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Implementation of digital twins in the process industry: A systematic literature review of enablers and barriers

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ABSTRACT

Since the introduction of the concept of “digital twins” (DTs) in 2002, the number of practical applications in different industrial sectors has grown rapidly. Despite the hype surrounding this technology, companies face significant challenges upon deciding to implement DTs in their organizations due to the novelty of the concept. Furthermore, little research on DT has been conducted for the process industry, which may be explained by the high complexity of accurately representing and modeling the physics behind production processes. To consolidate the fragmented literature on the enabling factors and challenges in DT implementation in the process industry, this study organizes the existing studies on DTs with a focus on barriers and enablers. On this basis, this study contributes to the existing body of knowledge on DTs by organizing the DT literature and by proposing conceptual models describing enablers of and barriers to DT implementation, as well as their mutual relationships.

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1. Introduction

Industry 4.0 is rapidly changing numerous industry sectors and enabling new business models (Cozmiuc and Petrisor, 2018) due to machine learning (ML) and artificial intelligence (AI), the (industrial) Internet of Things (IIoT), data analysis techniques, and the latest developments in information and communication technologies (Liu et al., 2021; Fuller et al., 2020; Yun et al., 2020; Ren et al., 2018; Moghaddam et al., 2018; Errandonea et al., 2020). One of the technologies under the Industry 4.0 umbrella is digital twins (DTs) (Rojek et al., 2021; Ho et al., 2021; Hsu et al., 2019). The initial practical implementations of DTs were in the aerospace industry (Negri et al., 2017), but DTs are increasingly being used in a wide variety of contexts, including but not limited to construction (Opoku et al., 2021), healthcare (Semeraro et al., 2021), industrial production (Negri et al., 2017; Rasheed et al., 2020; Kritzing et al., 2018), aviation (Mandolla et al., 2019) and automotive (Alcácer and Cruz-Machado, 2019) industries, meteorology, education and building

smart cities (Rasheed et al., 2020) or entire countries (Bolton et al., 2018).

Simulation techniques have been utilized for decades in a number of sectors, such as the aerospace, construction, automotive, and oil industries (Spalart et al., 2016; AbouRizk, 2010; Rodríguez et al., 2021; Lagrange, 2019). Although the DT concept builds on traditional simulation techniques, the technology offers other applications due to the aspect of real-time simulation (Fotland et al., 2020; Scheifele et al., 2018). The concept has only received significant attention in the literature in recent years (Fuller et al., 2020), with one area of focus being the process industry (Errandonea et al., 2020; Lee et al., 2019). This industry is defined as a sector that covers a wide range of complex manufacturing processes, from continuous facilities in the petrochemical industry to large-batch manufacturing in the glass and steel industries to small-batch manufacturing in the pharmaceutical and food industries (Braaksmas et al., 2011).

DTs are becoming increasingly important in the process industry (Zhou et al., 2019), and studies suggest significant benefits of using this technology (Kockmann, 2019; Pfeiffer et al., 2019; Uhlemann

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et al., 2017). However, the same researchers also highlight the need for more extensive research on DTs specifically addressing the process industry (Kockmann, 2019; Pfeiffer et al., 2019; Uhlemann et al., 2017). One issue is that the existing literature on DT implementation in the process industry is fragmented across several different topics and industry types, implying that an overview of the key enablers of and barriers to DT implementation does not exist. The immaturity of the relevant literature combined with the intrinsic complexity of production processes (Kockmann, 2019) makes it challenging for companies in this sector to make a decision on what approach is the best fit in terms of implementing DTs to grow their assets and operations. By collecting and organizing the existing knowledge on the DT concept, this paper aims to provide practitioners with a better basis for DT implementations and researchers with a stronger foundation for further development of the literature.

The purpose described above may be formulated as the following two research questions (RQs):

1. *What are the enablers of and barriers to the implementation of DTs in the process industry?*
2. *What are the relationships between the enablers and barriers in the implementation of DTs in the process industry?*

The remainder of this paper is structured as follows. Section 2 presents the conceptual background for this literature review and summarizes the current status of research on DTs in the process industry. Section 3 describes the methodology used to conduct the literature review using a content analysis-based approach and elaborates on each of its steps. Section 4 develops a framework based on the enablers and barriers identified during the literature review. Finally, Section 5 discusses the implications of this work for practice and research, as well as the limitations and opportunities for future research.

2. State of the art

The DT concept was first introduced in a 2002 lecture by Dr. Michael Grieves (Grieves and Vickers, 2017). Since then, many different definitions of DTs have been proposed in the academic literature. Therefore, although the research and number of publications on DTs are rapidly increasing, the DT concept is still rather fuzzy. Consequently, there is no universally agreed upon definition of DT (Cimino et al., 2019). In fact, many definitions can be found in the literature. These definitions are significantly different from each other in terms of scope, technologies, and features that a DT must have. From an overall perspective, DTs can be defined as virtual representations of physical assets enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision making (Rasheed et al., 2020). Table I summarizes some of the most cited definitions found in the literature in chronological order to show how the concept has evolved over the years.

2.1. Evolution of the DT concept

Since 2002, interest in the DT concept has grown exponentially, both in industry and academia (Kritzing et al., 2018; Qi et al., 2021; Moyne et al., 2020). However, DTs started attracting worldwide attention only in 2016, when the research and advisory firm Gartner included them among the top 10 strategic technology trends for 2017 (Rasheed et al., 2020; Gartner, 2016; Tao et al., 2019a, 2019b). Gartner also predicted that by the end of 2020, approximately 20 billion devices will be connected through the Internet of Things (IoT) (Hung, 2017; Qi and Tao, 2018) and that by 2021 half of the large

industrial companies will be using DTs, with a resulting 10% increase in effectiveness (Gartner, 2017). Therefore, in recent years several standard development organizations (SDOs) (ISO, 2020; Malakuti et al., 2020) have been working on standardizing the definition of DTs to facilitate common understanding, align stakeholder requirements and expectations, and improve clarity on the topic (Minerva et al., 2020).

A related stream of literature focuses on the distinction between DTs and cyber-physical systems (CPSs). Hsu et al. (2019) stated that although the two concepts have their own literature streams and are treated as separate entities, the literature treats them both as key enablers of Industry 4.0 but does not explain the differences between them. In modern literature, while some researchers use the two terms interchangeably, thus referring to the same thing (Lim et al., 2020; Yun et al., 2017; Hinchy et al., 2019), other authors have attempted to clarify the distinction between them (Lu et al., 2020; Leng et al., 2019; Uhlemann et al., 2017; Alam and Saddik, 2017). For example, Lu et al. (2020) argued that a DT is only one of the key components of a CPS, which also includes the physical twin and data exchange connection with its digital counterpart, the DT. For the purposes of this paper, the authors embrace the latter perspective and therefore consider DTs a fundamental component for the realization of CPSs.

2.2. DT benefits and opportunities

Both scholars and practitioners have acknowledged the potential and the opportunities provided by digitalization and DTs (Kockmann, 2019; Qi et al., 2021; Lim et al., 2020; Negri et al., 2020) across multiple industries. For example, Negri et al. (2020) showed how DTs can benefit organizations by streamlining production, reducing downtime, and consequently decreasing lead times. Lim et al. (2020) developed a reference framework for the development of DTs and applied it in a case study to model a tower crane. The benefits of using DTs reported in their study include reduced operator workload, the possibility to test different designs and scenarios without the risk of damaging equipment in the real world, and the possibility to reuse the knowledge generated by DTs in future projects. Qi et al. (2021) provided an overview of the key enabling technologies and tools for the development of DTs and listed the potential benefits associated with their use. In particular, the authors highlighted how DTs enable the use of big data for monitoring, optimization, diagnostic, and prognostic purposes.

In addition to the potential benefits and opportunities enabled by the implementation of DTs in real-world industrial scenarios, several reference architectures have emerged in the latest literature. For example, the Stuttgart IT Architecture for Manufacturing (SITAM) (Weber et al., 2017; Nakagawa et al., 2021; Nakagawa et al., 2021), IBM Industry 4.0 (Nakagawa et al., 2021; Nakagawa et al., 2021; Moghaddam et al., 2018), Eclipse BaSyx (Nakagawa et al., 2021; Nakagawa et al., 2021; Deuter and Imort, 2020), and RAMI 4.0 (Jaskó et al., 2020; Fahim et al., 2021; Pedone and Mezgár, 2018) are among the most advanced and popular reference architectures used in modern Industry 4.0 applications.

