Digital Twin in Manufacturing: A Systematic Literature Review

Abstract

Modern technologies and recently developed digital solutions make their way into all aspects of lives of individuals and businesses, and manufacturing industry is no exception. In the era of digital revolution of industry, manufacturing processes can benefit from digitalization technologies immensely. Digital twin (DT) is a technology concept that aims to create a digital mirror of a physical system with a constant data flow between two components. This idea can be used for monitoring and optimization of the present system as well as forecasting and estimating future states of it. There have been theoretical and practical studies conducted on DT in manufacturing area. This systematic literature review (SLR) aims to summarize the current state of literature and shine a light on open areas for future research. Using a rigorous SLR method, 247 relevant studies from 2015 to 2020 are examined to answer a set of research questions. The current state of DT in manufacturing literature is analyzed and explained with an emphasis on where the future studies may go in this area.

Keywords: Digital twin, digital-physical layer interaction, manufacturing, fourth industrial revolution, systematic literature

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1. Introduction

Digital solutions that replace or expand the previous systems create significant changes in the lives of people. Manufacturing is one of the areas where the effects of this transformation to digital systems can be observed thanks to the constant rise of modern technologies. The benefits of digitalization go hand in hand with the main targets of manufacturing organizations such as reducing cost and waste while increasing the quality, efficiency, and their share in the market. As one of the important result of the digital transformation; the ability to access, control, and manipulate the large amount of data easily has become an integral part of the company strategies. The concept of digital twins (DT) is a technology that can be used for digital transformation in manufacturing companies as well as managing the relevant data. The idea of twin systems, although both physical, was initially used in NASA's Apollo program in the 1960s [1]. Two physically duplicated systems were created to mirror the conditions of the spacecraft in the space using the twin of the vehicle that was situated on the ground.

The idea of accomplishing this system of twins with a digital was first suggested during a presentation on the product lifecycle management (PLM) in the University of Michigan in 2002 [2]. This conceptual model was then used as a "Mirrored Spaces Model" in the PLM courses next year [3]. However, it took some more time for general research interest to catch up with the idea. DT as a term appeared in the NASA publication [4] with the definition of "*an integrated multi-physics, multiscale simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc. to mirror the life of its corresponding flying twin*". Then, Grieves (2014) defined the three main parts of the DT concept as "*physical products in real space, virtual products in virtual space, and the connections of data and information that ties the virtual and real products together*". [5] also supported the idea of this three-piece structure by explaining DTs as the mapping of these components.

Within the frame of manufacturing, this three-piece structure is represented by the actual production system, its virtual representation, and the information transfer between these two systems based on simulation disciplines, data, and models. Using this information and data transfer between the physical and virtual components, forecasts and optimizations that will affect the physical manufacturing system can be completed [6].

As is often the case with modern concepts and terms, there has been some confusion between DT and other similar terminology such as *digital model, digital shadow*, and *digital thread*. [7] differentiated these terms based on whether the data flow between the physical and virtual objects is automatic or manual. Digitalization systems are called *digital model* if there is two-sided manual data flow, *digital shadow* if there is one-sided automatic data flow, and DT if

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there is two-sided automatic data flow. Additionally digital thread is defined as "*the communication framework that allows a connected data flow and integrated view of the asset's data throughout its lifecycle across traditionally functional perspectives*" [8]. Within the scope of this literature review, the term DT is selected as what defines the digitalization systems in manufacturing as to avoid confusion.

In this article, we suggest a layered structure to define and examine DTs using the three-piece structure of the physical system, the virtual mirrored system, and the data flow between the two systems. Two main layers, physical and digital, represent the actual real-life manufacturing system and the mirrored digital simulation of it, respectively. A fully functioning DT system obtains the real-life data from physical layer to feed it to the digital layer (digitalization of the real-life system). Digital layer of the DT structure runs the calculations and simulations based on the data and either constantly updates itself according to the physical layer (for example, with sensors or chips) or gives results for prediction and estimation of a future state of the physical system. Physical layer, in turn, is updated either automatically or manually based on the digital calculations and simulations. This loop of information sharing between layers must be the perpetual state of the system for it to be a sustainable DT. In these layers, different activities are carried out with different purposes that are connected to each other. The proposed structure is summarized in Figure 1.

In the first level of the structure, the general aim of the DT application is defined. If there is a real-life or simulation application of the theorized DT structure, it can either be a small-scale demo of the idea or the actual real world application. In both cases, the digitalization of the system will have a certain purpose such as optimization, prediction, estimation, monitoring, testing, etc. While these are the purposes of the digital layer, they are also tools used to affect the next level, the physical system. Results of these digitalization activities in the physical layer differ between applications, such as layout planning, process control, efficiency improvement, production planning, or predictive maintenance. If the physical layer is updated based on the digital model, there might be interactions between layers to keep the loop of information sharing between DT layers. At this level, the system might have several activities such as verification or feedback control.

The move of information between the DT layers starts with physical layer activities before any kind of feedback or information loop between layers can be created. In a manufacturing facility example, most of the data which will start the information flow come from the shop floor with activities such as production planning, process steps, or maintenance. Sensors are used to collect data from physical layer activities. Collected data regarding different aspects such as machine productivity, temperature, start-stop etc. is received and processed by

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Programmable Logic Controllers (PLC). On the digital layer of the system all data is processed with Manufacturing Executing System (MES). OLE for Process Control (OPC) communicates with PLC and converts the hardware communication protocols to a more meaningful language in the digital-physical interaction layer [9].

