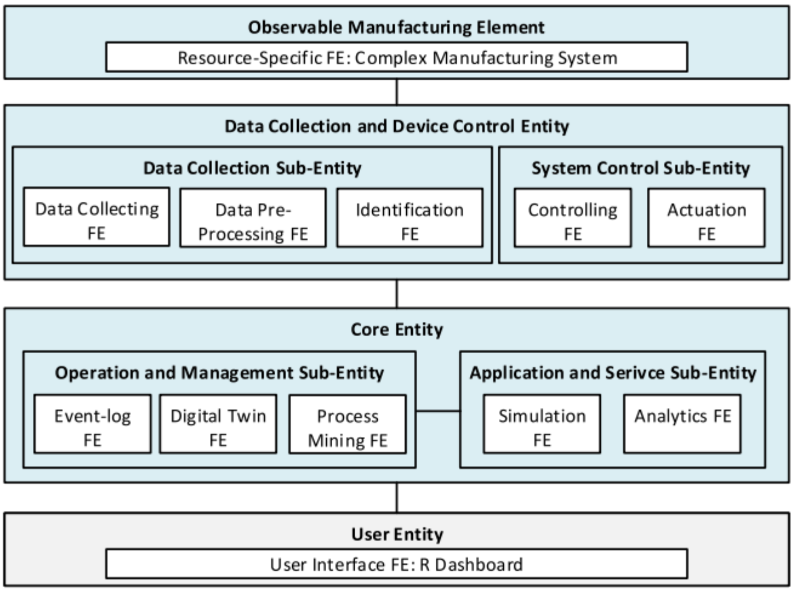

Figure 25: DT framework for bottleneck identification and throughput improvement [42]

Real-time data can be used not only in production processes, but also in logistics operations in order to reduce the high costs linked to them.

Here, we will only discuss one logistic operation that can benefit from implementing a DT: Automated Guided Vehicles (AGV).

An AGV is an autonomous vehicle designed to move in industrial or logistical environments, guided by technologies such as sensors, machine vision or magnetic guidance systems, without the need for human guidance.

The utilisation of a DT enables optimal route planning in a highly dynamic environment (Figure 26). The AGV can effectively scan the surrounding area and determine the most favourable path to a set destination via a simulator. Nonetheless, it is not competent enough to make dynamic decisions on its own. If an unexpected obstruction emerges on the route, the AGV must come to a halt, rescan the surroundings, and wait for the simulator to compute a new route. The integration of DT can significantly reduce the time spent, particularly in a dynamic setting. DTs can gather real-time data and update information pertaining to the surroundings at set intervals. Subsequently, a potential barrier can be detected beforehand, allowing the simulator to calculate the most effective route before the obstacle obstructs the automated guided vehicle [43].

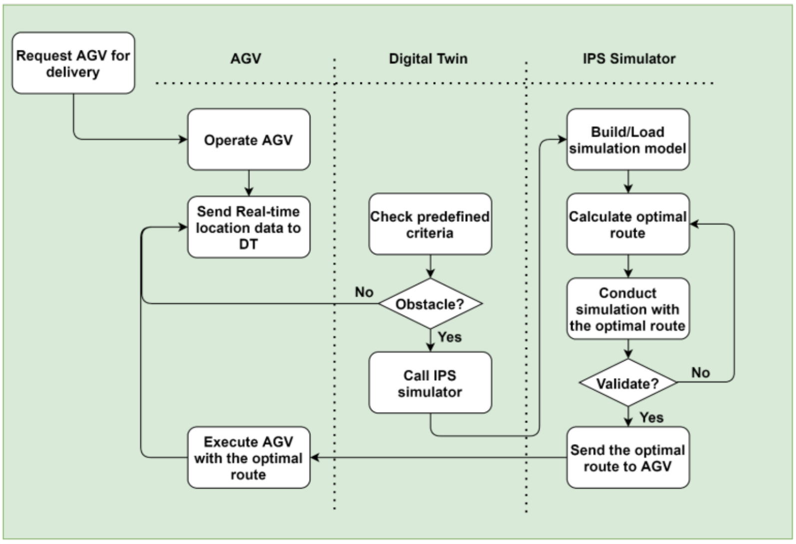

Figure 26: The optimal route planning [43]

5.3.2 DTs for layout design: analysis for optimization

As to production system and assembly line design, element arrangement is critical for effectiveness. Layout design issues may be crucial, affecting operational efficiency, internal logistics and the overall workflow. DTs emerged for this matter as essential tools, offering the capability of simulating, analysing and optimising the layout in the pre-physical implementation phase. We will delve into how DTs can help make better decisions and improve the design of production systems and production lines.

Guo et al. (2021) [53] developed a DT-based layout optimization approach by proposing three sub-frameworks: (i) the workshop partitioning sub-framework, which optimizes the workshop layout by analyzing twin data and simulating different partitioning configurations; (ii) the equipment layout optimization sub-framework, which adjusts the layout of equipment and facilities by collecting real-time data and value-adding to twin data; and (iii) the distribution route optimization sub-framework, which optimizes the material distribution route in order to reduce WIP backlog and to improve tooling efficiency. In this way, by leveraging real-time feedback and data analytics, the DT-based approach can optimize the layout of the workshop, the placement of equipment, and the distribution route of materials in order to improve production efficiency, reduce WIP backlog, and increase tooling utilization.

For the optimization of layout, a simpler model exists where instead of production line layout, the DT takes, as an input, the positioning of machines in a production line, layout of production lines, and scheduling of production processes, makes a simulation and presents outputs. The outputs can be turned into performance metrics such as productivity, throughput, efficiency, by use of metrics such as machine cycle time, material handling time, operator travel time. Therefore, the plant layout can be optimized by adjusting the positioning of machines, processes, and workstations on the factory floor. The optimized layout configuration is re-simulated to evaluate its performance and compared to previous configurations [54].

Based on dynamic and real-time changes in production processes, Lee et al. (2022) [51] suggest a DT framework, to optimally respond to these changes by suggesting improvements. The framework proposed consists of 2 layers:

- **Information layer**: this layer, which is integrated with the enterprise resource planning (ERP) and manufacturing execution systems (MES), contains information about the manufacturing design, the resources employed and the manufacturing bill-of-material.
- **Application layer**: it includes (a) an interface module which links data collected from the information layer to the simulation and optimization modules, (b) a DT simulation module to visualize and verify production processes and (c) an optimization module that uses algorithms to refine the process configuration and production line layout.

These frameworks can be compatible if integrated carefully. For instance, Guo et al.'s (2021) approach could benefit from the dynamic adjustments suggested by Lee et al. (2022). Overlaps may occur since both of them involve real-time data collection. Also, turning the outputs of simulations into performance metrics could be integrated with the other two models. However, there could be contradictions if more models are used in the same time if they prioritize different optimization criteria.

One way to transfer data from the interface module to the DT simulation model it could be used the framework proposed by Sommer et al. (2023) [52], to automate the DT generation. By scanning the shop floor and comparing the scanned objects with the objects' CAD existing in a reference database, a DT can quickly be created, using inputs like objects parameters (machine geometry and its positioning information), parameters that we can obtain via object recognition, all organization's specific parameters which we can not obtain through scanning (i.e. machine ID) (Figure 27).

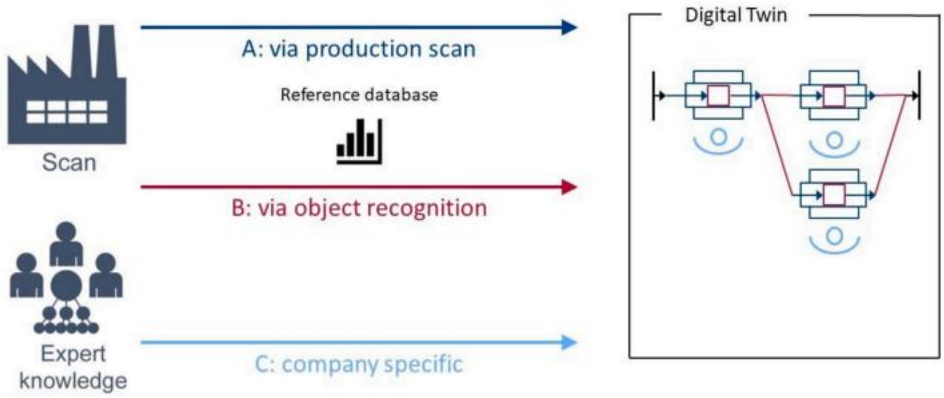

Figure 27: Inputs for an automatic generation of a DT [52]

5.3.3 DTs to handle flexibility

Being able to respond quickly to changes in customer needs, market requirements, and operational situations has become a crucial element for achieving success. Adaptability is essential for dealing with challenges such as fluctuations in demand, customized products, and emerging technologies. This flexibility -i.e the production system's capability of changing its internal characteristics- leads to better responsiveness, competitiveness, and long-term sustainability, enabling companies to navigate through dynamic scenarios with effectiveness.

Analysis for optimization through real-time state monitoring

To handle flexibility the frameworks found in literature all uses real-time state monitoring in order to make optimization to the manufacturing process.

To address manufacturing flexibility Zhuang et al. (2018) developed a DT framework for production management in the context of a product assembly shop floor. Here, real-time data from the physical shop floor flow to its DT which mirror the physical operation conditions and simulate the future's production operations. Dynamic data like temporary assembly tasks added, product lead time changed, equipment shutdown or failure, product quality problems found, product design and process changed, and other kinds of production disturbances are taken into consideration [60].

Similarly, Park et al. (2019) focused on the application of a DT in the context of personalized production, where production processes for different product groups struggle to respond to the dynamic situations arising from these processes, demonstrating that dynamic situations in the personalized production can be effectively handled through a combination of five applications: digital twin application, context-aware application, advanced planning application, advanced scheduling application, and device control application [61] .

To manage flexibility Yan et al. (2022) developed a DT framework for dynamic scheduling, allowing for real-time responses to changing operational variables and needs. In operating systems, an important variable to consider is machine failures. Should these occur or be predicted with enough lead time, rescheduling becomes necessary. If an anomaly is detected in the physical system, the information is transferred to the DT. The DT can then use simulation to reschedule production, taking into account new parameters such as a machine being unavailable (Figure 28) [55].