2.3. State of the art in the process industry

Focusing specifically on the process industry, the need for shorter production cycles, increased product output, flexibility in production, and more efficient quality assessment to remain competitive in the market requires the development and implementation of new technologies to analyze the increasing volume of process data (Eisen et al., 2020). On one hand, practitioners have acknowledged the benefits that can be achieved through DTs (Zhou et al., 2019;

Table I
Definitions of the digital twin concept in the literature.

Authors	Definition	Year	No. of Citations
Tuegel et al. (2011)	"An ultrahigh fidelity model of an individual aircraft by tail number that serves as a reengineering of structural life prediction and management."	2011	369
Glaessgen and Stargel (2012)	"An integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin."	2012	355
Rosen et al. (2015)	"Realistic model of the current state of the process and their own behavior in interaction with their environment in the real world."	2015	484
Grieves and Vickers (2017)	"A set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level."	2017	418
Stark and Damerau (2019)	"A digital twin is a digital representation of an active unique product (real device, object, machine, service, or intangible asset) or unique product-service system (a system consisting of a product and a related service) that comprises its selected characteristics, properties, conditions, and behaviors by means of models, information, and data within a single or even across multiple life cycle phases."	2019	17
Lu et al. (2020) adapted from Schleich et al. (2017)	"A high-fidelity representation of the operational dynamics of its physical counterpart, enabled by near real-time synchronization between the cyberspace and physical space."	2020	234
Minerva et al. (2020)	"A DT is a comprehensive software representation of an individual physical object (PO). It includes the properties, conditions, and behavior(s) of the real-life object through models and data. A DT is a set of realistic models that can simulate an object's behavior in the deployed environment. The DT represents and reflects its physical twin and remains its virtual counterpart across the object's entire lifecycle."	2020	25

Kockmann, 2019). On the other hand, the lack of practical implementations of DTs in the process industry (Lee et al., 2019) makes it challenging for process manufacturing companies to develop and implement DTs in their organizations from scratch.

Although the current literature specifically addressing the process industry is rather limited, some researchers have started investigating the requirements for the development and implementation of DTs in the process industry, their potential benefits, challenges, and key enabling technologies (Lee et al., 2019; Kockmann, 2019; Eisen et al., 2020; Perno et al., 2020; Xia et al., 2020; Liu et al., 2020; Wishnow et al., 2019; Zhang et al., 2017). Such studies are subsequently summarized.

2.4. Studies in the process industry

In Kockmann (2019), Kockmann summarizes the main findings of the annual ProcessNet Symposium held in Tutzing, Germany. At the 2018 symposium, which focused on digitalization in the process industry, the participants had the chance to discuss the latest trends, requirements, and strategies to achieve digitalization in that industry. The symposium resulted in the formulation of 12 theses to be used by process companies. During the symposium, practitioners in the process industry listed the benefits associated with the implementation of DTs in their organizations, including reduced time to market, reduced costs, and increased flexibility. DTs also enhance creativity and cooperation between employees.

Xia et al. (2020) developed a methodology for industrial process control using a three-step process. First, they constructed a virtual platform using state-of-the-art software to simulate the behavior of manufacturing cells in real time. Second, they worked on ensuring near real-time communication of data between the physical assets and their DTs. Finally, they developed an intelligent scheduling optimization engine using deep reinforcement learning techniques. The authors also listed the advantages of using DTs in a process manufacturing context, including the early detection of issues in product design, reduced costs by re-using standard tools and facilities, the minimization of risks in the production process through the simulation of manufacturing scenarios, the increase in process quality through the emulation of manufacturing processes, and the possibility to validate the mechanical and electrical integrated production processes early on. The main outcome of their study is the development of a methodology for developing and using DTs in robot manufacturing systems powered by deep reinforcement learning for intelligent scheduling.

Eisen et al. (2020) underlined the fundamental role of smart sensors in enabling process analytical technology and DTs in the process industry. The authors also listed the requirements and functionalities smart sensors require, including connectivity with legacy systems, self-calibration, and self-maintenance.

Lee et al. (2019) underlined the importance of risk management and process safety in the process industry and presented the challenges of interoperability and modeling accurate DTs. Furthermore, the authors highlighted the pivotal importance of standardization of data communication protocols between devices in an IoT network.

Given this background on DTs in the process industry, the present study aims to further clarify the key enablers of and barriers to the implementation of DTs in the process industry and to mitigate the current lack of agreement on the nature and definition of DTs. This is achieved with a content analysis-based literature review.

3. Methodology

This literature review was conducted using a content analysis-based approach, as described by Seuring and Gold (2012). Content analysis is a methodology comprising data analysis and interpretation (Elo et al., 2014) and is an objective and systematic means of quantifying and describing phenomena (Elo et al., 2014). When applied to literature reviews, content analysis ensures rigor, systematicness, and reproducibility (Seuring and Gold, 2012). The content analysis-based method used in this study consists of four steps (Seuring and Gold, 2012): (1) material collection, (2) descriptive analysis, (3) category selection, and (4) material evaluation. In the following subsections, each step is outlined.

3.1. Material collection

Four academic search engines were used to gather relevant literature—Clarivate Analytics' Web of Science, Elsevier's Scopus, IEEE Xplore, and ACM Digital Library. These were chosen because they include high-quality publications in fields that are relevant for this study, including engineering, computer science, and manufacturing.

Due to the immaturity of the current literature on DTs and the novelty of the concept, book chapters and papers published in conference proceedings have been included in the analysis, along with papers published in international journals. Table II shows the search strings used for each search engine. The structure of the search strings was derived directly from the RQs to ensure they

are answered properly through analysis of the most relevant literature (Petersen et al., 2008; Kitchenham, 2007). The initial version of the search strings was relatively simple and only included the keywords “digital twin”, “enabler”, and “barrier”. The search strings were extended through a series of iterations. With each iteration, new keywords were added to take synonyms into account, thus making the search strings more comprehensive.

The search strings in Table II were used over four search iterations to obtain an overview of the evolution of the literature on enablers of and barriers to DT implementation over time in the process industry. Table III summarizes the number of hits obtained in each database for every iteration. The results indicate a consistent increase in the number of publications on the topic, which is consistent with the increasing interest in DTs on the part of both researchers and industry practitioners (Kritzing et al., 2018; Qi et al., 2021; Moyne et al., 2020).

The steps followed to select and filter the relevant papers were the same for each iteration. In iteration 1, after combining the papers obtained from each database using the search strings from Table II, the total number of collected papers was 894. This number decreased to 737 after removing duplicates. These papers were subject to a two-step selection process, which was conducted by two researchers to reduce the risk of bias. The results were then compared, and a discussion was undertaken regarding the papers that were given a different score. This resulted in a final score for each paper that both researchers involved in the scoring process agreed upon.

The first step consisted of reading the abstract and title of each article and assigning them a score of 0, 1, or 2, depending on the degree of relevance to the RQs. Papers with no mention of enablers of or barriers to DT implementation in their title or abstract were given a score of 0. If an abstract indicated that the topic of the article includes enablers of or barriers to DT implementation without explicitly mentioning any specific factor in the title or abstract, it was given a score of 1. Papers that explicitly mention barriers, enablers, or both in their title or abstract were given a score of 2. Only the papers with a score of either 1 or 2 were kept for the next step in the selection process, and those with a score of 0 were excluded from the literature review. A total of 616 papers were discarded in this step, leaving 121 potentially relevant papers for the next step in the selection process, which consisted of reading the full text of the papers that received a score of 1 in the first step. The purpose of this approach was to identify relevant papers that only mention enablers of or barriers to DT implementation in their full text. This step resulted in a final list of 47 relevant papers. The article selection process for iteration 1 is summarized in Fig. 1.

In iterations 2, 3, and 4, the same steps were performed for all new papers that were not included in the previous iteration. At the end of iteration 4, a total of 79 papers were selected. These papers, which constituted the basis for the literature analysis, are listed in Table VI.

Table II
Search strings used for the literature study.