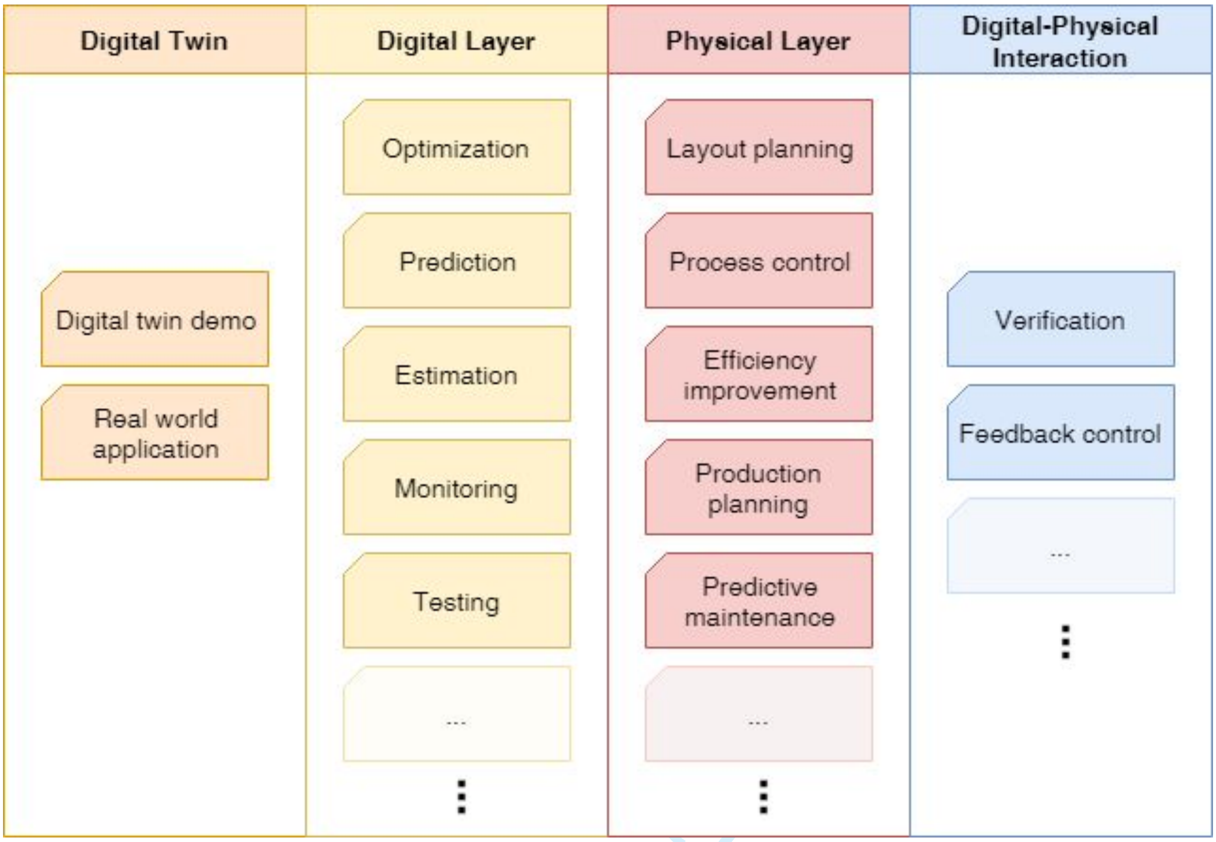

Figure 1: Physical-digital layer structure of DTs

For the literature review purpose of this article, we use the suggested layered DT structure to examine and categorize previous studies conducted on the DT theories or applications in manufacturing. Systematic literature reviews (SLR) are useful tools especially for research and application areas with modern technologies (such as DT) not only to summarize what has been done so far but also shine a light on potential future paths research in the area may follow.

Although it has not been many years since the first emergence of the DT concept, there have been many research materials regarding its application in manufacturing. However, to the best of our knowledge, a literature review concerning “DT in manufacturing” as comprehensive as this one has not been published yet. This article proposes a detailed literature review that covers many aspects of DT in the manufacturing. Our aim is to comprehensively analyze the current state of DT in manufacturing literature and classify the current DT theories and applications with regards to the application purposes, industries, and manufacturing stages. Mapping of studies with these types of information and linking the different aspects of studies with each other takes a picture of the literature and summarizes it. Additionally, findings of this study will be helpful in planning roadmaps for future research and applications.

The remainder of the paper is organized as follows. In Section 2, the methodology of the study is explained. The data we obtained as a result of the review of the articles are analyzed and presented in Section 3. In Section 4, open research areas and future research suggestions are discussed, and conclusions are summarized in Section 5.

2. Methodology

Further steps of an SLR must be designed rigorously in the preparation stage. Before beginning the data extraction from the previous studies, we defined our framework and steps that we would follow throughout this study. Budgen & Brereton (2006) suggest general guidelines to follow for SLRs. In this section, our literature review method in accordance with these guidelines is explained.

In this study, we use Goal-Question-Metric (GQM) method [11], [12] to define our research questions and metrics to answer them. Using the GQM approach, we defined the following main goals for this review. To reach the main goals, 12 research questions are raised:

G1: To identify the current state of literature of DT studies in manufacturing.

RQ1.1: What is the annual article count?

RQ1.2: Which countries have produced the most articles?

RQ1.3: Are the authors of DT in manufacturing studies mainly from academia or is there any interest in academic research from industry, too?

RQ1.4: What are the most common publication types for DT in manufacturing studies? (Journal article, conference proceeding, etc.)

RQ1.5: What are the most common research types for DT in manufacturing studies? (Exploratory research, theory, application, etc.)

RQ1.6: What is the financial support and funding behavior for DT in manufacturing studies throughout the years?

G2: To classify the purposes of using DT, methods of simulation, manufacturing stages and sectors for which digital twins are suggested, and future research directions of DT studies in manufacturing.

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> *RQ2.1*: In which sectors and for which economic activities are DT in manufacturing studies conducted?
>
> *RQ2.2*: For which stage of manufacturing the digital twins are applied / implemented / designed in the studies?
>
> *RQ2.3*: What are the most common application purposes for DT in the studies?
>
> *RQ2.4*: Is DT the most common digitalization concept used in the studies?
>
> *RQ2.5*: What type of simulation methods and tools are popular amongst DT in manufacturing studies?
>
> *RQ2.6:* What limitations are reported and what future research directions are suggested in the studies?

To answer the research questions, the metrics given in Table 1 are extracted from the selected articles. For the sector and economic activity classification, NACE (Nomenclature des Activités Économiques dans la Communauté Européenne) codes are employed [13]. To classify the application purpose of digital twins in manufacturing, we suggest a comprehensive hierarchical application structure for both physical and digital parts of digital twins. This structure is explained in detail in Section 3.2 of this article.

Table 1: Metrics for research questions

RQ	Metric	RQ	Metric
RQ1.1	Article count per year	RQ2.1	NACE codes of activities
RQ1.2	Article count per country	RQ2.2	Manufacturing stage
RQ1.3	Affiliation of author	RQ2.3	Application purpose
RQ1.4	Publication type	RQ2.4	Digitalization type
RQ1.5	Research type	RQ2.5	Simulation method and tool
RQ1.6	Funding center	RQ2.6	Limitations and future directions

Scopus is selected as the online database in which we completed the manual article search. With the aim of covering all possible relevant results, the following search string is used.

> *(TITLE-ABS-KEY ("digital twin") OR TITLE-ABS-KEY ("digital-twin") AND (TITLE-ABS-KEY (“production”) OR TITLE-ABS-KEY (“manufacturing”)))*

We conducted the final manual search on the 31st of December, 2019. Our final article pool consists of the literature that has been published online up to this date. After the initial search, we obtained 670 results. For the screening and elimination of results, we defined the inclusion and exclusion criteria given in Table 2. Search results that use DT in relation with process or final products are excluded. Similarly, we also excluded the articles that are interested in

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manufacturing stage but that mention DT only briefly (either as a relevant concept or a possible future idea).

Table 2: Inclusion / exclusion criteria

Inclusion Criteria		**Exclusion Criteria**	
I1	It is a DT application study in manufacturing	**E0**	It does not have an academic research content
I2	It is a theoretical DT methodology for manufacturing	**E1**	It is not in English
I3	It is an exploratory study about DT in manufacturing	**E2**	It is not about manufacturing or production stage of the production life cycle
I4	It is a previous review study on DT in manufacturing	**E3**	DT is only briefly mentioned
		E4	Full text is not available online

The duplicate search results and the results that are not actual academic research (**E0**) such as table of contents for conferences and editor's notes for journals are removed from the initial pool of 670 results. This gave us an article pool of 560 to apply the inclusion/exclusion criteria. 68 of these articles are not in English (**E1**) with 57 of the non-English ones being in Chinese.