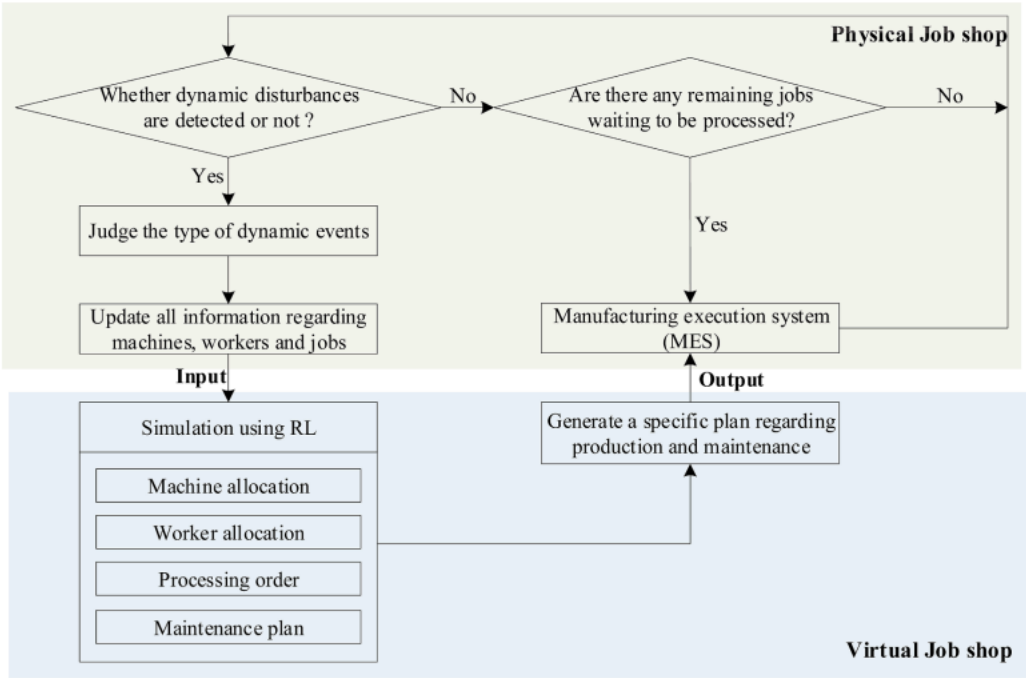

Figure 28: DT architecture for dynamic scheduling [55]

To achieve optimal re-scheduling Tliba et al. (2023) [56], presented a DT composed of two connected models within the physical system:

1. A scheduling model
2. The shop floor model with which simulation is carried out.

The initial scheduling is generated by the first model, based on data contained in the company's ERP concerning available resources, product details, and company constraints. The second model simulates the provided scheduling by triggering a simulation loop. If the result of the simulation is not optimal, the data is updated and reinserted into the scheduling module, which makes a new proposal to the shop floor model that generates a new simulation. This process continues until an optimal solution is found (Figure 29).

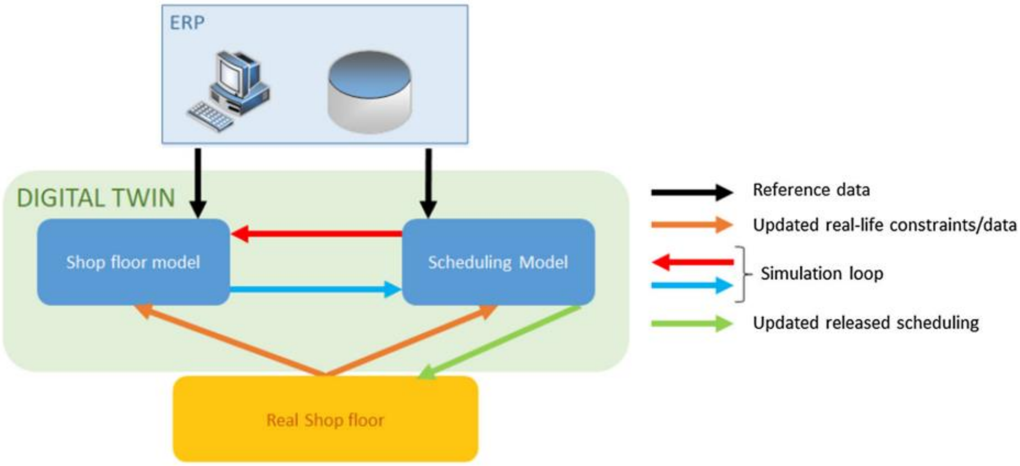

Figure 29: DT dynamic scheduling process [56]

While the four frameworks illustrated above focus on how overcome internal disruptions and dealing with internal sources of flexibility, Neto et al. (2023) [58], focusing on how to deal with customers' changing demand requirements, developed a DT framework with the aim of helping manufacturers to deal with mix flexibility -i.e the ability to change the short-term production mix in order to implement a desired sales strategy. In their proposed architecture (Figure 30) the shop floor is replicated in the virtual world through sensors that collect real-time data from the production system. This data includes information about the machines, buffers, processing times, routes, production schedules, and the position of pieces within the machines and buffers. All of this data enables the DT to simulate, returning an estimation of the production system key performance indicators (throughput), the expected delivery date for all products, and the predicted time slots in which the machines are expected to be idle to perform maintenance [58].

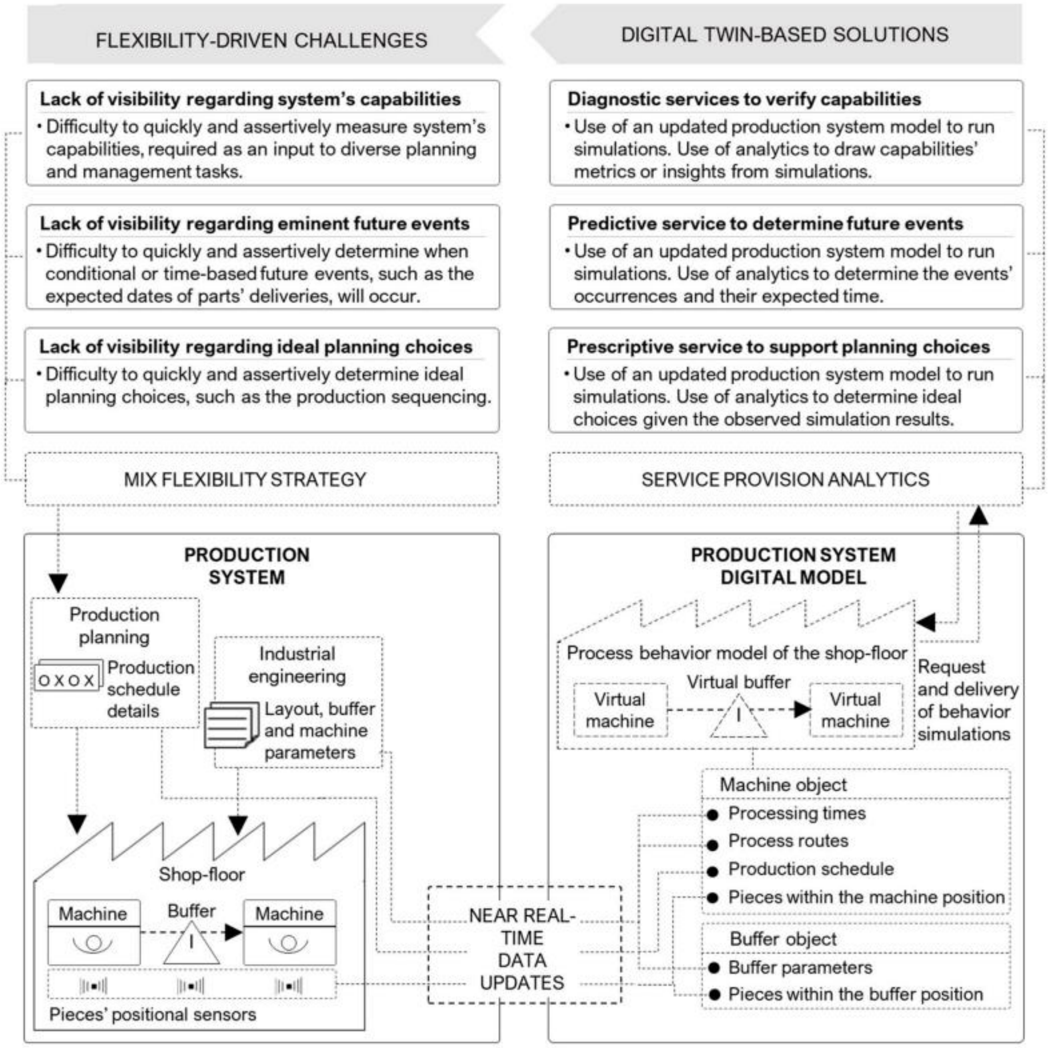

Figure 30: DT general architecture to handle flexibility [58]

Dos Santos et al. (2021) [59] also focused on implementing a flexible production line to meet changing market demand and minimise operational waste caused by unused operators or excessive production that does not meet the real needs of the customer. In the framework developed (Figure 31) the first step is the analysis of sales history using AI to predict future demand. It then uses a Discrete Event Simulation (DES) model within a DT architecture to simulate the production process, testing different variables such as the number of operators. Finally, a dashboard shows the guidelines for operational planning (resulting from the DES model), including the optimal resource sizing, the expected production (which may be differ from the expected demand in the case of batch production) and the expected lead time.

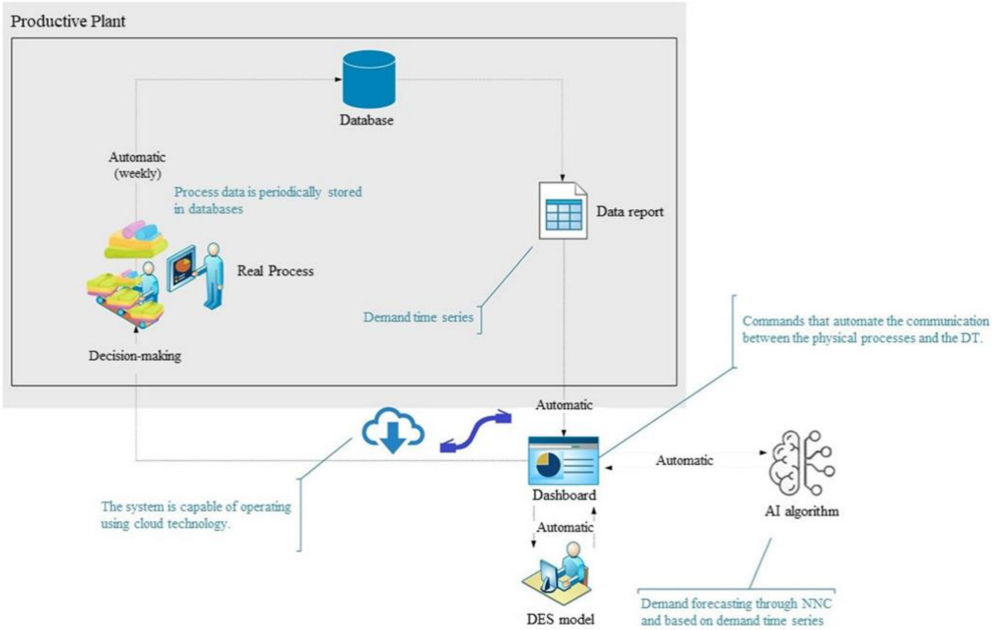

Figure 31: DT architecture for resource planning [59]

5.3.4 DTs collaboration

We will now focus on analysing how using multiple DTs which are able to collaborate can add significant value. It is in this context that the Digital Thread was introduced [62]:

> *"A Digital Thread connects real things and their twin models, but also the communication networks, the decision algorithms, the visualisations needed to work in design, construction, and operation within a mature Industry 4.0 environment"*

Failure analysis and prediction

It is possible for example to assemble several DTs of every production unit to recreate an entire production line in the virtual world. This can help in the prediction of possible failures, thus assuring a higher quality of the production process.