Database	search string
Web of Science	TS=(("digital twin" OR "digital shadow" OR "device twin" OR "device shadow" OR "digital alias" OR "virtual twin" OR "virtual shadow") AND (steel OR glass OR pharmaceutical OR ceramic OR stone OR clay OR metal OR chemical OR food OR beverage OR textile OR wood OR paper OR process OR manufacturing) AND (barriers OR obstacles OR enabl* OR driver)) AND LANGUAGE: (English)
Scopus	TITLE-ABS-KEY ("digital twin" OR "digital shadow" OR "device twin" OR "device shadow" OR "digital alias" OR "virtual twin" OR "virtual shadow") AND TITLE-ABS-KEY (steel OR glass OR pharmaceutical OR ceramic OR stone OR clay OR metal OR chemical OR food OR beverage OR textile OR wood OR paper OR process OR manufacturing) AND TITLE-ABS-KEY (barriers OR obstacles OR enabl* OR driver) AND LANGUAGE: (English)
IEEE Xplore	("digital twin" OR "digital shadow" OR "device twin" OR "device shadow" OR "digital alias" OR "virtual twin" OR "virtual shadow") AND (steel OR glass OR pharmaceutical OR ceramic OR stone OR clay OR metal OR chemical OR food OR beverage OR textile OR wood OR paper OR process OR manufacturing) AND (barriers OR obstacles OR enabl* OR driver)
ACM Digital Library	[All: "digital twin"] OR [All: "digital shadow"] OR [All: "device twin"] OR [All: "device shadow"] OR [All: "digital alias"] OR [All: "virtual twin"] OR [All: "virtual shadow"] AND [[All: steel] OR [All: glass] OR [All: pharmaceutical] OR [All: ceramic] OR [All: stone] OR [All: clay] OR [All: metal] OR [All: chemical] OR [All: food] OR [All: beverage] OR [All: textile] OR [All: wood] OR [All: paper] OR [All: process] OR [All: manufacturing]] AND [[All: barriers] OR [All: obstacles] OR [All: enabl*] OR [All: driver]]

3.2. Descriptive analysis

The 79 selected papers were listed in an Excel workbook. Here, bibliographic information for each article, including title, year of publication, authors, abstract, DOI, number of citations, and journal/conference of publication, was recorded. Fig. 2 illustrates the distribution of the selected papers by publication type. The selected papers include 49 journal papers, 28 papers published in conference proceedings, and 2 book chapters. All papers were published between 2016 and 2020. Fig. 3 shows that 34 of the 79 papers are discussions on DTs that do not include any practical application in industry, 6 papers present DT prototypes developed in a laboratory, 21 papers focus on discrete manufacturing, 5 focus on machinery, 1 focuses on remanufacturing processes, 1 focuses on injection molding, 1 focuses on energy systems, and only 10 address the process industry. These papers are listed in Table VI (paper nos. 7, 8, 9, 33, 38, 48, 61, 64, 70, and 75). Fig. 4 categorizes the papers based on methodology, showing that 34 are conceptual studies, 40 use case studies, 3 use surveys, and 2 use simulation and modeling.

3.3. Category development

The 79 selected papers were thoroughly analyzed. Each mention of barriers and enablers was noted in an Excel file, along with the bibliographic information of the paper citing it. After going through each paper and noting all mentions of enablers of and barriers to DT implementation, duplicates were merged, and the total number of mentions of each factor was calculated.

Identified enablers and barriers were organized using descriptive coding. As defined by Saldaña (2013), descriptive coding “summarizes in a word or short phrase—most often as a noun—the basic topic of a passage of qualitative data”. In this context, besides looking for common characteristics across enablers and barriers, the principles for the development of classifications defined by Eppler et al. (2011) were applied. The intent is to develop categories characterized by simplicity, visual clarity, usefulness, typicality, and unambiguity of labels. Using this process, seven barrier categories

Table III
Number of hits at each iteration of the literature search.

Database	Iteration 1 15/3/2020	Iteration 2 9/7/2020	Iteration 3 11/8/2020	Iteration 4 31/12/2020
Scopus	365	451	476	664
Web of Science	148	176	195	325
IEEE Xplore	132	138	146	207
ACM Digital Library	249	270	286	327
Total (after removing duplicates)	737	798	838	876
Growth (from iteration 1)	–	+8.27%	+13.7%	+18.86%

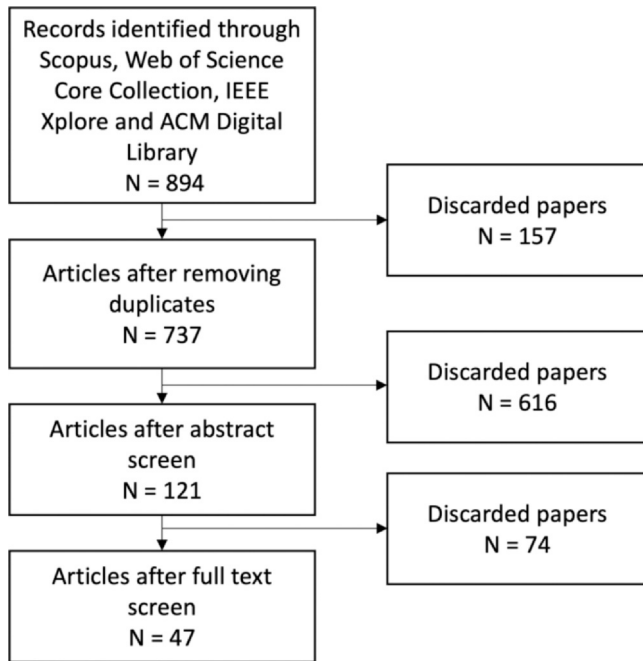


Fig. 1. Steps in the literature search process (iteration 1).

and eight enabler categories were identified. Table IV and V show the list of barriers and enablers, respectively, and their categorizations. The tables also show the number of mentions of each factor in the 79 analyzed papers. These factors were sorted by the number of times they were cited in the literature.

3.4. Material evaluation

The third column in Tables IV and V shows how many times a factor is mentioned in the analyzed papers. Although this number appears to be rather uniform for most of the mentioned enablers of and barriers to DT implementation, a few notable exceptions were identified. More specifically, the challenges of ensuring a high level of performance in real-time communication, implementing effective security and privacy protocols, and lack of integration have been

highlighted by other researchers a significant number of times. Regarding the enablers, simulation, ML and AI, cloud services, and IoT/IIoT appear to be frequently cited in the literature.

The replicability, transparency, and therefore external validity of the literature search process are ensured by the structured recording of each paper in an Excel workbook. Furthermore, the use of high-level categories to classify all enablers and barriers improves the clarity of the findings from the literature review.

4. Systematic analysis of DT barriers and enablers in the process industry

To clarify the findings from the literature review, a conceptual framework for the implementation of DTs in the process industry is developed in this section. The purpose of the framework is to strengthen the understanding of DTs in the process industry. The framework was developed in three steps:

- 1) Categorization of DT barriers
- 2) Categorization of DT enablers
- 3) Connecting barriers and enablers

4.1. Categorization of DT barriers

Table IV shows the barriers identified in the literature, which are organized according to different themes (categories). The identified barriers in the eight papers focusing on the process industry are highlighted. Among these barriers, a few are only mentioned in relation to studies from the process industry, while the remaining ones can be found across multiple industry sectors. As seen, of the seven barrier categories, six include at least one barrier specific to the process industry, whereas the remaining category only includes barriers from other industry sectors.

System integration issues concern the transition from old and outdated legacy equipment and systems to new state-of-the-art technologies. This barrier category includes both the issue of integrating new systems into the existing one and the issue of integrating different parts of existing systems together. Regarding the oil and gas industry, Wishnow et al. (2019) argued that one of the major challenges is the need to integrate any new asset or operational change into the existing infrastructure, which is typically the result of a significant investment and is therefore impossible to replace due to the unsustainable costs

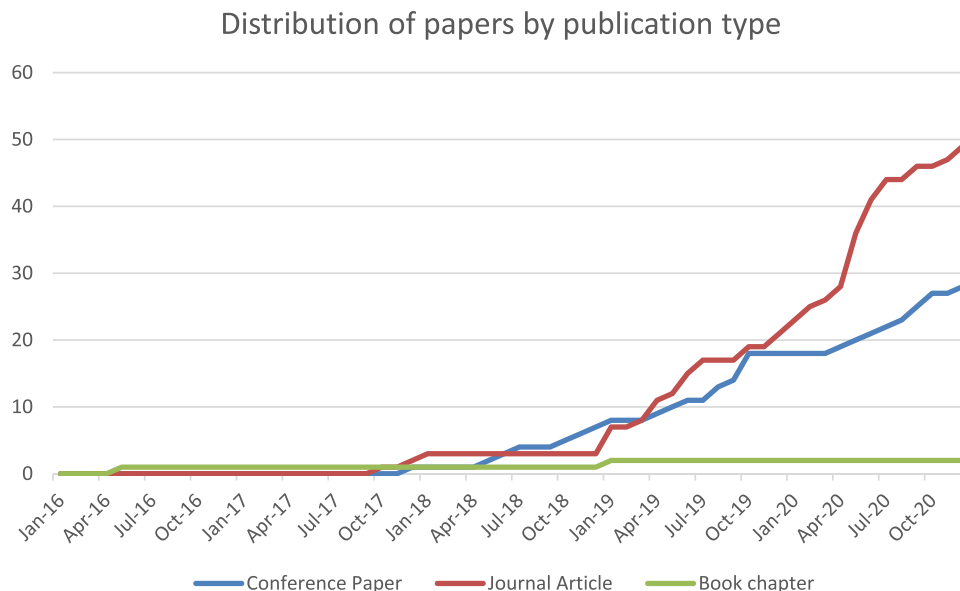


Fig. 2. Distribution of papers by publication type.