The remaining 492 articles were examined iteratively (first with titles, then with abstracts, and then finally with full-texts as needed) and we cut down the article pool to 301 relevant articles with the application of **E2** and **E3**. Upon removal of 54 articles that were not available to access online (**E4**), the final pool of 247 articles was reached for data extraction, analysis, and synthesis step of this SLR. This elimination process is summarized in Figure 3. Supplementary Material 1 gives the full list of 247 articles together with the assigned IDs to articles. The articles are referred using these IDs in relevant tables in Section 3.

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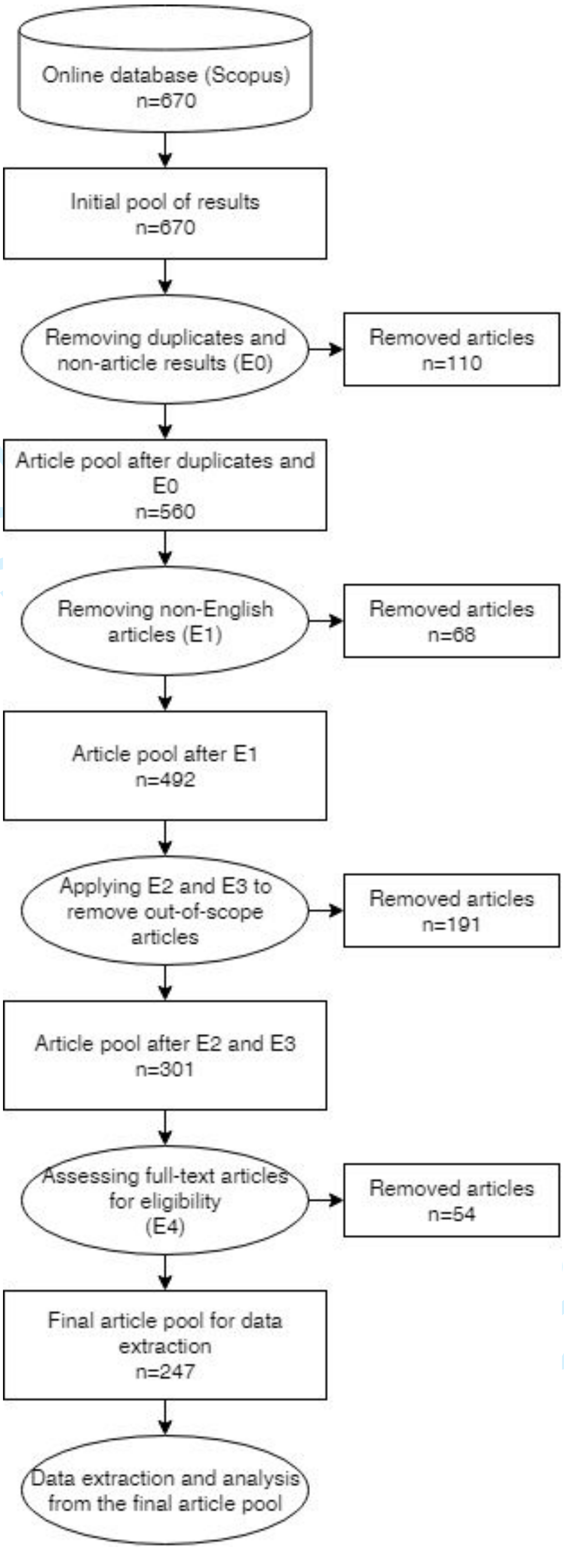

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184 Figure 3: Article selection process

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3. Findings

Before classifying, categorizing, and mapping primary studies conducted on DT theories or applications in manufacturing, it is important to summarize the previous reviews and surveys we found in our search sessions in this area. [6] conducted a review study to combine and analyze the definitions of DT used in scientific literature. They reviewed 26 articles released between 2012 and 2016. [14] examined 52 DT articles and grouped them according to their DT application purposes, implementation and system features, and DT services. The sectors and manufacturing activities for which digital twins were used are not the focus of this review. [15] aimed to find the implementation gaps for DT in maintenance activities. [16] investigated the role of cloud services and resource virtualization in the digital transformation of manufacturing. In this study, the DT is a sub-section of the main interest of the article, and four articles are investigated from 12 relevant results. Similar review studies are conducted on DT studies after the cut-off date of our article selection. [17] examined DT research articles in terms of engineering PLM and business innovation perspectives. [18] categorized and discussed DT publications in three main application areas: manufacturing, healthcare and smart cities.

When compared to aforementioned studies, this research has considered, evaluated and classified a vast number of papers according to various criteria defined. A novel contribution is that we presented a systematic map illustrating the data relationship between various levels of DT applications in our article pool. In order to constitute a basis for future studies, the papers are also categorized with respect to NACE codes, which is a standard way of coding business activities.

The primary studies in our final article pool are carefully reviewed in order to extract correct metrics to answer relevant research questions to reach two main goals of this SLR. In Section 3.1, RQs related to the first main goal of this study are answered. With this set of questions, we aim to identify the general demographics of DT studies in manufacturing area. Section 3.2 covers the findings about the second set of RQs related to our second main goal, which is to classify the DT studies in manufacturing area with regards to several aspects of theory and application while using the suggested layered DT structure to categorize the applications.

3.1. General Demographics of DT Studies in Manufacturing

In this section, RQ1.1, RQ1.2, RQ1.3, RQ1.4, RQ1.5, and RQ1.6 are answered using the final article pool of this SLR:

The annual article count gives a very basic information about the study distribution over time and tells the upwards and downwards trends in research interest on a subject. We found that

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247 articles that are included in our review go back to the year of 2015. We stopped our search on the 31st of December, 2019, thus several 2020 articles are also included in our results.

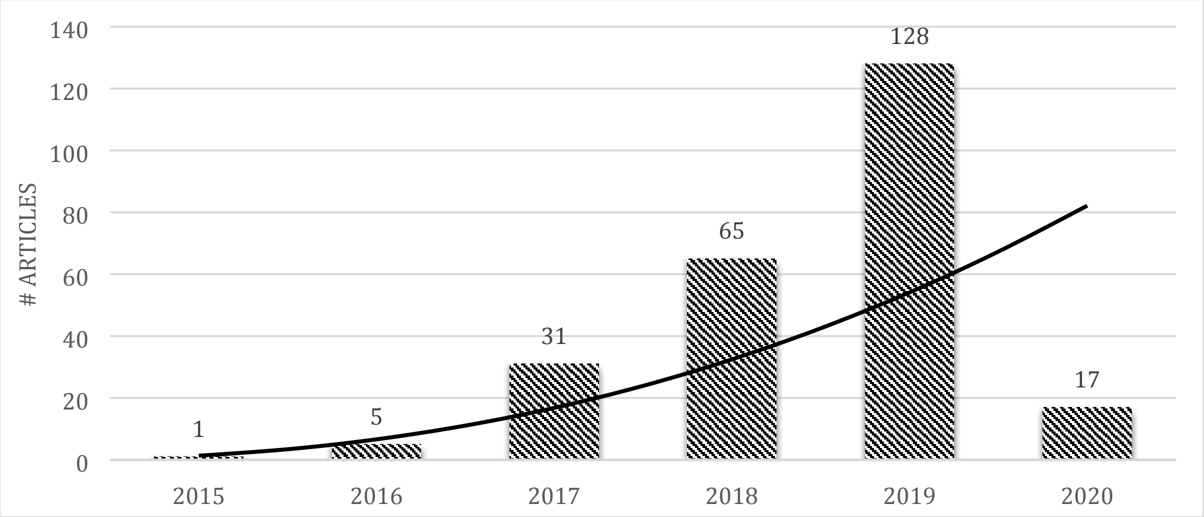

Figure 2: Article count per year

Figure 2 shows the distribution of number of publications over time. After limited amount of early research on the subject, there has been a fast upwards trajectory in the number of studies published annually. This steep upwards trend is directly related to the quick popularization of the concept of Industry 4.0 in general (in both academia and industry) and would not be limited to only DT focused studies. It should be noted that the number of 2020 articles that are in our results even before the year began has already reached the half amount of 2017 releases. We predict that this increase in yearly article count will keep the upwards trend.