Liu et al. (2023) proposes a framework with the goal to ensure the quality of a final assembly; it can be interpreted as the evolution of the process regarding assembly through geometry assurance that we have seen in 5.3.1.

Before introducing an architecture for DTs collaboration we must firstly give some definitions that we will use later on (Figure 32) [63]:

- **Digital Twin Manufacturing Unit (DTMU):** it is "the unit-level manufacturing system with a manufacturing function in the workshop and has the essential characteristics of a DT system" .
- **Distributed Digital Twin Manufacturing System (DDTMS):** it is "a workshop-level intelligent manufacturing system. It has three manufacturing spaces, including the workshop, agent, and manufacturing unit layer" .

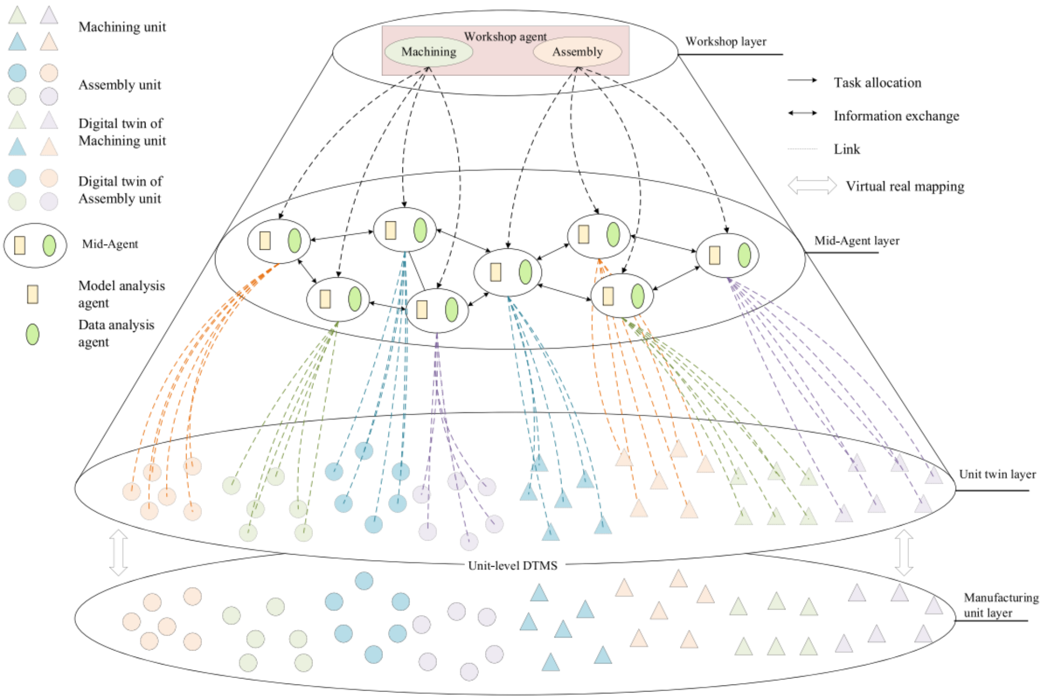

Figure 32: DDTMS [63]

- **Unit twin layer**: it is the set of all DTs of each production unit (assembly and machining units).
- **Mid-Agent layer**: it receives the information provided by the Unit Twin layer to analyse the production process through simulations. It is also the communication medium of each manufacturing unit.
- **Workshop layer**: it analyses industrial big data to define manufacturing tasks and optimizes combinations of manufacturing services.

The Digital Thread runs through the entire life cycle of the manufacturing process (machining, inspection, assembly, final inspection) (Figure 33). To do that its structure it is split into two layers:

- The **model analysis layer** receives information about the quality of each part to reproduce a DT and simulate all the operations and estimate the quality of the final product.
- The **data network analysis layer** analyses the production area at each stage and, based on the quality defect transfer, is able to adjust the next operation.

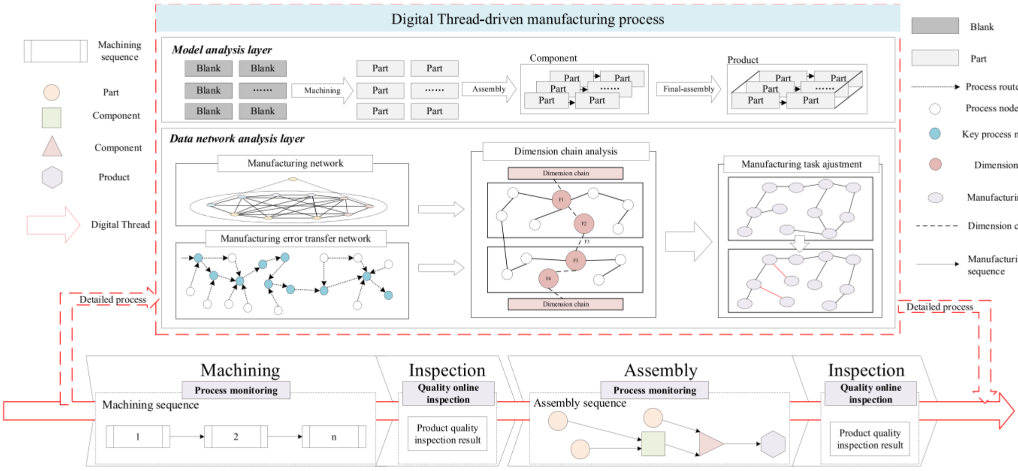

Figure 33: Digital Thread-driven manufacturing process [63]

Thanks to this structure, problems can be easily identified, and production adjusted accordingly.

Since the functioning of the Digital Thread depends on the functioning of several DTs, Sahal et al. (2021) analyse how it is possible to identify erratic operational data that can occur from each DT.

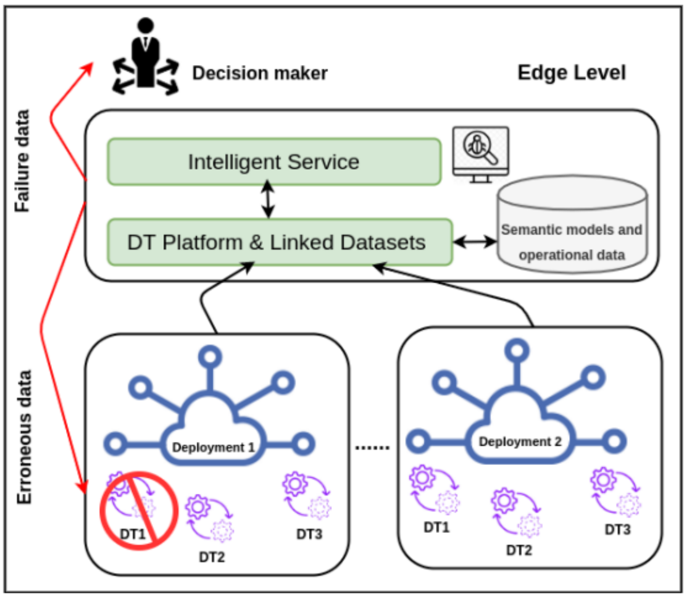

Figure 34: Framework for automatic error detection of collaborative DTs [64]

In Figure 34 a high-level framework for automatic error detection of collaborative DTs is presented. The analysis assesses whether the data from the DT indicates a failure or inconsistency, determining if the issue is localized or affecting all nearby DTs representing the same device. If a widespread problem is detected across all deployed DTs, the system can proactively notify decision-makers about the failure. On the other hand, if the issue is specific to one DT, the system disregards the inaccurate data, replacing it with the correct information to maintain consistency in the operational data across the production system [64].

The Liu's Digital Thread [63] ensures a comprehensive understanding of the manufacturing process, while Sahal et al.'s framework [64] enhances data reliability within this thread. By combining these models, manufacturers can swiftly identify and rectify issues, ensuring smooth operations and high-quality output.

5.3.5 Cognitive DTs

Cognitive DT (CDT) is an advanced perspective of the traditional DT and signals a turning point in the evolution towards Industry 4.0. Such a novel approach of CDT transcends the simple digital translation of physical objects and, in fact, involves the employment of artificial intelligence capabilities together with advanced data analytics. Indeed, cognitive functions make it feasible to transfer knowledge that is gained in one field to another field [65].

Skills which constitute the bedrock of cognition - attention, perception, memory, reasoning, learning, and problem solving. Herewith follow definitions of the terms that have been readapted to the DT context [68]:

- **Perception**: that's the process of preparing meaningful representations of the data relating to the physical twin and its surrounding physical environment for further processing.
- **Memory**: recall data of the twin's physical life and also data of the environment interacting with it.
- **Reasoning**: drawing conclusions which are consistent with a starting point.
- **Learning**: using a process to get to the conclusion and provide answers that can be applied to other domains. Problem solving, finding a solution to the proposed problem.
- **Problem solving.** finding a solution to a given problem.

Mortlock et al. (2021) [68] proposed a framework based on graph learning as a possible way of facilitation of cognition in DTs. This may be used to conduct different tasks (e.g., to generate new configurations that are necessary in the event of the product specification change). A graph can show critical relationships and provides a strong illustration, aiding in deduction or logical solution to problems through visual representation.