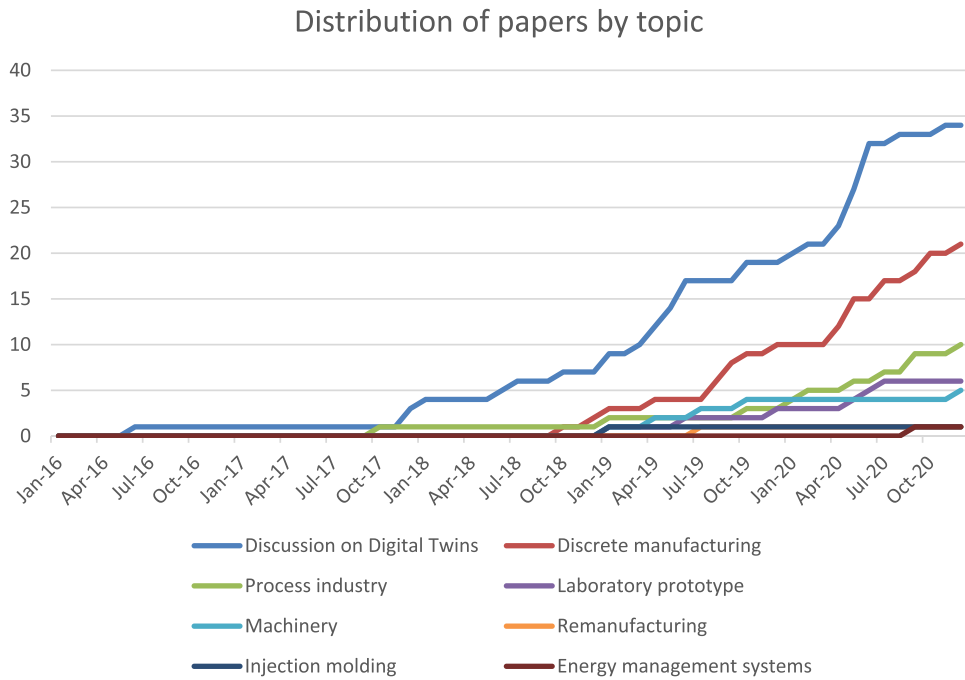


Fig. 3. Distribution of papers by topic.

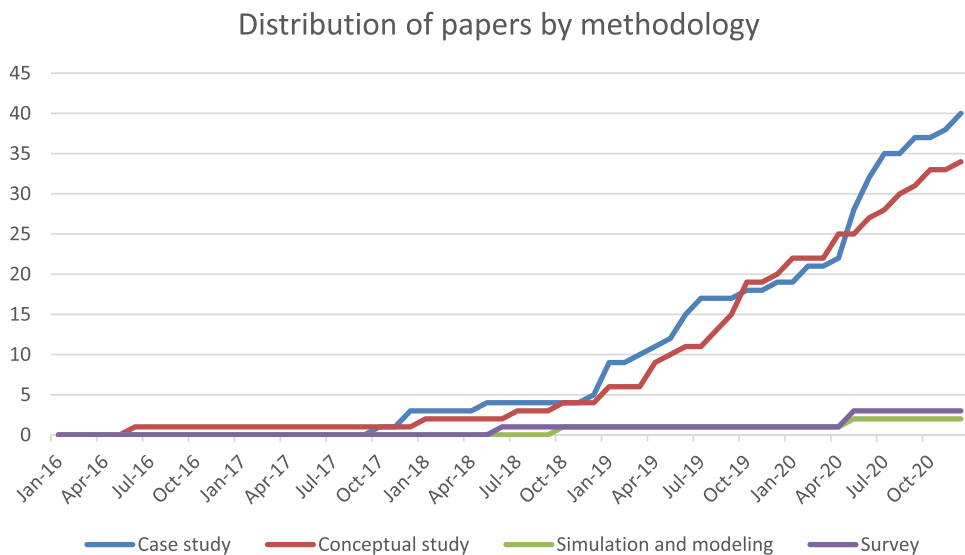


Fig. 4. Distribution of papers by methodology.

involved. Given the long lifecycle of such systems, the issue of integration becomes more prominent over time.

Security issues involve all risks associated with data acquisition, exchange, storage, and processing, as well as intellectual property protection. Data security is a major concern in every industry sector. [Xia et al. \(2020\)](#) highlighted the criticality of data security and the difficulty in ensuring it. [Rasheed et al. \(2020\)](#) expressed the need for data transparency and proposed Blockchain as an effective solution to ensure security and transparency.

Performance issues are directly related to limitations in the hardware and software resources that guarantee an efficient flow of data between physical and digital systems, thereby achieving the full potential of DTs in industrial applications. One of the most distinguishing characteristics of DTs is their ability to represent and

monitor the status of their physical twins in real time. However, ensuring real-time data exchange between the digital and physical twins is very challenging ([Liu et al., 2021](#); [Xia et al., 2020](#); [Redelinghuys et al., 2020](#)). [Zhang et al. \(2017\)](#) described the issue of ensuring an efficient stream of data from the physical assets to their DTs and the difficulty of working with big data in real-time communication.

Organizational issues group together challenges that companies face internally while dealing with new technologies, such as DTs. [Wishnow et al. \(2019\)](#) identified a major challenge in the oil and gas industry that they call the crew change issue. This problem is a consequence of the volatility in the job market in recent years, which caused many highly trained and skilled employees to leave companies. This phenomenon caused labor costs to drastically

Table IV
List and categorization of DT barriers.

Category	Barrier	Number of papers mentioning barrier
System integration issues	Lack of system integration	12
	Difficulty in ensuring interoperability	8
	Compatibility between new and legacy systems	4
	Difficulty of integrating legacy manufacturing systems with modern IoT/IIoT service ecosystems	2
Security issues	Security and privacy	17
	Difficulty in ensuring data transparency	2
	Difficulty in ensuring protection of intellectual property	2
	Need to share the DT among multiple application systems involving multiple stakeholders	1
Performance issues	Difficulty in ensuring a high level of performance in real-time communication	11
	Difficulty in ensuring efficient storage, processing, and analysis of large volumes of data	8
	Difficulty in ensuring a proficient interaction between the digital and physical assets	6
	Difficulty in ensuring reliability and robustness	6
	Difficulty in ensuring low latency communication, tracking, and reporting	4
	Difficulty in predicting complex systems	3
	Difficulty in ensuring the availability of relevant data for DT when needed	2
	Difficulty in ensuring a satisfactory level of accuracy	1
	Ability to track machine status and usage, also when no Internet connection is available	1
	Discovering and retrieving data from the IoT	1
	Difficulty in ensuring proper scalability	1
	Difficulty in ensuring flexibility and modularity	1
	High expected timeliness for DT development and implementation	1
	Risk of overfilling bandwidth	1
	Difficulty of finding a balance between enough (and relevant) information and overwhelming (irrelevant) information	1
Organizational issues	Bureaucracy, cultural inertia, and knowledge assessment	4
	Lack of specialists and expertise	3
	Difficulty in ensuring centralization, simplification, and standardization	2
	Difficulty in setting realistic expectations and trust	1
	Difficulty in identifying clear value propositions associated with DT solutions	1
	Lack of investments	1
	Difficulty in making suitable decisions and investments regarding the enabling technologies	1
	Isolated, fragmented, and stagnant data management	1
	Difficulty in combining product lifecycle management, manufacturing execution system, and operation management systems	1
	Uncertainties in the quality and reliability of data	3
Data quality issues	Data unavailability	2
	Difficulty in ensuring data validity	2
	Difficulty in ensuring data governance, ownership, and management	1
	Impossibility of directly measuring all data relevant for the DT	1
	Lack of methodologies and tools	5
Environmental issues	Low maturity of literature and practical industrial implementations of DTs	2
	Global advancements	1
	Difficulty in choosing the right software among a vast selection of open-source software	1
	Global connectivity	1
	Lack of high-fidelity models for simulation and virtual testing at multiple scales	1
	Multi-disciplinarity of environments for design and development	1
	Lack of education on the topic at universities	1
	High degree of heterogeneity in equipment manufacturers and their software solutions	1

increase for companies in this industry. The same authors also reported the issue of identifying a clear value proposition associated with DTs due to the novelty and uncertainty of the potential benefits of this technology.

