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REVIEW

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A literature review and design methodology for digital twins in the era of zero defect manufacturing

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ABSTRACT
In this paper, we analyze the literature concerning the implementation of digital twins (DTs) for zero-defect manufacturing (ZDM) following a systematic method and, guided by a preliminary finding that a structured and standardised approach to the development of the DT applications is lacking, we provide a standardised design methodology to guide researchers and practitioners in their efforts to develop DTs regardless of the domain. After examination and interpretation of the literature, we also present the results of our state-of-the-art analysis, discuss the current state and limitations of research and practice, and provide useful insights on this important and complex topic. The design methodology proposed in our study will benefit both practitioners and academicians by covering the essential elements to be considered when developing DTs for ZDM for any applications in this domain. The study also contributes to knowledge by presenting a structured overview of the specific research area with a comprehensive, systematic, and critical analysis of the literature and by providing answers to some fundamental questions in the context of DTs for ZDM. Finally, we provide suggestions for further developments in research and practice.

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Quality assurance; quality control; zero defect manufacturing; digital twin; standardise; methodology

1. Introduction

In the manufacturing community today, there is great deal of interest in digital twins (DTs), and the term is becoming more commonly used. Although the idea and definition of DTs were coined earlier, it was not until 2010 that the concept became popular with its appearance in *NASA's* draft version of its technological roadmap (Shafto et al. 2010). Since then, significant effort has been invested and a vast amount of work accomplished on the development of DTs for different purposes. A DT, in one of its simple definitions, is a digital representation of a real-world physical entity or system that assists us in understanding the present and predicting the future (Grieves). The sense of 'digital' in the context of DTs differs from that used to describe the data in the era of computer-integrated manufacturing (Grieves 2014). Batty (2018) defines a DT as 'a mirror image of a physical process that is articulated alongside the process in question, usually matching exactly the operation of the physical process which takes place in real-time' (Batty 2018). Hence, a DT is an important practical tool for engineers and operators to better understand how products currently perform and, more importantly, how they will perform in the future (Wang et al. 2018). The benefits of DTs are manifold and include real-time visualisation of products and processes, predictive analytics, troubleshooting of remote equipment, and building of digital threads by connecting different systems (Tao et al. 2019).

Manufacturing processes are becoming increasingly digital, and companies are having difficulties in understanding how to accordingly adjust their value proposition both strategically and operationally (Gibson et al. 2021). In that regard, DTs support companies in solving physical issues by detecting them more quickly, achieving a precise prediction of process outcomes, and creating better products with improved quality (Ding et al. 2019). A DT is superior to the traditional CAD (computer-aided design) and sensor-based IoT (internet of things) solutions as it considers the interactions between different components and life cycle processes (Liu et al. 2021a). The near real-time linkage and interactivity between digital and physical worlds enabled by a DT lead to better artificial intelligence (AI) models and smart manufacturing profiles that provide more comprehensive and realistic measurements leading to more accurate prediction capabilities (Dreyfus et al. 2021). In addition, increasing computing power capabilities along

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with recent advancements in data analytics and predictive algorithms provide an easier way of analyzing such measurements and collected sensor data to facilitate better decision-making (Cho et al. 2018).

Zero-defect manufacturing (ZDM) is one of the most effective approaches to improving product quality today. It is a new industry 4.0 paradigm that goes beyond traditional quality management approaches by using modern methods and digital technologies in production environments (Psarommatis et al. 2020a). In other words, ZDM is a philosophy regarding product and process quality based on a target that is simple and yet difficult to achieve: Do it right the first time. To that end, ZDM is integrated into the manufacturing process from the beginning instead of addressing problems and defects at a later stage, and it follows a cycle of continuous improvement aligned with standardised benchmarks (Psarommatis et al. 2020b; Psarommatis et al. 2021).

ZDM eliminates product defects by using data-driven corrective, predictive, and preventive tools and methods, thus improving manufacturing sustainability and service level to the customer (Psarommatis, Dreyfus, and Kiritsis 2022). The ever-increasing availability of data and advanced technologies that support emerging data-driven innovation results in more effective implementation of ZDM (Sousa et al. 2021). With the advancement of industry 4.0 technologies within smart factories, one of the fastest-growing and most promising approaches to ZDM is the use of DTs that incorporate the IoT, big data, *AI*, and machine learning (ML) (Psarommatis, Dreyfus, and Kiritsis 2022). Therefore, understanding how to properly implement DTs in the context of ZDM is of paramount importance to improving and maintaining product quality.

1.1. Purpose of the study

Our analysis of the available literature reviews on the topic, which is presented in Section 2 of this paper, revealed a lack of review studies with a particular focus on the implementation of DTs for ZDM. In particular, the literature on the topic could benefit from a unified design methodology for DTs and applications. This paper therefore analyzes the current literature on DTs for ZDM and, based on our findings that a common and standard way of structuring DT implementations is lacking, provides a design methodology to be used by both practitioners and academicians working on the topic. This research work points to a large unexploited potential for ZDM application in the industry, especially concerning a standardised and effective implementation and use of DTs for improving the quality of finished products in manufacturing environments. For academicians, the current paper paves the way for further studies by providing useful insights based on critical analysis of the previous literature and by discussing the industrial challenges and opportunities. For practitioners, the standardised DT design methodology provided in this paper could be of use in their efforts to design new DT applications for, but not limited to, ZDM.

The structure of the rest of the paper is as follows: Section 2 presents an analysis of the existing literature review papers on the topic of DT and ZDM to demonstrate the research gap that exists and support the need for the current literature review paper. Section 3 presents in detail the methodology and steps that were used for acquiring and filtering the papers to analyze. Next, Section 4 highlights the results from the conducted literature review, as well as some key shortcomings revealed. Section 5 provides a structured and unified design methodology for developing DT models. Finally, Section 6 concludes by illustrating some key discussion points derived from the literature analysis.

2. Comparison with previous literature reviews and motivation of this research

This section justifies the need for content analysis and the development of the proposed design methodology by summarising the findings of previous review papers on the combined topic of DTs and ZDM. Accordingly, we present the results of the pertinent literature reviews, determine points of concern that require further exploration, and finally point out the gap covered in the current paper.

Most of the pertinent literature reviews have been published within the last three years due to growing interest in the topic. The earliest of these focus on the applications of DTs in the industry in general (Tao et al. 2019). In Tao et al. (2019), the authors reviewed the state-of-the-art research on DTs to investigate the key components, recent developments, and major applications of DTs in the industry. In 2020, Jones et al. analyzed 92 DT publications covering a ten-year span and determined 13 characteristics that characterise a DT, identified knowledge gaps, and explored opportunities for further research (Jones et al. 2020). Both of these first attempts were generic in nature and attempted to understand the basic characteristics and implementation features of DTs. In a more focused analysis concerning implementation scenarios and use cases, Errandonea, Beltrán, and Arrizabalaga (2020) conducted a systematic review of the literature in which the concepts of DT and maintenance were involved. The paper investigated how DTs are applied for maintenance and presented open issues in research (Errandonea, Beltrán, and Arrizabalaga

2020). The literature review most pertinent to our line of research was that of Wärmefjord et al. (2020), in which the authors directed their attention toward previous research that studied tolerance analysis and geometry assurance when using DTs – hence a specific area of ZDM – and discussed industrial applications and challenges in this domain (Wärmefjord et al. 2020). However, unlike our current work, Wärmefjord et al. did not provide any insights to practitioners and academicians on how to better design DTs with a standardised approach; their study also did not highlight the shortcomings of DT applications on the topic. In addition, they focused on a very specific area of ZDM, as their focus was limited to geometry assurance only rather than a broader view of ZDM.