In the first step (Figure 35), the **graph formation**, products and their properties are retrieved (e.g., via a query) and organized into a graph, which prepares them for analysis. The **graph operation** involves the modelling of intricate mathematical functions, the aggregation of data, and the creation of condensed representations. Finally, in the last step, **learning objective,** the query and the problem to be solved are defined, as are the metrics and specifications used to optimize and refine the model.

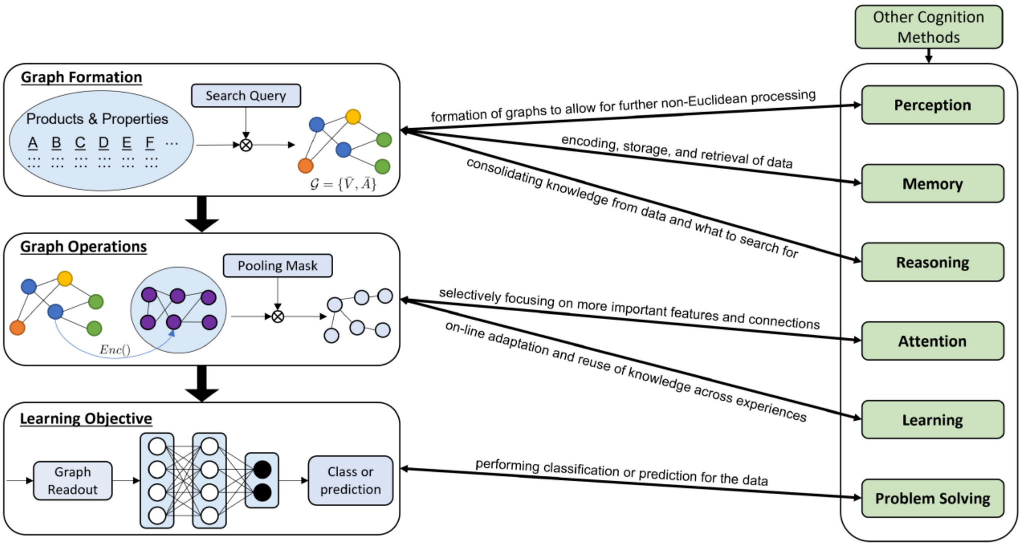

Figure 35: Graph learning framework [68]

The mentioned cognitive abilities can be utilised proficiently in identifying and handling aberrations in production processes, thus aiding in reducing the adverse consequences attributed to these anomalies.

Cognitive abilities such as those above can readily be employed to identify and deal with anomalies in production processes, which in turn can greatly reduce the deleterious consequences that can accompany such anomalies. To give a brief example, perception can be used to forecast and recognize anomalies, attention allocated to deal with them, memory to store relevant information that can be reused, reasoning to understand their origins and underlying causes, problem-solving to devise efficient solutions and learning to identify the information that is most important in such scenarios for use in new instances [66].

Obviously, these capabilities can be utilised with the assistance of supporting tools (Figure 36):

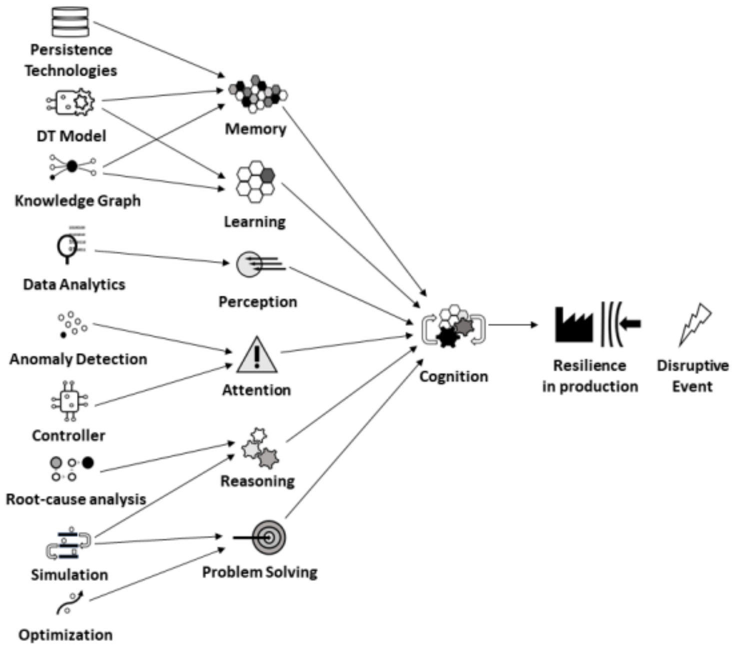

Figure 36 : Tools supporting cognition [66]

- Memory can be bolstered through the use of a database, a DT capable of incorporating information from a range of sources, or a knowledge graph, as has been previously demonstrated. The latter can also foster learning capabilities.
- Perception can be honed through meticulous analysis of data gathered from various sources.
- Anomalies and control instruments can capture attention.
- Analysis and simulation tools can stimulate reasoning and help evaluate the impact of anomalies, as well as identify potential solutions, among which lies the optimal one.

Rozanec et al. (2020) [69] envisioned four components that make a DT actionable thus aiding in the manufacturing shop floor context: **ontology** captures information about entities in the physical world, while a **Knowledge Graph** enhances the cognitive capabilities of the DT; **data** includes detailed information on the elements and operations of the production process; **algorithms**, including artificial intelligence algorithms, enrich the DT with cognitive capabilities and specific behaviours; finally **actions** are suggested to users based on advanced analyses performed by the DT.

After having examined the nature of a Cognitive DT and its abilities, we can now explore the synergistic deployment of multiple CDTs in the supply chain context (Figure 37).

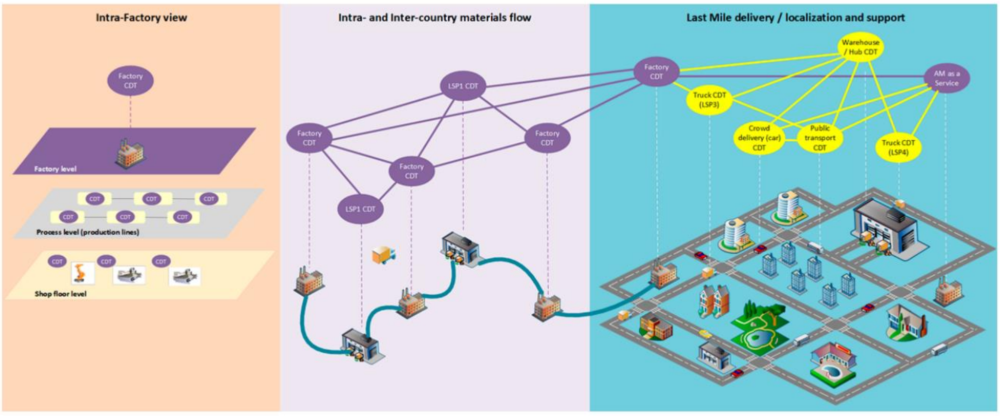

Figure 37: Interconnection of CDTs in the supply chain context [67]

In order to establish a connection using Cognitive DTs (CDTs), it is imperative to create a representation of all assets, processes and operators working in the supply chain. Afterward, the CDTs must be connected at both intra-factory and inter-factory levels throughout the supply chain [67].

5.3.6 DTs and sustainability

The sustainability emphasis is growing fast, prompting growing interest very publicly, along with ever more regulations (e.g., Corporate Sustainability Reporting Directory [84], requiring companies to report their sustainability progress) and voluntary certifications (EU Ecolabel, FSC, EPD, etc…). This not simply highlights the growing interest of companies to both comply with the legal requirements and demonstrate their sustainability commitment (but also their customers' increasing demand for transparency and accountability in this domain, as you can see from Figure 38, showing consumer preferences to buy more sustainable products over the last 5 years worldwide in 2022 [94] .

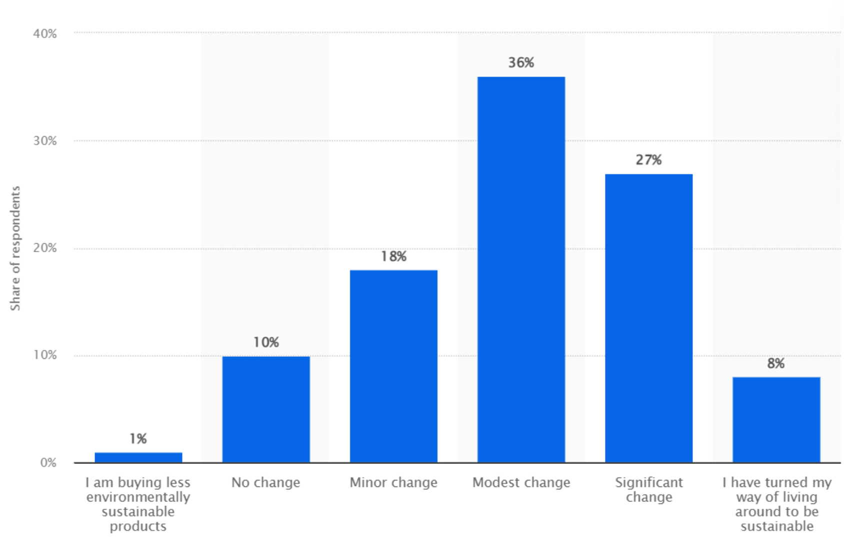

Figure 38: Degree to which consumers' purchasing behaviour and choices shifted towards buying more sustainable products over the past five years worldwide in 2022 [94]

For this reason, we will examine how DTs can assist businesses in overseeing and/or enhancing their level of sustainability.

One of the main questions addressed in this section is:: "How can we apply the just reviewed capabilities of a DT in a sustainability context?" By conducting research, Popescu et al. (2022) have explored the impact of each DT attribute on sustainability-related functions (Figure 39) [70].