Development issues encapsulate the challenges of developing accurate, reliable, and up-to-date models of a complex physical system. This is particularly challenging in the process industry, where production plants can present a high level of complexity and can therefore be difficult to model (Kockmann, 2019). Lee et al. (2019) highlighted the current lack of standard languages and ontologies to enable interconnection between models and systems within the product and process lifecycle in the process industry. The authors proposed ISO15926 as a suitable standard to facilitate the growth of Industry 4.0 applications in this industry. Furthermore, the authors highlighted how the richness of properties that describe the system can be a significant challenge in the development phase of a DT project because of the long time required to develop an accurate model and the high number of computational capabilities required to leverage such a deep and complex model. Development issues also represent the trade-off between the need for DTs to be accurate, reliable, and comprehensive and the investment in terms

of the time and resources required to develop DTs. In this regard, Ezhilarasu et al. (2019) and Rolle et al. (2019) pointed out the importance of finding the right compromise between a low-fidelity DT, which is not representative enough of the physical asset, and a costly high-fidelity DT, which is capable of generating enough value for the company to justify the steep initial investment.

Data quality issues cover challenges that range from the difficulty of gaining access to the right data to solve a specific problem to the issue of validating the obtained data to ensure accuracy and reliability. This barrier category affects all companies of all sizes and in all industry sectors (Redman, 2001). Xia et al. (2020) mentioned the challenge of unavailability or scarcity of data while describing the quality of the production process.

Finally, the external environment issues category groups together external non-technical barriers that are not necessarily intrinsic to an organization. For example, Fuller et al. (2020) debated the duality of global technological advancements. On one hand, companies are benefiting from such advancements, while on the other hand the different growth and adoption rates of new technologies pose a challenge for the companies willing to adopt them. On a different note, Wärmefjord et al. (2020) reported a deficit in the current

educational programs offered by universities worldwide, resulting in a lack of specific skills for the development of DTs in the future workforce.

With references to relationships established in the DT literature, the identified barriers in Table IV may be organized as illustrated in Fig. 5. This organization is subsequently further explained.

According to the literature, a company's DT decisions to a large extent are affected by the external environment (Rolle et al., 2019; Weyer et al., 2016; Xue et al., 2008; Magnanini and Tolio, 2021). Specifically, at the global level the technological and cultural trends from the external environment affect the ability of companies to make appropriate organizational decisions in relation to DTs. More specifically, the lack of standardization, methodologies, and tools for the development and implementation of DTs; the immaturity of the literature on the topic; and the lack of education at universities specifically addressing DTs have a negative impact on the ability of companies to make suitable decisions regarding DT implementation. In particular, a company's ability to find qualified specialists, set realistic expectations, and make suitable investments in enabling technologies can be compromised by external factors.

Next, at the organizational level, as demonstrated by the literature, DT development processes are to a large extent influenced by organizational decisions (Ezhilarasu et al., 2019; Magnanini and Tolio, 2021; Ugwu et al., 2003). For example, if a company has a poor data management strategy in place in which data are isolated, are scattered among a multitude of databases, and rarely get updated over time, ensuring a proper level of data quality, security, and integration is challenging. It is therefore crucial that a company that decides to embark on the digitalization journey and implement DTs sets up the right infrastructure to build a DT upon.

At the development level, DT projects typically develop IT components through iterations and the mutual interactions between them (P. Evangeline, 2020; Riesener et al., 2021; Larsen, 2020.; Wang and Luo, 2021). According to the literature review, DT development projects involve barriers related to system integration, data quality, system security, and the development of the core DT functionalities. In this context, the unavailability of data, the incompatibility

between different systems that are part of the DT, and the potential for sensitive data to be stolen can make it impossible to develop a DT, even in the form of a prototype or proof of concept. The development of core DT functionalities is performed until new requirements are identified, which marks the beginning of a new iteration in the DT development process.

Finally, the literature offers evidence that the development and implementation of DTs can significantly affect an organization's performance (Rasheed et al., 2020; Zhang et al., 2017; Magnanini and Tolio, 2021; Andronie et al., 2021). Specifically, at the organizational level after the DT development step is completed the actual performance of the DT can be evaluated in a real-world application. In this regard, a variety of factors can hinder the company's ability to effectively measure DT performance. Among these, the uncertainty of data quality and reliability and the risk of data unavailability makes it challenging to ensure a high level of performance in real-time communication and to ensure efficient storage, processing, and analysis of large volumes of data. Similarly, the lack of system integration, the need for security measures and protocols in data exchange, and the need for a trade-off between an acceptable fidelity level and computational costs have a negative impact on the ability to ensure proficient interaction and low latency in the communication, tracking, and reporting between the DT and its physical twin.

4.2. Categorization of DT enablers

Table V lists the enabling factors identified in the literature review, which are subsequently discussed.

AI is currently seen as one of the key enabling technologies for DTs (Fuller et al., 2020; Qi et al., 2021; Ezhilarasu et al., 2019; Qiao et al., 2019). Rasheed et al. (2020) described AI and ML as some of the major technological pushing factors to achieve the full potential of DTs. The authors also described the impact of AI in a variety of sectors, including education, transportation, manufacturing, and healthcare. Because DTs will generate large volumes of data in real time for fault detection and better scheduling of maintenance

Table V
List and categorization of DT enablers.

Category	Enabler	Number of papers mentioning enabler
AI	Machine learning, artificial intelligence, and computer vision	20
	Big data storage, processing, and analytics	16
IoT/IIoT	Internet of Things (IoT) and Industrial Internet of Things (IIoT)	28
	Sensors and actuators	20
	RFID, NFC, and QR codes	4
VR/AR	Virtual/augmented reality	9
	Availability of high computational power	6
Hardware	Resource virtualization	4
	Lower, decreasing hardware costs	1
	Cloud services	23
	OPC-UA	15
	MQTT	4
Communication technologies	MTConnect	3
	Ensuring seamless data transfer between life-cycle stages	1
	Network virtualization	1
	5 G/6 G networks	1
	Dynamic knowledge bases	4
Knowledge building	Reskilling and upskilling of labor force	2
	Knowledge-based intelligent skills	2
	Implementation of Industry 4.0 standards	1
	Asset modeling	2
Design process	Rapid individualized design based on reference models	1
	Ensuring autonomy and decentralization of DTs	1
	Simulation	17
	Optimization technologies	2
Development technologies	Blockchain	2
	Virtual machines	1
	Open-source software	1
	Centralized databases	1

Table VI

Final list of papers included in the literature review (after iteration 4).