The first half of 2021 saw an increase in review publications on the topic. Liu et al. (2021) (Liu et al. 2021a) analyzed DT concepts, technologies, and industrial applications. He and Bai (2021) focused on DT-based sustainable intelligent manufacturing and provided a direction for future development (He and Bai 2021). Referring to further development efforts for advancing DT technology, previous review studies also addressed simulation tools used with DT technology as well as conceptual architecture of the DT. Mourtzis (2020) investigated the simulation aspects of manufacturing systems with respect to their design and operations, and Stavropoulos and Mourtzis (2022) (Stavropoulos and Mourtzis 2022) analyzed and mapped DT architecture and applications for smart manufacturing on various levels including manufacturing processes and systems. The only review study we found that focused on standardisation of the DT development process was that of Zhang (2021), who proposed a DT data model for researchers and practitioners to incorporate into the DT development process (Zhang et al. 2020b). However, their study, with a particular focus on the methods and key technologies for DT data, lacks critical discussions on industrial challenges and applications and does not pay specific attention to ZDM. Finally, Serrano-Ruiz, Mula, and Poler (2021) took stock of the literature on smart manufacturing scheduling with a key focus on ZDM, but this work also did not address the standardisation issue for a common method of implementation (Serrano-Ruiz, Mula, and Poler 2021).

The contributions of our paper are compared to these previously mentioned review papers in Table 1, thus highlighting the novelty of and need for this current research work. Hence, guided by the gaps found by our preliminary analysis, our current research focuses on the specifics of DTs for applications in the ZDM context. As one of the insights gained during our analysis of the state of the art concerned the lack of a standard way to structure and guide DT implementations, we provide a standardised development approach for both researchers and industry practitioners as a guideline for future developments of any DT for ZDM. This approach can be generalised and applied to other domains as well.

3. Review methodology

A systematic review was carried out on the specific methods in the literature that are required to conduct a systematic content analysis and prepare a valid state-of-the-art analysis (Hsieh and Shannon 2005; Krippendorff 2018; Psarommatis et al. 2020a; Xiao and Watson 2017; Thomé, Scavarda, and José Scavarda 2016). The first step of the analysis was to collect the sample. This was achieved by searching on six major scientific databases: Scopus, ScienceDirect, IEEExplorer, Web of Science, Inspec and Compendex. These databases were selected because they index the majority of high-impact and well-known journals as well as high-impact conference proceedings in the domain of manufacturing. Table 2 summarises the information that was used to collect the papers to analyze. More specifically, Table 2 presents the databases used, the query that was used for the search on each online database, the search period, and the criteria that were used for screening the papers to derive the final paper set. The search period was selected to be from 2002 to 2021. The year of 2002 was not selected randomly; in 2002 the term 'digital twin' was first introduced by Grieves (2019).

For the query construction, Boolean operators were used to find all relevant articles combining different terms. To increase the reliability of our review and search method, two researchers independently searched the databases mentioned in Table 2 following the methods suggested by different methodology papers (Brereton et al. 2007; Templier and Paré 2015). The two different queries have different search keywords, but they share a common part. In both queries, we searched for the terms 'manufactur∗' and 'Industr∗' using the wildcard operator. This was done to get as many papers related to the manufacturing domain as possible. Furthermore, those keywords were searched in the abstract, title and keywords of the paper, whereas the rest of the keywords were searched only in the titles of the papers. This method was selected in order to retrieve a reasonable but representative number of papers.

The purpose of the present paper is to perform a systematic literature review for analyzing the literature on the topic of the use of DTs for quality-related topics. ZDM is the latest approach to quality improvement (QI), and therefore ZDM will be used alongside the quality term in the queries. Therefore, to retrieve relevant papers, the following two lean queries were built. The first search string containing the 'quality' AND 'digital twin' terms returned 524 papers in total (273 after removing

Table 1. Previous literature reviews and comparison to our current research work.

Authors	Year	ZDM	DT	Main scope	Discussions on industrial challenges and applications	Efforts toward Standardisation
Current Paper Psarommatis & May (2022)	2022	+	+	Digital twins for ZDM and a standardisation framework for DT development process	+	We propose a standardisation framework for DT development process
Serrano Ruiz et al. (2021)	2021	+	+	Smart manufacturing scheduling	–	–
He & Bai (2021)	2021	–	+	DT-based sustainable intelligent manufacturing	+	–
Zhang et al.	2021	–	+	Methods and key technologies for DT data	–	Proposed a DT data model for researchers and practitioners to incorporate into the DT development process
Liu et al. (2021a)	2021	–	+	DT concepts, technologies, and industrial applications	+	–
Wärmefjord et al. (2020)	2020	+	+	DT for tolerance analysis and geometry assurance	+	–
Errandonea et al. (2020)	2020	+	+	DT for maintenance	+	–
Jones et al. (2020)	2020	–	+	Characterisation of the DT and identification of gaps in knowledge	–	–
Tao et al. (2019)	2019	–	+	DTs in industry	+	–
Mourtzis (2020)	2020	–	–	Simulations for design and operation of manufacturing systems	+	–
Stavropoulos & Mourtzis (2022)	2022	–	+	DTs in industry 4.0	–	–

Table 2. The method used for screening papers.

Database	Scopus, ScienceDirect, IEEExplorer, Web of Science, Engineering Village (Inspec + Compendex)
Article Type	Scientific articles published in peer-reviewed journals and conferences
Searching Queries	• TITLE(quality AND digital twin) AND ABS-Title-Key(manufactur∗ OR Industr∗) • TITLE((ZDM OR 'Zero Defect Manufacturing') AND digital twin) AND ABS-Title-Key(manufactur∗ OR Industr∗)
Search Period	From 1st January 2002 to 1st July 2021 (digital twin was first introduced in 2002)
Screening Criteria	• Full paper available? • Article in English? • Article in the manufacturing domain? • Article related to DT? • Is it a review article? • Is the paper dealing with improving product or process quality? (YES: include, NO: exclude)

duplicates), and the second search query 'ZDM' AND 'digital twin' yielded 236 papers in total (192 after removing duplicates). Hence, a total of 465 different papers were initially collected from all of the databases. Next, the authors analyzed each paper and determined whether to include it in the final sample based on the screening criteria presented in Table 2. A total of 128 papers were included in our final analysis. Figure 1 illustrates the process of deriving the final set of papers for our analysis. Finally, all 128 final papers were analyzed in detail based on their content and the defined attributes, such as domain of application and technological implementation of DTs, leading to the results presented in Section 4.