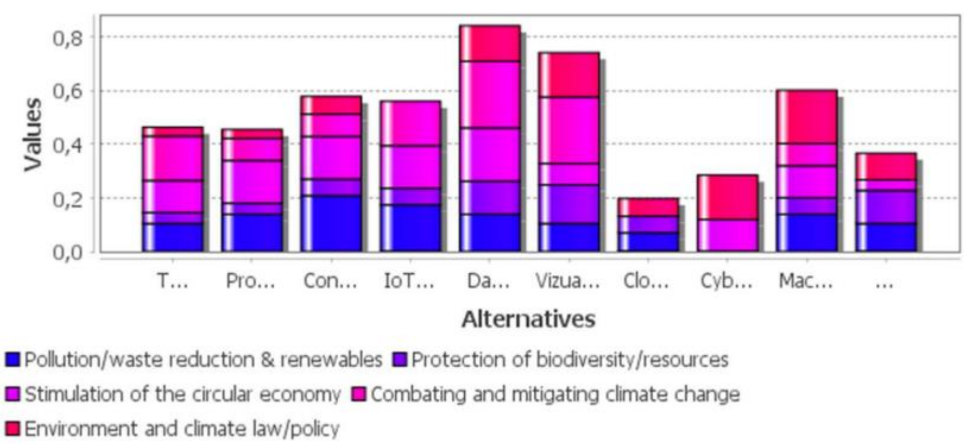

Figure 39: DT contribution to sustainability related functions [70]

It is observed that data analytics and visualisation capabilities contribute significantly to sustainability globally, while cloud processing storage and cybersecurity contribute significantly less. Moreover, the three sustainability-related functions that are most positively impacted by DT are pollution and waste reduction, circular economy simulation, and climate change mitigation and control.

Analysing the contribution that DTs can make to achieving the Sustainable Development Goals (SDGs), it can be seen that DTs can contribute in three ways [74]:

- **Efficiency in resource allocation**: for example, sensors to detect water leaks in water distribution systems can be used in a digital replica for predictive maintenance, thus helping to limit water wastage.
- **Safe innovation in green technologies**: new clean technologies can be tested in the virtual world to see if they could cause unintended harm.
- **Inclusive partnerships for sustainability**: simulations of entire environments (factories, power grids, farms), accessible to different stakeholders regardless of their geographical location, facilitate scientific collaboration and knowledge sharing to address environmental problems.

In addition, by collecting real-time data such as energy and carbon inputs/outputs, a DT can make Life Cycle Assessment (LCA) much more accurate and faster than current conventional methods [75].

The second question that arise in this context is, "how a DT could be used to boost sustainability contribution?" To answer this question, 3 steps were identified, each of which contributes increasingly to enhancing the sustainability impact of DTs [72]:

- DTs can be employed as a tool to provide information to regulatory bodies through a sub-model that assesses the impact on the ecosystem. It is evident that the DT has the capacity to oversee production, hence, it can be integrated alongside diverse tools such as Life Cycle Assessment, to analyse the worldwide environmental impacts of production.
- DTs can be utilised to manage assets and form decisions about their applications throughout their lifecycle, taking into account their impact on the system.
- DTs can serve as a control unit for each particular asset, guaranteeing that the impact of not only the individual asset but also the entire production system aligns with sustainability within planetary boundaries.

For these purposes it is essential to ensure interoperability between data, which have to cover information on substances, energy, materials used, as well as emissions and waste generated throughout the entire life cycle [72] .

A DT which takes into account sustainable production could be used in eco-design, as well as in the planning and monitoring of manufacturing processes [73].

In eco-design, it is crucial to design products in such a way that most of the materials used can be recycled. The DT offers a classification model that simplifies material selection based on their compatibility and degree of recyclability, eliminating the need for separation. Thus, the DT classifies materials in two ways:

1. The main material and desired level of compatibility are inputted, and subsequently, the DT selects a range of suitable materials.
2. In the instance where both main and additional materials are utilised, the DT provides the corresponding degree of compatibility directly.

When planning manufacturing processes, the DT can make decisions about machine and machining tools, machining parameters and tooling, always considering the sustainability aspect. For instance, when selecting tooling, the design team can assess elements that impact the energy required to cut, like tool lifespan, cutting edge number, cutting time, etc. [73].

Digital twins play also a crucial role in enhancing the sustainability of supply chains. DTs can contribute to: (1) **supply chain visibility** by enabling better monitoring of processes, identifying inefficiencies, and optimizing logistics; (2) **carbon foot print reduction** through the optimization of production processes, logistics, and energy consumption; (3) **transparency**, allowing exchange of data among supply chain partners through a shared digital platform [76].

5.4 Enablers, challenges and opportunities

The final section of this chapter has the goal to understand the enablers, challenges and opportunities that arise from DT implementation (the last phase saw in 5.3).

This section is important because it could help companies to understand the requirements that can enable the development of the DT frameworks saw in the section above. We also highlight the fact that the implementation of a DT within a manufacturing company is not without challenges, but that once these are overcome, several opportunities can arise for the company.

So, here we will illustrate the enablers for DT implementation (5.4.1), the opportunities deriving from DT adoption (5.4.2) and finally the challenges that a company can encounter during the implementation phase (5.4.3)

5.4.1 Enablers for DT implementation

Multiple documents in the literature analyse the enabling factors for implementing a DT and generate an extensive list of requirements. Therefore, as said in 5.1, we classified them for better understanding:

- The **systems and technology** category refers to the set of systems and technologies required to successfully implement a DT.
- The **process** category pertains to the implementation processes of a DT.
- The **people and competences** category refers to the requirements that employee have to meet.

- The **culture and strategy** category refers to the requirements that the company as a whole have to meet.

This subdivision is summarised in Table 3.

Enablers	
Systems and Technologies	Simulation [77], [78] IoT [77] [79] Cybersecurity [77] Big Data processing [77][79][80] Data storage [79] [80] Information model [80] Communication network [79][80] Data acquisition and cleansing [80] Time-sensitive data processing [78][80] Data visualization [78] [81] VR [78] [79] Development technologies [79] Notification system [78]
Process	Well-defined implementation plan [77] Accurate data fillings on enterprise software [77] Use of physical resources [81]
People and Competences	Skills to manage the technologies [77] [81] Good communication skills [77]
Culture and Strategy	Management commitment to long-term projects [77] Top management support [77] Capacity to make financial investments [77]

Table 3 : DT enablers

Systems and Technology

This first category of enablers comprises of:

- **Simulation**: testing various scenarios through simulation is essential to make informed decisions [77], [78]
- **IoT**: the Internet of Things enables devices to communicate and collect data through sensors [77][79].
- **Cybersecurity**: to prevent cyber-attacks and ensure the integrity of data, cyber security is critical. Protecting sensitive data is always vital for an organisation [77].
- **Big Data processing**: big data processing enables the analysis of large amounts of data, sometimes from multiple sources. It is also a prerequisite for real-time decision making [77][79][80].
- **Data storage**: there are two types of data storage that can be used to store the data collected through the use of sensors and IoT. Relational data storage has a table structure and is used to handle complex data, while non-relational databases are used when dealing with less structured data [79][80].
- **Information model**: the physical object is abstracted using a predefined information model that represents its specifications of interest. The standard plays a crucial role in providing the information model to describe different physical objects in manufacturing [80].
- **Communication network**: communication between the DT and its physical counterpart is essential as it is a two-way exchange of information [79][80].
- **Data acquisition and cleansing**: making decisions based on poor quality data can lead to wrong conclusions. Since real-world data will never be 100% accurate, it is important to understand which data should be ignored [80].
- **Time-sensitive data processing**: it is important to minimize the time gap between data collection and analysis, especially if the DT is intended to monitor in real time. Strict latency is essential in such cases [78][80]
- **Data visualization**: clear visualization of the data collected from the physical world via dashboards or graphs allows for quicker understanding and therefore faster decision-making [78][81].

- **Virtual Reality (VR)**: if remote assistance is required, the construction of a full-scale 3D model of the physical model to be twinned would be a great advantage [78][79]
- **Development technologies**: this requirement refers to the technologies needed to implement a DT [79].
- **Notification system**: a notification system is required for any type of warning that the DT needs to send to the operator so that a problem does not go undetected [78].

Process

This category pertains to the implementation processes of a DT. The enabling factors within this category include:

- **Well defined implementation plan**: defining a detailed action plan makes it possible to stay on schedule, and to analyse every possible scenario. As mentioned earlier, we must always consider whether or not the implementation will bring significant benefits [77].
- **Accurate data fillings on enterprise software**: data in business software serves as an analytical element for the DT. DTs can also prevent 'incidents' by analysing historical data. It is therefore important that this data is accurate [77].
- **Use of physical resources**: it involves the integration and efficient use of physical resources within the DT implementation process [81].

People and competences

This section is not about digital technology, but about the people who use it since they have to meet requirements too. More specifically:

- **Skills to manage the technologies**: the success of a DT project requires a thorough understanding of the technologies involved. Operators must be able to use and manage the key technologies required to effectively develop, implement and maintain a DT. As this is a relatively new technology, the company must be open to recruiting new people if it does not already have people with these skills [77][81].

- **Good communication skills**: as within any project, more people will be involved in the implementation. Knowing how to communicate is necessary for good teamwork [77].

Culture and strategy

In terms of corporate culture and strategy, these also have an impact on the implementation of a DT. The following requirements should be met:

- **Management commitment to long term projects**: implementing a DT takes time and analysis, and the whole team needs to be aware of this when embarking on the project [77].
- **Top management support**: the road to implementation is usually long and is rarely without difficulties. The support of top management will show confidence in the team dealing with it [77].
- **Capacity to make financial investments**: few companies have all the resources needed to implement a DT. Nor is it a cost-free project. Knowing how to make the right investments will benefit the business significantly [77].

5.4.2 Opportunities deriving from DT utilization

In the context of manufacturing companies, there are several highly significant benefits of implementing DTs. The strategic implementation of DTs opens up unconventional vistas in streamlining production processes, managing resources, and enhancing overall business effectiveness. Given this, in the context of their substantial role in enabling digital transformation and the progress of manufacturing practices, it is now important to dwell on the numerous advantages DTs afford. As a result, this section is devoted to shedding light on the advantages of integrating DTs into manufacturing firms, and to explain how these technological breakthroughs are revolutionizing the industrial landscape and creating new opportunities for growth and improvement.

Firstly, DT **accelerates prototyping and redesign processes** using simulations that assay multiple scenarios, shortening design and analysis cycles. It continuously compares predicted to actual performance, throughout the product lifecycle, leveraging the DT and the physical twin. It customizes for user needs, using usage data[82].

Secondly, DT DT is **cost-effective**, generating far less waste because most prototyping is with virtual resources; this, in turn, reduces aggregate costs. Unlike traditional prototyping, which uses expensive material and labour, DT also permits products to be virtually "torn up and tested" without incurring additional material costs, reducing overall product costs. Simulated testing, with some physical testing, means less material is "destroyed" [83].

Thirdly, DT's predictive capabilities enhance **problem forecasting and system planning** thanks to real-time data flowing between the physical asset and its DT [82].

Furthermore, DT **optimizes solutions and improves maintenance,** as it projects, and permits the visualization of defects and wear and tear in manufacturing machinery or systems, and simulates different scenarios to provide that best solutions (and maintenance strategies) exist. In this way, it may, for example, take the best possible decision of when to take a machine out of operation, and also optimize falls over in service, taking into account the state of the machinery [84].

