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Digital twins in manufacturing: an assessment of drivers, enablers and barriers to implementation

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Abstract

As we live through the fourth industrial revolution, cutting-edge technologies look to change the way manufacturing systems operate. In this context, an important technological framework gaining popularity is the digital twin, which enables a virtual mirror of a real subject, used in manufacturing to assess performance and predict behavior. In this study, we interview experts and review the literature to gain an overview of what exactly drives companies to look for digital twin solutions in the manufacturing environment, what factors enable these initiatives to be successful, and what are the barriers that compromise or slow down implementation efforts.

Keywords: Industry 4.0; digital twin; smart factory; manufacturing.

1. Introduction

The concept of the digital twin surfaced in 2003 when Michael Grieves introduced the idea of creating a digital equivalent of a physical system, so that physical resources could be preserved during design-related tasks, and diagnostic analyses could be enhanced [1,2]. Seven years after this first conceptualization, the National Aeronautics and Space Administration (NASA) recalled the concept of the digital twin in a technology roadmap. They argued that a digital model of a space vehicle could be employed to continuously forecast the systems' health during a flight, to simulate a mission before launch, or even to perform root-cause analysis in the case of catastrophic faults [3].

It was only after the publishing of Grieves' whitepaper in 2014 [1], however, during a context of evolution for information technologies, that the digital twins truly started to gain real traction. With the emergence of cyber-physical systems (CPS), the digital twin may serve as an online testing tool to ensure performance and error management analysis in real-time. This can be achieved as users send sensors operational data from the CPS to universal digital models of their assets, in order to perform simulations and other analyses that generate knowledge for the users [4].

In industry, the digital twin technology has already found its early adopters [5]. Furthermore, key information technology providers, such as Siemens, have developed platforms to enable companies to deploy digital twins in a plethora of applications, such as continuously assessing and predicting the performance of manufacturing systems, or supporting the optimization of production decisions [6].

In academia, an ever-increasing number of papers addressing the theme started to get published [7]. Although part of the research has been directed to study applications centered on the product, we focus on the digital twins of the manufacturing system. Under this boundary, research has been

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undertaken to elucidate: the key components and tools of state-of-the-art architectures (e.g. [7,8,9]); the potential applications of the technology (e.g. [10,11]); and the research issues faced by the emerging field (e.g. [10]).

In summary, manufacturing digital twin research appears to have reached a maturity level where a reasonable body of knowledge regarding theoretical foundations is available. However, few works collectively assess early industrial implementations of the technology, in order to identify the key characteristics of digital twin initiatives.

Our study focuses on these early implementation efforts, as we try to assess how exactly digital twins' concepts are taking form in real-life scenarios. Specifically, we try to understand what is leading companies towards the digital twin, which factors are enabling initiatives to thrive, and which barriers slow down implementation efforts. These aspects are stated in the following research questions:

- *Q1*: which are the factors that drive organizations to pursue digital twin initiatives in manufacturing?
- *Q2*: which are the factors that enable digital twin initiatives in manufacturing to be successful?
- *Q3*: which are the factors that end up causing friction or slowing down digital twin initiatives in manufacturing?

To address these questions, we interview subject-matter experts. Furthermore, we complement the gathered insights through a review of cases published in the digital twin literature, as well as through the examination of publicly available reports. The results of this analysis aim to provide clarity over some important contextual factors regarding digital twin real implementations in manufacturing.

The remainder of this paper is structured as follows: Section 2 formally presents the concept of the manufacturing digital twin. Section 3 describes the research design adopted to conduct this study. Section 4 presents the results. Section 5 outlines the final remarks.