In addition to the total number of yearly studies, we looked into the distribution of these studies between academia and industry. Even though DT technologies are of interest for companies in the industry, we found that the big part of the studies (196 articles, 79%) are conducted by the researchers in the academia. Only 6% of the articles (15) are initiated in the industry and the remaining 15% are collaborative studies (36) between academia and industry. While this shows there is not a large amount of academic research interest from industry, this result is not surprising even on a subject that is highly related to the modern industry and real world applications.

As per our findings, China is the leading country of digital twin in manufacturing studies with 54 out of 247 articles, followed by Germany (41) and the USA (20). In total, the studies examined in this SLR can be attributed to 37 countries.

An additional conclusion to draw from RQ1.2 (country of study) and RQ1.3 (affiliation of study) is the distribution of the sources of research interest between different countries. It is worth

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noting that although China is the leading country in terms of publications, most of them are strictly academic articles with little to none collaboration with the industry. On the other hand, we found that interest in DT studies is largely conducted by academia-industry collaborations in Germany, the homeland of the concept "*Industrie 4.0*". In the USA, the research efforts seem to be distributed between academia and industry evenly. Distribution of articles for ten countries with the largest contribution is given in Figure 3. The total number of academia, industry, and collaboration studies for each country is given in Table 3.

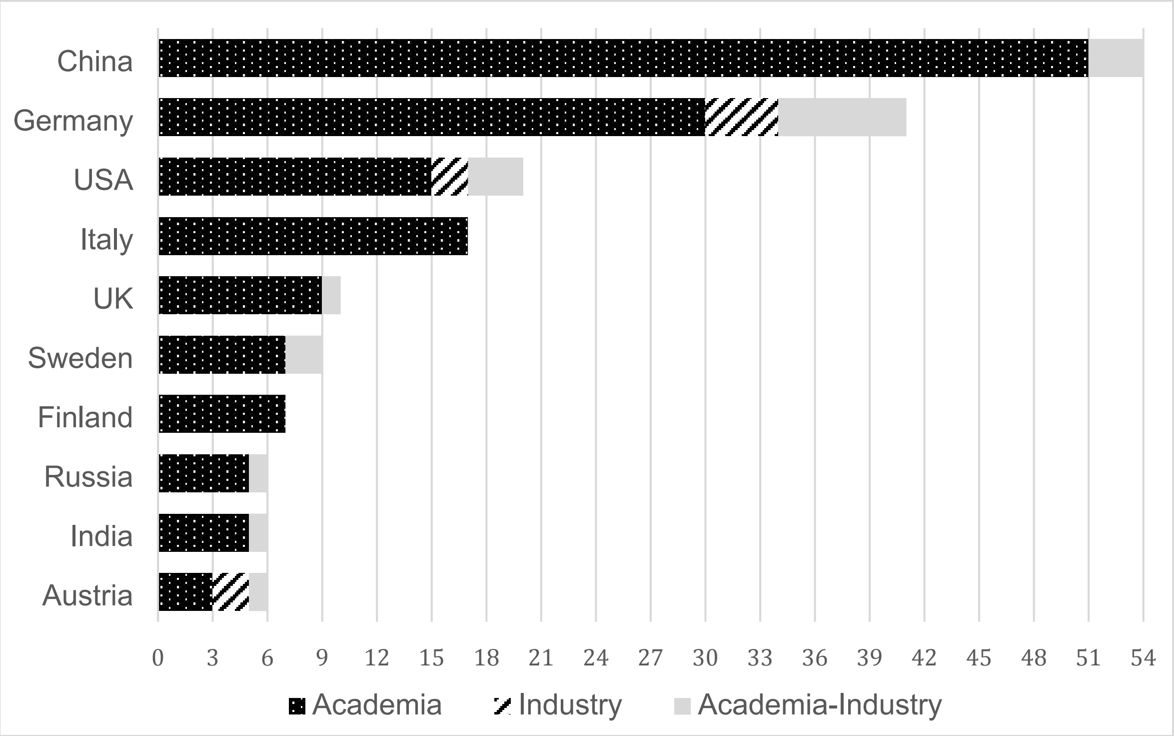

Figure 3: Source of research interest for ten leading countries: academia, industry, and collaboration

Table 3: Article count for countries with affiliations: A: academia, I: industry, and C: collaboration

Country	A	I	C	Total	Country	A	I	C	Total
China	51	0	3	**54**	South Korea	3	0	1	**4**
Germany	30	4	7	**41**	Brazil	3	0	0	**3**
USA	15	2	3	**20**	Korea	3	0	0	**3**
Italy	17	0	0	**17**	Romania	3	0	0	**3**
UK	9	0	1	**10**	Singapore	3	0	0	**3**
Sweden	7	0	2	**9**	South Africa	3	0	0	**3**
Finland	7	0	0	**7**	Belgium	2	0	0	**2**
Austria	3	2	1	**6**	Denmark	2	0	0	**2**
India	5	0	1	**6**	Japan	2	0	0	**2**
Russia	5	0	1	**6**	Portugal	2	0	0	**2**
Hungary	3	0	2	**5**	Switzerland	2	0	0	**2**
New Zealand	5	0	0	**5**	Australia	1	0	0	**1**
Slovakia	4	0	1	**5**	Canada	1	0	0	**1**

Spain	4	1	0	**5**	Cyprus	1	0	0	**1**
Estonia	4	0	0	**4**	Malta	1	0	0	**1**
France	2	0	2	**4**	Norway	0	1	0	**1**
Greece	4	0	0	**4**	Poland	1	0	0	**1**
Netherlands	4	0	0	**4**	**TOTAL**	**212**	**10**	**25**	**247**

Two studies conducted by researchers in the industry are published in journal article form while the remaining industry-based research efforts are presented in conferences. For the academia-based publications, the gap between conference proceedings and journal articles seem to be smaller with 77 journal articles and 105 conference proceedings originated in the academia.

Six of the eight book chapters we found on the subject of DT in manufacturing are set to be published in 2020, which implies that theoretical information on the subject has started to show up in academic books literature and manufacturing DT concepts have moved beyond initial articles and think pieces. The increase of conference papers, articles, and book chapters from 2015 to 2019 (and the accepted pre-publications of 2020) is given in Figure 4.