Article no	Bibliographic information
1	Borodulin K., Sokolinsky L., Radchenko G., Tchernykh A., Shestakov A., Prodan R., Towards digital twins cloud platform: Microservices and computational workflows to rule a smart factory, 2017, 10.1145/3147213.3149234
2	Arrichiello V., Gualeni P., Systems engineering and digital twin: A vision for the future of cruise ships design, production and operations, 2020, 10.1007/s12008-019-00621-3
3	Zhou G., Zhang C., Li Z., Ding K., Wang C., Knowledge-driven digital twin manufacturing cell towards intelligent manufacturing, 2020, 10.1080/00207543.2019.1607978
4	Evangelina P., Anandhakumar, Digital twin technology for “smart manufacturing”, 2020, 10.1016/bs.adcom.2019.10.009
5	Borangui T., Morariu O., Răileanu S., Trentesaux D., Leitão P., Barata J., Digital transformation of manufacturing. Industry of the future with cyber-physical production systems, 2020
6	Hasan H.R., Salah K., Jayaraman R., Omar M., Yaqoob I., Pesic S., Taylor T., Boscovic D., A blockchain-based approach for the creation of digital twins, 2020, 10.1109/ACCESS.2020.2974810
7	Eifert T., Eisen K., Maiwald M., Herwig C., Current and future requirements to industrial analytical infrastructure—Part 2: Smart sensors, 2020, 10.1007/s00216-020-02421-1
8	Wishnow D., Azar H.R., Rad M.P., A deep dive into disruptive technologies in the oil and gas industry, 2020
9	Lee J., Cameron I., Hassall M., Improving process safety: What roles for digitalization and industry 4.0?, 2019, 10.1016/j.psep.2019.10.021
10	Cimino C., Negri E., Fumagalli L., Review of digital twin applications in manufacturing, 2019, 10.1016/j.compind.2019.103130
11	Ezhilarasu C.M., Skaf Z., Jennions I.K., Understanding the role of a digital twin in integrated vehicle health management (IVHM), 2019, 10.1109/SMC.2019.8914244
12	Wang J., Ye L., Gao R.X., Li C., Zhang L., Digital twin for rotating machinery fault diagnosis in smart manufacturing, 2019, 10.1080/00207543.2018.1552032
13	Wang X.V., Wang L., Digital twin-based WEEE recycling, recovery and remanufacturing in the background of Industry 4.0, 2019, 10.1080/00207543.2018.1497819
14	Borangui T., Trentesaux D., Thomas A., Leitão P., Barata J., Digital transformation of manufacturing through cloud services and resource virtualization, 2019, 10.1016/j.compind.2019.01.006
15	Rolle R.P., Martucci V.D.O., Godoy E.P., Digitalization of manufacturing processes: Proposal and experimental results, 2019, 10.1109/METRO14.2019.8792838
16	Lu Y., Xu X., Cloud-based manufacturing equipment and big data analytics to enable on-demand manufacturing services, 2019, 10.1016/j.rcim.2018.11.006
17	Damjanovic-Behrendt V., Behrendt W., An open-source approach to the design and implementation of digital twins for smart manufacturing, 2019, 10.1080/0951192X.2019.1599436
18	Bauer T., Oliveira Antonino P., Kuhn T., Towards architecting digital twin-pervaded systems, 2019, 10.1109/SESoS/WDES.2019.00018
19	Tao F., Zhang H., Liu A., Nee A.Y.C., Digital twin in Industry: State-of-the-art, 2019, 10.1109/TII.2018.2873186
20	Leng J., Zhang H., Yan D., Liu Q., Chen X., Zhang D., Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop, 2019, 10.1007/s12652-018-0881-5
21	Souza V., Cruz R., Silva W., Lins S., Lucena V., Jr., A digital twin architecture based on the Industrial Internet of Things technologies, 2019, 10.1109/ICCE.2019.8662081
22	Nikolakis N., Alexopoulos K., Xanthakis E., Chrysosolouris G., The digital twin implementation for linking the virtual representation of human-based production tasks to their physical counterpart in the factory-floor, 2019, 10.1080/0951192X.2018.1529430
23	Zhang C., Zhou G., He J., Li Z., Cheng W., A data-and knowledge-driven framework for digital twin manufacturing cell, 2019, 10.1016/j.procir.2019.04.084
24	Qi Q., Tao F., Hu T., Anwer N., Liu A., Wei Y., Wang L., Nee A.Y.C., Enabling technologies and tools for digital twin, 2019, 10.1016/j.jmsy.2019.10.001
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28	Qi Q., Tao F., A smart manufacturing service system based on edge computing, fog computing, and cloud computing, 2019, 10.1109/ACCESS.2019.2923610
29	Preuveneers D., Joosen W., Ilie-Zudor E., Robust digital twin compositions for Industry 4.0 smart manufacturing systems, 2018, 10.1109/EDOCW.2018.00021
30	Liau Y., Lee H., Ryu K., Digital Twin concept for smart injection molding, 2018, 10.1088/1757-899X/324/1/012077
31	Kritzinger W., Karner M., Traar G., Henjes J., Sihn W., Digital twin in manufacturing: A categorical literature review and classification, 2018, 10.1016/j.ifacol.2018.08.474
32	Durão L.F.C.S., Haag S., Anderl R., Schützer K., Zancul E., Digital twin requirements in the context of Industry 4.0, 2018, 10.1007/978-3-030-01614-2_19
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39	Min S.-H., Lee T.H., Lee G.-Y., Zontar D., Brecher C., Ahn S.-H., Directly printed low-cost nanoparticle sensor for vibration measurement during milling process, 202010.3390/ma13132920
40	Gorodetsky V., Skobelev P., Marik V., System engineering view on multi-agent technology for industrial applications: Barriers and prospects, 2020.
41	Stanke J., Unterberg M., Trauth D., Bergs T., Development of a hybrid DLT cloud architecture for the automated use of finite element simulation as a service for fine blanking, 2020, 10.1007/s00170-020-05567-5
42	Kamath V., Morgan J., Ali M.I., Industrial IoT and Digital Twins for a Smart Factory: An open source toolkit for application design and benchmarking, 2020, 10.1109/GIOTS49054.2020.9119497
43	Sun S., Zheng X., Villalba-Díez J., Ordieres-Meré J., Data handling in Industry 4.0: Interoperability based on distributed ledger technology, 2020, 10.3390/s20113046
44	Wärmefjord K., Söderberg R., Schleib B., Wang H., Digital twin for variation management: A general framework and identification of industrial challenges related to the implementation, 2020, 10.3390/APP10103342
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(continued on next page)

Table VI (continued)

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49	Xu W., Cui J., Li L., Yao B., Tian S., Zhou Z., Digital twin-based industrial cloud robotics: Framework, control approach and implementation, 2020, 10.1016/j.jmsy.2020.07.013
50	Glatt M., Sinnwell C., Yi L., Donohoe S., Ravani B., Aurich J.C., Modeling and implementation of a digital twin of material flows based on physics simulation, 2020, 10.1016/j.jmsy.2020.04.015
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60	Anton S.D.D., Schotten H.D., Intrusion detection in binary process data: Introducing the Hamming distance to matrix profiles, 10.1109/WoWMoM49955.2020.00065
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69	Perzylo A., Profanter S., Rickert M., Knoll A., OPC UA NodeSet ontologies as a pillar of representing semantic digital twins of manufacturing resources, 43739, 10.1109/ETFA.2019.8868954
70	Bottani E., Vignali G., Carlo Tancredi G.P., A digital twin model of a pasteurization system for food beverages: Tools and architecture, 44075, 10.1109/ICE/ITMC49519.2020.9198625
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78	Shao Guodong, Kibira Deogratias, Digital manufacturing: Requirements and challenges for implementing digital surrogates, 43435, 10.5555/3320516.3320670
79	Platenius-Mohr Marie, Malakuti Somayeh, Grüner Sten, Goldschmidt Thomas, Interoperable digital twins in IIoT systems by transformation of information models: A case study with asset administration shell, 43739, 10.1145/3365871.3365873

operations (Rasheed et al., 2020), the ability to efficiently store such data is a crucial enabling factor for the successful implementation of DTs (Rasheed et al., 2020; Liu et al., 2020).

The IoT/IIoT is another key enabling factor for DTs in manufacturing (Ezhilarasu et al., 2019). The IoT enables communication between devices within the same system and the possibility to collect large volumes of data from the production process. This in turn enables a variety of use cases, including predictive maintenance and fault detection to perform maintenance operations only when necessary, thereby avoiding unplanned shutdowns and unforeseeable breakdowns of production equipment (Fuller et al., 2020). In

this sense, the data collected by sensors in a manufacturing plant can be analyzed to generate actionable insights that can be sent to actuators to automate repetitive tasks on the production line (Qi et al., 2021; Hinchy, 2019; Cai et al., 2020).

Virtual reality (VR) and augmented reality (AR) enable a variety of use cases for operators in a manufacturing plant, for example, to gain a deeper understanding of the production process, virtual commissioning, remote assistance, and operator training systems and to run simulations in a virtual environment (Alcácer and Cruz-Machado, 2019; Qi et al., 2021; Minerva et al., 2020; Perno, 2020). Although VR has grown significantly in recent years and has been

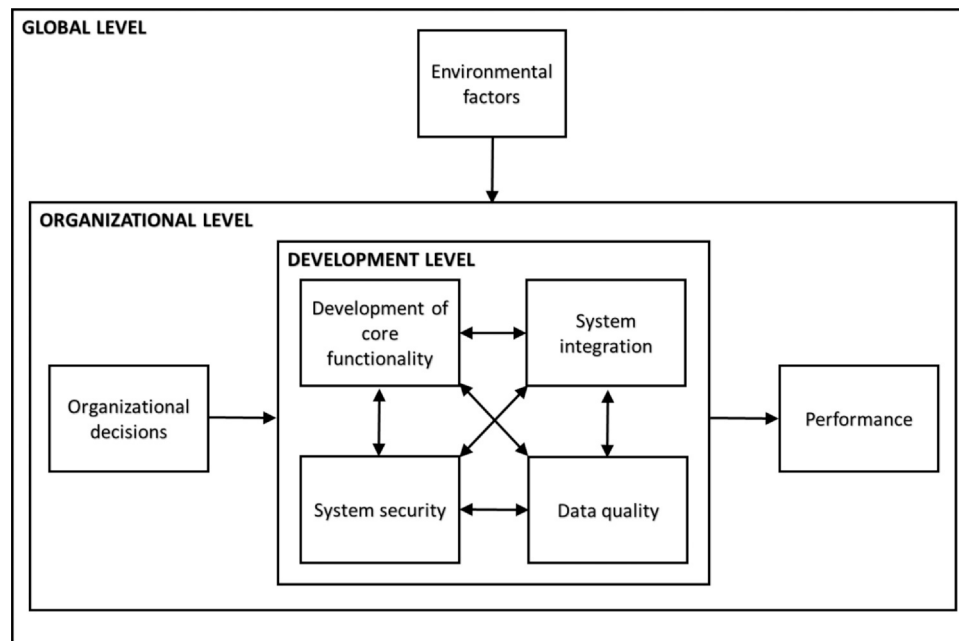


Fig. 5. Model describing the relationships between barriers.

applied in several sectors, particularly gaming, education, and healthcare and more recently manufacturing (Minerva et al., 2020; Nåfors et al., 2020), the potential benefits of the use of VR and AR in industrial applications are currently the subject of extensive research (Nåfors et al., 2020).