4. Quality-oriented DT literature review critical analysis

The results from the analysis of the 128 final papers will be presented in the current section. The goal of this analysis is to thoroughly investigate the domain of DTs that are related to quality factors, whether it is product or process quality. The section is organised in three individual sub-sections. In Section 4.1, the basic findings of this analysis will be presented, followed by Section 4.2 wherein the different application domains of DT are identified. Finally, Section 4.3 presents the results regarding the technical implementation of DTs. The following references are the 128 references found and have been used for the literature review that follows: (Söderberg et al. 2018; Kang, Chun, and Kim 2019; Steringer et al. 2019; Papacharalampopoulos, Stavropoulos, and Petrides 2020; Pombo et al. 2020; Groen et al. 2020; Dimitris Mourtzis, Angelopoulos, and Panopoulos 2021; Veera Aditya and Srikanth 2017; Wei et al. 2020; Yan and Ballu 2018; F. Guo et al. 2018; Dittrich et al. 2019; Shivajee, Singh, and Rastogi 2019; Urbina Coronado et al. 2018; Zidek et al. 2020; Padovano et al. 2018; Chen et al. 2020; Söderberg et al. 2017; Rezaei Aderiani, Wärmefjord, and Söderberg 2021; Wärmefjord et al. 2018; Afazov and Scrimieri 2020; Vrana and Singh 2021; P. Pereverzev, Akintseva, and Alsigar 2018; Wen-hao et al. 2020; Srikonda, Rastogi, and Oestensen 2020; Levy et al.

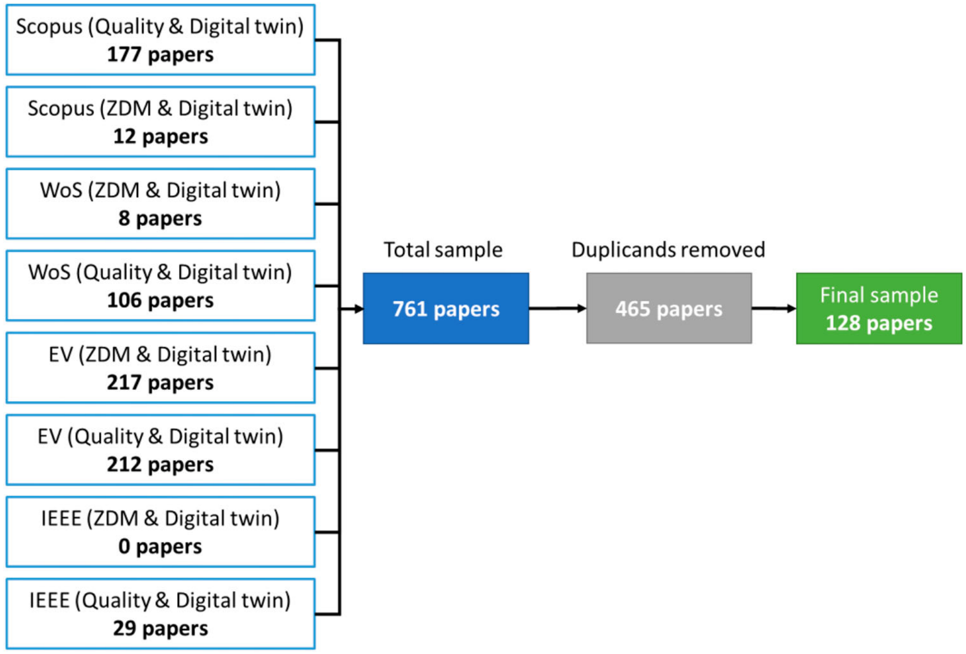

Figure 1. Literature review sample acquisition procedure.

2021; Lv et al. 2021; Sun et al. 2020; Liu et al. 2021b; Wang, Wang, and Liu 2020b; Cheng et al. 2020; Maginnis, Hapuwatte, and Keown 2019; Nikolaev et al. 2020; Baranwal et al. 2020; Mario, Alessandro, and Elena 2019; Constantinescu et al. 2020; Su et al. 2021; Borovkov et al. 2020; Blum and Schuh 2017; Tabar, Wärmefjord, and Söderberg 2020b; Zehetner et al. 2021; Gurjanov et al. 2021; Lechler et al. 2019; Barthelmey et al. 2019; Guerra et al. 2019; Howard 2019; Ma et al. 2019; Stojanovic and Milenovic 2019; Zambal et al. 2018; Borangiu et al. 2020; Felton and Ferguson 2020; Moyne and Iskandar 2017; Cao 2017; Bohlin et al. 2018; Wittig 2018; Kubota et al. 2018; Hehr et al. 2017; Becue et al. 2018; Longo, Nicoletti, and Padovano 2019; J. Liu et al. 2019; Anderson, Barvik, and Rabitoy 2019; Demartini et al. 2019; Gohari, Berry, and Barari 2019; Bellavista and Mora 2019; Damgrave and Lutters 2019; Ahuett-Garza and Coronado 2019; Centomo, Panato, and Fummi 2019; Rokka Chhetri et al. 2019; Qamsane et al. 2019; Mandolla et al. 2019; Ko et al. 2019; Cai, Zhang, and Zhu 2019; Zörrer et al. 2019; Yacob, Semere, and Nordgren 2019; P. P. Pereverzev, Akintseva, and Alsigar 2019; Wagner et al. 2020; C. Liu et al. 2020; Franciosa et al. 2020; Huang et al. 2020; S. Zhang et al. 2020a; Gramegna, Greggio, and Bonollo 2020; Lacueva-Perez et al. 2020; Bordatchev, Cvijanovic, and Tutunea-Fatan 2020; Z. Zhao et al. 2020; Hänel et al. 2020; Shahpar 2021; Zheng et al. 2020; Ferreira et al. 2020; Schmidt et al. 2020; Blake (n.d.); Santolamazza et al. n.d.; Changming, Yaqi, and Zhaoyu 2020; Židek et al. 2020; Pérez et al. 2020; Loaldi et al. 2020; Negri et al. 2020; Lindström et al. 2020; Min et al. 2020; Uhlenbrock et al. 2020; Hao et al. 2020; Ali, Umer, and Khan 2020; Centomo, Dall'ora, and Fummi 2020; Azangoo, Taherkordi, and Blech 2020; Stieber et al. 2020; Hürkamp et al. 2020; Tabar et al. 2020a; Wang, Jiao, and Zhang 2020a; Sedighiani et al. 2020; Liu et al. 2021; Moretti, Rossi, and Senin 2021; Liu et al. 2021b; Rausch et al. 2021; Ruhland et al. 2021; Zambrano et al. 2021; Hürkamp et al. 2021; Giuliano, Corrado, and Polini 2021; Xu et al. 2021; Wang et al. 2021; Pei et al. 2021; Xi et al. 2021; Klingaa et al. 2021; Cai, Zhu, and Zhang 2021; Guo et al. 2021; Pang et al. 2021; Gunasegaram et al. 2021; Psarommatis 2021).