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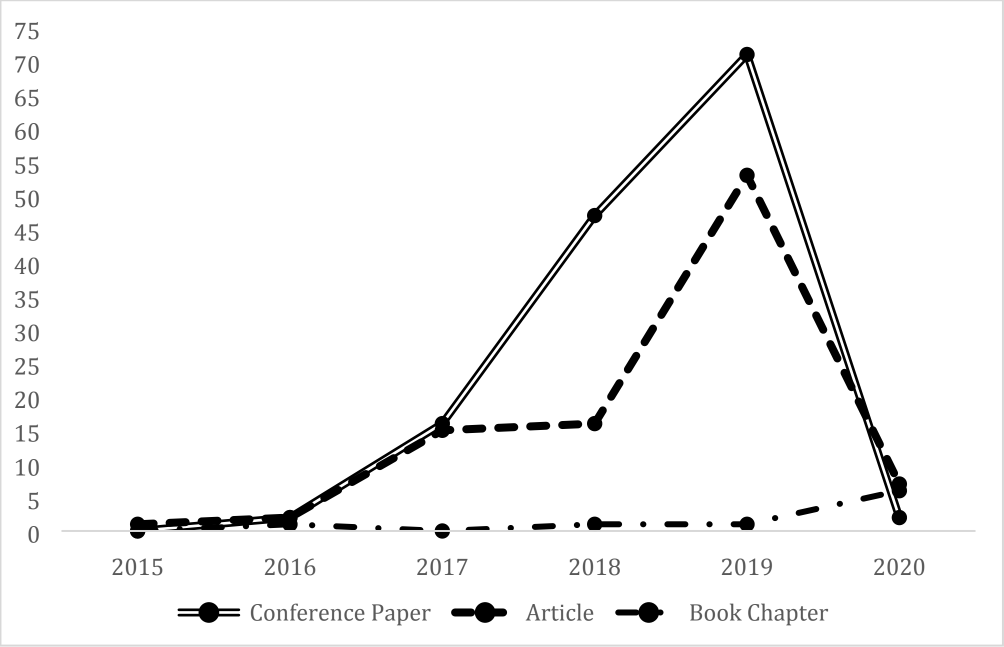

Figure 4: Yearly publication type numbers for conference papers, articles, and book chapter

Most common research types might give a good indication to the current state of literature. We categorized the research efforts in this area so far under the four groups of exploratory research, review, theoretical studies, and theoretical studies with an application. Exploratory researches aim to understand a problem in depth and develop definitions and give insights about final research design. Reviews summarize the existing literature on a topic to explain the current state of the topic. Theory studies include explanations of an event or phenomenon and they go beyond exploratory researches in the way of having a specific theory focused on a particular situation, even if it is without a real life application. Theory with application studies here are classified in two sub-groups. Studies with an actual real world application as well as studies with applications to simulate real world situations (demo, proof of concept) are considered in application with theory group of studies in our SLR.

We found that the majority of articles (199 articles, 81%) in our article pool suggest a specific theoretical use of DT while 152 of these also present results of a DT application, whether in the form of a real life system or a simulation of the theory they suggest. Note that at this point we do not make a distinction between fully functional real world applications of digital twins and small-scale demos used as proof of concept. The number of theoretical studies (with or without applications) takes up the large part of the article pool which implies that DT technology has already gone beyond the point of entry-level exploratory research for future ideas. With that said, the distribution of exploratory studies over time is spread around all years and there is still further exploratory researches to be published in 2020. Distribution of research types is given in Table 4. Application types in the studies are examined in detail to answer RQ2.3, RQ2.4, and RQ2.5 in Section 3.2.

Table 4: Research types

Research Type	Number	Percentage
Theory with Application	152	62%
Theory	47	19%
Exploratory Research	35	14%
Review	13	5%
TOTAL	**247**	**100%**

In practical studies, financial funding is a vital factor to help researchers carry their efforts to successful results. Our findings show that funding from different organizations was available to researchers for 143 studies (58%). These funds can also point to the strategic vision of the countries. More than 80% of the research efforts in China are financially supported by different organizations. In some countries with a smaller overall number of studies such as Austria, Estonia, Greece, Singapore, Belgium, Japan, Portugal, Canada, Cyprus, and Poland; all DT research efforts seem to supported by funding organizations. Percentages of funding availability and support for each country together with number of funded and non-funded studies can be seen in Figure 5.

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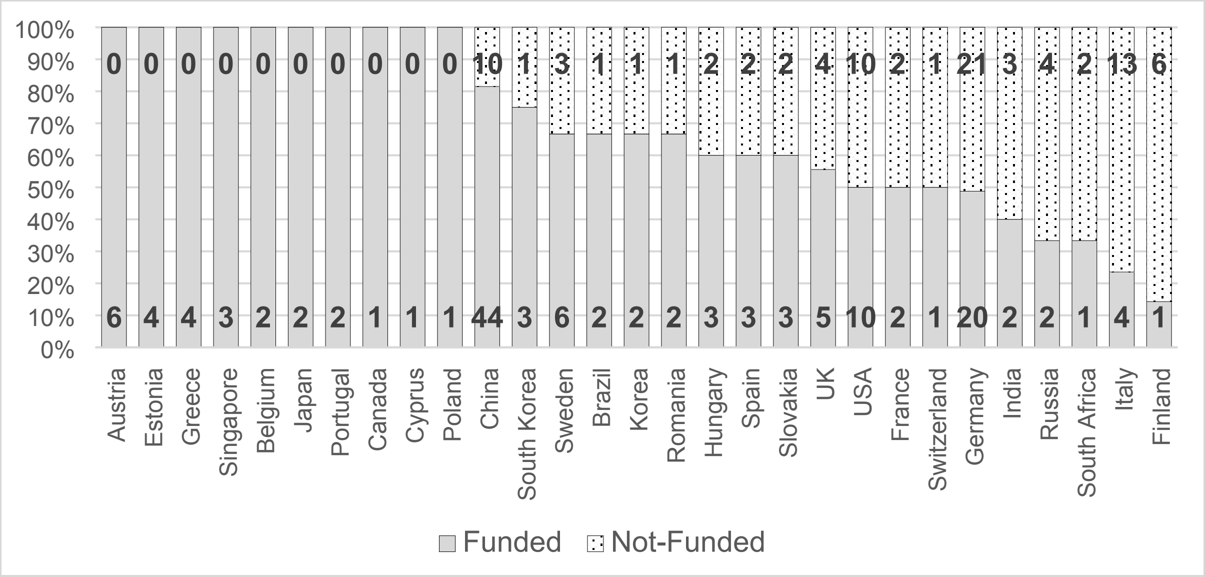

Figure 5: Funding availability percentages for countries

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3.2. Classification and Categorization of DT Studies in Manufacturing

In this section, the analysis of the literature goes beyond the general demographics of the article pool and now it focuses on the contents of the studies to reach the second goal of this SLR; RQ2.1, RQ2.2, RQ2.3, RQ2.4, and RQ2.5. RQ2.6, which is about open research areas and future direction suggestions is left for Section 4 to be covered in the entirety of the next section.

In order to classify the industry sectors and economic activities for which the digital twin applications are suggested, we use NACE codes which are a European Union (EU) standard for classifying business activities. They are four-digit classification codes which can be used to distinguish different activities and industries. These codes have hierarchical levels to categorize activities starting from very broad groups to very specific activities. One of the main level categories is “Manufacturing” and all 152 articles with any kind of DT application covered in our SLR naturally fall under this category. All manufacturing sub-activities of research in our article pool are given in Table 5.