2. Manufacturing digital twins

The structure of a manufacturing digital twin has been detailed by Tao and Zhang in [8], through a five-dimension framework. The architecture consists of the physical entities on the shop-floor (e.g. machines, operators, material); the virtual models generated to replicate several dimensions of those physical entities (e.g. structural and behavior models); a service platform to deliver decision-support analyses; a data layer to store data; and information connections between all other dimensions to ensure communication and timely updates. In such a structure, operational data from the connected shop-floor is transferred via network to the digital world. Then, virtual models replicate the conditions observed in the physical system and perform simulations to serve as inputs to the execution of a plethora of services. These services generally offer monitoring and predictive functions [10], applied in areas such as maintenance management (e.g. fault prediction) and production management (e.g. flexibility handling) [11]. Not only limited to predicting future scenarios, several digital twin formulations are also capable of prescribing actions to support managerial decision-making; a few of these prescriptive architectures, in addition, can autonomously control the physical system without the need of human intervention [10, 12]. An illustration of the general manufacturing digital twin architecture can be observed in Fig. 1, based on the framework of [8].

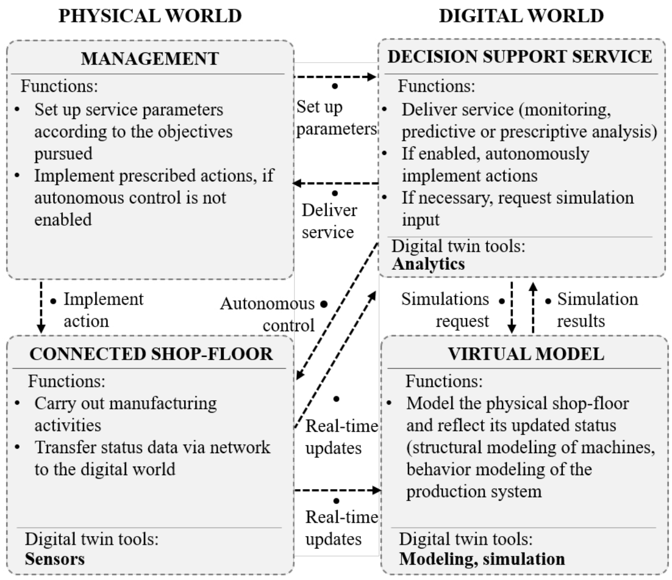

Fig. 1. Manufacturing digital twins.

3. Research design

In this section, we detail the protocol adopted in this study to assess manufacturing digital twins' drivers, enablers, and barriers to implementation. The assessment was conducted based on information gathered from three different sources: interviews with subject-matter experts; papers from the digital twin literature; and publicly available reports.

Subject-matter experts were chosen from three different backgrounds. Firstly, we looked for professionals who worked with organizations that can be classified as digital twin solution providers; these professionals have experience as external advisors to multiple manufacturing companies that have adopted digital twin-related technologies. Secondly, we looked for professionals who worked inside a manufacturing company during the execution of a digital twin-related project; these professionals have experience as internal technology managers. Thirdly, to promote balance between the views of practitioners and academics, we looked for researchers who developed studies regarding digital twins in manufacturing.

Experts that agreed to participate were presented with three questions, in which they were asked to explicitly point out factors which they considered to be drivers, enablers, and barriers to implementation of digital twins in manufacturing. The specific writing of the questions was based on the three research questions of this study. A total of six experts from Europe and America were consulted during this process. Three of them occupy senior positions in companies that have undergone digitalization projects associated with the concept of the digital twin. Two work in a large manufacturing technology organization that provides digital twin solutions. One is a researcher with a doctorate degree developed within the context of the digital twin.

In regard to information gathered from digital twin literature, scientific papers written in English from academic journals or conferences, published from 2010 onwards, were gathered from the Scopus database. The search query limited results to papers that contained the term 'digital twin(s)' in their titles, as well as one of the interchangeable terms 'manufacturing', 'operation', or 'production' in their titles, keywords or abstracts. Subject-area filters were utilized to exclude works belonging to unrelated fields (e.g. medical research). Lastly, a set of exclusion criteria was employed to rule out results outside the scope of the stated research questions (e.g. works dealing with product-focused digital twins, works that did not propose or did not test an architecture).