The **accessibility** of DT allows remote control and monitoring of physical devices, overcoming geographical restrictions. This was particularly beneficial during situations like the COVID-19 pandemic [85].

In hazardous industries like oil and gas or mining, DT's remote access and predictive nature **reduce the risk of accidents** [86] .

Lastly, DT contributes to **waste reduction** by simulating and testing prototypes in a virtual environment, minimizing material wastage. This virtual probing of prototype designs under various test scenarios enables the finalization of product designs before physical manufacturing, aligning with sustainability goals [87].

5.4.3 DT implementation challenges

The available literature leads us to conclude that there are several challenges to face in the journey to a full implementation of DTs. To explore this strand, we looked at six papers from the literature that provided insight into the challenges involved in implementing DTs.

Each of these papers addresses specific challenges related to the implementation of DTs. Although some of these challenges may overlap, the diversity of perspectives offered allows us to gain a comprehensive overview of the critical issues that may arise during this technology integration process.

After a careful analysis of the challenges described in the six reference documents, it was considered important to use a selection criterion that would allow all the challenges identified by the different authors to be organised more effectively and clearly. All the criteria analysed, which will be explained in more detail later, and the categories into which they were divided are summarised in Table 4.

Implementation challenges	
Engineering related challenges	System integration and interoperability [89], [90], [91]
	Necessity for standardization and simplification of processes [89], [90]
	Need of high-performance real-time communication systems [88], [89]
	High cost [89], [90], [92], [93]
	User interaction [90]
	Long-time implementation process [89], [90]
Organizational challenges	Multiple stakeholders [89]
	Cultural inertia [89], [92]
	Must set realistic expectations, trust and value proposition [89], [93]
	Lack of necessary skills and knowledge [90], [93]
Data related challenges	Data ownerships [90], [93]
	Data variety [90], [91]
	Data protection [89], [90], [93]
	Data sharing [90]

Table 4 : DT implementation challenges

Engineering related challenges

The lack of **system integration and interoperability** challenge represents the inability to integrate different systems or components in a synergistic way, leading to difficulties in communication and data exchange. Overcoming this challenge means overcoming differences in operating modes and data formats to ensure smooth collaboration between the different entities involved in the DT [90]. To overcome this problem, we could identify open technologies that can be easily integrated with the production production system [89].

The lack of common standards can hinder interoperability between systems, effective sharing of data and information, and collaboration between different DT platforms. Thus, the **need for standardisation and simplification of processes** represents a challenge in the implementation of DTs, as it requires the adaptation and harmonisation of standards and processes [89], [90].

The implementation of DTs requires **high-performance real-time communication systems** to enable the immediate exchange of data between the DT and its physical counterpart. This requires significant resources in terms of technical expertise and financial investment. In addition, ensuring the security and reliability of such systems is crucial, as they must handle sensitive data and help control critical processes in real time [89].

There are also **significant costs** associated with implementation. Often a company's resources are not sufficient, and it is often necessary to purchase expensive sensors, software modules, storage systems and hire new staff to acquire new skills that were not previously required [89], [90], [92], [93]

Human **interactions** with machines in the manufacturing environment can be prone to accidents, safety concerns in the workplace are a significant concern [90].

To avoid all the possible problems listed above, and to find a solution to the various challenges, **long implementation times** are often necessary [89], [90].

Organizational challenges

During the implementation of DTs, clear communication about responsibilities, competences, and common objectives is necessary due to the presence of **multiple stakeholders** [89].

Cultural inertia can also hinder the implementation of DTs. Workers may be hesitant to embrace the idea of a 100% reliable digital copy that can account for all physical world variables, leading to resistance [92]. Therefore, it is advisable to codesign the DT with operators to ensure complete transparency on the data collected [89]. A clear and achievable vision must be established, and **workers must be trusted** to achieve it [93].

Before deciding to adopt a DT, companies often **lack workers with the necessary skills** [92]. This includes Industry 4.0 specialists and digital expertise [91]. One possible solution is to interact with other companies that have successfully adopted a DT to fully understand the process, in addition to drawing new resources from outside [89].

Data related challenges

Regarding data and information flow, **data ownership** is a significant issue, not only in relation to DT but also in the broader context of digital transformation [93]. Sharing data across the entire value chain and adding more information over time can increase intellectual capital. Thus, the issue of data ownership is not insignificant [90].

The **data variety** needed to fully utilise the capabilities of a DT is not a significant issue, as data is produced and collected on a daily basis. However, the challenge arises from the need to integrate, cleanse and fuse the diverse data types [90], [91].

In the digital economy, various types of data are at risk, including personal data, financial data, information on the development of new technologies, and an organization's corporate and strategic information. **Cyber-attacks** are becoming more frequent and complex, posing a significant threat to data security. The consequences of such attacks can have a detrimental impact on an organisation's reputation, finances, and physical assets. Therefore, it is essential to take measures to prevent this risk [90].

Effective information and **data sharing** is crucial for different actors along the value chain, both internally and externally. However, corporate policies, cultures, and people's mindsets regarding data ownership often hinder this process. This presents a significant challenge for DTs, which goes beyond technological and engineering complexities. Failure to share information can result in the creation of data 'silos' [90].

6 Conclusions

This thesis presented an overview of the role of DT technology in contemporary manufacturing systems. Classification criteria were used to appraise the broader literature, and the associated benefits and challenges in its implementation were examined.

By classifying the documents according to the functions that they serve, the classification criteria enable to focus on those specific aspects of DTs most relevant to their area of interest, and in so-doing, provide insight into the various ways DTs can be exploited to streamline manufacturing activities. These include monitoring and optimizing production, layout design, sustainability, manage flexibility and their collaboration with other DTs.

Nonetheless, this study has some limitations. First, the review of literature in this study is restricted to the Scopus source of articles. The Scopus source itself may not be enough to cover the entire spectrum of research literature on DTs in the manufacturing domain. Besides, classification criteria are not exhaustive, and might not cover all the potential application of DTs. Finally, the provided frameworks in this thesis are not wide enough to include all possible use cases of DTs in manufacturing.

However, this thesis holds value in the sense that it has explored a variety of different features of the role of DT in manufacturing systems, and the findings underline the transformative potential of DTs, and their capacity to effect positive change in the manufacturing industry, leading to a new age of smart, connected and efficient production processes.

Bibliography

[1] A. C. Pereira and F. Romero, "A review of the meanings and the implications of the Industry 4.0 concept," *Procedia Manuf*, vol. 13, pp. 1206–1214, 2017, doi: 10.1016/j.promfg.2017.09.032.

[2] S. Weyer, M. Schmitt, M. Ohmer, and D. Gorecky, "Towards Industry 4.0 - Standardization as the crucial challenge for highly modular, multi-vendor production systems," *IFAC-PapersOnLine*, vol. 48, no. 3, pp. 579–584, 2015, doi: 10.1016/j.ifacol.2015.06.143.

[3] M. Javaid, A. Haleem, and R. Suman, "Digital Twin applications toward Industry 4.0: A Review," *Cognitive Robotics*, vol. 3, pp. 71–92, 2023, doi: 10.1016/j.cogr.2023.04.003.

[4] Gizem Erboz, "How To Define Industry 4.0: Main Pillars Of Industry 4.0," Gödöllő, Hungary, Nov. 2017.

[5] Statista, "Industry 4.0: in-depth market analysis," Apr. 2023.

[6] B. R. Barricelli, E. Casiraghi, and D. Fogli, "A Survey on Digital Twin: Definitions, Characteristics, Applications, and Design Implications," *IEEE Access*, vol. 7, pp. 167653–167671, 2019, doi: 10.1109/ACCESS.2019.2953499.

[7] M. Singh, E. Fuenmayor, E. Hinchy, Y. Qiao, N. Murray, and D. Devine, "Digital Twin: Origin to Future," *Applied System Innovation*, vol. 4, no. 2, p. 36, May 2021, doi: 10.3390/asi4020036.

[8] Gartner, "Gartner Top 10 Strategic Technology Trends for 2019." Accessed: Jan. 24, 2024. [Online]. Available: https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2019

[9] Google Trends, "GoogleTrends - Digital Twin." Accessed: Jan. 24, 2024. [Online]. Available: https://trends.google.com/trends/explore?date=today%205-y&q=digital%20twin&hl=it

[10] Global Market Insight, "Digital Twin Market Size By Application (Product Design & Development, Machine & Equipment Health Monitoring, Process Support &

Service), By End Use (Manufacturing, Healthcare, Automotive, Aerospace & Defense, Energy, Others) & Forecast, 2023 - 2032," Apr. 2023. Accessed: Jan. 24, 2024. [Online]. Available: https://www.gminsights.com/industry-analysis/digital-twin-market

[11] Statista, "Global digital twin market share in 2020, by industry." Accessed: Jan. 24, 2024. [Online]. Available: https://www-statista-com/statistics/1296192/global-digital-twin-market-share-by-industry/

[12] Statista, "Global digital twin market size in the year 2020 and 2025, by industry(in billion U.S. dollars)." Accessed: Jan. 24, 2024. [Online]. Available: https://www-statista-com/statistics/1296187/global-digital-twin-market-by-industry/

[13] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, "Digital twin-driven product design, manufacturing and service with big data," *The International Journal of Advanced Manufacturing Technology*, vol. 94, no. 9–12, pp. 3563–3576, Feb. 2018, doi: 10.1007/s00170-017-0233-1.

[14] M. Conroy, "Modeling, Simulation, Information Technology and Processing Roadmap," 2010. [Online]. Available: https://www.researchgate.net/publication/280310295

[15] J. Lee, E. Lapira, B. Bagheri, and H. an Kao, "Recent advances and trends in predictive manufacturing systems in big data environment," *Manuf Lett*, vol. 1, no. 1, pp. 38–41, 2013, doi: 10.1016/j.mfglet.2013.09.005.

[16] A. Banerjee, R. Dalal, S. Mittal, and K. P. Joshi, "Generating Digital Twin Models using Knowledge Graphs for Industrial Production Lines," Association for Computing Machinery (ACM), Jun. 2017, pp. 425–430. doi: 10.1145/3091478.3162383.

[17] E. Negri, L. Fumagalli, and M. Macchi, "A Review of the Roles of Digital Twin in CPS-based Production Systems," in *Procedia Manufacturing*, Elsevier B.V., 2017, pp. 939–948. doi: 10.1016/j.promfg.2017.07.198.