Table 5: NACE Codes for reviewed articles

NACE	Explanation
C	Manufacturing
C16	Wood products
C19	Petroleum products
C20	Chemical products
C21	Basic pharmaceutical products
C23	Non-metallic mineral products
C24	Basic metals
C25	Fabricated metal products
C26	Computer, electronic and optical products
C27	Electrical equipment
C28	Machinery and equipment
C29	Motor vehicles
C30	Other transport equipment

85 of the 152 articles with a DT application did not specify the business activity beyond the main level of “Manufacturing”. These 85 articles as well as the remaining 67 with a more specific activity area are listed in Table 5 with respect to their NACE codes. Article IDs used in Table 6 can be found in Supplementary Material 1. Most common business activities are found to be C24, C25, and C29.

DT can be used in all stages of a product lifecycle; from product design, manufacturing, and all shop floor activities to logistics and maintenance. As our scope is limited to the manufacturing and production step of this life cycle, we examined the distribution of DT applications for different stages of manufacturing. 41% of applications are found to focus on shop floor manufacturing activities (varying from assembly to drilling to cutting, etc.) whereas 40% of them are found to focus on manufacturing in general without any specific interest in an activity. The popularity of shop floor activities for research is logical as the cornerstone of a DT application is availability of data, and generally the ability to obtain data on shop floor is easier than other stages. Distribution of DT applications for manufacturing stages can be seen in Table 7.

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Table 6: Manufacturing business activities for DT applications

NACE	#	ARTICLE ID										
C	157	[S002]	[S003]	[S004]	[S005]	[S006]	[S007]	[S008]	[S011]	[S014]	[S017]	[S019]
		[S020]	[S023]	[S024]	[S025]	[S026]	[S027]	[S028]	[S029]	[S030]	[S031]	[S032]
		[S034]	[S036]	[S037]	[S038]	[S041]	[S042]	[S044]	[S045]	[S047]	[S048]	[S051]
		[S052]	[S053]	[S055]	[S057]	[S058]	[S059]	[S060]	[S062]	[S063]	[S066]	[S067]
		[S068]	[S069]	[S070]	[S071]	[S072]	[S076]	[S077]	[S078]	[S079]	[S081]	[S082]
		[S083]	[S084]	[S085]	[S087]	[S089]	[S090]	[S092]	[S096]	[S097]	[S099]	[S100]
		[S101]	[S102]	[S103]	[S104]	[S105]	[S106]	[S107]	[S109]	[S110]	[S114]	[S115]
		[S117]	[S118]	[S123]	[S124]	[S126]	[S127]	[S130]	[S134]	[S135]	[S136]	[S137]
		[S139]	[S141]	[S143]	[S144]	[S145]	[S147]	[S149]	[S152]	[S153]	[S154]	[S157]
		[S161]	[S162]	[S165]	[S166]	[S168]	[S169]	[S170]	[S170]	[S171]	[S172]	[S173]
		[S174]	[S175]	[S176]	[S177]	[S178]	[S182]	[S183]	[S185]	[S186]	[S189]	[S190]
		[S192]	[S193]	[S194]	[S195]	[S196]	[S198]	[S200]	[S202]	[S203]	[S204]	[S205]
		[S206]	[S207]	[S209]	[S210]	[S211]	[S212]	[S215]	[S216]	[S218]	[S219]	[S221]
		[S222]	[S223]	[S226]	[S227]	[S228]	[S231]	[S233]	[S234]	[S237]	[S238]	[S239]
		[S240]	[S242]	[S245]								
C.16	1	[S142]										
C.19	2	[S108]	[S167]									
C.20	8	[S080]	[S046]	[S112]	[S155]	[S158]	[S191]	[S197]	[S229]			
C.21	1	[S138]										
C.23	2	[S009]	[S015]									
C.24	19	[S010]	[S021]	[S033]	[S049]	[S061]	[S064]	[S094]	[S095]	[S098]	[S111]	[S121]
		[S122]	[S125]	[S128]	[S131]	[S132]	[S164]	[S188]	[S208]			
C.25	13	[S056]	[S065]	[S075]	[S088]	[S133]	[S148]	[S150]	[S184]	[S201]	[S213]	[S235]
		[S236]	[S244]									
C.26	9	[S091]	[S113]	[S116]	[S119]	[S146]	[S163]	[S180]	[S214]	[S241]		
C.27	5	[S156]	[S159]	[S181]	[S224]	[S230]						
C.28	7	[S013]	[S016]	[S035]	[S050]	[S199]	[S225]	[S246]				
C.29	14	[S001]	[S012]	[S040]	[S043]	[S073]	[S093]	[S129]	[S140]	[S151]	[S160]	[S179]
		[S187]	[S217]	[S243]								
C.30	9	[S018]	[S022]	[S039]	[S054]	[S074]	[S086]	[S220]	[S232]	[S247]		

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Table 7: Number of studies regarding manufacturing stage

Manufacturing stage	**Number of studies**
Manufacturing on the shop floor	101
Manufacturing in general	98
Planning	20
Design	12
Process control	6
Maintenance	5
Other	5
TOTAL	**247**

Beyond the general manufacturing on the shop floor, DT applications can be related with three main areas, namely production planning and control [1], maintenance [19],[20], and layout planning [21]. To the best of our knowledge, in our article pool there has not been a DT application related to layout planning stage of production.

The purpose of DT application is one of the most important distinctions between studies. To categorize the application purposes, we use the proposed digital-physical layered DT structure model. In the articles examined for this SLR, we found that authors specified the application purpose of their DT ideas at different levels. Five articles of the 152 DT applications include real world application of a DT whereas the remaining 147 have small-scale demos or simulations as proof of concepts. We can say that the current infrastructure and capabilities of applying DT technologies to fully functioning real world cases have not yet reached necessary maturity conditions.

In 96 of the studies with any kind of DT application, we found no specific application purpose given. In 88 of the studies, the application purpose is specified at the second level, that is the purpose of digitalization. 46 of these stop at the second level whereas others also give a purpose for the physical layer of DT. In total, 102 studies specify an application purpose with the output of the system to the physical layer, which is the third level. In 19 of the studies, we found a mention of a fourth level activity that is the further interaction between physical and digital layers such as verification of the transferred data.

Breakdown of 88 studies that give a DT application purpose at the second level (digital layer) is as follows. 47 studies use DT with optimization purposes. This is followed by 26 studies with simulation, 15 studies with prediction, 11 studies with monitoring, five studies with estimation, and one study with testing purposes. Note that 15 papers specified more than one digital layer purpose for their DT applications.

As for the third level of the DT structure, output of DT for the physical systems, efficiency improvements are found to be the most common aim of DT studies. Process control, predictive maintenance, production and layout planning are other activities focused by researchers. Validation of the system, verification, and feedback control are the fourth level activities mentioned in DT studies. Distribution of DT application purposes in relation with the DT structure we propose is given in Figure 7. Studies with regards to their DT application purposes are given in Table 7. Article IDs used in Table 8 can be found in Supplementary Material 1.