Since only a few academic papers possessed the specific information required to be part of this study, publicly available reports were used complementarily. As a result, reports written by credible organizations (e.g. government affiliated institutes and business consulting firms) that discussed any one of the three main aspects addressed in this study i.e. manufacturing digital twins' drivers, enablers, and barriers to implementation, were added for analysis.

To enable a better analysis of the information gathered from the three sources, we classified the obtained results in categories. The gathered driving factors were categorized between: (i) factors that are internal to the organization; and (ii) factors that are external to the organization. This division is particularly valuable when dealing with aspects associated with organizational context, as can be observed in [13]. Alternatively, both the gathered enabling factors and barriers to implementation were classified among the following categories: (i) process factors; (ii) systems and technology factors; (iii) people and competence factors; and (iv) organizational culture and strategy factors. This division was based on the framework proposed by [14]. Experts were made aware of these categories during the interviews, as they were asked to provide answers in as many categories as they could.

4. Results

In this section, we present the results of our assessment. A synthesis of the observed drivers, enablers and barriers to implementation of manufacturing digital twins can be observed in Fig. 2. Furthermore, the factors are thoroughly discussed in the following sections.

4.1. The drivers of digital twins in manufacturing

Drivers can be understood as factors and forces that induce companies to initiate and fully-implement digital twin-related projects. From an external perspective to the organization, experts have pointed out three main driving factors of the manufacturing digital twin.

Firstly, they pointed out the higher need for production flexibility, which stems from the current nature of market demand. The term 'flexibility' has been used by the experts to refer both to the achievement of a greater range of product variants, as well as to the capacity to dynamically reschedule production. In line with this view, the flexibility factor has indeed driven several digital twin cases in the literature. Some works propose architectures that are driven by the need to dynamically reschedule production in reaction to required modifications [15,16,18]. This is done by the rerunning of scheduling algorithms whenever a modification trigger is activated. The architectures proposed by [17] and [20] go beyond rescheduling, as they allow for the dynamic reconfiguration of manufacturing resources to achieve a reconfigurable production system. Complementarily, digital twins that are driven by the need of assisting in the management of a broad range of products were proposed by [19] and [21], in the context of mass customization and individualized demand.

As a second external driver, experts pointed out an ever-increasing level of business competition, which pressures companies to look for solutions in order to reduce costs, and improve quality and productivity. Under this group of factors, experts mentioned advantages such as quality defects detection, faults prediction, reduction of costs associated with testing, higher production throughput, and process variability reduction, as digital twin drivers. In the literature, several of these drivers were also brought up. Digital twin architectures driven by the goal of cost reduction were found to be mainly associated with the execution of predictive maintenance or smart fault prediction: in [22,25] the digital twin's use was driven by the need to estimate the remaining useful life of manufacturing equipment; In [23], the proposed architecture was driven by the objective of detecting when production equipment entered into an anomalous state, in which the risk of failures arises; in [24], the digital twin's use was driven by the need to better diagnose machine failures' origins and details. Furthermore, a digital twin architecture driven by the goal of quality improvement, through product quality prediction capabilities, was identified in [17]. Productivity improvement, on the other hand, was only explicitly mentioned as a digital twin driver in [26].

Lastly, the popularization of the digital twin as a 'buzzword' has also been mentioned by experts as an external driver of digital twins, since organizations end up embarking on implementation projects as a way of following what looks to be a global trend.

From an internal perspective to the organization, experts pointed out three drivers of the manufacturing digital twin. Additionally, two drivers were observed exclusively from reviewing the literature, and one driver was brought up in a report by Deloitte [27].