4.1. Basic findings of the DT literature review

Based on the selected search criteria, the first papers that examined DT for improving the quality of a process or a product were published in 2017. Figure 2(a) illustrates the distribution of papers from 2017 to 2021. The highest number of papers is observed in 2020, with almost double the number of papers compared to 2019 or 2021. The next analysis criterion was to identify under which QI framework each DT was developed. Seven categories were defined for this analysis, five of them representing the traditional QI methods such as Six Sigma (SS), Lean, Lean Six Sigma (L6S), theory of constraints, and total quality management (TQM). The sixth category is ZDM, and the authors defined another category named 'partial ZDM'. A significant portion (39.84%) of the total papers discussed some of the ZDM principles, such as using its predictions to prevents defects. All the papers that used ZDM principles but did not explicitly mention

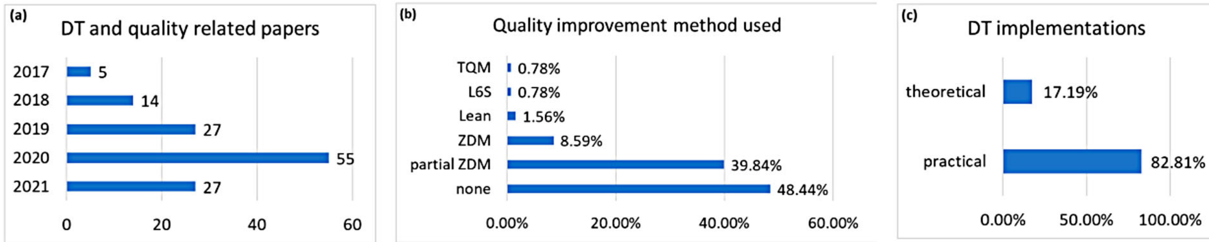

Figure 2. Review analysis basic findings: years distribution (a), QI method used (b), and type of implementation (c).

ZDM were classified in the 'partial ZDM' category. Figure 2(b) illustrates the distribution of the analyzed papers based on QI method. Most of the papers, 48.44%, did not use any form of QI method, followed by 39.84% that used the partial ZDM and 8.59% that explicitly mentioned the use of ZDM. Of the traditional QI methods, only Lean, L6S, and TQM were used, with 1.56%, 0.78%, and 0.78% respectively. Another insight that emerged from the literature analysis was the fact that some papers referred to DT implementations only from a theoretical perspective. In total, 17.19% of the analyzed papers were classified as theoretical whereas the rest, 82.81%, were categorised as practical (Figure 2(c)). This classification was performed based on whether the paper developed and presented an actual DT model rather than just a conceptual framework, explanation of how to develop a DT, or discussion of where DTs can be used and their benefits.

4.2. DT domains of implementation

The current section is devoted to presenting the different industrial and domain applications of DTs in the context of ZDM. Figure 3(a) illustrates the different industries in which DTs were used in the 128 analyzed papers. Remarkably, 60.16% of the analyzed papers presented the development of a DT without mentioning a specific industry to which it would be applied. The most common industries in which a DT was developed for quality purposes were aerospace and automotive with 13.28% and 10.16% respectively. The machine tool, metal, semiconductor, and marine industries followed with 3.91%, 3.13%, 2.34%, and 1.56% respectively. The rest of the identified industries in Figure 3(a) appeared only one time. Figure 3(b) illustrates the different purposes of the developed DTs and includes all of the categories that appeared in more than one paper. The categories in which only one paper appeared are classified in the 'one-time occurrence' category, which includes 11.72% of papers. The most common purpose of the developed DTs was to improve or assure product quality, with 37.5%. The second most common category was process quality, with 17.97%, meaning that these papers focused on improving the quality of the manufacturing process to avoid product defects and, by extension, product quality. Moving forward, some of the other categories are related to the manufacturing processes but focus on other process-related topics. Those categories are process optimisation and control as well as production control and predictive maintenance. Unlike the preceding categories that concerned the operations phase, the final categories concern the design phase. In 2.34% of the analyzed papers, the goal of the DT was to assist in the design phase either for the product or the production. Furthermore, 3.91% of the papers used DTs as simulation engines to virtually test the performance of a newly designed product. Only 5.47%

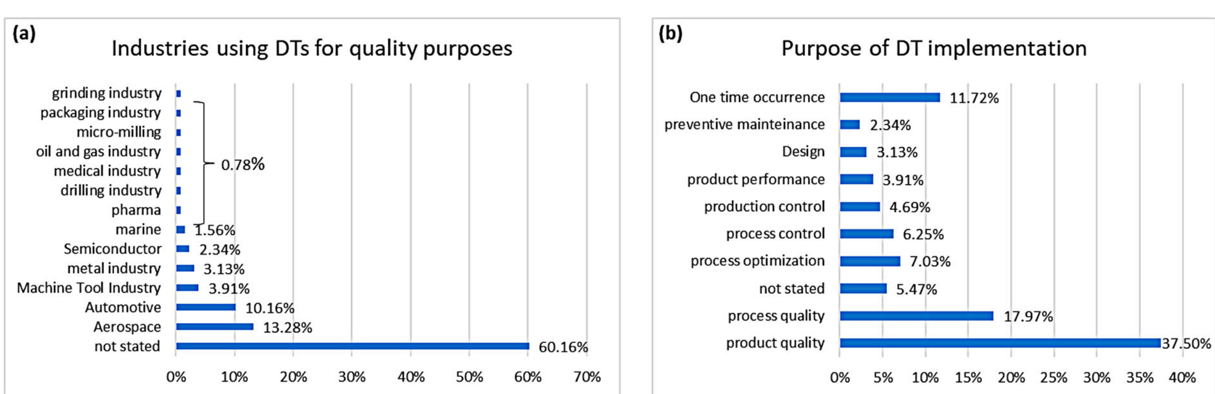

Figure 3. Most frequent industries in which DTs are implemented (a), and implementation purpose of DTs (b).