[18] Hempel, "Healthcare solution testing for future | Digital Twins in healthcare."

[19] Q. Qi and F. Tao, "Digital Twin and Big Data Towards Smart Manufacturing and

Industry 4.0: 360 Degree Comparison," *IEEE Access*, vol. 6, pp. 3585–3593, 2018, doi: 10.1109/ACCESS.2018.2793265.

[20] "Global Horizons Global Horizons Final Report United States Air Force Global Science and Technology Vision," 2013.

[21] J. Guo, N. Zhao, L. Sun, and S. Zhang, "Modular based flexible digital twin for factory design," *J Ambient Intell Humaniz Comput*, vol. 10, no. 3, pp. 1189–1200, Mar. 2019, doi: 10.1007/s12652-018-0953-6.

[22] K. M. Alam and A. El Saddik, "C2PS: A Digital Twin Architecture Reference Model for the Cloud-Based Cyber-Physical Systems," *IEEE Access*, vol. 5, pp. 2050–2062, 2017, doi: 10.1109/ACCESS.2017.2657006.

[23] M. Mabkhot, A. Al-Ahmari, B. Salah, and H. Alkhalefah, "Requirements of the Smart Factory System: A Survey and Perspective," *Machines*, vol. 6, no. 2, p. 23, Jun. 2018, doi: 10.3390/machines6020023.

[24] M. Grieves and J. Vickers, "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems," in *Transdisciplinary Perspectives on Complex Systems*, 2016, pp. 85–113.

[25] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital Twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018, doi: 10.1016/j.ifacol.2018.08.474.

[26] Siemens, "Digital Twin." Accessed: Feb. 01, 2024. [Online]. Available: https://www.plm.automation.siemens.com/global/it/our-story/glossary/digital-twin/24465

[27] F. Tao, Q. Qi, L. Wang, and A. Y. C. Nee, "Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison," *Engineering*, vol. 5, no. 4, pp. 653–661, Aug. 2019, doi: 10.1016/j.eng.2019.01.014.

[28] A. Madni, C. Madni, and S. Lucero, "Leveraging Digital Twin Technology in Model-Based Systems Engineering," *Systems*, vol. 7, no. 1, p. 7, Jan. 2019, doi: 10.3390/systems7010007.

[29] W. Yu, P. Patros, B. Young, E. Klinac, and T. G. Walmsley, “Energy digital twin technology for industrial energy management: Classification, challenges and future,” *Renewable and Sustainable Energy Reviews*, vol. 161, p. 112407, Jun. 2022, doi: 10.1016/j.rser.2022.112407.

[30] M. Enders, M. R. Enders, and N. Hoßbach, “Dimensions of Digital Twin Applications-A Literature Review Dimensions of Digital Twin Applications-A Literature Review Dimensions of Digital Twin Applications-A Literature Review Completed Research,” 2019. [Online]. Available: https://www.researchgate.net/publication/359715537

[31] M. Grieves, “Digital Twin: Manufacturing Excellence through Virtual Factory Replication,” 2014. [Online]. Available: https://www.researchgate.net/publication/275211047

[32] R. Stark, S. Kind, and S. Neumeyer, “Innovations in digital modelling for next generation manufacturing system design,” *CIRP Ann Manuf Technol*, vol. 66, no. 1, pp. 169–172, 2017, doi: 10.1016/j.cirp.2017.04.045.

[33] F. Tao, M. Zhang, Y. Liu, and A. Y. C. Nee, “Digital twin driven prognostics and health management for complex equipment,” *CIRP Annals*, vol. 67, no. 1, pp. 169–172, Jan. 2018, doi: 10.1016/j.cirp.2018.04.055.

[34] A. Redelinghuys, A. Basson, and K. Kruger, “A six-layer digital twin architecture for a manufacturing cell,” in *Studies in Computational Intelligence*, Springer Verlag, 2019, pp. 412–423. doi: 10.1007/978-3-030-03003-2_32.

[35] C. Boje, A. Guerriero, S. Kubicki, and Y. Rezgui, “Towards a semantic Construction Digital Twin: Directions for future research,” *Autom Constr*, vol. 114, p. 103179, Jun. 2020, doi: 10.1016/j.autcon.2020.103179.

[36] “Industry 4.0 and the digital twin Manufacturing meets its match A Deloitte series on Industry 4.0, digital manufacturing enterprises, and digital supply networks,” 2018.

[37] C. J. Parris, “Minds + Machines: Meet A Digital Twin.” Accessed: Jan. 27, 2024. [Online]. Available: https://www.youtube.com/watch?v=2dCz3oL2rTw

[38] R. Söderberg, K. Wärmefjord, J. S. Carlson, and L. Lindkvist, “Toward a Digital

Twin for real-time geometry assurance in individualized production," *CIRP Annals*, vol. 66, no. 1, pp. 137–140, 2017, doi: 10.1016/j.cirp.2017.04.038.

[39] C. Zhang, G. Zhou, J. He, Z. Li, and W. Cheng, "A data- and knowledge-driven framework for digital twin manufacturing cell," *Procedia CIRP*, vol. 83, pp. 345–350, 2019, doi: 10.1016/j.procir.2019.04.084.

[40] G. Zhou, C. Zhang, Z. Li, K. Ding, and C. Wang, "Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing," *Int J Prod Res*, vol. 58, no. 4, pp. 1034–1051, Feb. 2020, doi: 10.1080/00207543.2019.1607978.

[41] C. Zhang, G. Zhou, H. Li, and Y. Cao, "Manufacturing Blockchain of Things for the Configuration of a Data- and Knowledge-Driven Digital Twin Manufacturing Cell," *IEEE Internet Things J*, vol. 7, no. 12, pp. 11884–11894, Dec. 2020, doi: 10.1109/JIOT.2020.3005729.

[42] M. Kumbhar, A. H. C. Ng, and S. Bandaru, "A digital twin based framework for detection, diagnosis, and improvement of throughput bottlenecks," *J Manuf Syst*, vol. 66, pp. 92–106, Feb. 2023, doi: 10.1016/j.jmsy.2022.11.016.

[43] J. Baalsrud Hauge *et al.*, "Digital twin testbed and practical applications in production logistics with real-time location data," *International Journal of Industrial Engineering and Management*, vol. 12, no. 2, pp. 129–140, Jun. 2021, doi: 10.24867/IJIEM-2021-2-282.

[44] Y. Qamsane *et al.*, "A Methodology to Develop and Implement Digital Twin Solutions for Manufacturing Systems," *IEEE Access*, vol. 9, pp. 44247–44265, 2021, doi: 10.1109/ACCESS.2021.3065971.

[45] J. H. Loaiza, R. J. Cloutier, and K. Lippert, "Proposing a Small-Scale Digital Twin Implementation Framework for Manufacturing from a Systems Perspective," *Systems*, vol. 11, no. 1, p. 41, Jan. 2023, doi: 10.3390/systems11010041.

[46] K. Wärmefjord, R. Söderberg, B. Schleich, and H. Wang, "Digital Twin for Variation Management: A General Framework and Identification of Industrial Challenges Related to the Implementation," *Applied Sciences*, vol. 10, no. 10, p. 3342, May 2020, doi: 10.3390/app10103342.

[47] S. Huang, G. Wang, D. Lei, and Y. Yan, "Toward digital validation for rapid product

development based on digital twin: a framework," *The International Journal of Advanced Manufacturing Technology*, vol. 119, no. 3–4, pp. 2509–2523, Mar. 2022, doi: 10.1007/s00170-021-08475-4.

[48] F. Xiang, Z. Zhang, Y. Zuo, and F. Tao, "Digital Twin Driven Green Material Optimal-Selection towards Sustainable Manufacturing," *Procedia CIRP*, vol. 81, pp. 1290–1294, 2019, doi: 10.1016/j.procir.2019.04.015.

[49] X. Ma, F. Tao, M. Zhang, T. Wang, and Y. Zuo, "Digital twin enhanced human-machine interaction in product lifecycle," *Procedia CIRP*, vol. 83, pp. 789–793, 2019, doi: 10.1016/j.procir.2019.04.330.

[50] A. Detzner and M. Eigner, "A DIGITAL TWIN FOR ROOT CAUSE ANALYSIS AND PRODUCT QUALITY MONITORING," 2018, pp. 1547–1558. doi: 10.21278/idc.2018.0418.

[51] D. Lee *et al.*, "Digital Twin-Based Analysis and Optimization for Design and Planning of Production Lines," *Machines*, vol. 10, no. 12, p. 1147, Dec. 2022, doi: 10.3390/machines10121147.

[52] M. Sommer, J. Stjepandić, S. Stobrawa, and M. von Soden, "Automated generation of digital twin for a built environment using scan and object detection as input for production planning," *J Ind Inf Integr*, vol. 33, p. 100462, Jun. 2023, doi: 10.1016/j.jii.2023.100462.

[53] H. Guo, Y. Zhu, Y. Zhang, Y. Ren, M. Chen, and R. Zhang, "A digital twin-based layout optimization method for discrete manufacturing workshop," *The International Journal of Advanced Manufacturing Technology*, vol. 112, no. 5–6, pp. 1307–1318, Jan. 2021, doi: 10.1007/s00170-020-06568-0.

[54] Necip Akar, "Optimizing Cellular Manufacturing Facility Layout Design through Digital Twin Simulation: A Case Study," *Industrial Engineering and Innovation Management*, vol. 6, no. 6, 2023, doi: 10.23977/ieim.2023.060601.

[55] Q. Yan, H. Wang, and F. Wu, "Digital twin-enabled dynamic scheduling with preventive maintenance using a double-layer Q-learning algorithm," *Comput Oper Res*, vol. 144, p. 105823, Aug. 2022, doi: 10.1016/j.cor.2022.105823.

[56] K. Tliba, T. M. L. Diallo, O. Penas, R. Ben Khalifa, N. Ben Yahia, and J.-Y. Choley,

"Digital twin-driven dynamic scheduling of a hybrid flow shop," *J Intell Manuf*, vol. 34, no. 5, pp. 2281–2306, Jun. 2023, doi: 10.1007/s10845-022-01922-3.

[57] R. Ogunsakin, N. Mehandjiev, and C. A. Marin, "Towards adaptive digital twins architecture," *Comput Ind*, vol. 149, p. 103920, Aug. 2023, doi: 10.1016/j.compind.2023.103920.