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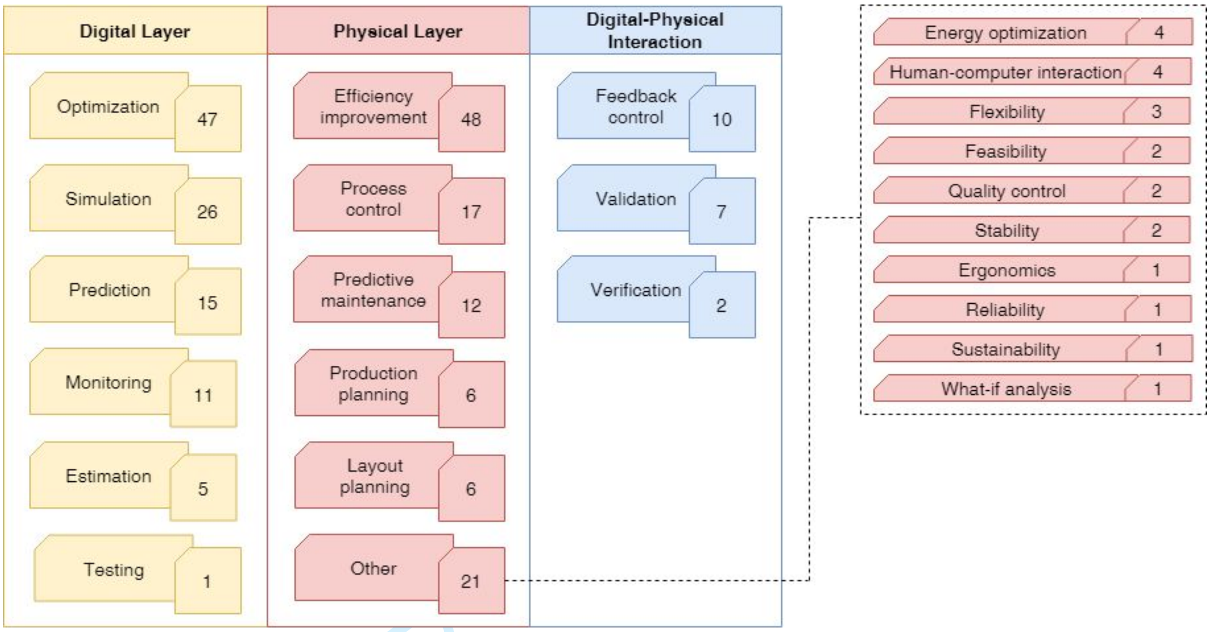

Figure 7: Distribution of DT application purposes

DT-adjacent terminology like *digital shadow* or *digital thread* is also employed in a small fraction of studies. 213 articles (91%) reviewed in this SLR use strictly DT as the digitalization concept. The remaining studies employ different terms and techniques such as *digital shadow* (12) or *digital thread* (5) either as the standalone method or as an addition to the DT concept.

Simulation is a necessary tool for creating DT as it allows the digital layer to predict how the system and system individuals might perform and how different parameters will affect it during its life cycle. The most commonly found simulation methods in our article pool can be listed as Discrete Event Simulation, Monte Carlo Simulation, 3D Simulation, CAD / CAM Simulation, Robotic Simulation, Augmented Reality, and Virtual Reality.

DT technology requires software tools to simulate the physical environment in the digital layer. Existing simulation tools have evolved to meet new requirements of DT technologies and also new software companies emerged to enter this hot topic area. Most commonly used simulation tools for DT are found as MATLAB-Simulink, FlexSim, Microsoft Kinect, Automation ML, Delmia, and LabVIEW 2018 in the article pool.

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Table 8: Article distribution with DT application purposes

Purpose		#	Article ID
Digital Layer	Optimization	47	[S004], [S005], [S015], [S029], [S030], [S032], [S038], [S056], [S062], [S068], [S088], [S108], [S113], [S115], [S118], [S119], [S121], [S128], [S132], [S133], [S134], [S141], [S143], [S147], [S149], [S150], [S151], [S153], [S159], [S161], [S167], [S175], [S183], [S189], [S194], [S195], [S199], [S201], [S208], [S216], [S218], [S221], [S225], [S230], [S231], [S243], [S244]
	Simulation	26	[S007], [S008], [S027], [S047], [069], [072], [079], [087], [S145], [S149], [S151], [S153], [S172], [S173], [S175], [S177], [S181], [S191], [S205], [S208], [S210], [S219], [S221], [S234], [S238], [S244]
	Prediction	15	[S029], [S034], [S049], [S056], [S089], [S098], [S100], [S103], [S113], [S128], [S182], [S183], [S205], [S235], [S240]
	Monitoring	11	[S013], [S025], [S055], [S071], [S089], [S090], [S099], [S111], [S130], [S196], [S231]
	Estimation	5	[S046], [S064], [S113], [S191], [S200]
	Testing	1	[S097]
Physical Layer	Efficiency improvement	48	[S004], [S010], [S012], [S016], [S032], [S033], [S036], [S040], [S044], [S046], [S049], [S062], [S070], [S077], [S088], [S090], [S096], [S103], [S108], [S125], [S133], [S139], [S140], [S141], [S143], [S149], [S150], [S151], [S153], [S161], [S167], [S182], [S186], [S187], [S190], [S191], [S193], [S197], [S201], [S213], [S214], [S215], [S218], [S221], [S224], [S225], [S243], [S244]
	Process control	17	[S026], [S030], [S045], [S067], [S089], [S112], [S116], [S131], [S138], [S144], [S155], [S157], [S162], [S198], [S207], [S231], [S247]
	Predictive maintenance	12	[S014], [S025], [S061], [S062], [S070], [S094], [S100], [S103], [S110], [S186], [S216], [S235]
	Production planning	6	[S093], [S115], [S122], [S148], [S184], [S199]
	Layout planning	6	[S001], [S015], [S093], [S175], [S213], [S230]
	Energy optimisation	4	[S062], [S091], [S095], [S139]
	Human-computer interaction	4	[S086], [S163], [S176], [S241]
	Flexibility	3	[S044], [S192], [S215]
	Feasibility	2	[S048], [S114]
	Quality control	2	[S009], [S035]
	Stability	2	[S018], [S056]
	Ergonomics	1	[S129]
	Reliability	1	[S018]
	Sustainability	1	[S142]
	What-if analysis	1	[S232]
*DPI**	Feedback control	10	[S015], [S088], [S141], [S143], [S175], [S201], [S218], [S225], [S230], [S235]
	Validation	7	[S026], [S075], [S108], [S144], [S176], [S199], [S200]
	Verification	2	[S049], [S119]

*DPI: Digital-Physical Interaction

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4. Future Research Directions

SLR findings can be useful for different parties like technology developers, end-users, and academic researchers. RQ2.6 in our SLR also directly relates to this. Combining the future research suggestions given in the articles we examined with the implications of open research areas from their content, numerous future research directions can be emphasized both for academic researchers interested in this area and the practical technology developers.

Theoretical research interest in DT applications continues to increase with the real world implementations. Once the large scale DT applications are integrated into standard company policies, they can prove to be essential to reduce costs, increase optimization, verify performance, predict future results, and improve quality by providing a well-established Internet of Things (IoT) network and a more visible factory. Although factories are becoming more and more capable in creating both physical and virtual layers for systems or products, connection and data transfer between two layers is still in need of improvements. The knowledge about digital technology and the overall know-how is not yet at a sufficient level for wider successful DT design and applications, the industrial knowledge is necessary for the accomplishment [22]. Assessment of the company knowledge about engineering, DT and analytics is necessary to predict the success of the DT implementation. Related to that, there is a limited number of articles with actual industrial case studies, as stated in several different publications [7], [23]–[26].