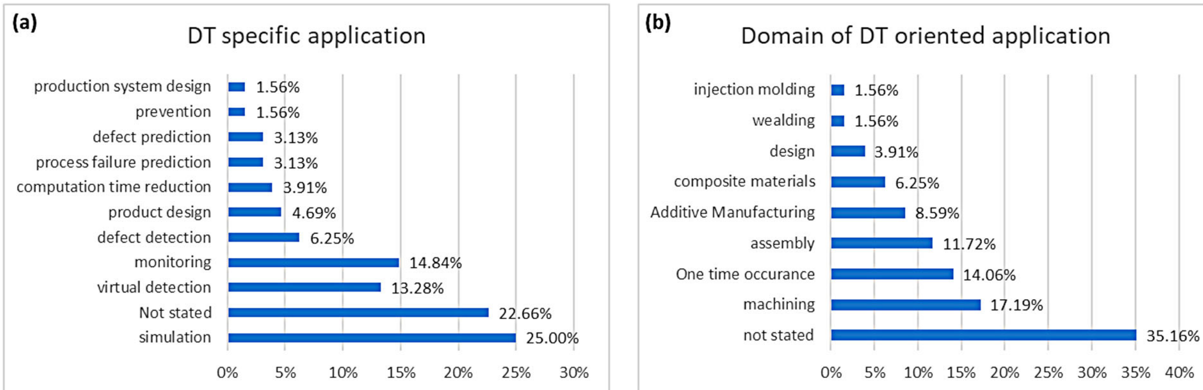

Figure 4. DTs' specific applications (a), and process of application (b).

were under the category of 'not stated,' and most of those were the theoretically oriented papers described in Figure 2(c).

Analyzing the results from the literature review even further, the specific DT applications were extracted and presented in Figure 4. In both Figure 4(a and b), it is notable that a high percentage of papers (22.66% of papers discussing specific applications and 35.16% of papers discussing specific processes) fell into the category 'not stated.' The application for which DTs were most often developed was simulation, with 25%. In those papers, the developed DTs were emulating simulation engines for purposes such as scheduling, process simulation, product performance, and finite element analysis. The next category, virtual detection, is derived directly from the ZDM concept (Psarommatis et al. 2020a; Psarommatis et al. 2021). Virtual detection is part of virtual metrology (Dreyfus et al. 2021), which estimates product quality without physically measuring and inspecting the part by analyzing the process data during its production. Furthermore, other categories related to ZDM are defect detection, defect prediction, and prevention, with 6.25%, 3.13%, and 1.56% of DT applications respectively. An interesting finding is the purpose of the papers within the category 'computation time reduction' with 3.91%. Those papers developed a DT of a system to reduce the computation time that the 'physical' system required to complete the task.

Figure 4(b) presents the different processes that DTs were called to emulate. As was observed in the other result graphs, a significant number of papers (35.16%) did not explain the details of their DTs. The processes for which DTs are most commonly used are machining (17.19%) and particularly milling, assembly (11.72%), additive manufacturing (8.59%), and manufacturing products out of composite materials (6.25%). Regarding the milling process, most of the time the purpose of the DT implementation was to determine the part's surface roughness and geometrical tolerances. Regarding the assembly process, almost all papers were concerned with the correct positioning of the components before assembly. The DTs that emulated the additive manufacturing process focused mainly on three topics: layer thickness, residual stress, and geometrical tolerances.

4.3. DT technological implementation

Proceeding with the more technical-oriented results from the literature review, it is important to remember that the results presented in Figure 5 concern DTs related to quality and not DTs in the manufacturing domain in general. A high percentage of the papers did not state specifically the technologies (32.87%) or data (35.42%) that were used for the DTs. In the 128 papers analyzed, 54 different technologies were identified that were used for DT development, but a large portion of those technologies were found only in one paper. These technologies were classified under the category 'one-time occurrence,' which constitutes 27.27% of the total papers. The most frequently used techniques were the finite element method (FEM) and neural networks, with 6.29% for both techniques. For neural networks, the most frequent forms were artificial and convolutional neural networks. Machine learning and CAD software follow closely with 5.59% and 4.90% respectively. The rest of the technologies were covered in less than 3% of the total papers. Although there were many different technologies used (54 in total), relatively few data types were used for developing the DTs; only 6.25% fell into the category 'one-time occurrence'. The most commonly used data was process and production data with almost identical percentages, 12.5%, and 11.81% respectively. Process data is a subset of production data. Production data contains more information about the production, not only data that concerns a specific process. The third type of data is 3D models with 9.72%, which is explained by the

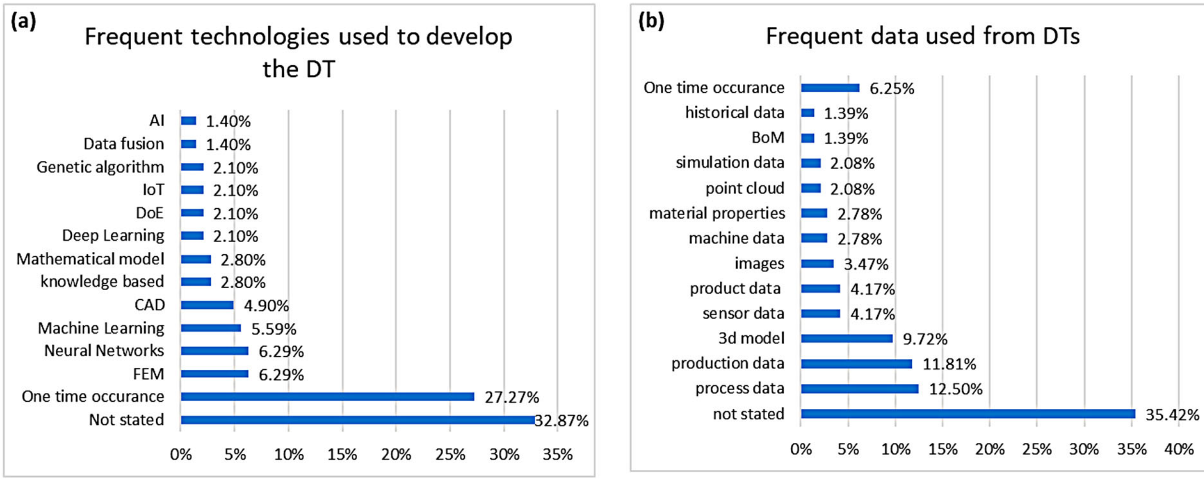

Figure 5. (a) most frequent technologies used for DT, (b) most frequent data used by the DTs.