[58] A. A. Neto, E. Ribeiro da Silva, F. Deschamps, L. A. do Nascimento Junior, and E. Pinheiro de Lima, "Modeling production disorder: Procedures for digital twins of flexibility-driven manufacturing systems," *Int J Prod Econ*, vol. 260, p. 108846, Jun. 2023, doi: 10.1016/j.ijpe.2023.108846.

[59] Carlos Henrique dos Santos and Gustavo Teodoro Gabriel, "Decision-making in a fast fashion company in the Industry 4.0 era: a Digital Twin proposal to support operational planning," *The International Journal of Advanced Manufacturing Technology*, Jul. 2021.

[60] C. Zhuang, J. Liu, and H. Xiong, "Digital twin-based smart production management and control framework for the complex product assembly shop-floor," *The International Journal of Advanced Manufacturing Technology*, vol. 96, no. 1–4, pp. 1149–1163, Apr. 2018, doi: 10.1007/s00170-018-1617-6.

[61] K. T. Park, J. Lee, H.-J. Kim, and S. Do Noh, "Digital twin-based cyber physical production system architectural framework for personalized production," *The International Journal of Advanced Manufacturing Technology*, vol. 106, no. 5–6, pp. 1787–1810, Jan. 2020, doi: 10.1007/s00170-019-04653-7.

[62] M. Helu, T. Hedberg, and A. Barnard Feeney, "Reference architecture to integrate heterogeneous manufacturing systems for the digital thread," *CIRP J Manuf Sci Technol*, vol. 19, pp. 191–195, Nov. 2017, doi: 10.1016/j.cirpj.2017.04.002.

[63] S. Liu, Y. Lu, X. Shen, and J. Bao, "A digital thread-driven distributed collaboration mechanism between digital twin manufacturing units," *J Manuf Syst*, vol. 68, pp. 145–159, Jun. 2023, doi: 10.1016/j.jmsy.2023.02.014.

[64] R. Sahal, S. H. Alsamhi, J. G. Breslin, K. N. Brown, and M. I. Ali, "Digital Twins Collaboration for Automatic Erratic Operational Data Detection in Industry 4.0," *Applied Sciences*, vol. 11, no. 7, p. 3186, Apr. 2021, doi: 10.3390/app11073186.

[65] M. A. Al Faruque, D. Muthirayan, S.-Y. Yu, and P. P. Khargonekar, "Cognitive Digital Twin for Manufacturing Systems," in *2021 Design, Automation & Test in Europe Conference & Exhibition (DATE)*, IEEE, Feb. 2021, pp. 440–445. doi: 10.23919/DATE51398.2021.9474166.

[66] P. Eirinakis *et al.*, "Cognitive Digital Twins for Resilience in Production: A Conceptual Framework," *Information*, vol. 13, no. 1, p. 33, Jan. 2022, doi: 10.3390/info13010033.

[67] K. Kalaboukas, J. Rožanec, A. Košmerlj, D. Kiritsis, and G. Arampatzis, "Implementation of Cognitive Digital Twins in Connected and Agile Supply Networks—An Operational Model," *Applied Sciences*, vol. 11, no. 9, p. 4103, Apr. 2021, doi: 10.3390/app11094103.

[68] T. Mortlock, D. Muthirayan, S.-Y. Yu, P. P. Khargonekar, and M. A. Al Faruque, "Graph Learning for Cognitive Digital Twins in Manufacturing Systems," Sep. 2021.

[69] J. M. Rožanec, "Towards Actionable Cognitive Digital Twins for Manufacturing," 2020.

[70] D. Popescu, M. Dragomir, S. Popescu, and D. Dragomir, "Building Better Digital Twins for Production Systems by Incorporating Environmental Related Functions—Literature Analysis and Determining Alternatives," *Applied Sciences*, vol. 12, no. 17, p. 8657, Aug. 2022, doi: 10.3390/app12178657.

[71] H. Hassani, X. Huang, and S. MacFeely, "Enabling Digital Twins to Support the UN SDGs," *Big Data and Cognitive Computing*, vol. 6, no. 4, p. 115, Oct. 2022, doi: 10.3390/bdcc6040115.

[72] R. Miehe, L. Waltersmann, A. Sauer, and T. Bauernhansl, "Sustainable production and the role of digital twins–Basic reflections and perspectives," *J Adv Manuf Process*, vol. 3, no. 2, Apr. 2021, doi: 10.1002/amp2.10078.

[73] I. Rojek, D. Mikołajewski, and E. Dostatni, "Digital Twins in Product Lifecycle for Sustainability in Manufacturing and Maintenance," *Applied Sciences*, vol. 11, no. 1, p. 31, Dec. 2020, doi: 10.3390/app11010031.

[74] A. Tzachor, S. Sabri, C. E. Richards, A. Rajabifard, and M. Acuto, "Potential and

limitations of digital twins to achieve the Sustainable Development Goals," *Nat Sustain*, vol. 5, no. 10, pp. 822–829, Jul. 2022, doi: 10.1038/s41893-022-00923-7.

[75] A. Barni, A. Fontana, S. Menato, M. Sorlini, and L. Canetta, "Exploiting the Digital Twin in the Assessment and Optimization of Sustainability Performances," in *2018 International Conference on Intelligent Systems (IS)*, IEEE, Sep. 2018, pp. 706–713. doi: 10.1109/IS.2018.8710554.

[76] S. S. Kamble, A. Gunasekaran, H. Parekh, V. Mani, A. Belhadi, and R. Sharma, "Digital twin for sustainable manufacturing supply chains: Current trends, future perspectives, and an implementation framework," *Technol Forecast Soc Change*, vol. 176, p. 121448, Mar. 2022, doi: 10.1016/j.techfore.2021.121448.

[77] A. A. Neto, F. Deschamps, E. R. da Silva, and E. P. de Lima, "Digital twins in manufacturing: an assessment of drivers, enablers and barriers to implementation," *Procedia CIRP*, vol. 93, pp. 210–215, 2020, doi: 10.1016/j.procir.2020.04.131.

[78] M. Perno and L. Hvam, "Developing a Framework for Scoping Digital Twins in the Process Manufacturing Industry," 2020. doi: 10.3233/ATDE200185.

[79] M. Perno, L. Hvam, and A. Haug, "Implementation of digital twins in the process industry: A systematic literature review of enablers and barriers," *Comput Ind*, vol. 134, p. 103558, Jan. 2022, doi: 10.1016/j.compind.2021.103558.

[80] Y. Lu, C. Liu, K. I.-K. Wang, H. Huang, and X. Xu, "Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues," *Robot Comput Integr Manuf*, vol. 61, p. 101837, Feb. 2020, doi: 10.1016/j.rcim.2019.101837.

[81] J. H. Loaiza, R. J. Cloutier, and K. Lippert, "Proposing a Small-Scale Digital Twin Implementation Framework for Manufacturing from a Systems Perspective," *Systems*, vol. 11, no. 1, p. 41, Jan. 2023, doi: 10.3390/systems11010041.

[82] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, "Digital twin-driven product design, manufacturing and service with big data," *The International Journal of Advanced Manufacturing Technology*, vol. 94, no. 9–12, pp. 3563–3576, Feb. 2018, doi: 10.1007/s00170-017-0233-1.

[83] M. Grieves and J. Vickers, “Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems,” in *In Transdisciplinary Perspectives on Complex Systems*, Springer, 2017, pp. 85–113.

[84] E. Glaessgen and D. Stargel, “The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles,” in *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference
20th AIAA/ASME/AHS Adaptive Structures Conference
14th AIAA*, Reston, Virigina: American Institute of Aeronautics and Astronautics, Apr. 2012. doi: 10.2514/6.2012-1818.

[85] W. Shen, C. Yang, and L. Gao, “Address business crisis caused by COVID-19 with collaborative intelligent manufacturing technologies,” *IET Collaborative Intelligent Manufacturing*, vol. 2, no. 2, pp. 96–99, Jun. 2020, doi: 10.1049/iet-cim.2020.0041.

[86] C. Stamford, “Gartner Survey Reveals 47% of Organizations Will Increase Investments in IoT Despite the Impact of COVID-19,” Gartner. Accessed: Jan. 28, 2024. [Online]. Available: https://www.gartner.com/en/newsroom/press-releases/2020-10-29-gartner-survey-reveals-47-percent-of-organizations-will-increase-investments-in-iot-despite-the-impact-of-covid-19-#:~:text=By%202023%2C%20One%2DThird%20of,survey*%20from%20Gartner%2C%20Inc.

[87] M. Singh, E. Fuenmayor, E. Hinchy, Y. Qiao, N. Murray, and D. Devine, “Digital Twin: Origin to Future,” *Applied System Innovation*, vol. 4, no. 2, p. 36, May 2021, doi: 10.3390/asi4020036.

[88] I. Ozkaya, “Architectural Concerns of Digital Twins,” *IEEE Softw*, vol. 39, no. 2, pp. 3–6, Mar. 2022, doi: 10.1109/MS.2021.3130872.

[89] N. Saporiti, V. G. Cannas, R. Pozzi, and T. Rossi, “Challenges and countermeasures for digital twin implementation in manufacturing plants: A Delphi study,” *Int J Prod Econ*, vol. 261, p. 108888, Jul. 2023, doi: 10.1016/j.ijpe.2023.108888.

[90] S. Singh, E. Shehab, N. Higgins, K. Fowler, T. Tomiyama, and C. Fowler, “Challenges of Digital Twin in High Value Manufacturing,” Oct. 2018. doi: 10.4271/2018-01-1928.

[91] Á. García, A. Bregon, and M. A. Martínez-Prieto, “Towards a connected Digital

Twin Learning Ecosystem in manufacturing: Enablers and challenges," *Comput Ind Eng*, vol. 171, p. 108463, Sep. 2022, doi: 10.1016/j.cie.2022.108463.

[92] M. Gulewicz, "Digital twin technology — awareness, implementation problems and benefits," *Engineering Management in Production and Services*, vol. 14, no. 1, pp. 63–77, Mar. 2022, doi: 10.2478/emj-2022-0006.

[93] M. Timperi, K. Kokkonen, L. Hannola, and K. Elfvengren, "Impacts of digital twins on new business creation: insights from manufacturing industry," *Measuring Business Excellence*, vol. 27, no. 3, pp. 433–448, Aug. 2023, doi: 10.1108/MBE-09-2022-0104.

[94] Simon-Kucher, "Degree to which consumers' purchasing behavior and choices shifted towards buying more sustainable products over the past five years worldwide in 2022," Statista. Accessed: Jan. 27, 2024. [Online]. Available: https://www-statista-com/statistics/1377869/global-shift-to-buying-sustainable-products/