Below, we discuss different future research areas with regards to different aspects of DT applications that have certain research gaps or that need practical improvements. Analyzing the current DT in manufacturing literature, the outcomes of current studies, and the work remaining to be completed in the future, we present the future research suggestions in eight categories.

Standardization and Interoperability:

Two important challenges of DT are standardization and interoperability. Fuller et al. (2020) highlighted the lack of standardization as a challenge that DT technology is currently facing. Standardization is vital to have for the technologies enabling the applicability and interoperability of the designs, systems, data flow and data analytics among different sectors and enterprises. Two-sided continuous, reliable and standardized data flow is required for full DT implementations. Correspondingly, Industry 4.0 applications, such as technologies to handle big data, cloud computing and IoT undertakes the crucial role for establishing a standardized communication infrastructure between physical and digital layers as well as between machines and humans, which paves the way for interoperability between various parties. In addition, the impacts of the DT applications to stakeholders and suppliers are a point of interest for studies [27]. The serviceability and sustainability of DT systems are other factors to consider when it comes to supply some parts of these systems [28]–[30]. Regarding interchangeability, standardization, and collaboration of DT systems, as [31], [32] point out, constitution of a consensus between cultures is a vital issue. Thus, stakeholders of the DT industry and academia could enable the standardization and interoperability of the state-of-the-art products to be launched to the market by bounding a commonly accepted

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communication protocol, defining regulations on how to process and constitute the reliability of on-time data in their future studies [33], [34].

Security:

As is the case with many modern technologies, the security issues regarding data, and cyber-security are some of the most highlighted challenges in digital transformation too. The companies who wish to implement DT to their manufacturing systems have to take into account the probable cyber-threats in an age where even the biggest technology corporations could face the detrimental effects of such threats as malware attacks, phishing, cross site scripting, etc. Improvements regarding security concerns and issues are also analogous with the worldwide requirement of legal baseline for the application of DT technologies [35]–[37]. Corporates and stakeholders in DT atmosphere must stand tall and get necessary precautions against cyber-threats. Consequently, while standing far from maturity, establishing a robust and isolated network, educating the personnel and improve their awareness to possible threats and hacking strategies, getting periodical penetration testing services from ethical hackers and installing relevant cryptographic security infrastructure could protect the DT systems from external attacks.

Cost:

Another important reason that makes DT applications currently infeasible for many manufacturers is the high investment and implementation costs. Potential reduction of costs is likely to boost up the proliferation of digitalization in manufacturing [38].

Technological Infrastructure and Interface:

Typically, both physical components and various software and network components that constitute the technological infrastructure are also listed as limitations for DT applications. Not only the quality of physical components but also the quality of data is a factor to be improved in order to increase the reliability of the DT applications [39].

Since the data transfer is autonomous and perpetual between digital and physical systems within DT, designing the interface between workers and the physical machines regarding inputs to system and handling the dynamic flow of data from humans to machines is another struggle to be faced [40]–[42].

Complexity:

As the DT modelling requires complex simulation and prediction capabilities, the challenges related to life cycle of complex products should also be evaluated [43]. The complexity of production parameters is another constraint for applications of the DT. Cause of the complexity can be shop floor layout, synchronization of data between digital and physical components,

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smart manufacturing or inventory optimization [44]–[47]. Challenges related to complexity should be considered in future researches about DT applications.

Quality Control:

Quality control is an integral part of any manufacturing process. As the production on shop floor will be autonomous and dynamically flowing, the quality control applications must change their way of working and adapt to DT systems. Integration of statistical quality control techniques with CAD-CAM models and prediction algorithms is essential to constitute a stable high quality production and keep the scrap at lowest level. Therefore, quality control methods and applications should not be neglected in the manufacturing related studies of DT.

There can be future research on the scope of MES as a control loop of DT applications. DT can be used at every stage of production for quality control, monitoring and prediction of variability in a process and this can be checked and controlled by MES. Future research may also be interested in other possible types of intelligent controls systems besides MES [14], [48]–[50].

Big data – Data Science – Machine learning:

Fusion of heterogeneous data, integration of digital and physical elements, efficient algorithms for the analytics of dynamic and continuously flowing big data while using as low CPU power as possible, machine learning algorithms to eliminate human centric errors, and minimize the requirement for human-machine interaction are key factors for successful DT implementations [51]–[57]. This means that data scientists will also have important theoretical research and application roles in the future of DT studies. A related currently open issue is the way deep learning techniques can be used to obtain the information from process, support decision making particularly for task scheduling, provide a robust monitoring and control operation and unique consolidation of data science, artificial intelligence and manufacturing sectors [9], [58]–[62]. [63] suggest that artificial intelligence applications with their prediction abilities can allow the production control process.

Accuracy and Reliability of Data:

[61] point out that the reliability and accuracy of current simulation models are still less than satisfactory. Insufficient analysis of data provided by virtual models is another challenge before the implementation of DT. Generally, analysis is limited to physical product data and virtual model data is ignored [64]. Even in the cases where virtual model data is collected, the comparison with physical model is lacking. The comparison between data from physical systems and data generated by digital layers may be used to forecast the future state of production [65], [66].

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5. Conclusion

In research areas where interest for future studies exists strongly, SLRs can be useful tools as they outline the current state of research while revealing potential future directions. In this SLR study, we aimed to present the current state of literature of DT studies in manufacturing. Upon reviewing 247 relevant studies according to defined research goals, we share a picture of current DT literature in manufacturing and give a roadmap for future studies.

We suggest a layered DT activity structure that summarizes the components of DT systems. The loop of information sharing between physical and digital layers of DT can be defined in layers that go from DT in the broadest sense to the specific activities of digital and physical layers. The previous applications of DT in manufacturing literature are classified according to this structure.

This SLR shows that there is a certain desire to digitalize manufacturing processes and increase the level of automation so as to improve the product quality, meet more requirements of customer demands while preserving standardization, improve efficiency while using the scarce resources, and reach many more customers while decreasing costs at all stages of product lifecycle. However, it is a point well made in literature so far that there is not a common understanding of DT and its practical role in manufacturing industry. Since there are numerous limitations and drawbacks in order to implement DT applications to currently operating production processes, there is still future work to do by different parties; such as equipment and information systems providers, academics working on theoretical studies and applications, or engineers working in the field of software, big data, IoT, or artificial intelligence.

Literature also shows that the main manufacturing sectors for DT applications so far are the ones with highest level of systematic processes, such as metal industry and motor vehicle industry. More on-hand autonomous solutions have been in use in these sectors before DT implementations as well. We also conclude that petroleum and natural gas industry has seen advances in terms of DT technologies. Due to the nature of the work in this industry, there are many uncertainties and unknowns to deal with. This leads to utilization of digital models in the daily work. DT know-how obtained in these sectors can be generalized and transferred to broader manufacturing areas.

Based on the findings and trends, we predict that the digitalization of manufacturing processes will increase and become more common in near future. The early adopters who give their attention to the importance of transforming the processes are most likely to make the best out of the future of manufacturing for themselves as well as the others. Such modern technologies

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as DT or general digitalization of systems can be what makes the difference for businesses in the era of the digital revolution of industry.

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