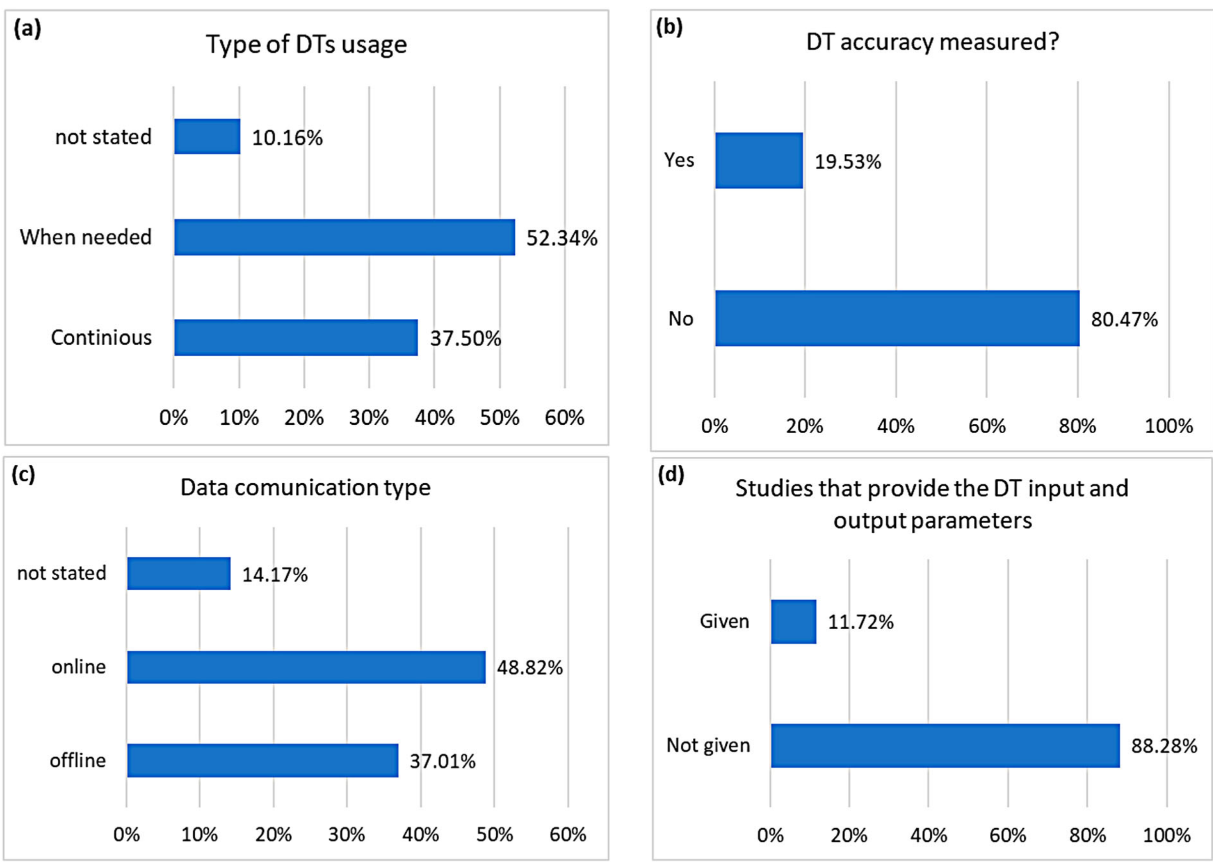

Figure 6. DT characteristics (a) type of DT usage, (b) accuracy measured?, (c) communication type, (d) given DT parameters.

technologies used (FEM and CAD). The rest of the data types are under 5% each.

Reviewing the 128 selected papers also yielded data about when DT was used. Figure 6(a) illustrates that in 52.34% of the analyzed papers, DTs were developed only when needed, while in 37.50% they were used continuously. An important aspect of DTs is their accuracy because this controls how efficient the DT will be; however, 80.47% of the analyzed papers did not measure the accuracy of their DTs. Moving forward to Figure 6(c), almost 50% of the DTs analyzed were developed to be online integrated into the production, meaning that they were automated, and data was fed into the DT automatically, whereas in offline DTs the data must be loaded manually. Finally, only 11.72% of the analyzed papers presented in detail the input and output parameters of their DTs. The rest of the papers, 88.28%, did not present explicitly which parameters were used as input and output.

4.4. DT literature shortcomings on DT development

From the literature analysis conducted and presented in the previous sub-sections (4.1, 4.2 and 4.3), it is evident that DT development does not follow a common structured methodology. This fact creates a great deal of confusion in the research and industrial communities because there is no common language. More importantly, it makes the re-use of DT models nearly impossible. Re-using existing DT models is essential for increasing the level of sustainability of manufacturing systems. Currently, it is very hard to compare different DT implementations because each DT model is developed in a different way and includes different information, and in most cases very little information is provided for the DT model. This can be observed in the very high percentages of papers classified in the 'not stated' and 'not given' categories in Figures 3–6. For example, 80.47% of the papers do not present the accuracy of the DT, making impossible to validate the performance of the DT method. Also, the input and output parameters in 88.28% of the analyzed papers were not given, making it impossible for the reader to understand how the corresponding DT works and therefore prohibiting the clear understanding and re-use of the DT method.

During the literature analysis, authors identified this lack of a standard approach for developing DT models and proposed a common structured approach for developing them (Section 5). There have been a few recent attempts to develop such design methodologies to much complex enterprise systems in the literature to support early phases of the digital twin development process Sandkuhl and Stirna 2020; Wang, Lee, and Angelica 2020c. Those studies propose methods applicable to only specific case studies and hence do not provide any unified method applicable to different industries and scenarios.

5. Proposal for a structured and unified design methodology for the development of DTs

The current section presents a common framework for the development of DTs by acting on the results from the detailed literature review. The goal is to move toward a more standardised way to develop DTs. The use of DTs is increasing as the technology becomes more mature, and standardisation of the development of DTs will ensure that all DTs developed are accompanied by the same information. This will help researchers, industrial actors, and users of DTs in general to evaluate DT implementations more easily.

Figure 7 illustrates the proposed design methodology for the development of DTs. The methodology is independent of the use case and therefore is meant to be used by all scientific and industrial communities. The information presented in the proposed design methodology might seem logical, but only 10.32% of the analyzed papers had all of the proposed information. In more detail, the first step is to define the purpose of the DT. For example, in the literature review conducted in Section 4, some of the top results were related to the DTs' final purpose – i.e. either product or process quality. Once this information is defined, then the actual design of the DT can be performed, starting with the most basic information that will control the rest of the steps: identifying which physical or virtual system, process, or system in general the DT will emulate. In many cases observed, this information is not clear or is mixed with other information, making it very difficult for the audience to truly understand a DT implementation. The next required information concerns when the DT is used – when needed, continuously, etc. Once this information is defined, the suitable application technologies can be identified, and a selection process should then take place to choose the most suitable technology for the specific use case.

A key characteristic of a DT is the parameters that are used as input and output. If we go back to the definition of what a DT is, it states that a DT is a digital representation of a system, and each system has numerous inputs and outputs. It is in the hands of the designers which they will select for their DT. The parameters should be set according to each use case in order not to increase the complexity of the DT without reason. Therefore, each DT development should be accompanied by a detailed list of input parameters. This will allow easy understanding of the DT by a broader audience and at the same time increase the re-usability of the DT in other use cases. By defining the input and output parameters at the same time, the required data for the DT is defined as well, which is a key factor in determining the sustainability of the DTs. Table 3 summarises all the information that must be defined for each DT application, with additional details and examples. The goal is that each DT is developed using the proposed design methodology and is accompanied by a table similar to Table 3 completed with the information related to the DT under development or developed.