As the first internal driver, experts pointed out that internal process improvement initiatives can lead to digital twin projects. This also results in applications associated with cost reductions, and productivity and quality improvements. Another internal driver mentioned by experts comes from an attempt to make the production process more transparent to stakeholders. Transparency in the shop-floor was also brought up as a driver of digital twins in the work of [15]. Additionally, experts mentioned that employees' training (via virtual models) is also a driver of digital twins' adoption in industry.

In the literature, employees' safety was identified as an internal driver of digital twins, as observed in [20], since the

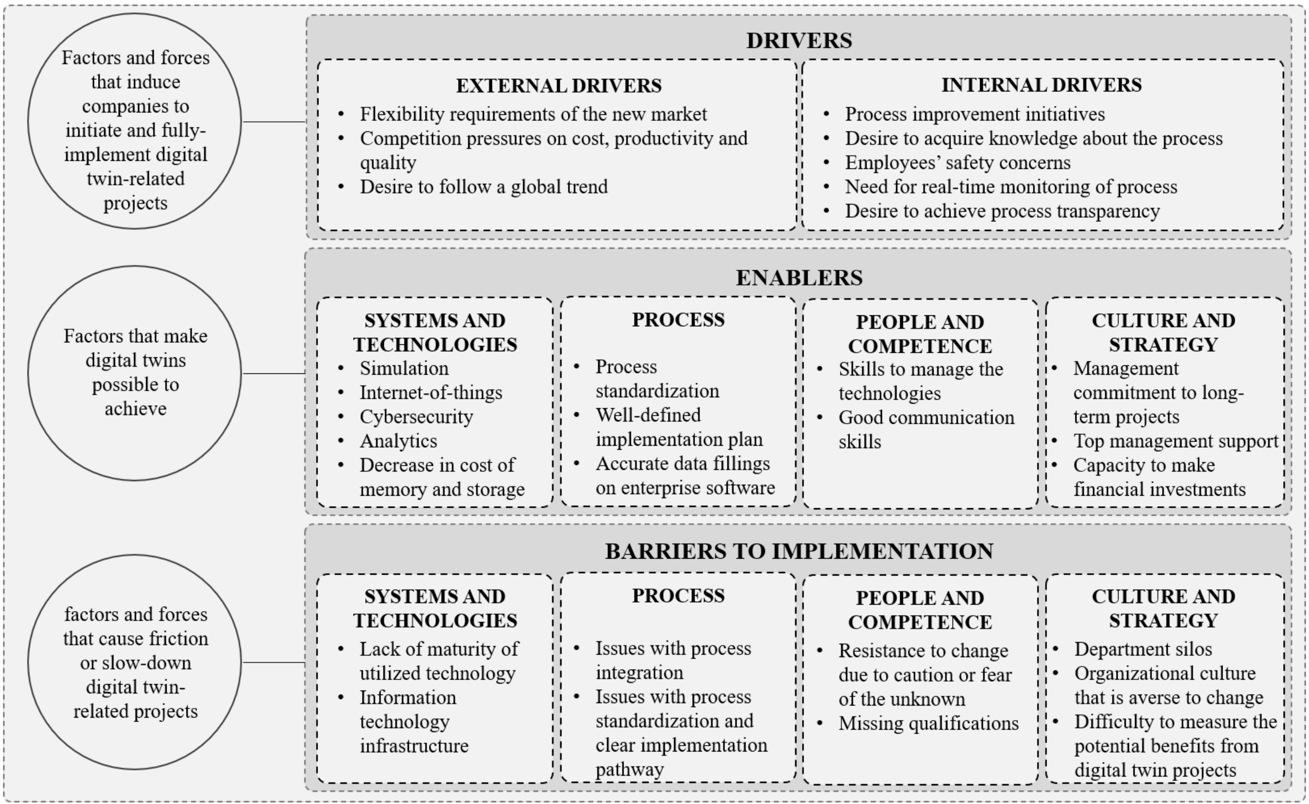

Fig. 2. Drivers, enablers and barriers to implementation of the digital twin in manufacturing.

technology can be used as a way to detect potential workplace hazards in the shop-floor. Furthermore, the simple need for rea-time monitoring of the physical system has been brought up in the work of [28] as a driver of manufacturing digital twin implementation. Lastly, knowledge about the process, enabled by the possibility of gathering a complete digital footprint of the production system, was pointed out as a driving factor of manufacturing digital twins by [27].