Regarding hardware, its decreasing costs (Evangeline, 2020) have made it significantly easier for companies to gain access to more powerful computational resources, which in turn enables higher accuracy, depth, and reliability in the DTs. Rasheed et al. (Rasheed et al., 2020) argued how this factor is going to have an impact on the depth of physics that can be incorporated into industrial controllers.

Communication protocols are a crucial enabler for DTs in industry (Rasheed et al., 2020; Eisen et al., 2020; Damjanovic-Behrendt and Behrendt, 2019). They allow devices within the same IoT to exchange data and input signals to perform specific tasks based on the input from the DT. Although a wide variety of communication standards (e.g., MTConnect, MQTT, and CoAP) is available, the most commonly used machine-to-machine communication protocol for industrial applications is the Open Platform Communication – Unified Architecture (OPC-UA), which is currently emerging as the standard for Industry 4.0 applications (Eisen et al., 2020).

The knowledge-building category pertains to the ability to generate new knowledge from the analysis of troubleshooting, planned shutdowns, maintenance reports (Wang et al., 2019), production data, bill of materials (BOMs), and sales data. This knowledge can be used, for example, to develop and manufacture better products, optimize production schedules, plan maintenance activities, and optimize production (Wang et al., 2019). Zhang et al. (2017) presented simulation as a key enabler of the DT being able to iteratively accumulate new and reusable knowledge on design and manufacturing processes. Blockchain is also foreseen to play a key enabling role for DTs in industry because it can ensure the security of data archives and data retrieval through advanced cryptography (Rasheed et al., 2020).

Design considerations need to be analyzed when developing DTs. Zhang et al. (2017) proposed an approach to rapidly design DTs using reference models of individual assets that can then be used as a base to develop DTs of similar assets. To do so, the focus is on important properties of the model, such as scalability, expansibility, fidelity, and interoperability (Zhang et al., 2017).

Finally, the development technologies category refers to a set of techniques used for DT development. Among these, simulation is by far the most commonly referenced in the literature, as it is at the core of the DT concept (Zhang et al., 2017). In fact, many researchers and industry practitioners refer to the two concepts interchangeably (Shao, 2019). An important topic of debate in the literature is the advantages and disadvantages of building DTs using expensive software platforms provided by large software providers (e.g., Honeywell, Microsoft, General Electric, Siemens) as opposed to using open-source software (Damjanovic-Behrendt and Behrendt, 2019). Kamath et al. (Weber et al., 2017) demonstrated how DTs can be built using an entirely open-source software architecture, avoiding the risk of vendor lock-in and the need to purchase expensive third-party software. Zhang et al. (Hinchey et al., 2019) and Xia et al. (Moyne et al., 2020) underlined the importance of optimization techniques as DT enablers.

4.3. Connecting barriers and enablers

Within the proposed model, the role of enablers is that of facilitators, which means that they can be seen as drivers for the successful development and implementation of DTs in a company. Following the method of Rasheed et al. (2020), the literature base of 79 papers was used to link the enablers identified in this study to the corresponding barriers, as shown in Fig. 6. In the figure, the arrows define the relationship between enablers of and barriers to the implementation of DTs by indicating which enabler categories have a positive impact on which barrier categories. The numbers placed on the arrows refer to the literature that supports the enabler–barrier relationship (explicitly or implicitly suggested). This is subsequently further discussed.

Development issues are mitigated by the latest advancements in AI, VR/AR, and development technologies. The use of AI coupled with big data analysis techniques enables the development of models and tools capable of finding trends, patterns, and correlations and making predictions based on the data from the real asset (Borangi et al., 2020; Lu and Xu, 2019). VR and AR have been considered as enabling technologies for the development of DTs in recent years (Nåfors et al., 2020). These technologies provide users with a more interactive way to use DTs and to enable the development of training

systems for new operators (Beloglazov et al., 2020). Finally, the advancements in simulation software have enabled the development of comprehensive models to represent physical assets with a high degree of accuracy. To further improve the performance of simulation models, techniques such as reduced order models (ROMs) need to be used (Chen et al., 2020). The increased availability and capabilities of these technologies allow us to reduce the time and resources required for the development of DTs and to develop increasingly accurate models.

Data quality issues are reduced by the latest advancements in software development and communication technologies. Ensuring the availability, validity, and quality of data used by the DT to represent its physical counterpart can be a challenging task (Fuller et al., 2020; Xia et al., 2020; Redelinghuys et al., 2020). To reduce the risk of any negative impact these issues might have on DT performance, extensive preparatory work needs to be done to establish a framework for efficient data exchange between the physical asset and its DT (Chen et al., 2020).

The use of cloud and edge computing and secure and reliable communication protocols help ensure data quality and validity (Rasheed et al., 2020; Borangiu et al., 2019). Furthermore, the use of centralized databases helps ensure a sufficient level of data quality in situations in which data are taken from heterogeneous sources (Brosinsky et al., 2020).

Security issues are minimized through communication technologies. Communication protocols such as OPC-UA, MTConnect, and MQTT, which are currently being used to develop DTs in industrial applications (Kritzinger et al., 2018; Damjanovic-Behrendt and Behrendt, 2019; Lu and Xu, 2019), support security protocols such as the use of passwords, encryption methods, and the secure sockets layer. Although extensive work is required to ensure that sensitive data can be safely transferred between physical assets and their DTs, such protocols are suitable for the development of DTs in industrial environments, as testified by the work of other researchers (Kritzinger et al., 2018; Damjanovic-Behrendt and Behrendt, 2019; Lu and Xu, 2019).

System integration issues are reduced through communication technologies and the recent developments in IoT/IIoT. An increasing number of vendors are developing and offering unified IoT/IIoT platforms and solutions designed to be compatible with existing systems (Rasheed et al., 2020; Eisen et al., 2020; Chen et al., 2020). To overcome the challenge of integration between legacy systems and new IoT/IIoT systems for the realization of DTs in industrial applications (Rolle et al., 2019; Borangiu et al., 2020), vendor-neutral communication protocols such as OPC-UA are being used (Redelinghuys et al., 2020; Glatt et al., 2021).

Environmental issues are reduced through knowledge building. Although the current literature on DTs has not yet reached a mature state and there is a dearth of consolidated methodologies and tools for the development and implementation of DTs in the manufacturing industry (Melesse et al., 2020; Gorodetsky et al., 2020), the first real-world examples of DTs in industry are now emerging. In particular, the use of Industry 4.0 standards enables companies to lay the foundation for the successful development of DTs by implementing a robust and integrated data framework to exchange data between a physical asset and its DT (Chen et al., 2020). Furthermore, workforce reskilling and upskilling will have a positive impact on environmental issues because it will contribute to the development of new methodologies, tools, and standards for the creation of DTs (Akyazi et al., 2020).

Organizational issues are mitigated by knowledge-building technologies and design processes. Workforce reskilling and upskilling (Akyazi et al., 2020) and the implementation of Industry 4.0 standards (Chen et al., 2020) enable companies to keep their workforces updated on the latest technological trends, to overcome the lack of specialists and expertise on DTs (Uhlemann et al., 2017), and ultimately to make qualified decisions on the topic. Furthermore, the

definition of requirements for DT helps companies make appropriate decisions on data management and suitable enabling technologies before starting the DT development and implementation process.