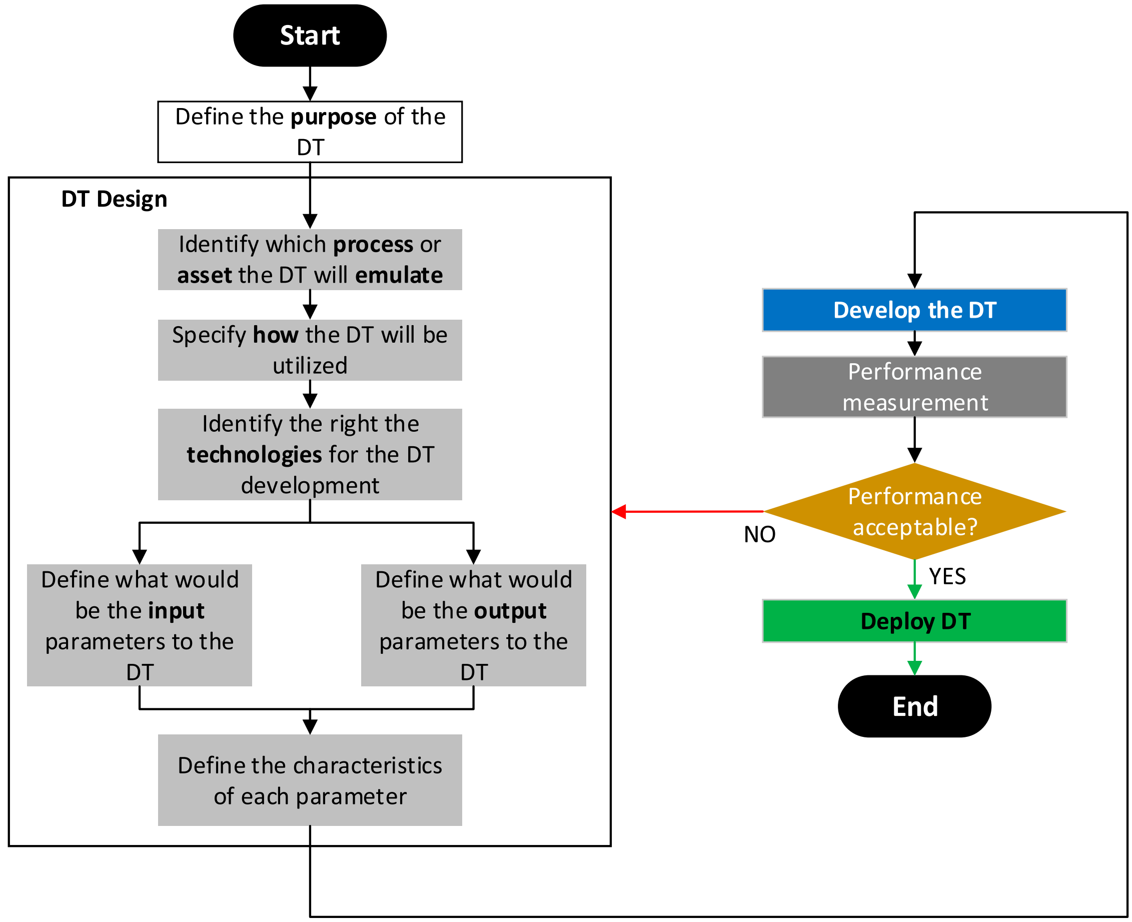

Figure 7. DT design methodology.

Table 3. Basic information required for DT development.

DT fundamental information before implementation	
Industry	For which industry will the DT be developed? In some cases, this might be important because some industries such as pharmaceutical, medical devices, aerospace, etc. have specific regulations that must be followed. There might be more than one industry to which the DT can be applied. Examples: automotive, composite materials, aerospace, etc.
Purpose of the DT	Define the global goal of the application. If DT will be a part of a bigger system, what is the global goal of the total system? Examples: product quality, process quality, product design, production control, etc.
Process or asset that the DT describes	Define which process or asset the DT will model. Examples: milling machine, the cutting process of a milling machine, scheduling tool, inspection process, defect detection, defect prediction, etc.
Type of use (continuously, when needed, both, etc.)	Define how the DT will be utilised over time. Two sub-parameters should be defined: Usage frequency (DT will be used continuously, DT will be used when it is needed, DT will operate on hybrid mode, etc.) Whether the DT will be dynamic or static (does the DT adapt to alterations of the initial conditions or not)
Technologies used for the DT	Define the technologies that will be utilised for the development of the DT. Examples: ML (specify which method), AI, design of experiments, knowledge-based, etc.
Input parameters	Define explicitly the input parameters of the DT. Define also the type of data that each parameter handles (e.g. single value, historical time series data, real-time data with the interval rate, etc.) For each input parameter, the following should be defined: Parameter name Units (if applicable) Type (single value, historical data, real-time data, etc.) Interval rate of new values (if applicable)
Output parameters	Define explicitly the output parameters of the DT. For each output parameter, the following should be defined: Parameter name Units (if applicable) Type (single value, historical data, real-time data, etc.) Interval rate of new values (if applicable)

6. Discussion

In this section, we present our discussions and insights based on our analysis of the literature on DTs for ZDM and critical examination of the results in Section 4. We classify these discussion points in three main topics: DT definition, DT design and development, and DT implementation and applications.

6.1. Discussions around DT definition

6.1.1. Scholars should increase their efforts to introduce and promote ZDM as a common terminology

In this paper, the authors defined in the results section a category titled 'partial ZDM' that needs further discussions and elaboration. This refers to research studies that consider part of ZDM principles – for instance, predicting defects in order to identify and trigger prevention mechanisms – but that do not mention ZDM. This may be because ZDM is a term that has only been widely used within the last five years, and there is still much work to be done by scholars to introduce and promote ZDM as a common terminology for all research works that utilise one of the ZDM strategies defined in Psarommatis et al. (2020a). This was one of the key points highlighted in the aforementioned paper by the authors.

6.1.2. A common definition of DT is missing in the mind of researchers and practitioners

Different researchers tend to call different concepts or implementations DT. Hence, the field could benefit from a common understanding and a universally accepted definition. The fact that there are several works that mention DTs in the title but do not cover any real applications concerning DTs for ZDM hinders valuable research on real and proper DT implementations. In that regard, the standardised design methodology developed in Section 5 of this paper could help researchers and practitioners to gain a better understanding of the essential elements to be considered for any DT implementation.

6.2. Discussions around DT design and development

6.2.1. There is no uniformity in the development of DTs for ZDM; a standardised design methodology is needed

Many factors such as target industry, the purpose of the DT, the process described by the DT, input-output parameters, the technical scope of the DT, the technologies used, the summarised method of creating the DT, the accuracy of the DT and its algorithms, and whether the DT is used continuously or when needed were not even mentioned in the majority of the papers analyzed. A guideline to direct researchers to better design and develop DTs is required. Moreover, although accuracy can be considered one of the most critical parameters for a DT, the majority of the research studies did not even measure accuracy. As a starting point toward these efforts, we developed a standardised design methodology for the development of DTs for ZDM applications that can also be generalised to other applications. The aim here is to introduce a standardised way to develop DTs, thus supporting practitioners in their development efforts and providing an easier way of evaluating DT implementations.