Due to the boundaries of our study, we have not included in this analysis drivers associated with digital twins that have applications outside the scope of the manufacturing process. As examples, experts mentioned product-oriented digital twin drivers such as: time-to-market reduction, warranty claims prediction, and customer experience improvement.

4.2. The enablers of digital twins in manufacturing

Enablers comprehend those factors that make digital twins possible to achieve. In an attempt to discuss more than just the commonly mentioned technological factors, we also tried to assess process enablers, people and competence enablers, and organizational culture and strategy enablers.

In regard to systems and technology factors, experts mentioned simulation, the internet-of-things (IoT), and cybersecurity as key technologies to enable the manufacturing digital twin. The first two technologies are aligned with the literature, as both were ubiquitously deployed in the observed cases. Simulation, in particular, was associated both with structural models of machines and its components, as seen in [22,24,25], where aspects such as mechanical and electrical functions are modelled; as well as with models at the production system level, as seen in [15,16,19], where the behavior and dynamics of the shop-floor and its processes are modelled. Storage and computing power have also been brought up by experts as digital twins' enablers. Complementarily, a report by PwC [29] mentioned that the decrease in cost of memory and storage, and the proliferation of sensors, have created an environment in which IoT-powered architectures can thrive. Lastly, the use of analytics commonly appeared in the literature as a technological enabler, in cases where the digital twin offered a predictive or decision-support service. As a result, machine learning techniques such as supervised classification and regression were utilized (e.g. [23]), as well as deep learning techniques, such as long short-term memory (LSTM) networks (e.g. [17]).

In regard to process-related factors, experts pointed out process standardization, a well-defined implementation plan, and accurate data fillings on enterprise management software as enablers of the digital twin in manufacturing. In accordance with the second of these factors, the charting of a clear implementation path has been observed by McKinsey's research [30] to be a key characteristic of the few companies that managed to break through pilots and achieve full implementation of technology-related projects in manufacturing. Now referring to the third of these factors, data quality in the current era of data science and analytics has become an important research topic on its own, as shown by [31]. The issue gains momentum since problems with data quality have been observed to increase as organizations have more capacity and desire to use this data for analysis [31].

Concerning people and competence factors, experts mentioned the skillset required to manage all the new technology, as well as the competence of good communication, as enablers of the manufacturing digital twin. Regarding this last factor, and transcending the context of the digital twin per se, the skill of good communication has already been noted by previous research as a key factor in the generation and preservation of organizational performance [32].

Lastly, concerning organizational culture and strategy enablers, experts mentioned factors that somehow characterize the key role of an internal sponsor, required from the organizational leadership when dealing with a digital twin project. Specifically, enabling factors mentioned by the experts consisted of management commitment to long-term projects, top management support, and the capacity to make financial investments. As another way of summarizing these three factors, an expert additionally mentioned the achievement of a 'research and development-oriented culture' as an enabler of the digital twin.

4.3. The barriers to implementation of digital twins in manufacturing

Barriers to implementation refer to factors and forces that cause friction or slow-down digital twin-related projects in manufacturing. Similarly to the classification used during the assessment of the enabling factors, we have categorized the barriers as process factors, systems and technology factors, people and competence factors, and organizational culture and strategy factors.