Performance issues are mitigated by the increased availability of powerful hardware. A decrease in hardware costs (Evangeline, 2020) and the increasing computational power provided by the latest hardware solutions (Rasheed et al., 2020; Ezhilarasu et al., 2019) enable the use of high-performance hardware to accurately represent physical assets in the digital world through advanced simulation and ML models and to ensure seamless real-time communication between a physical asset and its DT (Yaqoob et al., 2020).

5. Discussion

Although a certain hype surrounds DTs, the extant literature on DTs is fragmented across various topics and lacks a common understanding of the nature and potential of DTs in industrial applications. More specifically, as shown in our review, the literature on the barriers and enabling factors in the implementation of DTs in the process industry lacks a clear and common understanding of the most important factors involved in such processes, which can be daunting in the absence of a clear overview of such factors. This paper comprises a content analysis-based literature review to enhance clarity in this research area. This study identified a list of enablers of and barriers to the implementation of DTs across multiple industries through a content analysis-based literature review. The identified barriers and enablers were categorized through descriptive coding and are summarized in Tables IV and V, respectively. Furthermore, a novel framework was developed based on the identified enablers and barriers. The framework consists of the identification of the relationship between barrier categories (Fig. 5), the enabling effect of each enabler category (section 4.2), and the mapping between each enabler category and the corresponding barriers they have an impact on (Fig. 6).

This paper raised two RQs. The first RQ focuses on identifying the factors affecting DT implementation in the process industry. This RQ was answered by means of a systematic literature review on which basis categorizations of enablers of and barriers to DT implementation were developed (Tables IV and V). The second RQ focuses on the relationships between the identified enablers and barriers. This RQ was answered by using relationships established in the literature to develop a model that connects identified enabler and barriers (Fig. 6).

5.1. Implications for practice

The proposed model is a tool that can be applied by process industry practitioners to address the main challenges associated with DT implementation. Specifically, the organization of enablers and barriers into models describing their relationships may provide practitioners in the process industry with guidance through the DT implementation process. When using the proposed framework, practitioners in the process industry should pay extra attention to the enabling factors and barriers that refer to real-world applications in the process industry.

5.2. Limitations and future research

The most significant limitation of this literature study is the limited amount of research that has been carried out on DTs in the process industry, resulting in a low number of relevant papers for this literature review. In this regard, the number of publications targeting this industry is likely to grow exponentially in the near future due to the fast-growing interest in DTs. Therefore, it is possible that certain enablers and barriers have yet to be identified and that the developed classifications might need to be extended.

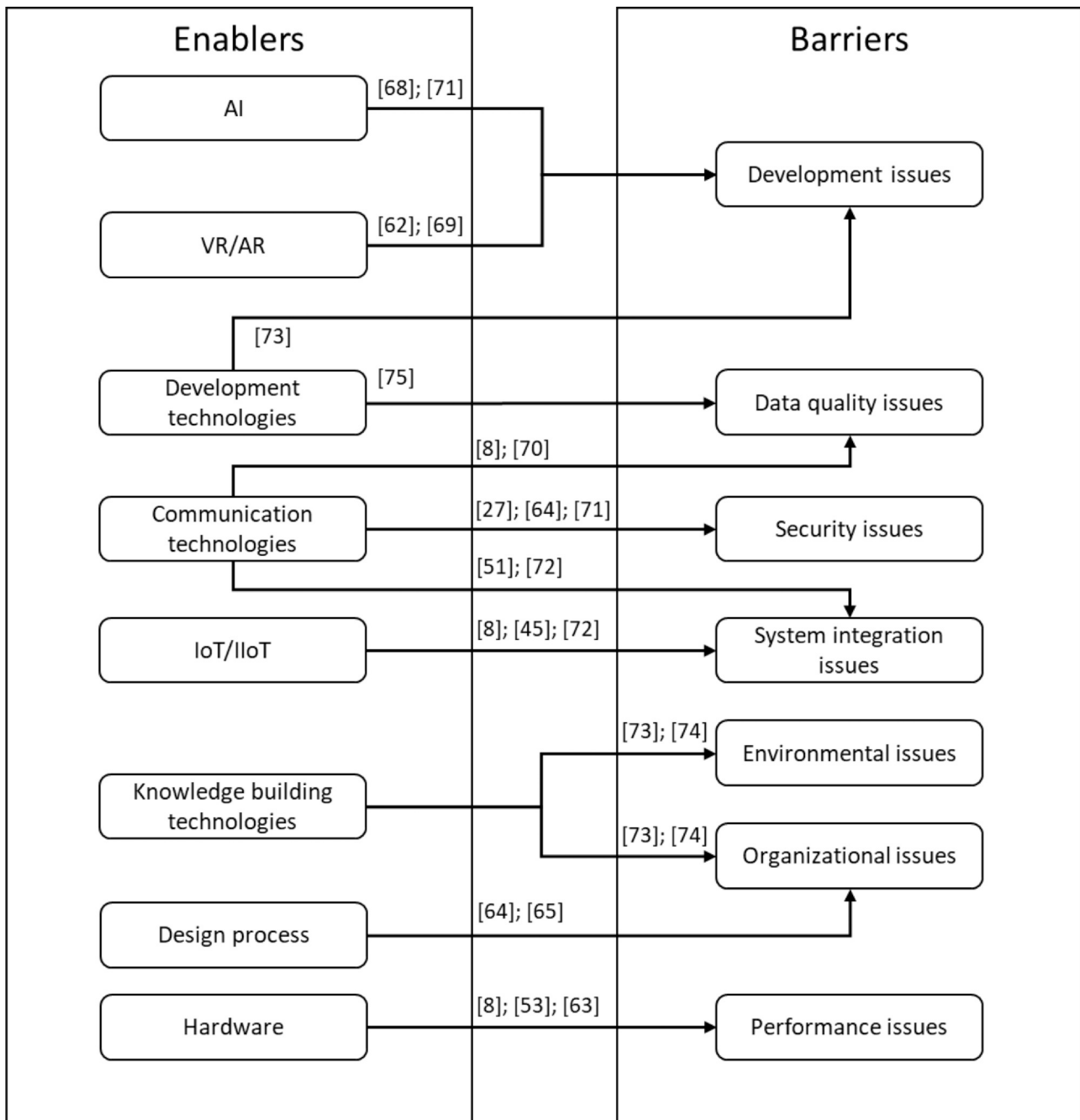


Fig. 6. Mapping between enablers and barriers for DT implementation.

Consequently, further research is expected to extend this study by growing the list of enabling factors and barriers with additional examples and to develop the proposed model further. This will involve carrying out tests in process manufacturing contexts to further validate the model and prove its usefulness and efficacy in a real-world industrial context. The models provided in the current paper provide a foundation for this work by clarifying the DT concept and its use in the process industry.

The significant increase in the reports of DT applications, as demonstrated by the literature review, suggests that DT is a technology that has reached maturity, thus supporting more widespread use in the near future. To support this development, future research should focus on extending the conceptual models proposed in this paper through studies of practice that should aim at providing further

understanding of the applicability of the models to the process industry. Furthermore, the findings from this literature review suggest that some barriers need to be further investigated so their impacts can be mitigated, thereby providing a basis for further DT implementations in the process industry.

6. Concluding remarks

The present paper contributes to the research on DTs by organizing the literature on DTs and providing a conceptual model describing how the identified categories of barriers to DT implementation in the process industry affect each other. Furthermore, this paper presents a model describing the enabling effect of the identified enabler categories on the corresponding

barrier categories. The model is based on the findings of the content analysis-based literature review. To the best of the authors' knowledge, no previous research on enabling factors and challenges to DT implementation in the process industry has been conducted. Therefore, this paper aims at filling this gap in the current literature.

Another finding in relation to this paper's focus on the process industry from the content analysis-based literature review is the severe lack of research with this focus. Specifically, only 10 of the 79 analyzed papers either focused on the process industry or included it within the scope of the study. The organization and categorization of barriers through descriptive coding identified a set of relationships between these barriers. Environmental barriers affect organizational factors, which in turn have an impact on system integration, system and data security, and data quality. These then have an impact on DT development. Finally, the development phase affects DT performance. The first implication of these relationships is that the starting point for companies wanting to implement DTs should be to consider environmental factors to gain an overview of which external factors are currently affecting the company's ability to digitalize their processes and build DTs of their assets. The next step would be to consider organizational factors, as failing to do so may nullify any effort spent on the other phases. The same goes for the DT development phase, which may suffer if the preceding issues of system integration, security, and data quality factors are not addressed. Finally, proper DT performance cannot be expected when the core DT development issues are not considered and taken care of.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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