6.2.2. More detailed and technical research is required concerning the development of DTs for ZDM

Most papers analyzed in the literature review are generic and provide either architecture or conceptual ideas. The majority of the papers that claim to develop DTs include mostly frameworks but not real DT implementations. This non-conformity between the title, abstract, and real content of research studies becomes a major issue for research. To overcome this, more detailed and technical works on the topic are required. In addition, this research area could benefit from a better understanding of the difference between a framework for DT and a real DT developed for practical applications.

6.2.3. A proper method and Key Performance Indicators (KPIs) are needed to measure performance of DTs for ZDM applications

As highlighted previously, the majority of the studies as well as the current state of DTs lack a proper method and key performance indicators to evaluate DT performance. Although there are a few studies addressing KPIs and their roles for DTs (Mourtzis, Fotia, and Vlachou 2017; Tambare et al. 2021), these works are limited in their scope to facilitating better management and implementation of DTs. A better evaluation of performance through proper KPIs could help improve management of the effectiveness of DTs. However, most of the studies in the literature do not even measure the accuracy of the algorithms used for their implementation.

6.3. Discussions around DT implementation and applications

6.3.1. There has been a significant shift from traditional QIs to ZDM

Another observation in the Results section was that the percentage of studies that utilise traditional QI methods was on a significant decline, adding up to a very small portion of the total. This could be considered yet another sign that migration to ZDM is happening. ZDM strategies are more aligned with DT applications compared to traditional QI, and therefore ZDM is preferred over QI for the development of DTs. Furthermore, most studies do not have a structured approach to dealing with quality and using QI frameworks would be beneficial in the development of DTs.

6.3.2. There has been an effect of the COVID pandemic on ZDM research; the implementation of DTs is still in its infancy

As highlighted in Section 4.1 and Figure 1 in particular, the rate of increase in ZDM DT publications gradually grew from 2017 until 2021, reaching a peak in 2020. However, when we consider the first half of 2021, this growth stalls (i.e. compared to a 100% increase from 2019 to 2020, the number of papers in 2021 is expected to be very similar to that in 2020). One of the reasons for this sudden stop in the rate of increase in research concerning ZDM DTs could be the effect of the COVID pandemic on research in general. To make a better judgment of whether the topic reached its maturity level based on the number of research studies and the resulting number of publications, it will be necessary to compare publications in 2022 and 2023. Since the topic is yet in its infancy, we believe that the applications in this research area will continue to grow at an increasing rate.

6.3.3. Some technologically more advanced industries like aerospace and automotive are dominant among the research concerning the implementation of DTs for QI

Although there are several industries mentioned and covered in the literature about the implementation of DTs for ZDM, such as the machine tool, metal, semiconductor, and marine industries, the majority of research studies and practical implementations concern DT applications in the automotive and aerospace industries.

6.3.4. More consideration and discussions are needed on data availability, data security, data quality, and data integration when implementing DTs

The analyzed literature did not contain discussions or considerations of four critical data aspects of DT applications. Before implementing any DTs in any domain, including ZDM, it is crucial to ensure that the required data is collected and available, data security protocols are in place, bad data is excluded, and gaps in data streams are properly managed. However, the literature on the topic did not provide enough evidence of these considerations. Since these data aspects are key factors that affect industrial implementations, there should be more focus on optimising them to achieve more efficient and effective DTs for ZDM scenarios. Although some previous work discussed the issues of data sharing and security (Zhang et al. 2020b; Leng et al. 2020; Li, Zhou, and Zhang 2021), often these issues are not considered in DT design and development.

DTs lie within the concept of the virtual enterprise, which is gaining ground as digital technologies are growing exponentially; however, many challenges are arising and need to be considered. Many believe that data integration is one of the most important factors when dealing with digital technologies, which is the case for development of DTs because they rely entirely on data and digital technologies (Zhao, Xie, and Zhang 2002; Liu et al. 2008). In a manufacturing environment, there are numerous different sources and types of data – structured data, semi-structured data, and unstructured data – that are used for a variety of purposes. Currently, different companies collaborate in a variety of ways, which makes efficient data integration and data interoperability imperative. Furthermore, digital technologies can significantly improve the resilience and sustainability of global manufacturing systems (Yu et al. 2021). A key technology for supporting better data exploitation, data integration, knowledge extraction, and systems interoperability are ontologies, which are data models enriched with context (Ameri et al. 2022); a system of ontologies is referred to as a 'semantic framework.' Combining DT technology with ontologies creates a new type of DT called a 'cognitive twin,' which is an augmented version of the DT, as stated by many researchers (Zheng, Lu, and Kiritsis 2021; Rožanec et al. 2021).

7. Conclusions

In this paper, we analyzed the literature on digital twins for zero-defect manufacturing following a systematic method. Based on our detailed investigation of the content of the selected papers, we presented results of our critical state-of-the-art analysis, discussed the current state and limitations of research and practice, and provided insights on this important and complex topic. In addition, because our preliminary analysis indicated a lack of approaches and guidelines for standardising the implementation of DTs for ZDM, we developed and presented a methodology for standardising the design procedure that aims at structuring future designs and developments of DTs around considering and communicating all essential elements for any DT applications in this domain. We think this DT design procedure would be useful for both practitioners and researchers working on the topic of ZDM in their efforts to develop DT-based applications. Hence, this research work contributes to practice in the sense that the DT design procedure developed in Section 5 of this study as well as the useful insights provided in Section 6 concerning discussions around the topic based on the critical analysis of results will guide the way toward better and more structured future DT implementations in the ZDM domain. On the research side, our study contributes to knowledge by providing a comprehensive, systematic, and critical analysis of the literature on DTs for ZDM that offers a structured overview of the specific research area along with a standardisation approach that could be used by researchers in designing any further research works on the topic. In addition, the research also contributed to knowledge with the answers to some fundamental questions in the context of DTs for ZDM.

Furthermore, key considerations have been derived and discussed. First, one of the main findings pinpointed a lack of uniformity in the development of DTs for ZDM; to address this lack, we designed and presented a methodology for standardising the design of DTs in Section 5. Another discussion point focused on the effect of the COVID pandemic on ZDM research and the maturity of DT implementations in the ZDM domain, which were found to still be in their infancy. The state of different industries was also discussed, including the dominant ones in DT research such as automotive and aerospace; the sectors with as-yet unexploited potential such as the semiconductor, machine tool, metal industry, and marine sectors; and finally, the industries lagging behind such as pharma, medical, oil and gas, and packaging, among others. We also suggested that researchers devote more attention to promoting ZDM as common terminology. The shift from traditional QIs to ZDM has also been highlighted with numbers and further discussions. Other suggestions for further developments and research in the area include gathering all actors around a common definition of ZDM; development of novel performance measurement methods specific to DTs for ZDM applications; and exploring the critical areas of data availability, data security, and data quality for implementing DTs.

Disclosure statement

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Data availability statement

Data available within the article. The authors confirm that the data supporting the findings of this study are available within the article.

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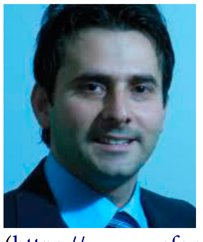

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