Concerning systems and technology, experts mentioned the lack of maturity of some of the utilized technologies (especially those employed to allow for decision support and autonomous action) as potential barriers to implementation, depending on the complexity of the digital twin application. This view appears to support the comprehension of digital twins' service capabilities as a path of evolving maturity. As discussed in Section 2, digital twins are capable of delivering different types of services: from status monitoring, to effectively prescribing solutions, to the extent of actually controlling the physical system autonomously. Therefore, the lack of maturity of prescriptive analytics techniques may somehow become a barrier to applications in which the unreliability of these technologies represents a risk. As an additional insight in this context, the Acatech digital competencies maturity index [33] (developed in the context of Industry 4.0) highlights the view that digital transformation initiatives are highly complex, and require a step-by-step implementation that may take several years. The achievement of connectivity and status visibility are pointed as initial steps of this process, but predictive and autonomous response capacities are only achieved by the end of the digital transformation journey. Lastly, experts also mentioned the information technology (IT) infrastructure as a possible barrier to the implementation of the digital twin in manufacturing.

With reference to processes, experts pointed out issues with process integration as a barrier to implementation. The matter of integration is also further addressed when discussing culture and strategic barriers. Therefore, although not mentioned as an enabling factor, it appears the integration among different parts of the organization plays a crucial role in the success of digital twin implementations. This conclusion would not be implausible considering the importance of organizational integration in similar digital transformation projects, such as the so-called horizontal and vertical integrations of Industry 4.0 [34]. Issues with process standardization and lack of a structured project pathway were also brought up by experts as barriers to an effective implementation of the digital twin. This issue links well with the process-related enablers addressed in Section 4.2. Regarding the achievement of adequate processes, an expert also observed that the bigger the organization, the bigger the challenge.

Concerning people and competence, experts pointed out that employees with missing qualifications, and the people's resistance to change, are barriers to successful implementations of the digital twin. As it will be discussed later in this section, resistance to change can also be a characteristic of organizational culture; therefore, it can be hard to draw the line between which part of this aspect originates from the nature of people and which part originates from the organization itself. One expert went into more detail as to why people adopt this attitude of resistance when faced with innovative technologies. The expert argued that the phenomenon results from the fact that the current rate in which technology evolves is much faster than the rate in which workers and managers can absorb and understand these evolutions. Therefore, the resistance to change comes simply from the caution or fear of exchanging the current comfortable reality for the unknown.

In regard to organizational culture and strategy, experts mentioned the occurrence of department silos as a barrier to digital twin implementations, addressing yet again the key importance of organizational integration. Department silos have also been considered a top challenge for other digital transformation technologies, as observed in the survey conducted in [35]. Having an organizational culture that is averse to change due to its strong history with well-functioning approaches was also mentioned as a barrier. This issue is particularly interesting, because the loyalty of strong companies to the well-tested practices that have led them to success is a comprehensible behavior, although it slows down the adoption of disruptive technologies, as is the case with the digital twin. Finally, the difficulty to measure the potential benefits from digital twin projects was the last-mentioned barrier to implementation. This aspect resonates well with some of the culture and strategy enablers discussed in Section 4.2. On top of embarking on projects that require both long-term commitment as well as financial investments, companies also have to embrace a level of uncertainty regarding the real benefits that will result from their efforts.

5. Conclusions

In this study, we have attempted to go past the theoretical structure of the manufacturing digital twin to verify how the concept is building its connection with the real industry landscape. This connection was verified through the comprehension of which factors are currently driving organizations towards the technology; which factors enable implementations to thrive; and which factors cause friction or slow down implementation efforts. The provided clarity over these factors may shed light on the practical relevance of this highly popular technological framework.

In summary, the value of digital twins in manufacturing results from the convergence of driving factors, such as the increase of competitive pressure and new market requirements for flexibility, with key enablers, such as the development of IoT and cutting-edge analytics technologies. In the middle of this path, however, organizations may encounter the barriers of dealing with long projects with uncertain results, and the barriers of dealing with innovative technologies that are not fully mature, neither well-tested. As an answer to these adversities, factors such as the active and continuous support from top management, the establishment of clear processes, and a focus on integration, have appeared in our study as valuable instruments to make the path of full implementation a success.

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